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Joydebpur, Gazipur-1701

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PREFACE

The principal objective of irrigation and water management research is to determine how best the water resources, be it from underground, surface or rainfall can be utilized for crop production and how to minimize the harmful effect of this water. This inevitably demands research on how to exploit available sources of water, convey and distribute them to farms and apply the same to the individual crop field. The next important aim is to increase the crop water use efficiency in order to obtain maximum production per unit drop of water thereby increasing economic return and improving livelihood of the farmers. To achieve this goal, research need to be conducted on when and how much water should be applied, and when irrigation is not necessary at all.

The general objectives of the division are to conduct research on: a) proper irrigation scheduling and rain water management of the upland crops and drainage thereof, b) finding appropriate technologies for conveyance, distribution, application and utilization of water resources for crop production, c) assessment of ground water reserves and its development for agricultural use, d) water management in saline and drought prone areas e) wastewater management f) micro irrigation, and g) impact of climate change on irrigated agriculture.

There are great potentialities that need to be developed in the management of ground and surface water resources. In many crops improved irrigation system has the potential to double the production. Rice crop, on average, require 1000 mm of water for the growing season whereas most upland crops require 200 to 500 mm water when applied efficiently. All these indicate that there remains tremendous possibility of increasing crop production by bringing more upland crops under irrigation and by properly controlling and managing the available water resources.

The task requires, amidst others, research in larger scale and in diversified crops. However, the division has got a very limited number of scientists and facilities to address the aforementioned research problems. With this manpower and facilities, we are trying our best to the benefit of our agricultural concerns.

Research and development activities of Irrigation and Water Management Division are directed towards the economic development of the country. The division is working to help the nation becoming self-sufficient in food, to generate employment in agriculture and to increase income of farmers through the development of appropriate water management practices and techniques widely acceptable to all categories of farmers. This report presents the findings of both on-station and on-farm studies conducted during 2018-19. This year, the division carried out researches in the areas of crop water requirement and irrigation scheduling, water application and distribution methods, on-farm water management, saline and wastewater management, groundwater management and dissemination of developed water saving technologies at the farmer's level and improvement of farmers' traditional irrigation practices.

Finally, I like to express my sincere thanks to the scientists/staffs concerned with these studies and to all who helped in bringing out this report.

Dr. Md. Anower Hossain
Chief Scientific Officer (in-charge) and Head

CONTENTS

Research Achievement 2019-2020

Name of the Technology	**Main Features of the Technology**	**How Country/ Farmer/User Will be Benefited**
Crop Production in Saline areas by Drip Irrigation and Mulching  	• Drip irrigation in raised bed with mulch is an integrated way to reduce soil salinity substantially (from 10 dS/m to 4.5 dS/m) to make soil environment favorable for crop growth. • The crops are planted maintaining the recommended spacing on 30 cm raised bed. Then straw or polyethylene mulch is applied after plant establishment. • Irrigation is applied through drip system at 2 – 3 days interval for 15 to 25 minutes depending on crop and soil types, crop stages and crop evapotranspiration. • In this technique, crops can be grown in comparatively high saline soils.	• Farmers can be benefited by growing high value crops with higher crop and water productivity. • More lands can be brought under cultivation of horticultural crop in coastal areas. • The higher productivity of crops will help increasing income generation (35 to 60%) and enhancing livelihood of the coastal farmers.

OPTIMIZE FERTIGATION MANAGEMENT TO MINIMIZE NITRATE LEACHING FROM DRIP IRRIGATED BRINJAL FIELD

D.K. Roy[1], S.K. Biswas[1], K.F.I. Murad[2] and K.K. Sarker[3]

Abstract

This research was carried out in the research field of Irrigation and water Management Division (IWM) of Bangladesh Agricultural Research Institute (BARI), Gazipur during 2019-2020 to optimize fertigation management for minimizing nitrate leaching from drip irrigated brinjal field. BARI Bt. Brinjal 4 cultivar was used for the experiment. There were four different irrigation treatments comprising two levels of irrigation intervals and two irrigation timings [Drip irrigation at 4-day interval with fertigation at the beginning of the irrigation cycle (T_1), Drip irrigation at 3-day interval with fertigation at the beginning of the irrigation cycle (T_2), Drip irrigation at 4-day interval with fertigation at the end of the irrigation cycle (T_3), and Drip irrigation at 3-day interval with fertigation at the end of the irrigation cycle (T_4)]. It was observed that yield and yield contributing characters varied significantly among the irrigation treatments. It was also observed that treatment T_4 received the highest amount of irrigation (270 mm) followed by the treatments T_2 (260 mm), T_3 (202 mm), and T_1 (195 mm). Results of modelling for optimizing fertigation management is not presented in this report due to unavailability of complete data set for modelling at this stage of the study.

Introduction

Groundwater pollution from use of nitrogenous fertilizer in intensive agriculture is becoming one of the major concerns in recent years. Appropriate management of nutrient and water in agricultural activities is the key to minimizing groundwater pollution and maximizing crop productivity (Abdelkhalik et al., 2019; Ajdary et al., 2007; Azad et al., 2018). Optimized management practices aiming at reducing the amount of water and nitrogen application without compromising with the yield reduction are able to reduce the extent of groundwater pollution through nitrate leaching (Shrestha et al., 2010). Based on the crop nitrogen requirement, this management strategy should incorporate soil moisture regulation for nitrate transport as well as managing the amount and timing of application of nitrogen fertilizers (Shrestha et al., 2010). Drip fertigation is a promising irrigation technology, which improves water and nutrient use efficiency to enhance crop productivity. If designed and managed properly, drip fertigation is likely to maximize nutrients uptake by plants and minimize water and solute losses beyond the root zone of the plants. However, optimization strategy of fertigation management plays an important role in the implementation of drip fertigation to obtain better crop yields and reduced soil and groundwater contamination. Therefore, the main objective of this study is to develop a drip fertigation management strategy that includes supplying adequate nitrogen to brinjal crop, minimizing nitrate leaching to groundwater, and avoiding nitrogen accumulation in the soil at the end of the crop growing season.

Development of any management strategy requires evaluation of several scenarios through optimization approach. These scenarios are very difficult, if not impossible to obtain from the field experimental setup. A simulation model is often employed to generate different scenarios using a particular set of data obtained from the field. Many simulation models have been implemented to simulate water flow and solute transport in soil, among which HYDRUS-1D and HYDRUS (2D/3D) (Simunek et al. 2011) has been extensively used because of its ability to incorporate root distribution as well as water and nutrient uptake by the crop. Present study intended to utilize HYDRUS (2D/3D) simulation to generate various scenarios of drip fertigation management and

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the corresponding nitrate concentration within and beyond the root zone. Therefore, the objective of this study was to optimize drip fertigation management to minimize nitrate leaching.

Materials and Methods

The field experiment was conducted during the rabi season of 2019-2020, between the months of December and April, in the research field of Irrigation and Water Management Division (IWM), Bangladesh Agricultural Research Institute (BARI), Gazipur. The experimental field was located between 24.00^o N latitude and 90.25^{o}E longitude with an altitude of 8.40 m above MSL. The sand, silt and clay proportions of the soil in the experimental field were 36.5, 35.4 and 28.1, respectively. Top 30 cm of the soil layer had a field capacity, wilting point and bulk density values of 28.5%, 13.72% and 1.46 g cm^{-3}, respectively. The nutrient content of the experimental soil in the form of N, P_2O_5 and K_2O were 51.1, 12.5 and 265.6 kg ha^{-1}, respectively while the organic matter content of the top soil was recorded as 1.04%.

BARI Bt. Brinjal 4 cultivar was used for the study. The experiment was laid out in a randomized complete block design with four drip fertigation treatments replicated thrice. The treatments were as follows:

T_1 = Drip irrigation at 4-day interval with fertigation at the beginning of the irrigation cycle
T_2 = Drip irrigation at 3-day interval with fertigation at the beginning of the irrigation cycle
T_3 = Drip irrigation at 4-day interval with fertigation at the end of the irrigation cycle
T_4 = Drip irrigation at 3-day interval with fertigation at the end of the irrigation cycle

The unit plot size was 5 m × 4 m. The experimental blocks were separated by 2 m and the plots within each block were separated by 1 m wide buffer strips in order to prevent lateral seepage of applied irrigation water into the adjacent plots. Brinjal plants of 28 days old were transplanted on 08 December 2019 with a plant spacing of 100 × 75 cm. Farm yard manure at the rate of 10 t ha^{-1} was properly mixed with the soil during the land preparation. Fertilizers were applied at the rate of 375 kg N, 250 kg P, 250 kg K, and 100 kg gypsum per hectare. Half of the nitrogen and phosphorus, and the full doses of potassium and gypsum were applied during the land preparation while the remaining half of the nitrogen and phosphorus was applied with drip fertigation. The fertilizers were applied for a duration of 10 minutes within the few minutes of the start of the irrigation event (fertigation at the beginning of the irrigation cycle), and the irrigation process was continued to its desired level after the fertigation event. On the other hand, for fertigation at the end of the irrigation cycle, the fertigation was performed for 10 minutes at the later part of the irrigation duration, and just after the completion of fertigation the irrigation process was continued to its entire duration to avoid emitter clogging.

Estimation of irrigation water

The irrigation water was applied to bring the soil moisture at field capacity considering effective root zone depth. Soil moisture was determined before each irrigation by gravimetric method. Irrigation was applied up to the field capacity of the soil. Measured amount of water was applied to all treatments in ring basin method.
The normal depth of water needed to apply was determined using the following equation:

$$d = \frac{FC - MC_i}{100} \times A_s \times D \quad (1)$$

where, d = depth of irrigation, mm; FC = field capacity of the soil, %; MC_i = moisture content of the soil at the time of irrigation, %; A_s = apparent specific gravity of the soil; D = root zone depth, mm.

Rainfall data were collected from the weather station, Joydebpur, Gazipur. Effective rainfall was calculated on daily basis during the growing period.

Water Productivity Index (WPI)

Water productivity index was calculated using the following equation:

$$WPI = Y/q \quad (2)$$

where, WPI = Water Productivity Index, kg/m^3; Y = the yield (kg/ha) for the season in the specific area; q = total supply of water including effective rainfall per ha for the season in the specific area, m^3/ha.

Statistical analysis

Statistical analysis was carried out to obtain the variance for different parameters. Treatment effects were analyzed by a one-way ANOVA using statistical toolbox of MATLAB.

Results and Discussion

Yield and yield contributing characters of brinjal during 2019-2020 growing season were analyzed statistically, and are presented in Table-1. It is observed from Table-1 that irrigation treatments had significant effects on all the yield and yield contributing characters of brinjal. The highest marketable yield was obtained from treatment T_4 (32.91 t/ha) followed by the treatments T_2 (32.64 t/ha), T_3 (31.84 t/ha), and T_1 (31.29 t/ha).

Table-1. Yield and yield contributing characters of brinjal during 2019-2020 growing season

Treatments	Length of fruit, cm	Diameter of fruit, cm	Unit weight of fruit, g	Cull yield, t/ha	Marketable yield, t/ha
T_1	7.92	6.45	425	8.71	31.29
T_2	8.54	7.25	450	7.36	32.64
T_3	8.01	5.92	432	8.16	31.84
T_4	8.85	7.93	438	7.09	32.91
F	6.74	27.35	141.14	17.18	47.08
Prob.>F	0.014	0.0001	2.88×10^{-7}	0.0008	1.98×10^{-5}

Multiple comparison tests were performed to determine which treatments were different than the others in terms of yield and yield attributing characters of brinjal. Multiple comparison test for the treatments in terms of the length of fruit of brinjal is presented in Figure 1.

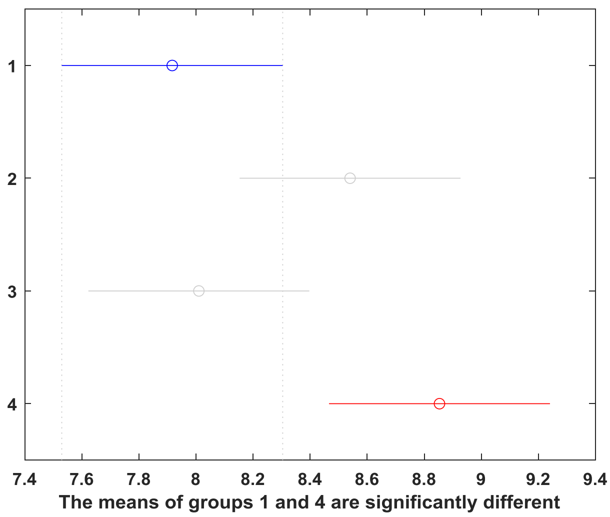

Figure 1. Multiple comparison test for the treatments in terms of the length of fruit

The multiple comparison test suggested that the means of groups 1 and 4 were significantly different; no groups had means significantly different from group 2; the means of groups 3 and 4 were significantly different; and two groups (group 1 and group 3) had means significantly different from group 4. For the diameter of fruit, the multiple comparison test for different treatments (presented in Figure 2) revealed that two groups (group 2 and 4) had means significantly different from group 1; two groups (group 1 and 3) had means significantly different from group 2; two groups (group 2 and 4) had means significantly different from group 3; and two groups (group 1 and 3) had means significantly different from group 4.

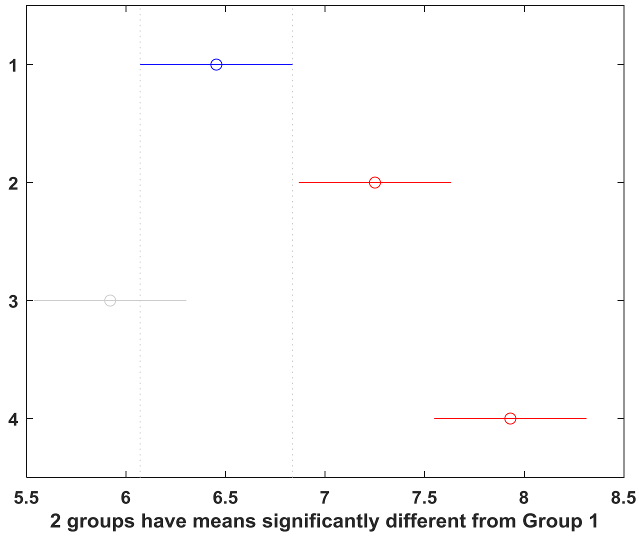

Figure 2. Multiple comparison test for the treatments in terms of the diameter of fruit

Multiple comparison test for the treatments in terms of the unit weight of fruit of brinjal is presented in Figure 3, which suggested that three groups (groups 2, 3, 4) had means significantly different from group 1; three groups (groups 1, 3, 4) had means significantly different from group 2; three groups (groups 1, 2, 4) had means significantly different from group 3; and three groups (groups 1, 2, 3) had means significantly different from group 4.

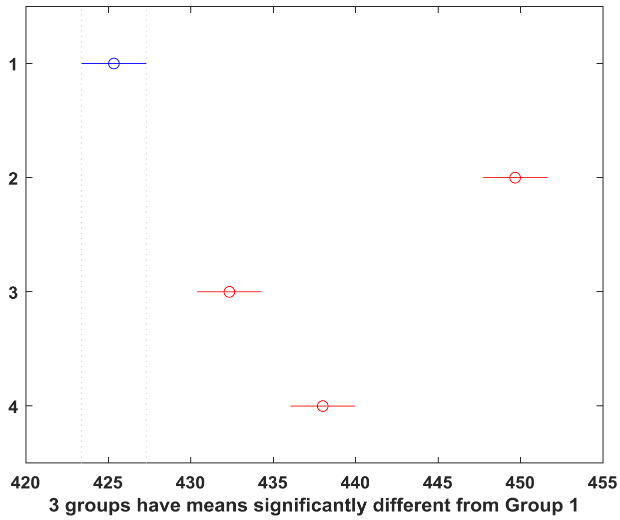

Figure 3. Multiple comparison test for the treatments in terms of the unit weight of fruit

Treatment variations for the marketable yield obtained from the multiple comparison test are presented in Figure 4. It is observed from Figure 4 that two groups (groups 2 and 4) had means significantly different from group 1; the means of groups 2 and 1 were significantly different; the means of groups 3 and 4 were significantly different; two groups (groups 1 and 3) had means significantly different from group 4.

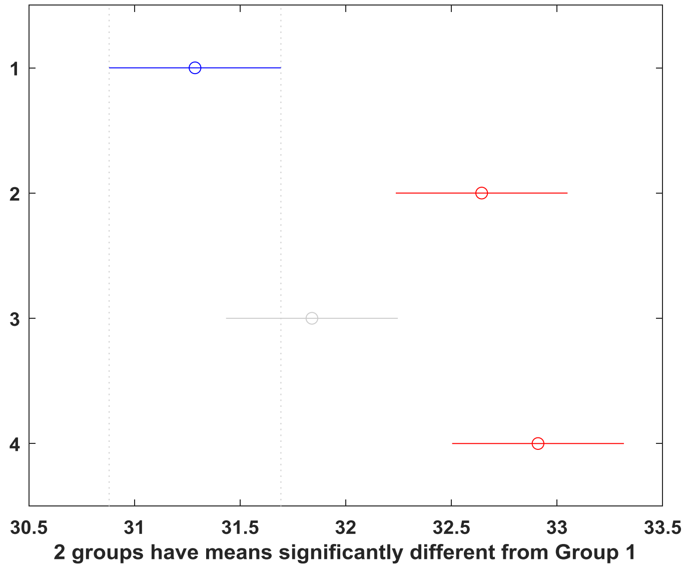

Figure 4. Multiple comparison test for the treatments in terms of marketable yield

Multiple comparison test for the treatments in terms of the cull yield of brinjal is presented in Figure 5, which suggested that three groups (groups 1, 2, 3) had means significantly different from group 1; two groups (groups 1 and 3) had means significantly different from group 2; three groups (groups 1, 2, 4) had means significantly different from group 3; and two groups (groups 1 and 3) had means significantly different from group 4.

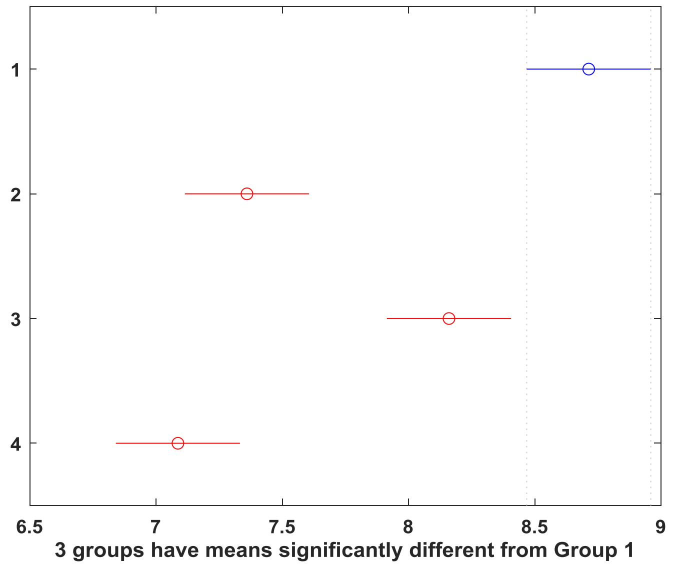

Figure 5. Multiple comparison test for the treatments in terms of cull yield

Seasonal water use and water productivity

Treatments T_1 and T_3 received 23 numbers of irrigation events whereas treatments T_2 and T_4 received a total number of 31 irrigations. The irrigation events were accomplished based on the design of the experiment. Treatment T_4 received highest amount of irrigation (270 mm) followed by the treatments T_2, T_3, and T_1. Effective irrigation for the crop growing period was calculated as 223 mm (80% of total rainfall). Water used by the plants in different treatments during growing season is shown in Table-2.

Table-2 Water use and water productivity of brinjal in different treatments

Treatments	Amount of irrigation water, mm	Effective rainfall, mm	Soil water contribution, mm	Seasonal water use, mm	Yield, t/ha	Water productivity, kg/m^3
T_1	195	223	18.92	436.92	31.29	7.16
T_2	260	223	12.55	495.55	32.64	6.59
T_3	202	223	24.33	449.33	31.84	7.09
T_4	270	223	28.18	521.18	32.91	6.31

Conclusion

The data required for modelling of nitrate leaching were not available at the time of this reporting. Therefore, the results of the modelling study could not be presented in this report. Since the experimental results are incomplete and partial findings are presented in this report, a definite conclusion is not possible to make at this stage. Therefore, further study is required to be cinducted.

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DAILY AND MULTI-STEP AHEAD FORECASTING OF POTENTIAL EVAPOTRANSPIRATION USING MACHINE LEARNING ALGORITHMS WITH LIMITED CLIMATIC DATA

D.K. Roy[1], S.K. Biswas[1], and M.A. Hossain[2]

Abstract

Accurate prediction of potential evapotranspiration (ET_0) is essential for efficient planning and management of limited water resources through judicial irrigation scheduling. The FAO-56 Penman-Monteith approach to ET_0 estimation was adopted to compute ET_0 from data obtained during the period 2004–2019 from a weather station located in Gazipur Sadar Upazilla, Bangladesh. These meteorological variables (e.g., daily maximum and minimum temperatures, wind speed, relative humidity and sunshine duration) and computed ET_0 values were used as inputs and outputs, respectively, for modelling daily and one-step ahead ET_0 predictions. For modelling, this study evaluates the prediction accuracy and estimation capability of two deep learning algorithms, a Long-Short Term Memory (LSTM) network and a bi-directional LSTM (Bi-LSTM) network. The prediction accuracy of LSTM and Bi-LSTM networks is compared with six commonly used machine learning algorithms, i.e. Adaptive Neuro Fuzzy Inference System (ANFIS), Gaussian Process Regression (GPR), M5 Model Tree, Multivariate Adaptive Regression Spline (MARS), Probabilistic Linear Regression (PLR), and Support Vector Machine Regression (SVR). Ranking of the prediction models was performed using weights calculated by Shannon's Entropy that accounts for a set of benefit (higher values indicate better model performance) and cost (smaller values indicate better model performance) performance indices. Results revealed that the LSTM model was found to be the best performer followed by Bi-LSTM, GPR, SVR, MARS (piecewise-linear), ANFIS, MARS (piecewise-cubic), M5 Model Tree, and PLR models. In the next stage, a one-step ahead prediction of ET_0 values was conducted using only the past values of ET_0 time series. Four modelling approaches (LSTM, Bi-LSTM, sequence-to-sequence regression LSTM network (SSR-LSTM) and ANFIS) were used for one-step ahead ET_0 predictions. Partial Auto Correlation Functions were used to obtain the time-lagged information from the ET_0 time series, and to determine the input and output variables for the LSTM, Bi-LSTM, and ANFIS models. On the other hand, in SSR-LSTM the responses are the training sequences with values shifted by one time-step. That is, at each time step of the input sequence, the LSTM network learns to predict the value of the next time step. Results of this modelling work revealed the superiority of Bi-LSTM followed by SSR-LSTM, ANFIS, and LSTM models identified by the ranking values computed using Shannon's Entropy. The overall results indicate that the deep learning approaches especially LSTM and Bi-LSTM models could be successfully employed to predict daily and one-step ahead ET_0 values, respectively.

Introduction

Agriculture is considered to be the largest consumer of global freshwater reserves. Therefore, a careful and judicious management of irrigation practices would allow significant water savings. To achieve this water saving, an accurate estimation of the evapotranspiration (ET) is required, which is regarded as one of the major components of water balance. ET plays an important role in surface energy and water budgets, and is an important parameter in the interactions between vegetation, soil, and the atmosphere (Liu et al., 2013). Accordingly, proper management of water resources in irrigated agriculture is largely dependent on an accurate estimation of this vital component of the hydrologic cycle. In general, precise quantification of ET aids in the design and management of efficient irrigation systems, simulation of crop yields, determination of the hydrologic water

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balance, along with the planning and allocation of water resources (Kisi, 2016). ET can be measured directly by experimental techniques such as the Bowen ratio energy balance method, lysimeter approaches, or eddy covariance systems (Kool et al., 2014; Martí et al., 2015; Zhang et al., 2013) or estimated by computing potential or reference evapotranspiration (ET_0) from meteorological variables. As direct methods of ET measurement are costly, complex and largely unavailable in many regions (Allen et al., 1998; Ding et al., 2013), indirect methods based on ET_0 estimation have become popular in many regions where direct experimental techniques are not available. The FAO-56 Penman-Monteith (FAO-56 PM) model is recommended by the United Nations' Food and Agriculture Organization (FAO) as the standard reference method for estimating ET_0 and validating other methods (Allen et al., 1998). The FAO-56 PM method having been recognized as a universal approach to ET_0 estimation, this method can be used in a wide range of environmental and climatic conditions without the requirement of any local calibration. This well-established method has been validated using lysimeters under a range of different climatic conditions (Landeras et al., 2008). Since ET_0 is solely affected by meteorological conditions, it can be calculated using the FAO-56 PM method by drawing upon several meteorological variables (e.g., relative humidity, wind speed, solar radiation, and minimum/maximum air temperatures. Once the ET_0 is estimated, the actual evapotranspiration (ET_a) can be calculated by means of the ET_0 and crop coefficients.

In recent years, Artificial Intelligence (AI) models have been successfully applied to the modelling of ET_0 in different hydrologic regions. Artificial Neural Networks (ANN) were the first AI models implemented to estimate ET_0 (Kumar et al., 2002). Other applications of AI models in estimating ET_0 includes the use of Random Forests (RF) (Feng et al., 2017a; Huang et al., 2019), Generalized Regression Neural Networks (GRNN) (Feng et al., 2017a, 2017b), Extreme Learning Machine (ELM) (Abdullah et al., 2015; Dou and Yang, 2018; Feng et al., 2017b, 2016), Support Vector Machine (SVM) (Ferreira et al., 2019; Huang et al., 2019; Tabari et al., 2012), Genetic Programming (GP) (Gocić et al., 2015), Gaussian Process Regression (GPR) (Karbasi, 2018), Multivariate Adaptive Regression Splines (MARS) (Kisi, 2016), M5 Model Tree (M5Tree) (Kisi, 2016), Multivariate Relevance Vector Machine (MVRVM) (Torres et al., 2011), Gene-Expression Programming (GEP) (Gavili et al., 2018; Shiri et al., 2014b, 2012, Wang et al., 2019, 2016), and Adaptive Neuro Fuzzy Inference System (ANFIS) (Doğan, 2009; Dou and Yang, 2018; Gavili et al., 2018; Shiri et al., 2013; Tabari et al., 2012).

Deep learning (DL) has recently been recognized as a developed and sophisticated sub-domain of machine learning techniques in the arena of artificial intelligence. The DL-based modelling has gained popularity in the successful application to various domain of science including language processing (Plappert et al., 2018), image classification (Fan et al., 2019), computer vision (Fang et al., 2019), speech recognition (Cummins et al., 2018), and time series prediction (Tien Bui et al., 2020; Xu et al., 2019; Yang and Chen, 2019). The usage of DL has also been observed in developing prediction models in the research niche of groundwater level forecasting (Bowes et al., 2019; Supreetha et al., 2020), and prediction of short-term water quality variable (Barzegar et al., 2020). Recurrent Neural Network (RNN) models are able to preserve a memory of previous network states, and are better suited for predicting groundwater levels through modelling time series of groundwater table data observed at an observation well. For this reason, numerous recent studies related to groundwater modelling (Chang et al., 2016; Daliakopoulos et al., 2005; Guzman et al., 2017) have focused on the successful application of the RNNs. However, the standard RNN architectures cannot properly grab hold of the long-term reliance between variables (Bengio et al., 1994) due mainly to the occurrences of two problems: vanishing and exploding gradients. These are situations where the network weights either reach to zero or turn out to be enormously large during training of the network.

Long Short-Term Memory (LSTM) networks, a variant of typical RNN architectures, is capable of overcoming the training drawbacks (vanishing and exploding gradient problems) of RNNs through retaining valuable information for model development while avoiding unnecessary or redundant information being passed to the subsequent states in the model development process. LSTM has successfully been applied to the research arena of natural language processing, and financial time series prediction (Fischer and Krauss, 2018), traffic congestion and travelling period predictions (Zhao et al., 2017). In spite of wide applicability in various research domains, LSTM models has only recently been utilized for the forecast of hydrologic time series (Hu et al., 2018; Liang et al., 2018; Tian et al., 2018; Zhang et al., 2018). Recently, Jeong et al., (2020) applied LSTM-based modelling to estimate groundwater level using the corrupted data (with outliers and noise) and found that robust training of an LSTM model using a developed cost function ("least trimmed squares with asymmetric weighting and the Whittaker smoother") can adequately model noisy groundwater level data. The prediction ability of an LSTM network was found superior than that of a RNN in predicting hourly groundwater level values in a coastal city (susceptible to periodic flooding) of Norfolk, Virginia, USA (Bowes et al., 2019). Mouatadid et al., (2019) used a coupled "maximum overlap discrete wavelet transformation" and LSTM for achieving precision and robustness in the forecasting of irrigation flow. Zhang et al., (2018) proposed an LSTM network for predicting depths in water table in agrarian areas and obtained an acceptable prediction result by utilizing simply an uncomplicated data pre-processing technique. Based on their findings, one can argue that an LSTM network does not require a massive data smoothing or pre-processing in producing an acceptable prediction accuracy. The integrated use of Gated Recurrent Unit and Convolutional Neural Network (CNN-GRU) can also be found in recent literature (Pan et al., 2020) for developing water level prediction models in which CNN-GRU outperformed an LSTM model with regard to Nash-Sutcliffe (NS) Efficiency Coefficient, Average Relative Error, and Root Mean Squared Error. The prediction accuracy of a lion algorithm optimized LSTM network was found superior than an ordinary LSTM network for the prediction of groundwater level using the historical groundwater level data obtained from an observation well and rainfall data collected from a weather station located in the Udupi district, India (Supreetha et al., 2020). To the best of the author's understanding, an LSTM network has not previously been used to predict daily and multi-step ahead ET_0 predictions especially in the Gazipur district of Bangladesh.

The key motivation and focus of this study were to: (1) delve into the potential of a DL-based prediction model, LSTM in predicting daily and one-step ahead ET_0 predictions using data obtained from a weather station located in Gazipur Sadar Upazilla; (2) weigh against the prediction capability of the developed LSTM models with that of the commonly used machine learning algorithms; and (3) provide a ranking of the developed modelling approaches using Shannon's Entropy based decision theory. To the best of the authors' understanding, this is the first time a combination of several deep and shallow machine learning algorithms is employed for predicting daily and one-step ahead ET_0 predictions.

Materials and Methods

Study area and the data

The study area is situated in the Gazipur Sadar Upazilla having an aerial extent of 446.38 km^2. It is located between 23.88°N and 24.18°N latitudes and between 90.33°E and 92.50°E longitudes. Meteorological data including daily maximum and minimum temperatures, wind speed, relative humidity and sunshine duration) for a period of 15.5 years (1 January 2004 to 30 June 2019) were obtained from a weather station located in the Gazipur Sadar upazilla (lat. 24.00°N, long. 90.43°E, elevation of 8.4 m above mean sea level) of Gazipur District, Bangladesh. The study area receives an average annual rainfall of 2036 mm, of which roughly 80% occurs during the monsoon season (May to August). In general, the study area has a subtropical climate, with heavier rainfall events in the summer and lighter rainfall events in winter. Descriptive statistics of the input variables are presented in Table-1. The mean values of minimum and maximum temperatures range between 21.2 °C and 30.9 °C, while the mean relative humidity across the year is approximately 80%. The wind speed in the study area ranges between 59 km/d and 437 km/d with a mean value of 242 km/d and a standard deviation of 90.69 km/d. The sunshine duration peaks at 11 h on a sunny day, while its minimum value is 0 on a cloudy day with the mean and standard deviations of 5.54 h and 3.09 h, respectively. All meteorological variables showed negative (left) skewness (Table-1), indicating the data have a longer left tail than right tail in their distribution. The kurtosis values of maximum temperature and relative humidity showed positive values indicating these datasets had "heavy tails" or outliers. The negative kurtosis values of minimum temperatures, wind speed, and sunshine durations indicate "light-tailed" distributions of these variables.

Table-1. Statistics of meteorological variables acquired from a weather station in Gazipur Sadar Upazilla, Bangladesh

Variables	Min	Max	Mean	Standard deviation	Skewness	Kurtosis
Minimum temperature, °C	4.40	14.50	21.17	5.64	-0.63	-0.88
Maximum temperature, °C	12.00	38.00	30.93	3.92	-1.10	2.11
Relative humidity, %	38.00	89.00	80.22	8.20	-0.63	0.75
Wind speed, km/d	59.00	437.00	241.15	90.69	-0.06	-1.32
Sunshine duration, h	0.00	11.40	5.54	3.09	-0.40	-1.04

The study area with the location of the weather station is presented in Figure 1.

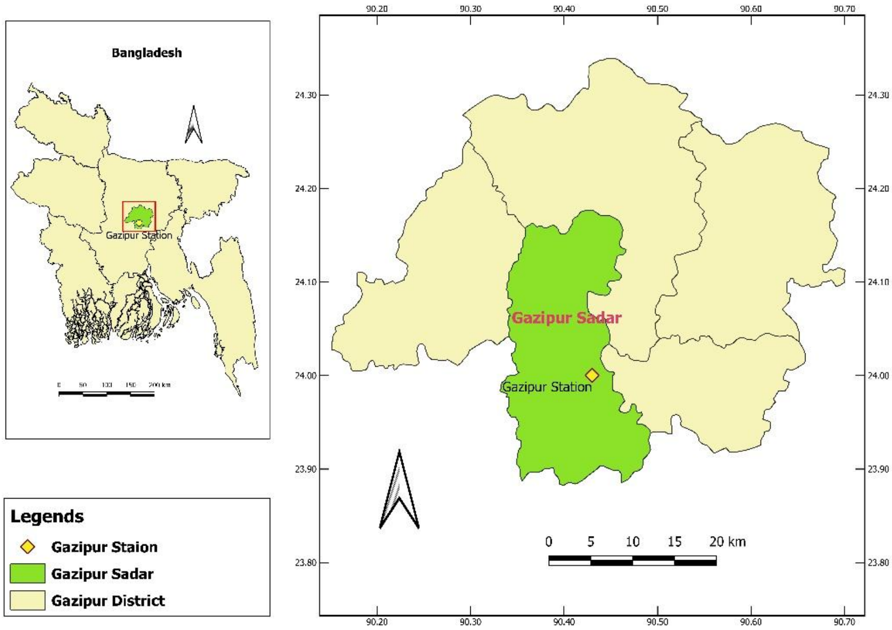


Figure 1. Map of the study area.

The ET_0 values for the study area across the study period were computed from the climatic variables using the FAO-56 PM model. These computed ET_0 values were used as target variables for the developed LSTM and other machine learning based models. This method is widely accepted and has become a common practice in situations where ET_0 values are difficult to obtain experimentally (Allen et al., 1998; Feng et al., 2017b; Shiri et al., 2014a). The FAO-56 PM model is given as:

$$\mathrm{ET}_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_{\mathrm{mean}} + 273} u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

where, ET_0 is the reference evapotranspiration, mm/d; R_n is the net radiation at the crop surface, MJ/m^2/d is the heat flux density of soil, MJ/m^2/d ; Δ is the slope of the saturation vapor pressure curve, kPa/°C; γ is the psychometric constant; e_s is saturation vapor pressure, kPa; e_a is the actual vapor pressure, kPa; u_2 is the wind speed at a height of 2 m, m/s; and T_{mean} is the mean air temperature at 2.0 m height, °C.

Computed ET_0 values range between 0.92 mm/d and 8.02 mm/d with a mean and standard deviation of 3.80 mm/d and 1.32 mm/d, respectively. Moreover, the skewness and kurtosis values varied between 0.30 and -0.67. The climatic variables and the computed ET_0 constituted the input-output training patterns for the machine learning algorithms. The resulting time-series of ET_0 values are presented in Figure 2.

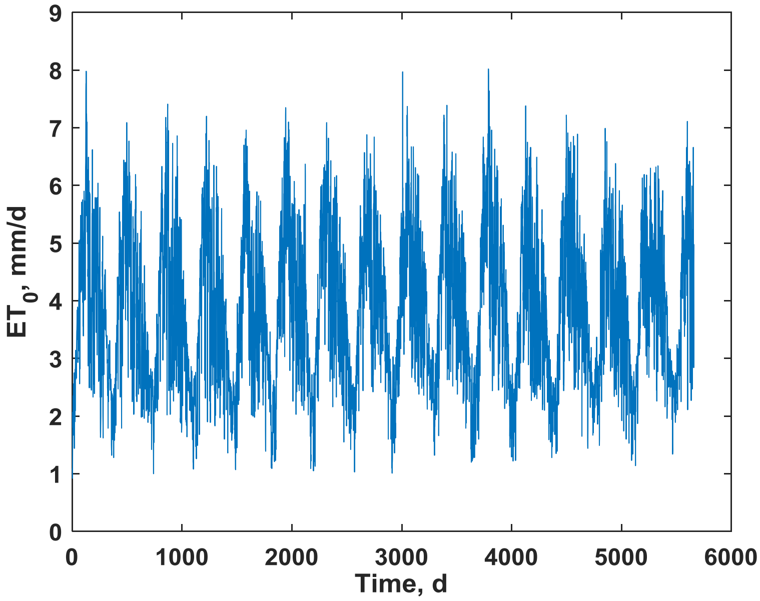


Figure 2. ET_0 time series.

The dataset contains 5660 daily entries (from 01 January 2004 to 30 June 2019) of meteorological variables and computed ET_0 values. The entire dataset was divided into training and test sets: 80% of the total samples (4528 entries – from 01 January 2004 to 24 May 2016) was used to train the models whereas the remaining 20% (1132 entries – from 25 May 2016 to 30 June 2019) was used to test the developed models. The performance evaluation indices calculated and presented in this study was based on the test dataset.

Standardization of input variables

To eliminate the adverse influence of dimensionality of the data, standardization was performed using the *Z*-Score method (Mathworks, 2019b) in order to scale the data with zero mean and unity standard deviation. For a random variable X with mean μ and standard deviation σ, the z-score of a particular value of x is given by:

$$z = \frac{(x - \mu)}{\sigma} \tag{2}$$

The z-score of a data point x for the sample data with mean $\bar{X}$ and standard deviation S can be represented by:

$$z = \frac{(x - \bar{X})}{S} \tag{3}$$

The z-score values quantify the distance of a certain data point from the mean in regard to the standard deviation of the dataset. The standardized data thus obtained has the mean value (μ) of 0 and the standard deviation (σ) value of 1. It is also noted that the standardized data holds the shape properties of the actual data, i.e. the standardized data has the same skewness and kurtosis values as the actual data.

Prediction models

Long-Short Term Memory (LSTM) networks

An LSTM neural network is a variant and improved version of RNNs that is capable of learning long-term reliance amongst the time-steps of a ‘sequence data’. LSTMs are especially suitable for predicting sequence data because they address vanishing and exploding gradient problems of standard RNNs through integrating gating functions and state dynamics (Hochreiter and

Schmidhuber, 1997). The architecture of the LSTM network consists of numerous memory blocks linked together through layers, every one of which contains numerous recurrently linked memory cells. An LSTM memory cell comprises of three multiplicative components referred to as gates – such gates are the forget, input, and output gates (Yuan et al., 2018). The major components of a basic LSTM network consist of a sequence input layer that is employed to input a sequence (time series data) to the LSTM network, and an LSTM layer that is used for learning long-term reliance among the time-steps of a sequence (time series) data. To solve a simple regression problem, an LSTM network is comprised of four layers: the network begins with a sequence input layer followed by an LSTM layer while the network closes with a completely connected layer followed by a regression output layer. This simple LSTM network can be represented graphically as Figure 3.

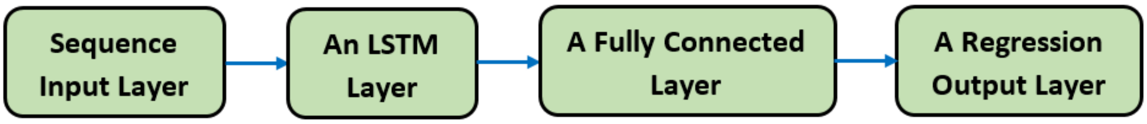


Figure 3. A basic LSTM network architecture for regression problems.

A more complex and deeper LSTM network is created by adding extra LSTM layers into the network. Dropout layers are often inserted right after each additional LSTM layers in order to prevent model overfitting. An LSTM layer architecture illustrating the flow of a time series X having C features (channels) of length S is presented in Figure 4.

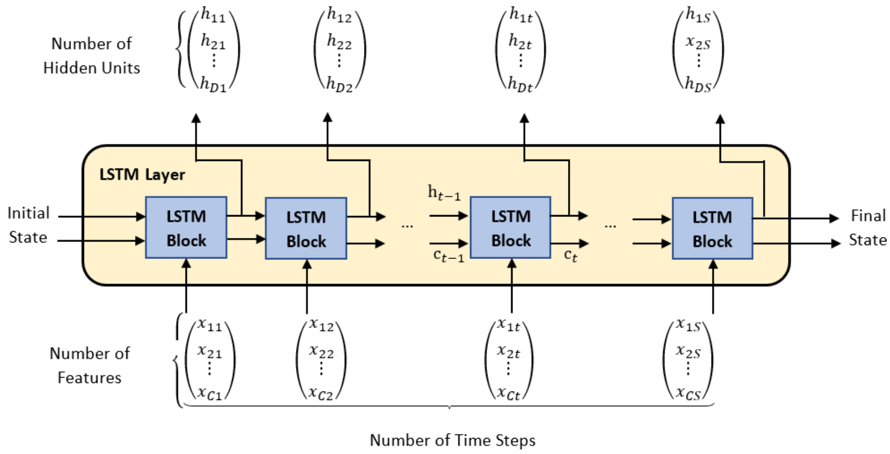


Figure 4. An LSTM layer architecture (Mathworks, 2019c). Here, the cell state and the output (concealed state) at the time step t are denoted by $\mathbf{c}_t$ and $\mathbf{h}_t$, respectively.

The starting LSTM block utilize the networks' initial state and the starting time-step of the sequence to calculate the first output and the modified cell state. In order to calculate tth time step's output and the modified cell state $\mathbf{c}_t$, the block employs the networks' present state $(\mathbf{c}_{t-1}, \mathbf{h}_{t-1})$ and the following time phase of a sequence. There are two types of states in a layer, namely hidden state (also referred to as an output state) and cell state. The purpose of the hidden state is to contain output of an LSTM layer for any particular time step t whereas the cell state stores the evidence acquired from the prior time phases. For every single time phase, an LSTM layer either puts in evidences to or takes away evidences from the cell state. The gates are used as the controlling components of these modifications for any particular LSTM layer. The following four components are employed to regulate the cell and hidden states of an LSTM layer:

a. Input gate (i): Control level of cell state update;
b. Forget gate (f): Control level of cell state reset (forget);
c. Cell candidate (g): Put in information to the cell state;
d. Output gate (o): Control level of cell state added to hidden state.

Figure 5 depicts the mechanism by which the gates forget, update, and produce output of the cell and hidden states.

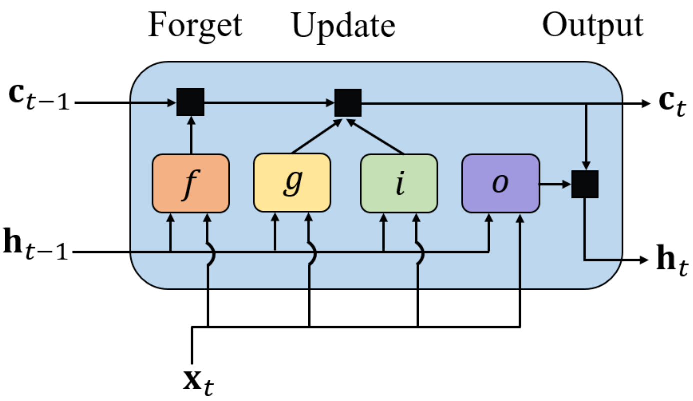


Figure 5. Illustration of the data flow at the time step t.

An LSTM layer has three adjustable parameters, namely the input weights (W), recurrent weights (R), and the bias (b). The matrices of W, R, and b are considered as the concatenations of the input – output weights, and the biases of each component, respectively. The matrices of W, R, and b are concatenated using the following mathematical forms:

$$W = \begin{bmatrix} W_i \\ W_f \\ W_g \\ W_o \end{bmatrix}, R = \begin{bmatrix} R_i \\ R_f \\ R_g \\ R_o \end{bmatrix}, b = \begin{bmatrix} b_i \\ b_f \\ b_g \\ b_o \end{bmatrix}, \tag{4}$$

where, i denote the input gate, f represents the forget gate, g depicts the cell candidate, and o indicate the output gate. The cell and hidden states at any particular time step t is represented by the following two equations:

$$\mathbf{c}_t = f_t \odot \mathbf{c}_{t-1} + i_t \odot g_t \tag{5}$$

$$\mathbf{h}_t = o_t \odot \sigma_c(\mathbf{c}_t) \tag{6}$$

where, $\odot$ refers to the Hadamard product (also known as the element-wise multiplication of vectors), σ_c symbolizes the 'state activation function'. This 'state activation function' is generally calculated using the hyperbolic tangent function ($\tan h$) (Mathworks, 2019c).

Each of the components of an LSTM layer (input gate (i_t), forget gate (f_t), cell candidate (g_t), and output gate (o_t)) at time step t are described by the following equations:

$$i_t = \sigma_g(W_i\mathbf{x}_t + \mathrm{R}_i\mathbf{h}_{t-1} + b_i) \tag{7}$$

$$f_t = \sigma_g\left(W_f\mathbf{x}_t + \mathrm{R}_f\mathbf{h}_{t-1} + b_f\right) \tag{8}$$

$$g_t = \sigma_c\left(W_g\mathbf{x}_t + \mathrm{R}_g\mathbf{h}_{t-1} + b_g\right) \tag{9}$$

$$o_t = \sigma_g(W_o\mathbf{x}_t + \mathrm{R}_o\mathbf{h}_{t-1} + b_o) \tag{10}$$

where, σ_g designates the gate activation function. A sigmoid function is usually employed to compute σ_g. The sigmoid function can be represented by the following equation:

$$\sigma(x) = (1 + e^{-x})^{-1} \tag{11}$$

In addition, Bidirectional LSTM models (Bi-LSTM) with the similar architecture of LSTM models were also developed. An LSTM network is able to learn long-term dependencies between time steps of sequence data whereas a Bi-LSTM learns bidirectional long-term dependencies between time steps of time series or sequence data. These dependencies can be useful when we want the network to learn from the complete time series at each time step.

For both LSTM and Bi-LSTM models, network architectures with three hidden layers were employed. Each of the hidden layers were followed by a dropout layer to prevent model overfitting. The numbers of hidden neurons for the first, second, and third hidden layers were 100, 50, and 20, respectively whereas the dropout rates assigned for the associated dropout layers were chosen as 0.4, 0.3, and 0.2, respectively. These optimum values were obtained upon conducting several trials. Various training options for the LSTM and Bi-LSTM models were obtained through trials, and the best options were used for model training. Optimum combinations of different training options are presented in Table-2.

Table-2. Optimum combinations of different training options

Options	Corresponding parameters or values
Optimization solver	'adam'
Maximum epochs	1000
Gradient threshold	1
Initial learning rate	0.01
Minimum batch size	150
Sequence length	1000

Four layers were used for the training purpose: a sequence input layer equivalent to the number of input variables or features, a LSTM layer corresponding to the number of hidden units, fully connected layer associated with the number of output variables or the responses, and a regression layer.

For developing LSTM and Bi-LSTM models, all possible combinations of the five input variables (Minimum temperatures, Maximum temperatures, Relative humidity, Wind speed, and Sunshine hours) were used. A total of 31 models were developed based on the 31 combinations (single, two-input combinations, three-inputs combinations, four-inputs combinations, and all five inputs) of input variables. Two-, three-, and four-inputs combinations are presented in Table-3.

Table-3. Different combinations of two-, three-, and four-inputs

Two Inputs combinations	***Three Inputs Combinations***
Min Temp, Max Temp	Min Temp, Max Temp, Humidity
Min Temp, Humidity	Min Temp, Max Temp, Wind Speed
Min Temp, Wind Speed	Min Temp, Max Temp, Sunshine Hours
Min Temp, Sunshine Hours	Min Temp, Humidity, Wind Speed
Max Temp, Humidity	Min Temp, Humidity, Sunshine Hours
Max Temp, Wind Speed	Min Temp, Wind Speed, Sunshine Hours
Max Temp, Sunshine Hours	Max Temp, Humidity, Wind Speed
Humidity, Wind Speed	Max Temp, Humidity, Sunshine Hours
Humidity, Sunshine Hours	Max Temp, Wind Speed, Sunshine Hours
Wind Speed, Sunshine Hours	Humidity, Wind Speed, Sunshine Hours
Four Inputs Combinations	
Min Temp, Max Temp, Humidity, Wind Speed	
Min Temp, Max Temp, Humidity, Sunshine Hours	
Min Temp, Max Temp, Wind Speed, Sunshine Hours	
Min Temp, Humidity, Wind Speed, Sunshine Hours	
Max Temp, Humidity, Wind Speed, Sunshine Hours	

The developed 31 models were ranked based on their prediction accuracies using Shannon's Entropy by incorporating a set of benefit (Correlation Coefficient, Nash-Sutcliffe Efficiency, Index of Agreement) and cost (Normalized Root Mean Squared Error, Maximum Absolute Error, Median Absolute Deviation) performance evaluation indices. The best input combinations thus obtained were used to develop the other shallow machine learning algorithms.

Adaptive Neuro Fuzzy Inference System

As multi-layered adaptive fuzzy inference systems, ANFIS-based prediction models are regarded as universal approximators given their capacity to handle fuzziness or vagueness of the input parameters (Jang et al., 1997). Holding the advantages of both fuzzy logic-based fuzzy set theory and artificial neural networks, ANFIS models can model complex systems' nonlinear processes by capturing and mapping nonlinear relationships between predictor and response variables (Sugeno and Yasukawa, 1993; Takagi and Sugeno, 1985). Among others, the Sugeno type of ANFIS model offers a simple architecture while providing a reasonably good learning ability (Jang et al., 1997). ANFIS models are developed by tuning the parameters of initial FISs developed using the Fuzzy c-mean clustering algorithm (FCM) (Bezdek et al., 1984). This algorithm serves to compress the training dataset into a given number of identical clusters. Using a clustering approach significantly reduces the number of modifiable parameters (both linear and nonlinear) of FIS models. The Sugeno type ANFIS model employs Gaussian input membership functions, but linear type output membership functions. A Gaussian membership function is determined by two parameters $\{c, \sigma\}$, and is expressed mathematically as (Jang et al., 1997):

$$gaussian\ (x, c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \qquad (12)$$

where, c is the centre of the membership function, and σ is the width of the membership function. An ANFIS architecture developed from a Sugeno type FIS is presented in Figure 6.

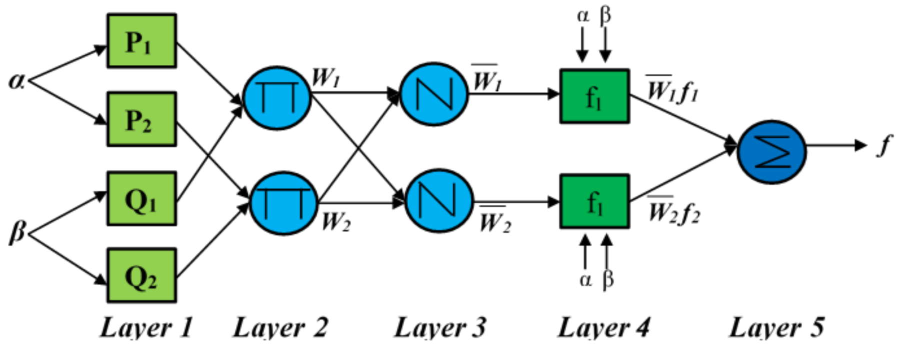


Figure 6. ANFIS architecture based on a two-input first-order Sugeno FIS (Jang, 1993).

The ANFIS structure in Figure 6 represents a first-order Sugeno FIS with two inputs (α and β) and one output (f), for which the fuzzy if-then rule sets can be expressed as:

$$Rule\ 1: If\ \alpha\ is\ P_1\ and\ \beta\ is\ Q_1\ then\ f_1 = p_1\alpha + q_1\beta + r_1 \qquad (13)$$

$$Rule\ 2: If\ \alpha\ is\ P_2\ and\ \beta\ is\ Q_2\ then\ f_2 = p_2\alpha + q_2\beta + r_2 \qquad (14)$$

The proposed Sugeno ANFIS has five layers: a fuzzy layer, a product layer, a normalized layer, a defuzzification layer, and a total output layer. The detail on these layers are discussed in Jang (1993). The commands and functions of MATLAB (Mathworks, 2019a) were employed in developing ANFIS-based prediction models.

Gaussian Process Regression

Gaussian process theory (Rasmussen and Williams, 2006) forms the basis of GPR, which is a nonparametric prediction modelling approach originated from the probability theory. GPR follows Gaussian distribution and provides prediction from a functional relationship between the output, Y and input variables, $X(i)$. This functional relationship can be expressed as (Bishop, 2006)

$$Y = f\big(X(i)\big) + \varepsilon \qquad (15)$$

where, ε is a Gaussian noise with variance σ_n^2.

A Gaussian process is typically associated with two functions (mean and covariance) that have distinctive roles in developing a GPR model. The mean function defines expected value of the function at any specific point within the variable space and is given by (Rasmussen and Williams, 2006)

$$m(x_i) = E[f(x_i)] \qquad (16)$$

The covariance function is considered to be the most important and prominent element of GPR model formation. The covariance function defines the nearness or similarity between the input and output variables and is represented by

$$k(x_i, x_j) = E\left[\left(f(x_i) - m(x_i)\right)\left(f(x_j) - m(x_j)\right)\right] \quad (17)$$

Then, the Gaussian process is obtained by

$$f(x) \sim gp\left(m(x_i), k(x_i, x_j)\right) \quad (18)$$

The parameters associated with the mean and covariance functions are commonly known as free or hyperparameters, which defines the characteristics of the forecasting probability dictribution. Hyper or free parameter values are derived from maximum value of the log-likelihood function of the training datasets.

The GPR based prediction models were developed by utilizing the commands and functions of MATLAB.

M5 Model Trees

The development of M5 model trees is based on the principles of M5' method (Wang and Witten, 1997; Quinlan, 1992). This method builds individual trees according to the M5' method, i.e., usage of the Standard Deviation Reduction criterion. Model trees (MT) combine a conventional regression tree with the possibility of linear regression functions at the leaves. However, note that whether a leaf node actually contains more than just a constant, depends on pruning and smoothing (if both are disabled, a model tree will not differ from a regression tree). MTs (Quinlan, 1992) fall into machine learning category and are promising numerical prediction method. The efficiency and robustness of model tree algorithms in prediction has been well established (Solomatine and Dulal, 2003; Bhattacharya and Solomatine, 2005). A model tree is an inverted tree with a root node located at the top of the tree and the leaves at the bottom. The data instants are first entering to the root nodes an input. In the MT root a test is carried out on the input data and the results of this test causes the tree to be split into branches, each of these branches are representing a possible answer. The MT will continue to split into branches until all the data in different classes have been classified.

MTs are employed to solve regression and classification problems. MTs and regression trees are a form of Decision Tree (DT) which has been developed for regression problems (Quinlan, 1992). The key difference between MTs and regression trees is that the leaves of regression trees produce a constant value, while MTs yield into linear models in their leaves (Samadi et. al., 2014). These linear models enable MTs to predict numeric values for a given data sample. MTs are efficient for large data set and have higher prediction accuracy in comparison with regression trees (Solomatine and Siek, 2006). A complex modelling problem can be divided into a number of simple sub-tasks and the answer would be combining the solution of all these tasks. M5 MT method divide the data space into smaller subspaces by divide-and-conquer method (Bhattacharya and Solomatine, 2005). This method uses the hard (i.e. yes-no) splits of input space into regions and narrowing the input parameter space into subspaces and builds a linear regression model in each of these subspaces. As a result of this splitting procedure, M5 MT produces a hierarchy (a tree) with splitting rules in non-terminal nodes and the expert models in leaves (Solomatine and Dulal, 2003).

The "model tree" is a technique for dealing with continuous class learning problems. It was developed by Quinlan (1992) and was exemplified in a learning algorithm known as the "M5 model tree". A model tree is like a regression tree, but it builds trees whose leaves are associated with a multivariate linear model. The nodes are then chosen over the attributes that maximize the expected error reduction as a function of the standard deviation of the output parameters. Building the model tree consists of three steps:

a) Building the initial tree: A decision-tree induction algorithm is introduced to create a tree. Instead of maximizing the information gain at each interior node, a splitting criterion is presented that minimizes the intra-subset variation in the class values down each branch.
b) Pruning the tree: this is based on minimizing the estimated absolute error of the multiple linear regression models. It starts from each leaf by using the regression plane rather than a constant value (Solomatine and Yunpeng, 2004).
c) Smoothing the tree: this is done to compensate for severe discontinuities that cannot be avoided between adjacent linear models at the leaves of the pruned tree.

A MATLAB toolbox "M5PrimeLab" (Jekabsons 2016) was used to develop M5 model trees for predicting daily reference ET_0 values with various climatic variables as inputs and ET_0 values as outputs.

Multivariate Adaptive Regression Spline (MARS)

An adaptive approach of prediction model formation, MARS (Friedman, 1991) is a rapid and flexible nonparametric technique that is able to build regression models by dividing the total decision space into numerous interludes of input variables. Individual splines or Basis functions are then fitted to each interlude to build the final regression model (Bera et al., 2006). MARS utilizes both a forward and a backward step during the model developmental phase. Initially, MARS builds a relatively large and complex model by utilizing a given number of Basis functions specified by the user in the forward step. The backward step is implemented in MARS to eliminate some input variables that have relatively less influence on predicting the output variable (Salford-Systems, 2016). This backward step also helps keeping the developed model as simple as possible and at the same time prevents model overfitting.

The input-output relationships of the MARS based prediction models are represented by (Roy and Datta, 2017)

$$BF_i(x) = \max\left(0, x_j - \alpha\right)\ OR\ BF_i(x) = \max\left(0, \alpha - x_j\right) \tag{19}$$

$$y = f(x) = \beta \pm \gamma_k * BF_i(x) \tag{20}$$

where, i = index for Basis functions, j = index for input variables, BF_i = i^{th} Basis function, x_j = j^{th} input variable, α = a threshold value selected by the MARS model during model development, β = a constant value, γ_k = corresponding coefficient of $BF_i(x)$, and y = output variable (model predictions).

AMATLAB toolbox "ARESLab" (Jekabsons 2016) was used to develop MARS based prediction models. ARESLab is a MATLAB toolbox for building piecewise-linear and piecewise-cubic regression models using the MARS approach. In general, it is expected that the piecewise-cubic modelling will give better predictive performance for smoother and less noisy data. In this study, both piecewise-linear and piecewise-cubic modelling approaches were used to predict daily ET_0 values.

Probabilistic Linear Regression

Probabilistic Linear Regression (PLR) performs linear regression through applying Bayesian inference technique in carrying out statistical analysis. It often utilizes Expectation-Maximization (EM) algorithm (Dempster et al., 1977) or Mackay fix point iteration method (MacKay, 1992) in which case the approach is referred to as empirical Bayesian linear regression. The PLR based prediction models are generally formulated by utilizing the EM algorithm. The algorithm is based on maximizing the log-likelihood function or log-posterior density function. While performing maximization, these functions are combined with certain latent variables.

Support Vector Regression (SVR)

SVR is a statistical learning theory based extension of Support Vector Machine (SVM) algorithm (Yu et al., 2006). SVMs have been a very popular machine learning tool for a wide range of classification and regression applications (Yoon et al., 2011). SVRs are component of SVMs for regression problems that are formulated through the nonlinear mapping of the data from the input space to a higher dimensional feature space in which linear regression can be performed (Basak et al., 2007). A detailed description of the SVR theory can be found in Chevalier et al. (2011). A jist of this theory is presented here. For a linear SVR model, the training dataset can be represented by

$$\{(\overline{x_1},\ y_1), (\overline{x_2},\ y_2), \ldots, (\overline{x_l},\ y_l)\} \tag{21}$$

$\overline{x_l} \in R^d,\ y_i \in R$, and l = number of data points

In this case, the solution function can be expressed as

$$f(\bar{x}) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*)\langle \overline{x_l}, \bar{x}\ \rangle + b \tag{22}$$

where, $\langle .,. \rangle$ = dot product of two points; α_i, α_i^*, and b = coefficients computed by the SVR algorithm. It is imperative to assume that the model is defined in terms of dot products between the data. For a number of patterns of the training data, the term $\alpha_i - \alpha_i^*$ will become zero which suggests that not all of the patterns will have a significant influence on the final solution. The patterns that contributes to the final solution are known as the support vectors.

For nonlinear SVR models, tha data needs to be transformed to a higher dimensional feature space from the input space by utilizing a nonlinear mapping function $\emptyset$ (Zhang and Ge, 2012). The calculation of the mapping function becomes increasingly difficult as the data is progressively mapped into higher dimensions. This drawback can be overcomed by implementing the Mercers Theorem as presented below.

$$\langle \emptyset(\bar{u}), \emptyset(\bar{v}) \rangle = \mathrm{k}(\bar{u}, \bar{v}) \tag{23}$$

The Mercers Theorem states that for a particular mapping $\emptyset$, the dot product of any two points $(\bar{u}, \bar{v})$ can be computed using a kernel function k. This computation of the dot product does not require the explicit computation of the high dimensional nonlinear mapping. The kernel function is one of the most important parameters that determine the prediction performance in the case of nonlinear SVR models.

Ranking of the prediction models: Shannon's Entropy

The first step of weight assignment is to develop a decision matrix of prediction models and performance evaluation indices. Assuming there to be m prediction models and PI performance evaluation indices, such that the decision matrix can be expressed as (Wu et al., 2011):

$$ET_{ij} = \begin{bmatrix} ET_{11} & ET_{21} & \cdots & ET_{m1} \\ ET_{12} & ET_{22} & \cdots & ET_{m2} \\ \vdots & \vdots & \vdots & \vdots \\ ET_{1PI} & ET_{2PI} & \cdots & ET_{mPI} \end{bmatrix} \tag{24}$$

The next step is to standardize the decision matrix to minimize the effects of index dimensionality. Accordingly, the values of performance indices were standardized between 0 and 1, such that $S_{ij} \in [0,1], i = 1,2, \ldots, m; j = 1,2, \ldots, PI$. S_{ij} is then expressed as (Wu et al., 2011):

$$S_{ij} = \begin{cases} \dfrac{ET_{ij}}{\max(ET_{i1}, ET_{i2}, \ldots, ET_{iPI})}, & for\ benefit\ indexes \\ \dfrac{X_{ij}}{\min(ET_{i1}, ET_{i2}, \ldots, ET_{iPI})}, & for\ cost\ indexes \end{cases} \tag{25}$$

Individual prediction models' entropy weights were assigned using entropy-based ranking of the models. The ranking followed five steps:

Step 1: Computation of each index's entropy value using the concepts of Shannon's information entropy. The entropy value of the j^{th} index was calculated as (Li et al., 2011):

$$Entropy_j = -k \sum_{i=1}^{m} f_{ij} \ln f_{ij} \tag{26}$$

where,

$$f_{ij} = S_{ij} \Big/ \sum_{i=1}^{m} S_{ij} \tag{27}$$

$$k = 1/\ln m \tag{28}$$

Step 2: Calculation of each index's entropy weight. The j^{th} index's entropy weight was calculated as:

$$w(entropy)_j = \frac{1 - Entropy_j}{PI - \sum_{j=1}^{PI} Entropy_j} \tag{29}$$

This entropy weight indicates the importance of the index in the decision-making process. The higher the value of the entropy-based weight, the greater information the particular index carries, and the more significant this index is in decision-making.

Step 3: Calculation of each model's rank weight is done by summing up the product of each index's entropy weight and the standardized value of that index. This step is mathematically represented by:

$$w(entropy)_i = \sum_{j=1}^{PI} S_{ij} \times w(entropy)_j \tag{30}$$

Step 4: Determination of model ranking

$$\max\,[w(entropy)_i], \dots., \min[w(entropy)_i]\,; \text{for } i = 1,2,\dots,m \tag{31}$$

Step 5: Calculation of entropy weight for individual prediction models

$$W(entropy)_i = w(entropy)_i \Big/ \sum_{i=1}^{m} w(entropy)_i \tag{32}$$

Performance evaluation indices

Correlation Coefficient, R

$$R = \frac{\sum_{i=1}^{n}\left(ET_{i,a} - \overline{ET_a}\right)\left(ET_{i,a} - \overline{ET_p}\right)}{\sqrt{\sum_{i=1}^{n}\left(ET_{i,a} - \overline{ET_a}\right)^2}\sqrt{\sum_{i=1}^{n}\left(ET_{i,p} - \overline{ET_p}\right)^2}} \tag{33}$$

Nash-Sutcliffe Efficiency Coefficient, NS (Nash and Sutcliffe, 1970)

$$NS = 1 - \frac{\sum_{i=1}^{n}\left(ET_{i,a} - ET_{i,p}\right)^2}{\sum_{i=1}^{n}\left(ET_{i,a} - \overline{ET_a}\right)^2} \tag{34}$$

Index of Agreement, IOA

$$NS = 1 - \frac{\sum_{i=1}^{n}\left(ET_{i,a} - ET_{i,p}\right)^2}{\sum_{i=1}^{n}\left(\left|ET_{i,p} - \overline{ET_a}\right| + \left|ET_{i,a} - \overline{ET_a}\right|\right)^2} \tag{35}$$

Relative RMSE, RRMSE

$$RRMSE = \frac{RMSE}{\overline{ET_a}} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(ET_{i,a} - ET_{i,p}\right)^2}}{\overline{ET_a}} \tag{36}$$

Maximum Absolute Error, MAE

$$MAE = \max\left[\left|ET_{i,a} - ET_{i,p}\right|\right] \tag{37}$$

Median Absolute Deviation, MAD

$$MAD\left(ET_a, ET_p\right) = median\left(\left|ET_{1,a} - ET_{1,p}\right|, \left|ET_{2,a} - ET_{2,p}\right|, \dots, \left|ET_{n,a} - ET_{n,p}\right|\right) \quad for\ i = 1,2,\dots,n \tag{38}$$

where $ET_{i,a}$ and $ET_{i,p}$ are ET_0 values at the i^{th} step obtained by from the FAO-56 PM and ANFIS models, respectively; $\overline{ET_a}$ is the mean value of the FAO-56 PM ET_0 values; n is the number of data points.

Results and Discussions

Daily prediction of ET_0 values using various machine learning algorithms

To determine the optimum numbers of input variables combinations, 31 possible combinations of five input variables were used to develop 31 LSTM and Bi-LSTM models. Learning (training) and validation (testing) of the models were performed simultaneously. Prediction errors on the test dataset in terms of RMSE criterion for the 31 developed models are presented in Table-4.

It is apparent from Table-4 that LSTM model predictions were slightly better than those of the Bi-LSTM models when RMSE criterion was used as a deciding factor. It is also observed that both the LSTM and Bi-LSTM models produced the lowest RMSE values (best daily ET_0 predictions) when all five variables were used. The performance of LSTM (RMSE = 0.081 mm/d) is slightly better than that of the Bi-LSTM (RMSE = 0.087 mm/d) model. However, in situations where adequate data is not available, the use of fewer input variables may be used to achieve a reasonably accurate prediction of ET_0 values.

Nevertheless, making decisions in such situations is difficult as RMSE criterion alone is not a reasonable decision-making tool. To assist in the decision-making process, three benefit (the higher the better: R, NS, IOA) and three cost (the lower the better: NRMSE, MAE, MAD) performance evaluation indices were incorporated in the Shannon's Entropy based decision theory. R, NS, IOA, NRMSE, MAE, and MAD criteria were calculated on the test dataset for all the 31 LSTM and Bi-LSTM models. These statistical performance evaluation indices were used to calculate ranking of these 31 models using Shannon's Entropy.

Table-4. Prediction errors of deep learning models (LSTM and Bi-LSTM) with different input combinations on test dataset

Model No.	Different Input Combinations	Test RMSE, mm/d	
		LSTM	Bi-LSTM
Single Input Combinations			
M1	Min Temp	0.880	0.964
M2	Max Temp	0.775	0.781
M3	Humidity	1.124	**1.211**
M4	Wind Speed	**1.177**	1.105
M5	Sunshine Hours	0.732	0.807
Two Inputs combinations			
M6	Min Temp, Max Temp	0.765	0.779
M7	Min Temp, Humidity	0.729	0.751
M8	Min Temp, Wind Speed	1.004	1.049
M9	Min Temp, Sunshine Hours	0.527	0.514
M10	Max Temp, Humidity	0.634	0.602
M11	Max Temp, Wind Speed	0.734	0.743
M12	Max Temp, Sunshine Hours	0.501	0.430
M13	Humidity, Wind Speed	0.727	0.760
M14	Humidity, Sunshine Hours	0.531	0.983
M15	Wind Speed, Sunshine Hours	0.527	0.627
Three Inputs Combinations			
M16	Min Temp, Max Temp, Humidity	0.570	0.574
M17	Min Temp, Max Temp, Wind Speed	0.729	0.722
M18	Min Temp, Max Temp, Sunshine Hours	0.512	0.447
M19	Min Temp, Humidity, Wind Speed	0.726	0.723
M20	Min Temp, Humidity, Sunshine Hours	0.337	0.377
M21	Min Temp, Wind Speed, Sunshine Hours	0.470	0.501
M22	Max Temp, Humidity, Wind Speed	0.567	0.566
M23	Max Temp, Humidity, Sunshine Hours	0.300	0.239
M24	Max Temp, Wind Speed, Sunshine Hours	0.409	0.394
M25	Humidity, Wind Speed, Sunshine Hours	0.337	0.333
Four Inputs Combinations			
M26	Min Temp, Max Temp, Humidity, Wind Speed	0.577	0.561
M27	Min Temp, Max Temp, Humidity, Sunshine Hours	0.262	0.229
M28	Min Temp, Max Temp, Wind Speed, Sunshine Hours	0.382	0.404
M29	Min Temp, Humidity, Wind Speed, Sunshine Hours	0.271	0.238
M30	Max Temp, Humidity, Wind Speed, Sunshine Hours	0.107	0.116
All Inputs			
M31	Min Temp, Max Temp, Humidity, Wind Speed, Sunshine Hours	**0.081**	**0.087**

*RMSE = Root Mean Squared Error, LSTM = Long-Short Term Memory Networks, Bi-LSTM = Bi-directional Long-Short Term Memory Networks.

The ranking results with the corresponding ranking values are shown in Table-5.

Table-5. Ranking of the LSTM and Bi-LSTM models using Shannon's Entropy

Sl. No.	LSTM		Bi-LSTM	
	Model	Ranking Value	Model	Ranking Value
1	M31	0.996	M31	0.966
2	M30	0.906	M30	0.913
3	M27	0.702	M27	0.704
4	M23	0.687	M23	0.696
5	M20	0.657	M29	0.688
6	M29	0.652	M25	0.642
7	M25	0.640	M20	0.621
8	M28	0.604	M24	0.600
9	M24	0.600	M28	0.594
10	M21	0.584	M12	0.581
11	M12	0.563	M18	0.576
12	M18	0.561	M21	0.563
13	M14	0.560	M26	0.557
14	M22	0.558	M9	0.555
15	M26	0.556	M22	0.551
16	M15	0.555	M16	0.551
17	M9	0.555	M10	0.535
18	M16	0.554	M15	0.522
19	M10	0.535	M17	0.488
20	M11	0.496	M19	0.485
21	M17	0.493	M11	0.482
22	M19	0.491	M7	0.478
23	M13	0.491	M13	0.475
24	M7	0.483	M6	0.462
25	M5	0.482	M2	0.460
26	M6	0.470	M5	0.451
27	M2	0.470	M14	0.384
28	M1	0.415	M1	0.376
29	M8	0.364	M8	0.336
30	M3	0.306	M4	0.311
31	M4	0.209	M3	0.256

It is observed from Table-5 that models that used all 5 input variables (M31) was the top ranked predictors followed by M30, M27, and M23 for both LSTM and Bi-LSTM algorithms. Models M3 and M4 appeared to be the worst performers when using LSTM or Bi-LSTM algorithms for model development. Therefore, the results suggest that all input variables would be employed to achieve better predictions of the daily ET_0 values, at least for this example problem presented in this study. Consequently, in order to provide a fair comparison, other prediction models (ANFIS, GPR, M5 Model tree, MARS, PLR, and SVR) were developed using all five input variables available for the study area. The similar performance evaluation indices were calculated for all the developed models. The prediction results are presented in Table-6.

Table-6. Performance indices of the developed prediction models on the test dataset

Model	Performance Evaluation Indices					
	R	NS	IOA	NRMSE, mm/d	MAE, mm/d	MAD, mm/d
LSTM	0.998	0.995	0.999	0.021	0.666	0.025
Bi-LSTM	0.998	0.995	0.999	0.023	0.582	0.027
ANFIS	0.991	0.981	0.995	0.043	0.706	0.061
GPR	0.993	0.985	0.996	0.038	0.650	0.052
M5 Tree	0.985	0.970	0.993	0.054	1.153	0.062
MARS_C	0.992	0.983	0.996	0.041	0.869	0.054
MARS_L	0.992	0.983	0.996	0.040	0.760	0.054
PLR	0.973	0.943	0.985	0.075	1.489	0.114
SVR	0.993	0.985	0.996	0.038	0.676	0.050

*MARS_C = Piecewise Cubic, MARS_L = Piecewise Linear

The prediction outcomes presented in Table-6 indicate that all of the proposed prediction models are effective at predicting daily ET_0 values as indicated by the various performance evaluation indices. While no individual model performs the best for all evaluation indices, individual models approximate daily ET_0 values better than others. In general, all prediction models have satisfactory prediction accuracies as all models have higher values R, NS, and IOA as well as lower values of NRMSE, MAE, and MAD. LSTM and Bi-LSTM models had superior performance than others based on all performance evaluation indices. PLR was found to be the worst performing model.

To further appraise the performances of the developed models, boxplots of absolute errors between the actual and predicted ET_0 values are considered. Figure 7 illustrates the absolute error boxplots for all the developed models. Boxplots provide a comparative evaluation for the statistical distributions of the absolute errors of the ET_0 values and aids in measuring the level of overall spread of the errors made by each prediction model. The horizontal lines in each of the boxplots designate the median of the absolute errors of prediction while the mean (average) of the absolute errors is marked by the black circles. Absolute error boxplots also demonstrated the superior performance of the LSTM and Bi-LSTM models.

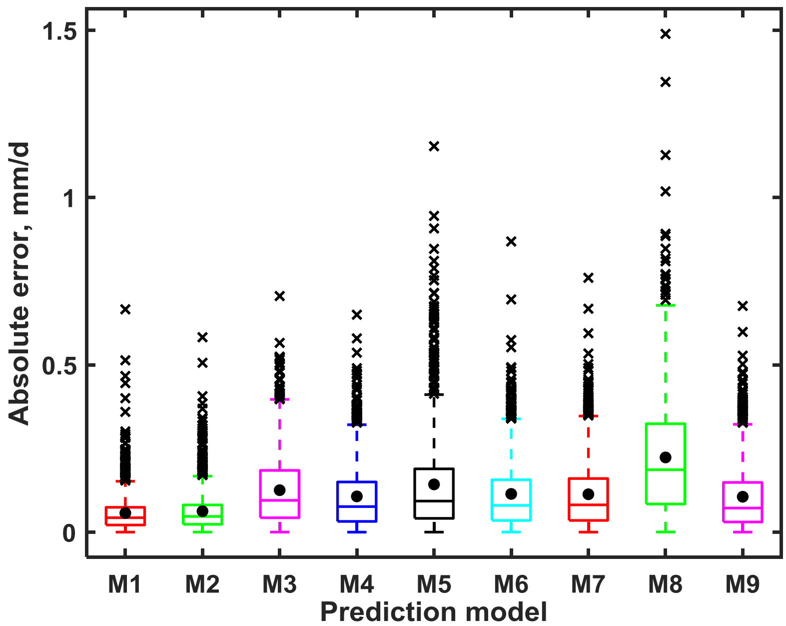


Figure 7. Absolute error boxplots. M1 – M9 represents LSTM, Bi-LSTM, ANFIS, GPR, M5 Tree, MARS_C, MARS_L, PLR, and SVR models.

As far as the two best models are considered, LSTM model performs better than Bi-LSTM when NRMSE and MAD criteria were considered whereas Bi-LSTM outperforms LSTM model based on MAE criterion. On the other hand, both LSTM and Bi-LSTM performed equally well with respect to R, NS, and IOA criteria. Therefore, it is concluded that models showed varying accuracies depending on the performance evaluation indices computed on the actual and predicted ET_0 values, which indicates a contradiction in the prediction performance when different performance evaluation indices are used. Decision making in this situation is very difficult which can be facilitated by employing a decision theory that incorporates a number of different performance evaluation indices in the decision making. This study employs Shannon's Entropy as a decision-making tool.

The ranking of the models based on Shannon's Entropy is presented in Table-7. The higher the values of Shannon's Entropy, the better is the performance of the model. Table-7 suggests that LSTM was the top performing model followed by Bi-LSTM although the difference between the ranking values of these two models was negligible.

Table-7. Ranking of the prediction models based on Shannon's Entropy

Model	Shannon's Entropy Value	Rank
LSTM	0.979	1
Bi-LSTM	0.978	2
ANFIS	0.807	6
GPR	0.839	3
M5 Tree	0.734	8
MARS_C	0.794	7
MARS_L	0.810	5
PLR	0.665	9
SVR	0.836	4

One step-ahead prediction of ET_0 values using LSTM networks and ANFIS

Linear prediction design

A linear neuron is designed to predict the next value in the ET_0 time series given the last five values of the series. This is basically a dynamic linear network which can predict a signal's next value from current and past values. The ET_0 time series was then converted to a cell array by the signal convert. The first four values of the ET_0 signals were used as initial input delay states, and the rest except for the last step were used as inputs. The targets of the model were then defined to match the inputs, but shifted earlier by one-time step. With these inputs and outputs, a linear layer with a single neuron was designed for predicting the next time step of the signal given the current and four past values. The resulting linear layer is illustrated in Figure 8.

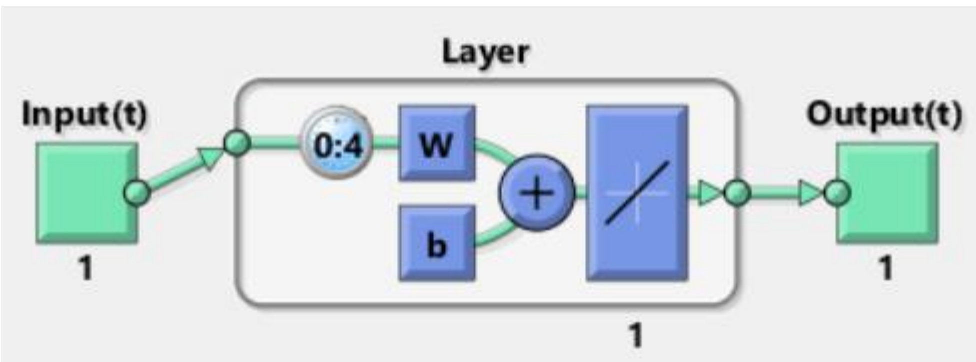


Figure 8. Schematic representation of the developed linear layer network.

The developed linear network acts like a function on the inputs and delayed states to get its time response. The resulting output signal was then plotted with the targets, and is presented in Figure 9.

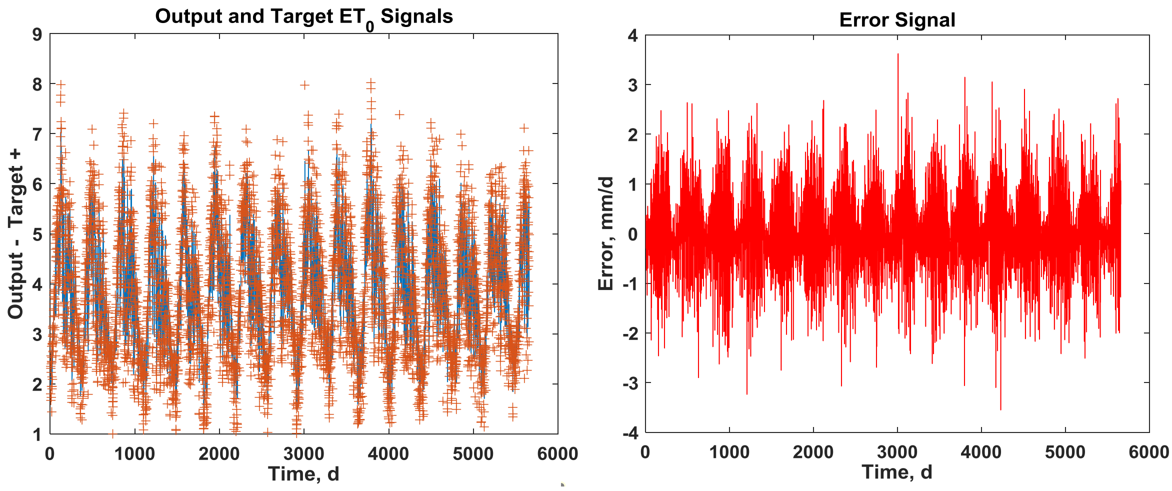
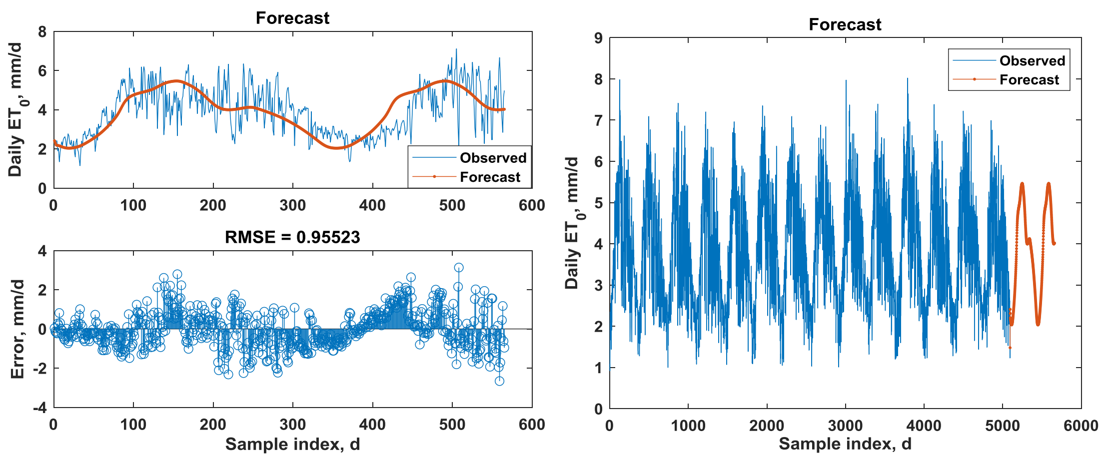


Figure 9. Prediction performance: (a) Actual (Target) vs Predicted (Output), (b) Prediction error.

One-step ahead prediction of ET_0 time series using sequence-to-sequence regression LSTM network (SSR-LSTM)

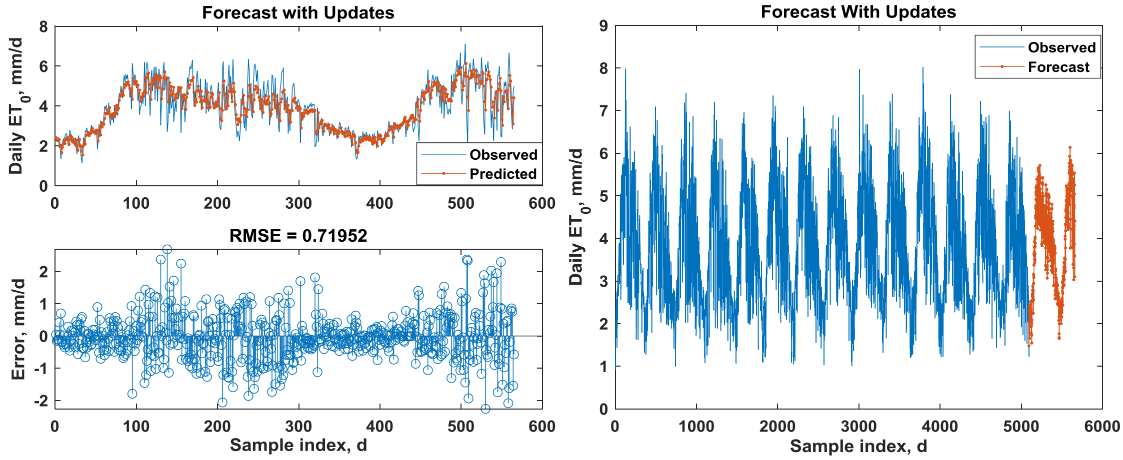
A sequence-to-sequence regression LSTM network (SSR-LSTM) was trained using the ET_0 time series data. In SSR-LSTM, the responses are the training sequences with values shifted by one-time step. That is, at each time step of the input sequence, the LSTM network learns to predict the value of the next time step. The entire time series of ET_0 values was divided into training (90%) and test (10%) sets. For a better fit and to prevent the training from diverging, the training data was standardized to have zero mean and unit variance. To forecast the values of future time steps of a sequence, the responses were specified to be the training sequences with values shifted by one-time step. That is, at each time step of the input sequence, the LSTM network learns to predict the value of the next time step. The predictors were the training sequences without the final time step. The LSTM network had one hidden layer with 200 hidden neurons. Other parameters of the network were selected on a trial and error basis. The solver was set to “adam” and the network was allowed to train for 250 epochs. To prevent gradients from exploding, the gradient threshold was set to 1. Initial learn rate was specified as 0.005, and the learn rate was dropped after 125 epochs by multiplying a factor of 0.2. To initialize the network state, the training data was first used for the prediction. Then, the first prediction was made using the last time step of the training response. The process of prediction was continued through looped over the remaining predictions, and at each loop the previous prediction was inputted to the network for predicting and updating the network state. Prediction performance of the developed network is presented in Figure 10.



(a)

Figure 10. Prediction performance: (a) Actual and Forecasted ET0 values computed on test dataset, (b) Projected Forecast.

It is observed from Figure 10 that although the model captured the trends of the test dataset (Figure 10 (b)), the model outputs were relatively flat when compared with the original time series (Figure 10 (a)). Therefore, the prediction performance needs to be improved. This improvement can be achieved through updating the network state with the observed values instead of the predicted values. This was performed by resetting the network state in order to prevent previous predictions from affecting the predictions on the new data. After resetting the network state, it was initialized by predicting on the training data. Then, the prediction was made on each time step. For each prediction, the next time step was predicted using the observed value of the previous time step. The predicted values were compared with the test data, and is presented in Figure 11.



(a)

Figure 11. Prediction performance after update network state with observed values: (a) Actual and Forecasted ET_0 values computed on test dataset, (b) Projected Forecast.

One step ahead prediction with input variables selected using PACF

In this approach, PACF functions were determined to acquire time-lagged statistics from the daily time series data of ET_0. This time-lagged information was used to evaluate the temporal dependencies between ET_0 for a current week (ET_t) and the ET_0 values at a certain point in an earlier period (i.e. a time lag of $ET_{t-1}, ET_{t-2}, ET_{t-3}, ET_{t-4}$, and ET_{t-5}, etc.). These temporal reliance in the ET_0 time series were evaluated for 50 lags (i.e., from ET_{t-1} to ET_{t-50}) as depicted in Figure 12. In Figure 12, the 95% confidence band is indicated by the blue lines. Daily lag times of ET_0 values were used as inputs to the prediction models while the output from the models was the one-day ahead ET_0 values. The selection of optimal combination of inputs for the models was executed through careful examination of the PACF functions.

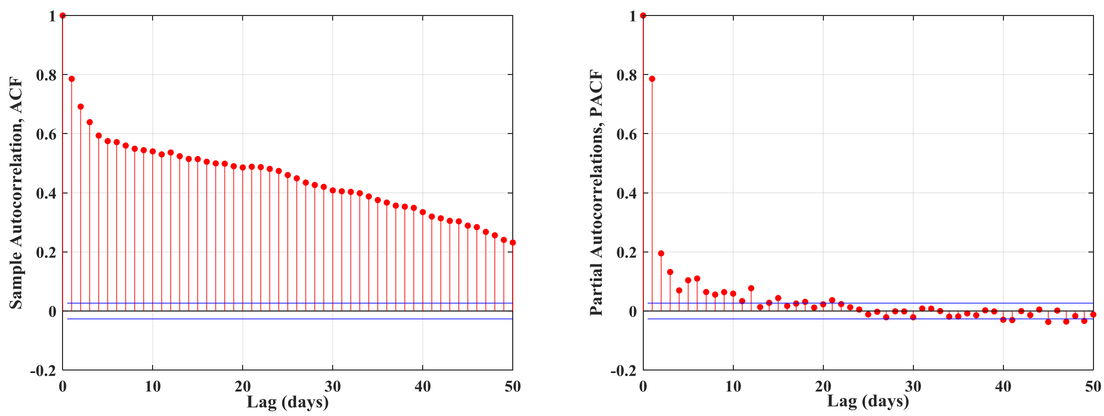


Figure 12. Plots of sample and partial autocorrelation functions for 50 lags.

Based on the PACF plot presented in Figure 12, the selected input variables included:

$$ET_t, ET_{t-1}, ET_{t-2}, ET_{t-3}, ET_{t-4}, ET_{t-5}, ET_{t-6}, ET_{t-7}, ET_{t-8}, ET_{t-9}, ET_{t-10}, ET_{t-11}$$

The output variable was the one day ahead ET0 values, i.e. ET_{t+1}.

One step ahead prediction using ANFIS, LSTM, and Bi-LSTM

After satisfactory training of the ANFIS model, results were evaluated with respect to various performance evaluation indexes computed on the actual and predicted test dataset. The model predictions are presented in Figure 13 in the forms of hydrographs and scatterplots. It is observed from the hydrographs and scatterplots presented in Figure 13 that the model predictions were reasonably accurate with respect to RMSE criterion. The RMSE criterion did not differ substantially between the training (RMSE = 0.759 mm/d) and testing phase (RMSE = 0.789 mm/d). The training and test R values were also very close. Actual and predicted ET_0 values with error plots and projected ET_0 during testing data's time span for the LSTM, and Bi-LSTM models are presented in Figures 14 and 15, respectively. It is observed from Figures 14 and 15 that the developed LSTM, and Bi-LSTM models were capable of mapping the input-output patterns quite reasonably and accurately. In order to have a closer look on the prediction capabilities of the developed models, other statistical performance evaluation indices such as R, NS, IOA, NRMSE, MAE, and MAD were calculated. The performance evaluation results are presented in Table-8.

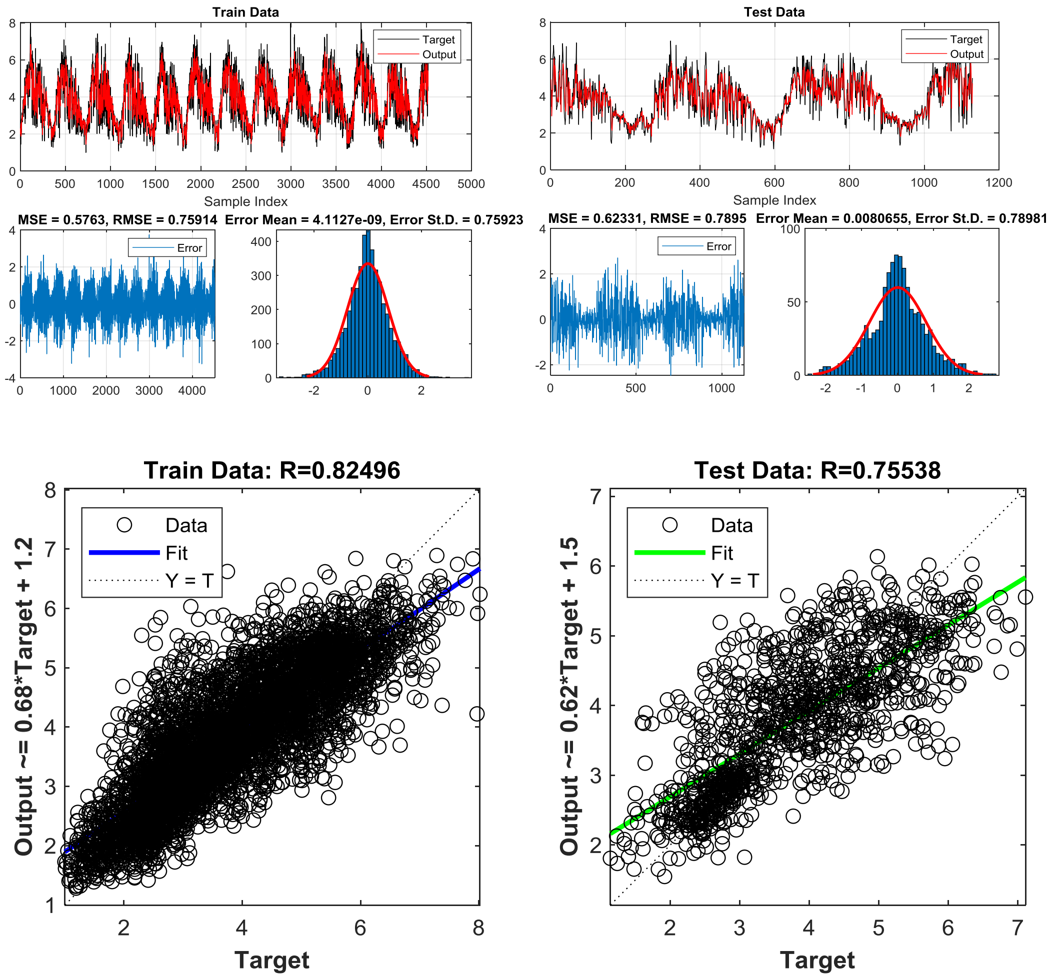


Figure 13. Actual VS Predicted ET_0 and Regression plots during training and testing of the ANFIS model.

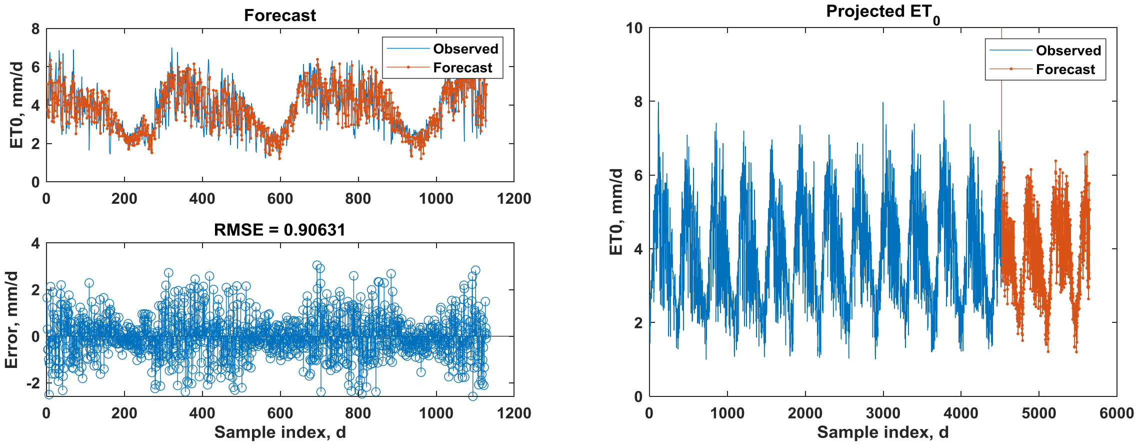


Figure 14. Actual VS Predicted ET_0 with error plots and projected ET_0 during testing phase of the LSTM model.

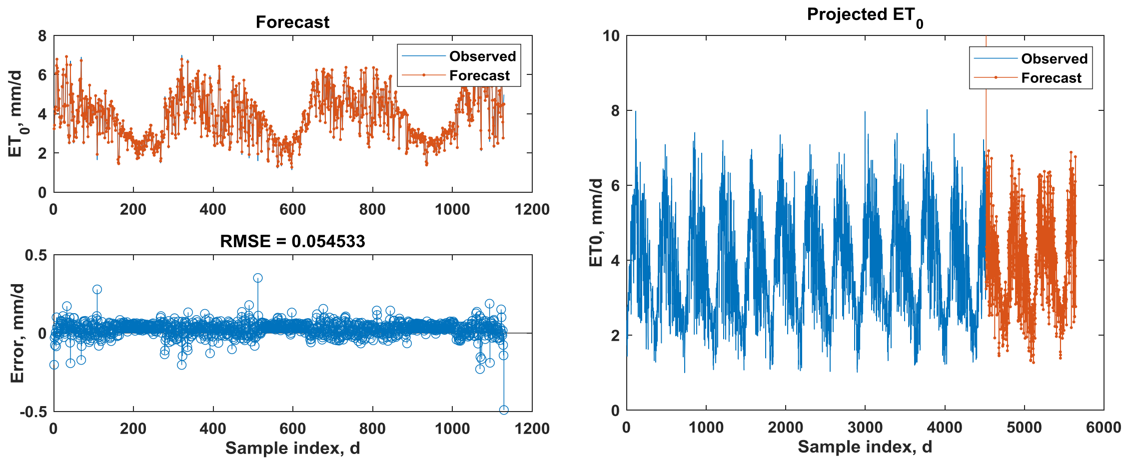


Figure 15. Actual VS Predicted ET_0 with error plots and projected ET_0 during testing phase of the Bi-LSTM model.

It is observed from Table-8 that the prediction of Bi-LSTM outperforms the other models with respect to all performance indices considered. Although the prediction results did not show substantial contradiction, Shannon's Entropy was calculated by incorporating all performance evaluation indices in order to make a solid conclusion regarding the ranking of the prediction models. The ranking results are presented in Table-9.

Table-8. Performance indices calculated on test dataset

Model	Statistical Performance Evaluation Indices					
	R	NS	IOA	NRMSE, mm/d	MAE, mm/d	MAD, mm/d
ANFIS	0.755	0.567	0.858	0.207	2.710	0.308
Bi-LSTM	0.999	0.998	0.999	0.014	0.491	0.017
LSTM	0.698	0.429	0.833	0.237	3.047	0.334
SSR-LSTM	0.818	0.666	0.898	0.184	2.687	0.279

The ranking indicated the superior performance of Bi-LSTM model whereas the sequence of the other models in descending order of performance were: SSR-LSTM– ANFIS – LSTM.

Table-9. Ranking of the prediction models based on Shannon's Entropy

Model	Shannon's Entropy Value	Rank
ANFIS	0.273	3
Bi-LSTM	1.000	1
LSTM	0.244	4
SSR-LSTM	0.297	2

Conclusions

Precise and reliable prediction of reference evapotranspiration can effectively be employed in developing a sustainable and efficient agricultural water management strategy. This study aimed at developing a robust prediction tool for daily and one-step ahead ET_0 values through deep learning algorithms: Long Shot Term Memory (LSTM) networks and bidirectional LSTM networks. The performance of these two deep learning algorithms were compared with the commonly used machine learning algorithms. For daily ET_0 prediction, a number of meteorological variables were used as inputs to the models whereas the computed ET_0 values were used as outputs from the models. For one-step ahead predictions, the suitable daily lag times of ET_0 values were used as inputs to the prediction models while the output from the models is the one-step ahead ET_0 values. The selection of optimal combination of inputs for the models in one-step ahead prediction was executed through careful examination of the PACF functions. In both cases, a set of statistical performance evaluation indices were calculated, and these indices were incorporated to calculate Shannon's Entropy in order to provide a ranking of these prediction models. The ranking results for daily prediction demonstrated that the LSTM model was the best performer among others based on the proposed ranking method. The ranking of the models was: LSTM>Bi-LSTM>GPR>SVR>MARS_L>ANFIS>MARS_C>M5 Model Tree>PLR. On the other hand, Bi-LSTM model was the best performing model in predicting one-step ahead ET_0 predictions, and the ranking of the models was: Bi-LSTM>SSR-LSTM>ANFIS>LSTM. The key findings of this research were (i) deep learning-based LSTM and Bi-LSTM models could be employed in predicting daily and one-step ahead prediction of ET_0 values, (ii) Shannon's Entropy based decision theory could be utilized to provide a ranking of several prediction models in order to make an unbiased decision regarding the suitability of a prediction model. This study investigated the daily and one-step ahead ET_0 predictions. However, the performance of the proposed deep learning models needs to be evaluated for predicting multiple-step ahead predictions. Therefore, the study should be continued to evaluate the prediction performance of the proposed models for the multiple-step ahead predictions.

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HISTORICAL TRENDS OF WATER USASE OF MAJOR CROPS AND CROPPING PATTERNS IN THE NORTH-WESTERN DISTRICTS OF BANGLADESH

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Abstract

Historical trend analysis of the water usages by major crops and cropping patterns in the drought prone north-western region of Bangladesh can provide valuable information that is useful for future management of irrigation water in wider scale. This study was done to estimate the actual crop evapotranspiration (ET), total and crop-usable effective rainfalls (TER and ER, respectively) and irrigation requirement (IR) of 8 major crops and 8 cropping patterns over historical period (1985 to 2015) by using SWBcropwat model and analyse the trends of these water parameters by using MAKESENS tool for the 16 districts of the region. The results revealed that the ET of the dry season crops and cropping patterns had a significant ($p \leq 0.05$) decreasing trends in all districts. Whereas, the ER decreased significantly for most dry season crops in 4 districts. TER was often greater than ER for monsoon crops, which could not fully utilize TER always because of its non-uniform temporal distributions. IR showed significantly decreasing trend for the dry season crops in 11 districts and increasing trend for the monsoon crops in 5 districts. Although ET and IR decreased in most cases, their total volumetric quantities showed significantly increasing trends due to expanded irrigated area over time.

Introduction

Application of water and its managed usage has been an essential factor worldwide in raising productivity of crop agriculture and ensuring predictability in outputs. Crop-water requirement varies substantially across the globe, reflecting differences in cropping intensity, crop choice, soil characteristics, irrigation water availability, agricultural management and climatic condition. Information on crop-water requirement is important for selection of crops and cropping patterns and their irrigation scheduling in any particular area. When water is scarce, knowledge on the magnitude of water demand is crucial for decision-making about agricultural planning based on limited water resources.

Irrigated agriculture has become central to the current rapid agricultural development and food security in Bangladesh. Rice being the staple food is currently grown on 73.7% of the total cultivated land, constituting 93.4% of the total cereal production (BBS, 2017). The projected population in the country, 185 million in 2030 and 202 million in 2050 (United Nations, 2017), indicates an additional requirement of 12.4 and 21.0 million tons of rice respectively by 2030 and 2050 (Mainuddin and Kirby, 2015). So, irrigation will remain critical in supplying foods (Peacock, 1996), and the consumption of agricultural water will continue to increase during the coming decades (CAWMA, 2007). Moreover, domestic and industrial usages of water are on the rise; these are likely to grow by 100% and 440%, respectively by 2050 (BDP2100, 2017). So, there will be growing competitions for getting water among the various users. Furthermore, while climate change is likely to cause shortage of drinking and irrigation water in one hand, will increase demand of irrigation from less than 1% for 2030 in average condition to maximum 3% for 2050 in dry condition (Kirby et al., 2016) on the other hand. Rainfall variability, although uncertain, featuring extreme high and low rainfall, is critical for agricultural productivity and water availability. Thus, water availability for future food security is challenging and will become more

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challenging if further increase in irrigated area takes place, especially in vulnerable areas like the Barind region of the North-West Bangladesh.

The Barind tract being one of the most intensive agricultural and irrigated regions supplies about 35% of irrigated boro rice and 60% of wheat of the whole country. About 78% irrigated land in this region is covered by groundwater (Hasanuzzaman et al., 2017). Particularly, over 97% of the total area in Rajshahi district and over 99% of the total area in Bogura district of the Barind region are currently irrigated by groundwater (BBS, 2017); usage of surface water for irrigation is very limited in these districts because of its limited availability. The Barind region is facing a number of challenges, such as rapid population growth, declining cultivable land, inadequate water availability during dry season (October–April), declining groundwater table (Salem et al., 2017, Mojid et al., 2019) and extreme events like floods and droughts. Some parts of the Barind region are now of greatest concern over falling groundwater tables since groundwater usage has become unsustainable in those areas (Kirby et al., 2016). Impacts of climate change are now visible in the Barind tract in the form of temperature variations, erratic rainfall patterns with low monsoon rains, decreased duration of rainy season, intense short-duration rainfall, increased number of droughts, and prevalence of rough weather. Thus, availability of adequate water during farming seasons has become uncertain. Consequently, it has now become essential to understand the future possible changes in agricultural water requirements to improve water resources management in the region. Demand management is regarded as an important part of the overall solution of water scarcity. The importance of accurately estimating crop-water demand for irrigation forecast and agricultural water management has been widely recognized (Hossain et al., 2017) since proper plan for the application of desired amount of water at right time can conserve the water resources.

Trends of water requirement, estimated from the observed recent past long-term daily climate data and comparison with the trends of local climatic parameters may provide a better insight into the changes in water demand (Acharjee et al., 2017). Water requirement and cropping patterns are very closely related and very important for efficacious crop production. If water requirements of each crop and cropping pattern of a region are known, agriculture of the region can be planned based on its available water resources. Keeping the above observations in mind, this study was done to−

- Observe of the historical trends of monthly total rainfall, effective rainfall and evapotranspiration in the sixteen districts of northwest region of Bangladesh;
- Analyse the crop evapotranspiration and contribution of rainfall to the total irrigation requirement, and their trends for the major crops and cropping patterns.

Materials and Methods

Locations

Sixteen districts of the northwest region of Bangladesh, Bogura, Chapainawabganj, Joypurhat, Naogaon, Natore, Pabna, Rajshahi and Sirajganj in Rajshahi division, and Thakurgaon, Rangpur, Panchagar, Nilphamari, Lalmonirhat, Kurigram, Gaibandha and Dinajpur in Rangpur division were selected for the study.

Data collection

Daily climatic data (precipitation, temperature, wind speed, sunshine hours, solar radiation and relative humidity) for 31 years (1985-2015) were collected from the Bangladesh Meteorological Department (recorded at the meteorological stations located in Bogura, Rajshahi, Ishurdi, Dinajpur, Syedpur, and Rangpur) with the help of an on-going collaborative project (SDIP II: Sustaining groundwater irrigation for food security in the North-West region of Bangladesh) with CSIRO, Australia. Data on crops such as length of growth stage, crop co-efficient, root depths, depletion factors, yield reduction factors, maximum ponding depth, minimum ponding depth, refill ponding depth, planting date and planting duration were collected from sub-district (called upazila) and district Agricultural Offices through SDIP II project.

After expert consultation and literature review, a total of eight most commonly practiced crops and cropping patterns were selected for this study. The selected cropping patterns were: Aman-Boro−Fallow, Aman–Wheat−Fallow, Aman–Maize−Fallow, Aman–Potato−Fallow, Aman−Fallow-Aus, Aman–Wheat-Aus, and Aman–Wheat–Boro. We grouped the minor crops as Other Rabi (for dry season crops) and Other Kharif (for wet season crops) and put them into Other Rabi–Other Kharif pattern. The Other Rabi includes pulses, spices, oilseeds and vegetables of the Rabi season, and Other Kharif includes mungbean and vegetables of the Kharif season. For simplicity, we presented 'T. Aman' as 'Aman' and dropped out 'Fallow' from the cropping patterns. In the dominating cropping patterns, Boro, Aman, Potato, Wheat and Maize were the major crops. Aus was also found in many occasions in other cropping patterns. So, we selected the major crops, Other Rabi and Other Kharif.

CROPWAT model

Actual crop evapotranspiration (ET), total effective rainfall (TER), crop-usable effective rainfall (ER) and irrigation requirement (IR) were estimated by using a daily Soil-Water Balance Model, which is exactly similar to CROPWAT (SWBcropwat) model, which is a macro in MS excel sheets. TER is the amount of rainfall after deducting all losses and available for usage by crops, while ER is the portion of TER that crops could utilize. Details on SWB model were reported in Mainuddin et al. (2014).

ET, TER, ER and IR were estimated for eight major crops and cropping patterns of all 16 districts in the NW region for 31 years (1985–2015). Also estimated are the volumetric quantities of ET, ER and IR for each crop by multiplying ET, ER and IR by crop acreage. These were summed up district-wise for all crops, crop-wise for all districts and also for all crops for the whole NW region (16 districts).

Trend analysis

The trend of seasonal ET, ER and IR, and their volumetric quantities of the eight major crops and cropping patterns were determined by using Mann-Kendall-Sens (MAKESENS) trend statistics (Salmi, 2002). The used statistical methods are the non-parametric Mann-Kendall test for analyzing the presence of monotonic increasing or decreasing trend and the non-parametric Sen's method for estimating the slope of a linear trend (Salmi, 2002). MAKESENS utilizes two statistics, called Z-statistics and S-statistics to estimate trend. Based on data type, especially sensitivity of change, the MAKESENS model determines statistical significance of the trend at $p \leq 0.10$, 0.05, 0.01 and 0.001. The Mann-Kendall test requires at least four values, and calculation of the confidence intervals for the Sen's slope estimate requires at least ten values in a time series.

Results and Discussion

ET, ER and IR of Major Crops

The observed Mann-Kendall trend statistics (Z) being negative revealed significantly ($p \leq 0.05$) declining trend of ET of the crops during 1985 to 2015 in all 16 districts, except Aman and Other Kharif for which ET increased (positive Z) insignificantly in most districts (Table-1a). ER showed decreasing trend except that it increased in Nowabganj for Aus, Aman, Boro and Other Rabi and in Pabna, Natore, Nilphamari, Panchagarh and Thakurgaon for Aman and Other Kharif, with significant increase in Nilphamari (Table-1b). The decrease in ER was mostly significant in Sirajganj, Joypurhat, Rangpur and Thakurgaon. IR generally revealed decreasing trend, except for Aman and Other Kharif that showed increasing trend (Table-1c). It decreased significantly for most crops except in Rangpur, Dinajpur, Thakurgaon, Nilphamari and Panchagahr. IR increased significantly for Aman in Naogaon, Kurigram, Thakurgaon, Lalmonirhat and Panchagahr, and for Other Kharif in Panchagahr. IR and its trend showed significant spatial variability over the years due to significant changes in ET and ER. ER was generally lower than ET for Aus and Other Rabi. However, ER was close to ET for Aman and Other Kharif in most of the years; it was also close to ET in the 8 Northern districts. Although TER was greater than ET during large rainfall events, ER was lower than ET because of non-uniform rainfall distribution over the crop period, thus necessitating irrigation application.

Table-1a. Mann–Kendall trend (Z) of actual crop evapotranspiration (ET, mm/season) of eight major crops for each district of NW Bangladesh

Crop	Rajshahi	Nowabganj	Naogaon	Natore	Pabna	Sirajgonj	Bogura	Joypurhat	Gaibandha	Kurigram	Rangpur	Dinajpur	Thakurgaon	Panchagarh	Nilphamari	Lalmonirhat
Boro	-3.68***	-3.64***	-3.64***	-3.89***	-3.82***	-3.53***	-5.00***	-5.00***	-4.76**	-4.22***	-3.93***	-4.25***	-3.96***	-3.96***	-3.32***	-3.93***
Wheat	-4.75***	-4.82***	-4.82***	-5.42***	-5.60***	-5.10***	-5.14***	-5.14***	-4.67***	-3.93**	-3.89***	-4.32***	-4.42***	-4.42***	-2.50*	-3.93***
Potato	-4.82***	-4.78***	-4.78***	-5.39***	-5.67***	-5.14***	-5.03***	-5.17***	-4.82***	-4.03***	-4.00***	-4.60***	-4.60***	-4.60***	-2.71**	-4.03***
Maize	-4.03***	-4.21***	-4.21***	-4.92***	-4.96***	-4.96***	-5.03***	-5.03***	-4.57***	-5.03***	-4.17***	-4.39***	-4.39***	-4.39***	-2.32*	-4.03***
Other Robi	-4.53***	-4.60***	-4.60***	-5.28***	-5.35***	-4.89***	-4.92***	-4.92***	-4.42***	-3.78***	-3.85***	-4.03***	-4.14***	-4.14***	-2.25*	-3.78***
Aus	-4.49***	-4.49***	-4.45***	-3.81***	-3.57***	-2.92**	-3.43***	-3.43***	-3.94***	-3.57**	-3.40***	-2.80**	-2.62**	-2.69**	-3.03**	-3.57***
Aman	0.64	0.61	0.61	0.71	0.54	-1.57	-0.34	-0.34	0.54	-0.24	-0.07	-0.34	1.46	1.46	2.57*	-0.04
Other Kharif	-0.21	-0.07	-0.07	0.11	0.39	-0.25	-0.75	-1.14	-0.39	-0.25	-0.25	1.53	1.46	1.46	2.36*	-0.25

+, *, ** and *** signs indicate significant at p≤0.10, ≤0.05, ≤0.01 and ≤0.001 level of significance, respectively.

Table-1b. Mann–Kendall trend (Z) of crop-usable effective rainfall (ER, mm/season) of eight major crops for each district of NW Bangladesh

Crop	Rajshahi	Nowabganj	Naogaon	Natore	Pabna	Sirajgonj	Bogura	Joypurhat	Gaibandha	Kurigram	Rangpur	Dinajpur	Thakurgaon	Panchagarh	Nilphamari	Lalmonirhat
Boro	-1.34	0.68	-0.64	-1.03	-1.50	-2.39*	-0.66	-0.10	0.14	-0.44	0.27	-1.16	-1.70^{+}	-0.59	-1.12	-0.14
Wheat	-0.95	-0.07	-1.65^{+}	-1.00	-0.18	-1.25	-1.46	-2.72**	-1.55	-1.20	-2.18*	-1.81^{+}	-2.79**	-1.76^{+}	-1.61	-1.50
Potato	-0.95	-0.07	-1.65^{+}	-1.00	-0.18	-1.25	-1.02	-2.72**	-1.55	-1.20	-2.18*	-1.81^{+}	-2.79**	-1.76^{+}	-1.61	-1.50
Maize	-1.75^{+}	-0.59	-1.62	-2.75**	-1.82^{+}	-2.12*	-1.02	-2.05*	-1.39	-1.89^{+}	-1.59	-1.09	-2.43*	-1.09	-2.46*	-0.66
Other Robi	-1.04	0.07	-1.70^{+}	-1.24	-0.13	-1.07	-1.39	-2.55*	-1.30	-1.05	-2.33*	-1.89^{+}	-2.82**	-1.76^{+}	-1.62	-1.48
Aus	-1.63	0.75	-0.53	-1.02	-0.07	-3.57***	-2.55*	-1.90^{+}	-3.60***	-3.50***	-3.40***	-0.80	-2.69**	-2.38*	-1.12	-3.13**
Aman	-1.39	0.61	0.61	0.71	0.54	-1.57	-0.34	-0.34	0.54	-0.24	-0.07	-0.34	1.46	1.46	2.57*	-0.04
Other Kharif	-0.21	-0.07	-0.07	0.11	0.39	-0.25	-0.75	-1.14	-0.39	-0.25	-0.25	1.53	1.46	1.46	2.36*	-0.25

Table-1c. Mann–Kendall trend (Z) of irrigation requirement (IR, mm/season) of eight major crops for each district of NW Bangladesh

Crop	Rajshahi	Nowabganj	Naogaon	Natore	Pabna	Sirajgonj	Bogura	Joypurhat	Gaibandha	Kurigram	Rangpur	Dinajpur	Thakurgaon	Panchagarh	Nilphamari	Lalmonirhat
Boro	-1.43	-3.28**	-1.50	-1.93^{+}	-1.46	0.64	-2.28*	-1.56	-2.24*	-1.46	-1.21	-1.26	1.03	-1.32	-0.89	-1.71^{+}
Wheat	-2.18*	-2.93**	-2.28*	-2.57*	-3.21*	-3.00**	-3.03**	-2.03*	-2.78**	-2.60**	-2.28*	-1.50	0.43	-1.61	-1.78^{+}	-2.78**
Potato	-1.96*	-3.03**	-2.07*	-2.57*	-3.14**	-2.89**	-3.07**	-2.11*	-2.85**	-2.64**	-1.89^{+}	-1.46	1.11	-1.61	-1.68^{+}	-2.78**
Maize	-2.43*	-2.82**	-2.18*	-2.43*	-2.71**	-2.14*	-3.07**	-3.25**	-2.85**	-2.25*	-2.00*	-2.28*	0.14	-2.18*	-0.54	-3.35***
Other Robi	-1.96*	-2.96**	-2.18*	-2.57*	-3.07**	-3.00**	-3.00**	-2.18*	-2.68**	-2.60**	-1.93^{+}	-1.46	-0.04	-1.53	-1.64	-2.75**
Aus	-0.48	-2.79**	-1.53	-1.50	-0.92	0.34	-0.85	-1.77^{+}	-1.87^{+}	-1.36	-1.70^{+}	-0.80	0.36	-1.09	-0.99	-1.60
Aman	2.89**	1.09	2.52*	1.86^{+}	1.75^{+}	1.69^{+}	1.86^{+}	1.17	1.70^{+}	2.38*	0.97	1.86^{+}	-0.46	1.47	1.16	2.55*
Other Kharif	0.11	-0.18	0.96	1.14	0.36	1.39	0.00	-0.25	0.14	1.25	1.39	1.07	-0.36	2.07*	0.71	1.25

+, *, ** and *** signs indicate significant at p≤0.10, ≤0.05, ≤0.01 and ≤0.001 level of significance, respectively.

Table-2a. Mann–Kendall trend (Z) of actual crop evapotranspiration (ET, mm/season) of eight major cropping patterns for each district of NW Bangladesh

Crop	Rajshahi	Nowabganj	Naogaon	Natore	Pabna	Sirajgonj	Bogura	Joypurhat	Gaibandha	Kurigram	Rangpur	Dinajpur	Thakurgaon	Panchagarh	Nilphamari	Lalmonirhat
Aman_Wheat	-2.60**	-2.53*	-2.53*	-2.93**	-2.57*	-4.69***	-3.35***	-3.35***	-3.14**	-0.25	-2.25*	-0.71	-0.86	-0.86	0.00	-2.18*
Aman_Maize	-3.18**	-3.10**	-3.10**	-3.60***	-3.32***	-4.71***	-4.10***	-4.10***	-3.96***	-3.14**	-3.18**	-2.25*	-2.28*	-2.28*	-1.07	-3.14**
Aman_Potato	-2.71**	-2.68**	-2.68**	-2.93**	-2.64**	-4.71***	-3.68***	-3.68***	-3.10**	-2.28*	-2.36*	-0.89	-0.96	-0.96	-0.04	-2.28*
Aus_Aman	-3.32***	-3.28**	-3.28**	-2.75**	-2.46*	-2.53*	-1.89^{+}	-1.89^{+}	-2.71**	-2.89**	-2.78**	-0.75	-0.61	-0.61	-0.43	-2.89**
Boro_Aman	-3.50***	-3.43***	-3.43***	-3.35***	-3.21**	-3.25**	-3.18**	-3.18**	-3.57***	-3.60***	-3.64***	-2.11*	-2.18*	-2.18*	-1.61	-3.60***
Aus_Aman_Wheat	-4.14***	-4.14***	-4.14***	-3.46***	-3.28**	-4.35***	-3.82***	-3.82***	-4.00***	-3.85***	-3.82***	-2.28*	-2.39*	-2.39*	-1.78^{+}	-3.85***
Boro_Aman_Wheat	-3.96***	-3.85***	-3.85***	-3.89***	-3.93***	-4.53***	-4.64***	-4.64***	-4.57***	-4.28***	-4.35***	-3.14**	-3.14**	-3.14**	-2.28*	-4.28***
Other_Other	-3.32***	-3.28**	-3.28**	-3.14**	-2.85**	-4.82***	-4.10***	-4.10***	-3.14**	-2.57*	-2.75**	-1.71^{+}	-1.75^{+}	-1.75^{+}	-0.75	-2.57*

Table-2b. Mann–Kendall trend (Z) of crop-usable effective rainfall (ER, mm/season) of eight major cropping patterns for each district of NW Bangladesh

Crop	Rajshahi	Nowabganj	Naogaon	Natore	Pabna	Sirajgonj	Bogura	Joypurhat	Gaibandha	Kurigram	Rangpur	Dinajpur	Thakurgaon	Panchagarh	Nilphamari	Lalmonirhat
Aman_Wheat	-0.86	-0.25	-1.07	-0.36	0.89	-1.43	-1.28	-2.18*	-1.21	-0.75	-1.61	-0.21	-1.03	-0.43	0.71	-1.07
Aman_Maize	-1.68^{+}	-0.46	-1.50	-2.11*	-1.14	-2.39*	-1.32	-1.75^{+}	-1.61	-1.89^{+}	-1.75^{+}	-0.93	-1.78^{+}	-0.79	-1.18	-1.00
Aman_Potato	-0.86	-0.25	-1.07	-0.36	0.89	-1.43	-1.28	-2.18*	-1.21	-0.75	-2.18*	-0.21	-1.03	-0.43	0.71	-0.89
Aus_Aman	-1.21	0.07	0.00	-0.75	0.25	-3.39***	-1.71^{+}	-1.75^{+}	-2.70**	-3.10**	-3.03**	-0.11	-1.28	-1.36	0.79	-3.07**
Boro_Aman	-0.39	1.46	-0.14	-0.57	-1.07	-2.25*	-0.46	-0.39	-0.07	-0.25	0.46	-1.03	-1.11	0.43	-1.03	-0.43
Aus_Aman_Wheat	-1.07	0.29	-0.11	-0.68	0.64	-2.82**	-2.28*	-2.50*	-2.57*	-2.68**	-3.03**	-0.36	-2.50*	-2.21*	-0.21	-2.78**
Boro_Aman_Wheat	-0.39	1.39	-0.46	-1.03	-1.25	-2.46*	-0.86	-1.07	-0.21	-0.54	-0.32	-1.43	-1.78^{+}	-0.25	-1.57	-0.46
Other_Other	-0.82	-0.21	-1.50	-0.39	0.36	-1.18	-1.36	-2.64**	-1.50	-1.11	-2.28*	-0.04	-1.43	-0.82	-0.36	-0.93

+, *, ** and *** signs indicate significant at p≤0.10, ≤0.05, ≤0.01 and ≤0.001 level of significance, respectively.

Table-2c. Mann–Kendall trend (Z) of irrigation requirement (IR, mm/season) of eight major cropping patterns for each district of NW Bangladesh

Crop	Rajshahi	Nowabganj	Naogaon	Natore	Pabna	Sirajgonj	Bogura	Joypurhat	Gaibandha	Kurigram	Rangpur	Dinajpur	Thakurgaon	Panchagarh	Nilphamari	Lalmonirhat
Aman_Wheat	2.39*	0.00	0.57	0.71	0.68	0.00	0.00	-0.14	0.29	1.25	0.25	0.68	1.03	0.18	0.25	1.39
Aman_Maize	1.18	-0.57	-0.14	0.04	0.29	-0.89	-1.25	-1.11	-0.86	0.54	-0.36	-0.32	0.43	-0.89	0.04	0.54
Aman_Potato	2.43*	-0.04	0.61	0.82	0.86	0.00	0.00	-0.25	0.21	0.86	0.39	0.71	1.11	0.50	0.36	1.61
Aus_Aman	1.07	-1.50	-0.32	-0.32	0.00	1.46	0.39	-0.57	-0.86	-0.14	0.11	-0.21	0.14	-0.21	0.29	0.50
Boro_Aman	-0.07	-1.68^{+}	-0.61	-0.43	-0.25	1.03	-0.86	-1.00	-0.89	-0.96	-0.93	-0.54	-0.04	-0.82	-0.39	-0.46
Aus_Aman_Wheat	0.21	-1.71^{+}	-0.89	-0.64	-0.39	0.75	-0.57	-1.39	-1.39	-0.50	-0.39	-0.39	0.36	-0.61	-0.11	-0.14
Boro_Aman_Wheat	-0.64	-2.50*	-1.11	-1.14	-1.03	01.4	-1.78^{+}	-1.21	-1.39	-0.86	-1.11	-0.86	-0.46	-1.39	-0.71	-0.75
Other_Other	-1.93^{+}	-1.96*	-0.43	-0.61	-1.71^{+}	-1.46	-1.53	-1.39	-1.03	-0.50	0.50	-0.32	-0.36	-0.11	-0.25	-0.07

Table-3 summarizes the minimum, maximum and average Sen's slopes for ET, ER and IR for each crop over the 16 districts. We mentioned before that Aman and Other Kharif showed increasing trend in ET, ER and IR in some districts and decreasing trend in the other districts. The rates of variation in ET, ER and IR for these crops are mostly lower compared to the other crops (Table-3). The greatest declining trend in ET was for Boro (3.48 mm/season/year) and the least declining trend was for Other Rabi crops (1.5 mm/season/year). The corresponding decline in ER was 1.64 mm/season/year for Boro and 0.35 mm/season/year for wheat. For IR, the corresponding decline was 2.92 mm/season/year for Boro and 1.03 mm/season/year for Other Rabi crops.

Table-3. The minimum, maximum, average and standard deviation of Sen's slope (S, mm/season/year; Eq.1) of the trend lines for actual crop evapotranspiration (ET), crop-usable effective rainfall (ER) and irrigation requirement (IR) of eight major crops of the North-West region of Bangladesh

Crop	ET				ER				IR			
	Min	Max	Avg	Std	Min	Max	Avg	Std	Min	Max	Avg	Std
Boro	–5.99	–2.10	–3.48	0.84	–5.86	1.25	–1.64	1.89	–5.74	1.47	–2.92	1.57
Wheat	–2.44	–0.02	–1.75	0.59	–1.24	0.86	–0.35	0.57	–1.87	–0.53	–1.20	0.35
Potato	–3.53	–1.37	–2.01	0.55	–1.24	0.00	–0.55	0.39	–3.19	–0.51	–1.24	0.61
Maize	–4.85	–2.39	–3.12	0.62	–2.50	–0.30	–1.40	0.62	–3.46	–0.65	–2.23	0.69
Other Rabi	–2.01	–1.08	–1.50	0.31	–1.20	0.00	–0.44	0.34	–1.50	–0.41	–1.03	0.30
Aus	–3.34	–1.00	–2.32	0.66	–2.50	1.56	–1.41	1.06	–6.00	0.86	–2.19	1.54

ET, ER and IR of Major Cropping Pattern

The Mann-Kendall Z for ET showed a significant ($p \leq 0.01$) decreasing trend of ET except for some cropping patterns in four North-Western districts (Table-2a); ET decreased significantly only for Aman–Wheat–Boro pattern in Nilphamari and Aman–Wheat, Aman–Potato, Aman–Aus and Other–Other patterns in Thakurgoan, Panchagarh and Dinajpur. ER showed mostly decreasing trends except in Nilphamari, Nowabganj and Pabna, which showed slight increasing trends for 3 to 5 cropping patterns (Table-2b). Three to four cropping patterns revealed significant decreases in ER in Rangpur, Joypurhat and Sirajganj; in the other districts, ER decreased significantly for 1 to 2 cropping patterns only. ER was lower than ET in all districts except for Aus–Aman pattern for which ER and ET were mostly closer since growth period of this cropping pattern was in the rainy season. IR showed decreasing trends for 2 to 3 cropping patterns in Rajshahi, Sirajganj and Thakurgaon and for 4 to 8 cropping patterns in all other districts, with significant decrease for only 2 cropping patterns in Naogaon (Table-2c). Of the increasing trend in IR, only 2 cropping patterns in Rajshahi showed significant trends.

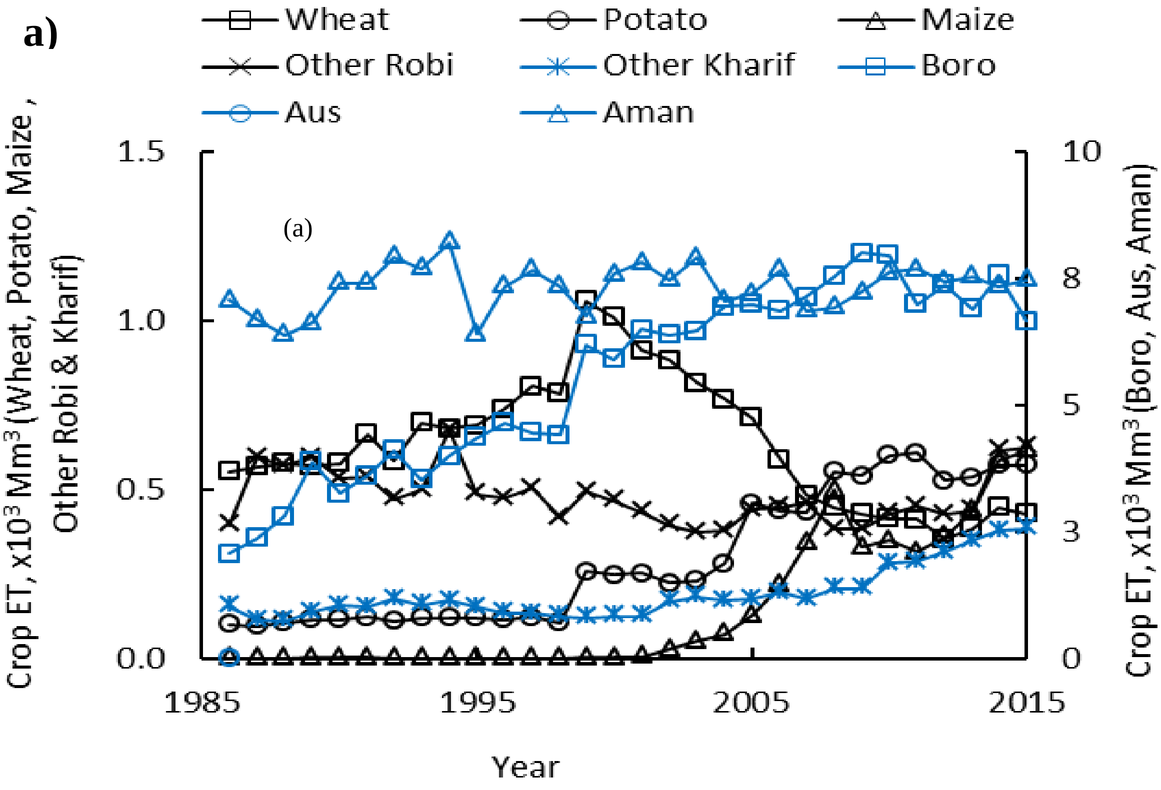
Table-4 summarizes the minimum, maximum and average values of Sen's slope (S) for ET, ER and IR. Both the maximum and minimum slopes revealed decreasing trend of ET for all cropping patterns with the overall average trend ranging from 1.60 mm/year for Aman–Wheat to 5.03 mm/year for Aman–Wheat–Boro pattern. The maximum slope showed increasing trend in ER except for Aman–Maize pattern while the minimum slope showed decreasing trend for all cropping patterns. The decreasing rate of ER varied from 0.66 mm/season/year for Aman–Wheat to 2.07 mm/year for Aman–Wheat–Aus indicated decreasing trend, with the overall average slope showing increasing trends for Aman–Wheat and Aman–Potato patterns and decreasing trends for all other cropping patterns.

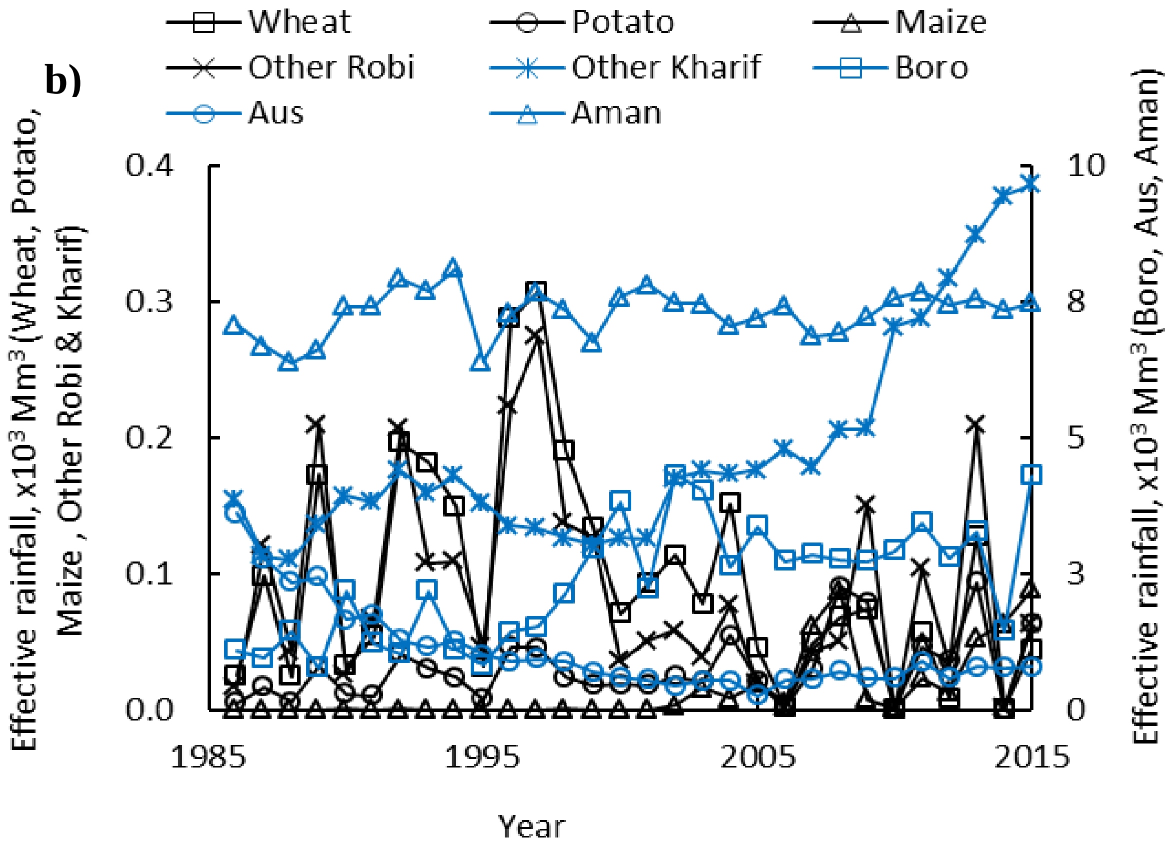
Table-4. The minimum, maximum, average and standard deviation of Sen's slope (S, mm/season/year; Eq.1) of the trend lines for actual crop evapotranspiration (ET), crop-usable effective rainfall (ER) and irrigation requirement (IR) of eight major cropping patterns of the North-West region of Bangladesh

Crop	ET				ER				IR			
	Min	Max	Avg	Std	Min	Max	Avg	Std	Min	Max	Avg	Std
Aman–Wheat	–2.99	0.00	–1.60	0.87	–1.95	0.72	–0.66	0.68	–0.13	1.83	0.63	0.61
Aman–Maize	–4.18	–1.21	–2.87	0.83	–2.87	–0.39	–1.43	0.61	–1.89	1.09	–0.27	0.93
Aman–Potato	–3.16	–0.01	–1.81	0.79	–2.00	0.72	–0.72	0.76	–0.12	2.05	0.74	0.65
Aus–Aman	–3.39	–0.42	–1.96	0.88	–3.38	0.79	–1.35	1.26	–3.43	2.79	–0.14	1.50
Boro–Aman	–5.47	–1.94	–3.10	0.87	–5.70	1.54	–1.18	1.84	–3.85	2.11	–1.41	1.27
Aus–Aman–Wheat	–6.02	–2.51	–3.97	0.89	–4.48	0.94	–2.07	1.75	–4.76	1.91	–1.16	1.57

Volumetric Quantity of ET, ER and IR

The variations of volumetric quantities of ET, ER and IR for different crops are displayed in Figure 1 for the entire NW region. Water used through ET and IR increased systematically over the years only for Boro. For the other crops, water due to ET, ER and IR increased over some time-span and decreased over other time-span. Water used through ET and IR increased systematically for wheat up to 1999 after which they declined sharply up to 2007 before becoming almost stable (Figure 1). Contrasting temporal variation was found for potato; the quantities of water remained almost invariant up to 1999 after which they continued increasing until becoming stable in 2011. Maize was cultivated noticeably from 2002, leading to gradually increasing water usage through ET and IR, with a sudden increase in acreage in 2007. Water used through ET for Other Kharif increased gradually starting from 2002, revealing continuous increase in acreage of these crops. However, the quantity of irrigation did not increase noticeably since these crops utilized rainfall as evident in Figure 1. For the remaining crops, there was no systematic variation in water usage through ET and IR over the years. Water used through ET, ER and IR decreased for wheat, Other Rabi and Aus, with significant decrease for Aus and Other Rabi due to ET only (Table-5). For the other crops, water usages increased, mostly significantly, except for Aman due to ET and ER. Figure 5 illustrates variations of the estimated volumetric quantity of water due to ET, ER and IR for all major crops for the entire NW region. While considering the whole NW region, water usage due to ET, ER and IR increased significantly at 166.54 Mm3/year, 22.28 Mm3/year and 225.80 Mm3/year, respectively.


a)
Wheat
Potato
Maize
Other Robi
Other Kharif
Boro
Aus
Aman
(a)
Crop ET, x10^3 Mm^3 (Wheat, Potato, Maize , Other Robi & Kharif)
Crop ET, x10^3 Mm^3 (Boro, Aus, Aman)
1.5
1.0
0.5
0.0
10
8
5
3
0
1985
1995
2005
2015
Year


b)
Wheat
Potato
Maize
Other Robi
Other Kharif
Boro
Aus
Aman
Effective rainfall, x10^3 Mm^3 (Wheat, Potato, Maize , Other Robi & Kharif)
Effective rainfall, x10^3 Mm^3 (Boro, Aus, Aman)
0.4
0.3
0.2
0.1
0.0
10
8
5
3
0
1985
1995
2005
2015
Year

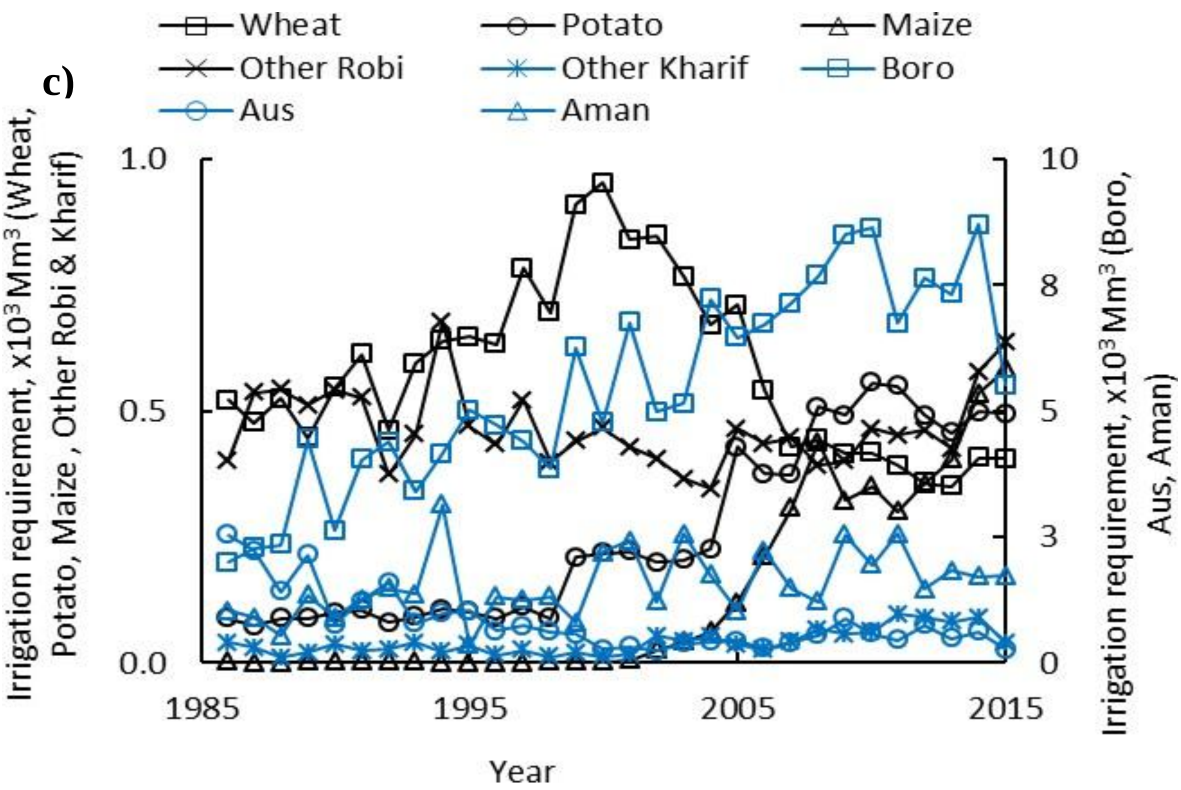


Figure 1. Variation of volumetric quantity of (a) actual crop evapotranspiration, (b) crop-usable effective rainfall, and (c) irrigation requirement of the major crops of the NW region of Bangladesh over the period of investigation.

Table-5. Mann–Kendall trend (Z) and Sen's slope (S, Mm^3/season/year) of estimated actual crop evapotranspiration (ET, Mm^3/season/year), irrigation requirement (IR, Mm^3/season/year), and effective rainfall (ER, Mm^3/season/year) of eight major crops for the North-West region of Bangladesh

Crops	ET		ER		IR	
	Z	S	Z	S	Z	S
Boro	6.21***	200.12	4.00***	86.12	5.71***	204.27
Wheat	–1.43	–7.10	–1.78^{+}	–2.79	–1.75^{+}	–4.93
Potato	5.99***	19.25	2.00*	0.99	5.85***	17.64
Maize	5.89***	16.49	4.50***	0.67	5.99***	15.88
Other Rabi	–2.25*	–4.13	–1.21	–1.59	–1.03	–1.45
Aus	–4.03***	–57.75	–4.10***	–56.76	–3.78***	–38.49
Aman	0.99	11.49	1.07	8.78	2.60**	32.34
Other Kharif	4.82***	6.26	4.89***	6.24	3.50***	1.81

+, *, ** and *** signs indicate significant at p≤0.10, ≤0.05, ≤0.01 and ≤0.001 level of significance, respectively.

Conclusion

The NW region of Bangladesh being vulnerable to climate changes is subject to face water scarcity and extreme climatic events like droughts and erratic rainfalls. So, local-level actual crop evapotranspiration (ET), total rainfall (TER), crop-usable effective rainfall (ER) and irrigation requirement (IR) of major crops and cropping patterns are essential for the region's long-term agricultural planning and water resources management. Significant ($p \leq 0.05$) decreasing trend of ET of most crops and cropping patterns during 1985 to 2015 in all 16 districts of the region exposed overall suppressing effect of climate change on crop-water demand. Significantly decreasing trends of ER for most crops in several districts demonstrate the necessity of satisfying more crop-water demand from irrigation in the future. With increasing crop-acreage, unplanned crop-planting and high irrigation share, water scarcity is becoming increasingly critical in many areas. Future research can focus on optimizing acreage of different crops and cropping patterns to maximize economic benefit and maintain sustainable level of groundwater use.

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IRRIGATION EFFECT ON COWPEA PRODUCTION IN CHATTOGRAM REGION

M.P.Haque[1], M.K.R. Bhuiyan[2], M .A. Hossain[3], andS.K. Biswas[4]

Abstract

The study was conducted at the research field of Regional Agricultural Research Station, Hathazari, Chattogram during the rabi season of 2018-19 and 2019-20 to identify the critical stages of irrigation and optimize irrigation in cowpea production. Five treatments were applied: T_1 (rain-fed i.e. local practice), T_2(irrigation at 3 weeks interval), T_3 (irrigation at flowering stage), T_4 (irrigation at pod formation stage), T_5 (irrigation at flowering and pod formation stages). The highest yield (2.2 ton/ha and 2.3 ton/ha in2018-19 and 2019-20 respectively) and highest water stress coefficient (K_s= 1 to 0.6) were found at higher frequency irrigation (T_2). The maximum irrigation (182mm and 194mm) was applied at T_2. In rain-fed condition (T_1), cowpea yield was lowest (1.2 ton/ha). The sustainability of cowpea in low water stress co-efficient (up to 0.05) indicated that field crop was drought tolerant. Irrigation at pod formation stage yield was higher than flowering stage in case of only one irrigation facilities. The pod formation stage was more sensitive to deficit irrigation than flowering stage. Based on the economic analysis, irrigation at three weeks interval was more beneficial (BCR=1.45).Irrigation At flowering and pod formation stage (T5), the water productivity (1.2 Kg/m3) was higher.

Introduction

Cowpea is a leguminous and an important source of proteins, present in tropical and subtropical areas (Ehlers & Hall, 1997).Cowpea contributes to the improvement of soil fertility by the fixation of nitrogen (N) in the soil (60 - 70 kg•N•ha–1 to the subsequent crop). Although suitable to grow at all regions of Bangladesh, it is extensively grown in the south-eastern part in the rice-based cropping systems after the harvest of transplant Aman rice. Cowpea production technology, in this region, completely depends on rain fed condition. As farmers are used to grow cowpea in fallow land after Aman for earning the extra income from this land, they have a little bit interest to irrigation water management. Irrigation boosts up the yield of cowpea (Tyem & Chieng, 1985). Thus, there is a scope of more profitable cowpea production through proper irrigation timing and water management in this region.

Materials and Methods

A field experiment was conducted at the research field of Regional Agricultural Research Station, Hathazari, Chattogram during the rabi season of 2018-19 and 2019-20. The seeds were sown at 18 November and harvested at 25 March.BARI Felon 1 was sown in 50 cm spacing from line to line, 10 cm from plant to plant and 100 cm border using randomised complete block (RCB) design with five treatments and three replications. The plot size was 4m by 4m and fertilizer was applied Urea@ 30kg/ha, TSP@ 45kg/ha, MP@ 30 kg/ha .The five irrigation treatments are:

- Rain fed condition i.e. Local practice (T_1)
- Irrigation at 3 weeks intervals (T_2)
- Irrigation at flowering stage (T_3)
- Irrigation at pod formation stage (T_4),
- Irrigation at flowering and pod formation stages (T_5)

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Amount of water to be applied during each irrigation was estimated by measuring soil moisture depletion from the field capacity. The water was applied by hose pipe.

Moisture content measurement

Water content was calculated gravimetrically or volumetrically. Gravimetric soil water content is the mass ofwater divided by the mass of dry soil. It was measuredby weighing a mass of wet soil, drying the soil for 24 hours at 105 ^{0}C in Oven, and then reweighing the sample(Waller & Yitayew, 2016).

$$\Theta_{grav}\ (gm/gm)= \frac{Mass\ of\ water(gm)}{Mass\ of\ dry\ soil\ (gm)} = \frac{Mass\ of\ wet\ soil\ (gm)-Mass\ of\ dry\ soil\ (gm)}{Mass\ of\ dry\ soil} \quad (1)$$

$$\Theta_v\ (cm^3/cm^3)= \theta_{grav}\times soil\ bulk\ density\ (gm/cm^3) \quad (2)$$

Crop water requirement

Crop water requirement was calculated with the following formula.

$$ETc = Kc \times ETo \quad (3)$$

where,

ETc = crop water requirement

Kc = crop coefficient for cowpea initial 0.5, mid 0.7, end 0.35 (Allen et al., 2006).

ET_O = Reference crop evapotranspiration calculated by FAO penman-monteith equation.

Actual crop water requirement or adjusted crop water requirement due to water stress was calculated by

$$ETa = ETc \times Ks. \quad (4)$$

where, Ks= water stress coefficient $=\frac{\theta-\theta pwp}{\theta t-\theta pwp}$, Θt= threshold water depletionand θpwp= permanent wilting point.(Waller & Yitayew, 2016)

Crop response factor (Ky)

Crop response factor was calculated with Stewart equation (Stewart et al., 1977) i.e. later cited in FAO 33 paper ((Doorenbos& Kassam, 1979) in the following formula.

$$(1-\frac{Ya}{Ym}) = Ky(1-\frac{ETa}{ETm}) \quad (5)$$

Crop water productivity

Crop water productivity (CWP) is the ratio of the actual marketable crop yield (Y_{act}) and actual seasonal crop water consumption by evapotranspiration (ET_{act})(Zwart & Bastiaanssen, 2004).

$$CWP = \frac{Yact}{ETact} \quad (6)$$

Results and Discussions

The highest yield was found in irrigation at three weeks intervals (T_2) and lowest yield was at rain fed condition (T_1). Irrigation at pod formation (T_4) yields higher than flowering stage (T_3). Yield with treatments wise are shown in Table-1 and Table-2. The maximum water (182mm and 194mm) was applied at T_2 and rain fed condition (T_1) plotsgot effective rain 12.8mm and 28.7mm which is 70% of rainfall(Singh, 2014).

Water stress at rain fed condition (T_1) was higher than any other treatments and lesser in (T_2) irrigation at three weeks interval (Fig-2 and Fig-3). Soil moisture level at all treatments was remained between field capacity and wilting point (Fig-6 and Fig-7).

The more crop response factor (Ky) value, the more sensitive to water deficit irrigation. The steeper the slope (i.e. the higher the Ky value), the greater the reduction of yield for a given reduction in ET because of water deficits in the specific stage. In this experiment, water sensitivity order was (Fig-1 and Fig-2):Flowering stage < Pod formation stage

Crop water productivity at irrigation at flowering stage plus pod formation stage (T_5) was highest although benefit-cost ratio was highest at irrigation at three weeks interval cowpea production shown in Table-3 and Table-4.

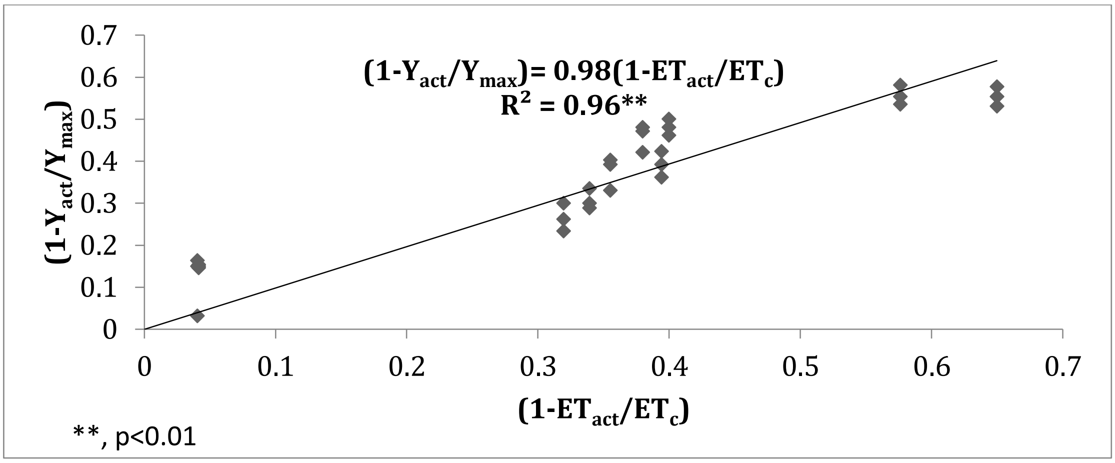

Fig-1.Relative yield reduction and relative deficit evapotranspiration relationship.

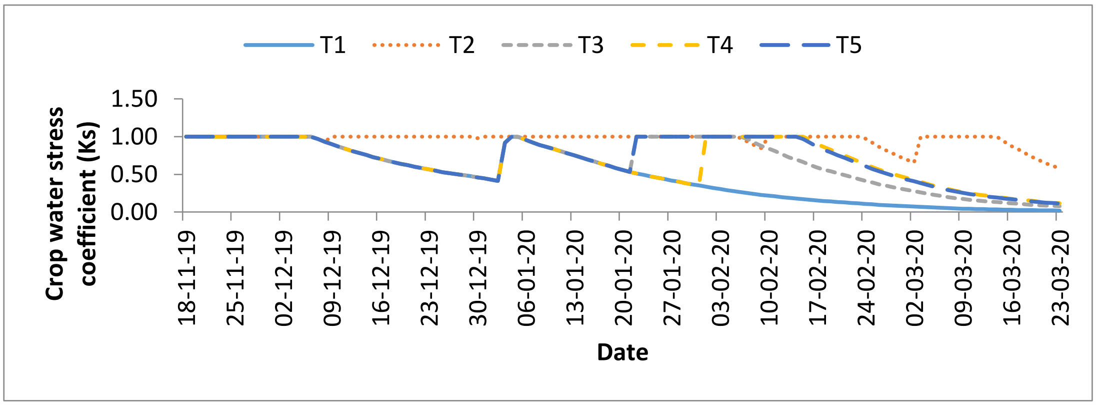

Fig-2. Crop water stress coefficient (Ks) with respect to different level of water application in 2018-2019.

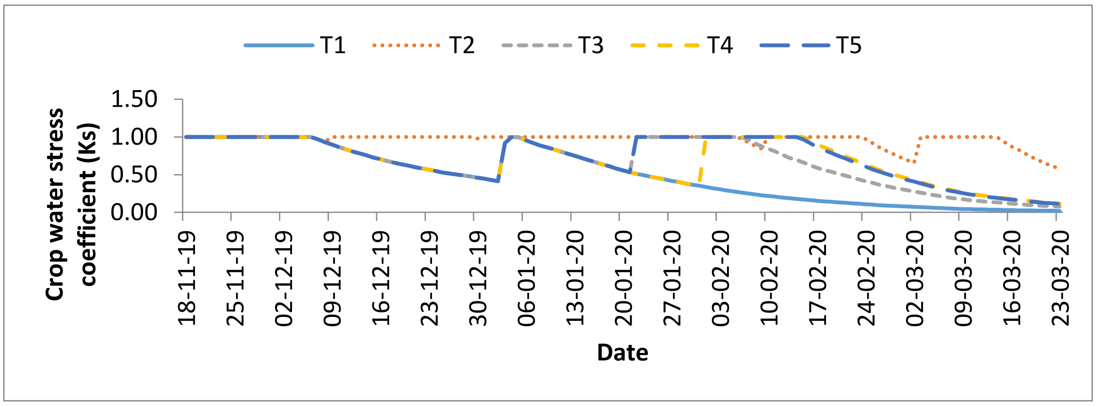

Fig-3: Crop water stress coefficient (Ks) with respect to different level of water application in 2019-2020.

Table-1. Irrigation effect on cowpea production in 2018-2019

Treatment	Height (cm)	No of branches per plant	No of pods per plant	No of seeds per pod	Seeds weight per pod (gm)	Grain weight per plant (gm)	1000 seeds weight (gm)	Yield (ton/ha)
T_1	33.00	4	12	10	0.57	6.8	56.67	1.16
T_2	43.67	6	16	11	0.81	12.96	73.64	2.21
T_3	40.33	4	13	10	0.61	7.93	61.00	1.35
T_4	31.67	5	14	10	0.66	9.24	66.00	1.58
T_5	45.67	4	15	11	0.71	10.65	64.55	1.82
CV (%)	10.60	13.55	3.39	3.30	1.30	1.23	1.34	1.34
$LSD_{(0.05)}$	7.76	1.19	0.97	0.90	0.02	0.22	1.62	1.62

Note: *T_1=Rain fed , T_2= Irrigation at 3 weeks interval, T_3= Irrigation at flowering stage, T_4= Irrigation at pod formation stage, T_5= Irrigation at flowering and pod formation stages*

Table-2.Irrigation effect on cowpea production in 2019-2020

Treatment	Height (cm)	No of branches per plant	No of pods per plant	No of seeds per pod	Seeds weight per pod (gm)	Grain weight per plant (gm)	1000 seeds weight (gm)	Yield (ton/ha)
T_1	33.0	4	12	10	0.58	6.75	56.64	1.15
T_2	43.6	6	16	11	0.83	13.49	73.66	2.30
T_3	40.4	4	13	10	0.62	8.27	61.50	1.41
T_4	31.7	5	14	10	0.66	9.51	66.33	1.62
T_5	45.7	4	15	11	0.73	11.19	64.63	1.91
CV (%)	1.18	14.7	6.56	5.7	1.7	6.72	1.14	6.71
$LSD_{(0.05)}$	0.87	1.35	1.75	NS	0.02	1.24	1.38	0.21

Note: *T_1=Rain fed , T_2= Irrigation at 3 weeks interval, T_3= Irrigation at flowering stage, T_4= Irrigation at pod formation stage, T_5= Irrigation at flowering and pod formation stages*

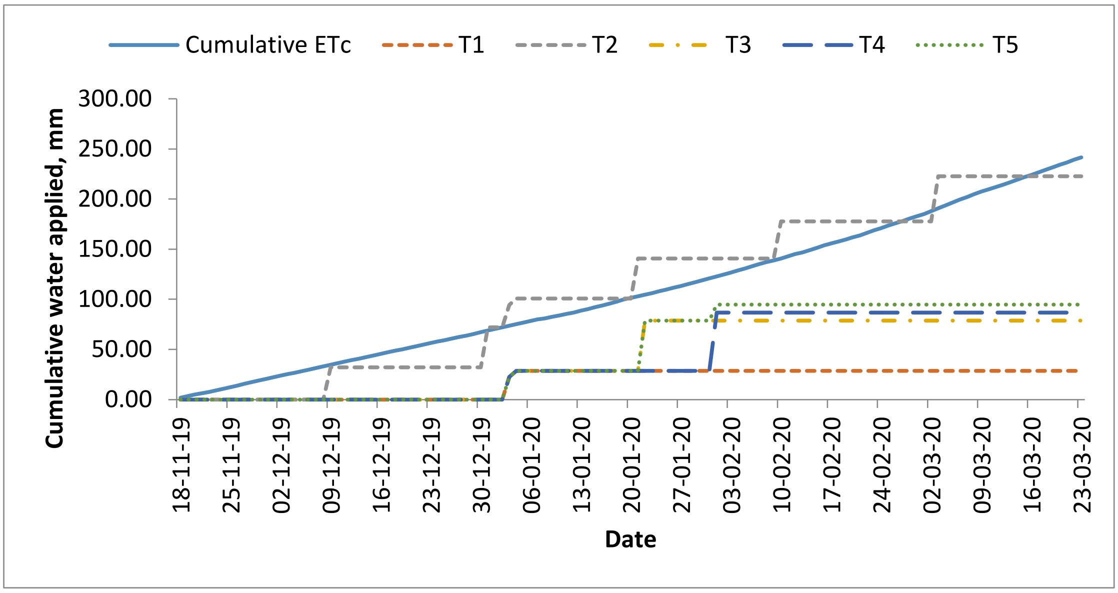

Fig-4. Treatment wise Cumulative crop ET and Water application (mm) in 2018-2019.

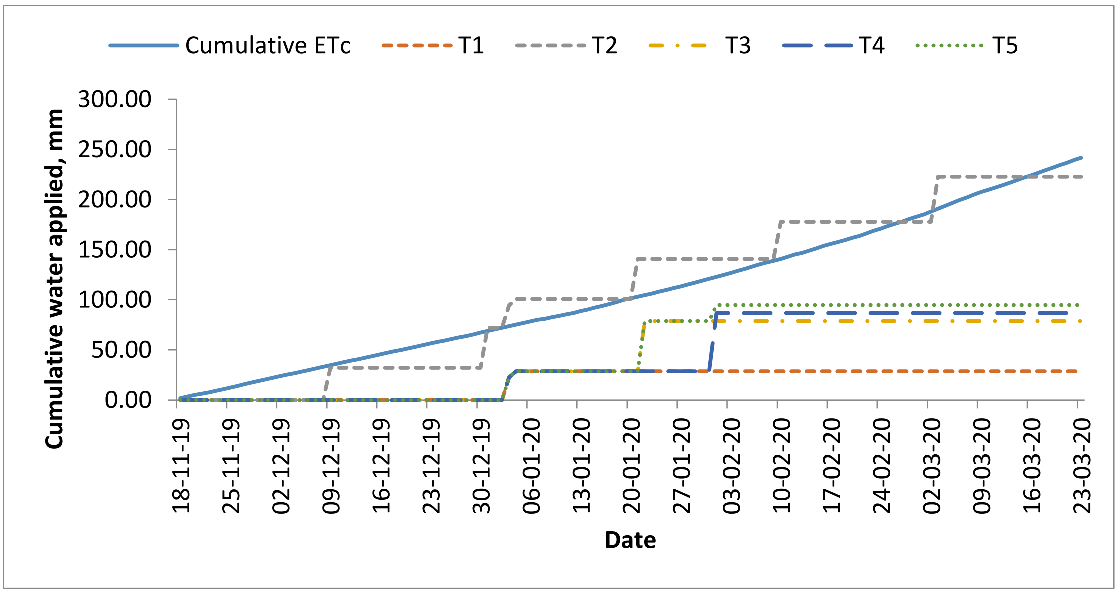

Fig-5. Treatment wise soil moisture (%), Cumulative crop ET and Water application (mm) in 2019-2020.

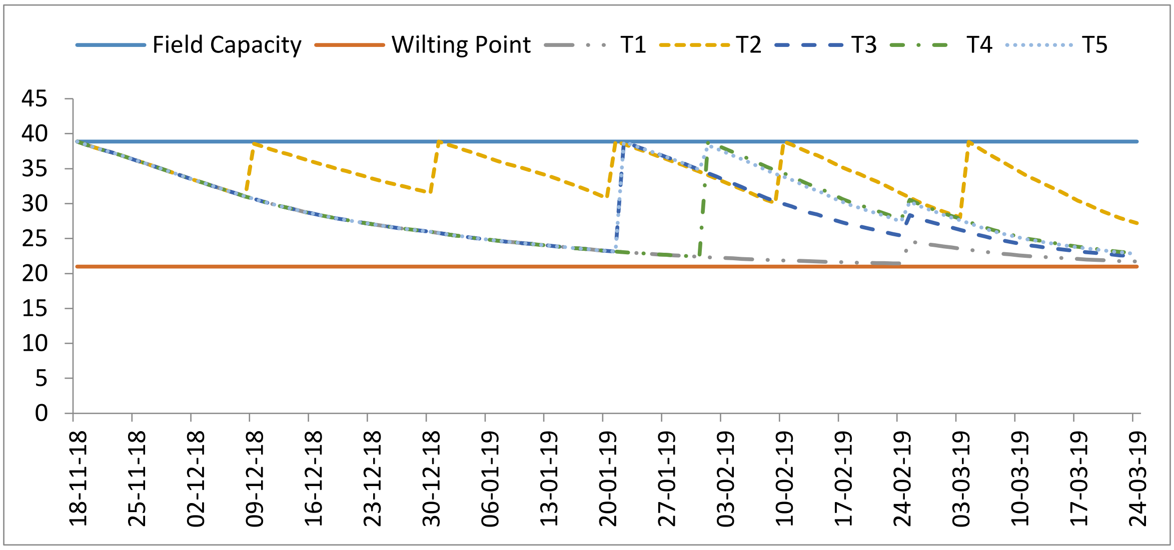

Fig-6. Treatment wise soil moisture (%) in 2018-2019.

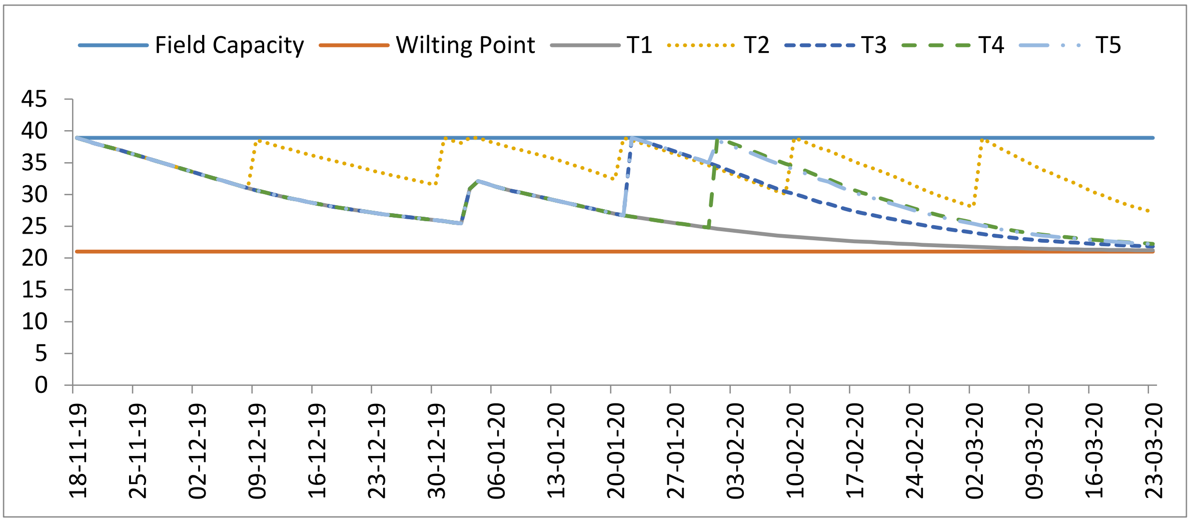

Fig-7. Treatment wise soil moisture (%) in 2019-2020.

Table-3. Economic analysis of cowpea production and Crop water productivity in 2018-2019

Treatment	Irrigation no.	Amount of irrigation (mm)	Effective rainfall (mm)	Actual ET	Yield (ton/ha)	Crop Water productivity (Kg/m3)	Benefit (Tk/ha)	Cost(Tk/ha)	Benefit/ Cost Ratio
T_1	0	0	12.8	84.39	1.16	1.37	23200	22040	1.05
T_2	5	181.2	12.8	231.02	2.21	0.96	44200	30000	1.47
T_3	1	63	12.8	144.64	1.35	0.93	27000	25000	1.08
T_4	1	66	12.8	146.01	1.58	1.08	31600	25000	1.26
T_5	2	79	12.8	159.22	1.82	1.14	36400	27000	1.35

Note: *T_1=Rain fed , T_2= Irrigation at 3 weeks interval, T_3= Irrigation at flowering stage, T_4= Irrigation at pod formation stage, T_5= Irrigation at flowering and pod formation stages*

Table-4. Economic analysis of cowpea production and Crop water productivity in 2019-2020

Treatment	Irrigation no.	Amount of irrigation (mm)	Effective rainfall (mm)	Actual ET	Yield (ton/ha)	Crop Water productivity (Kg/m3)	Benefit (Tk/ha)	Cost(Tk/ha)	Benefit/Cost Ratio
T_1	0	0	28.7	102.14	1.15	1.13	23000	22040	1.04
T_2	5	194	28.7	231.27	2.30	1.00	46000	30000	1.53
T_3	1	50	28.7	149.44	1.41	0.94	28200	25000	1.13
T_4	1	58	28.7	155.40	1.62	1.05	32400	25000	1.30
T_5	2	66	28.7	164.01	1.91	1.17	38200	27000	1.41

Note: *T_1=Rain fed , T_2= Irrigation at 3 weeks interval, T_3= Irrigation at flowering stage, T_4= Irrigation at pod formation stage, T_5= Irrigation at flowering and pod formation stages*

Conclusion

The more frequent irrigation yields more production in cowpea. The three weeks interval irrigation gives highest yield (2.2 ton/ha). The pod formation stage is the critical stage of irrigation than flowering stage. Irrigation at three weeks interval is more profitable on the basis of economic return (BCR=1.5).Crop water productivity (1.2 Kg/m^3)is higher at flowering and pod formation stage.

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YIELD AND WATER PRODUCTIVITY INDICES OF DIFFERENT ONION VARIETIES UNDER SPRINKLER IRRIGATION

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Abstract

To evaluate the performance of four onion varieties under sprinkler irrigation and their sensitivity to water stress, a study was conducted at the experimental field of IWM Division, BARI during the winter season of 2018-2019and 2019-2020. The experiment comprised of five irrigation treatments with sprinkler system based on 60%, 80%, 100%, 120% and 140% of crop water use (ETc) laid out in split-plot design with three replications. Irrigation water was applied at a fixed 6-day interval with sprinkler system throughout the crops growing season. Onion sensitivity to water stress was determined using a yield response factor (Ky) that derived from the linear relationship between relative evapotranspiration deficits (1-ETa/ETm) and relative yield decrease (1-Ya/Ym). Statistical analysis revealed that plant height was not much affected by the level of irrigation while, leaf number, bulb diameter, bulb unit weight and total bulb yield was affected significantly ($P<0.05$) by the irrigation regimes. Among the four onion varieties, the highest plant height, bulb diameter and unit bulb weight contributed to the highest yield of 24.53 t/ha and 34.07 t/ha in first and second year, respectively, for BARI Piaj-4 (V_4) followed by 22.04 t/ha and 31.02 t/ha for Taherpuri King (V_3) under 120% water regime. Taherpuri super (V_2) produced the second lowest yield of 17.73 t/ha in the first year and 25.97 t/ha in the second year which was comparable to the lowest yield of 16.57 t/ha and 24.60 t/ha produced by the variety BARI onion -1 (V_1). Value of Ky determined for the whole growing season was found higher for V_4 (Ky: 1.12) and V_3 (Ky: 1.13) than other two varieties (0.85 for V_1 and 0.87 for V_2) indicates that both varieties V4 and V3 are highly sensitive to water stress. This fact is also evident by the water productivity (WP) with higher values obtained under higher water regimes (120% ETc) in case of V4 and V3; but for other varieties, higher WP was obtained from 80% ETc water regime. The amounts of water used for evapotranspiration under different irrigation regimes ranged from 151 to 253 mm, 153 to 256 mm, 158 to 260 mm and 161 to 262 mm, respectively, for V_1, V_2, V_3 and V_4 in the year 2018 - 2019 and 163 to 268 mm, 165 to 270 mm, 168 to 272 mm and 167 to 272 mm in the following year with minimum at 60% ETc and maximum at 140% ETc water regime. Though seasonal evapotranspiration was higher under wetter water regimes, yield was somewhat lower and consequently WP was the lowest. Considering Ky as a limiting factor, application of irrigation at 80% ETc was a marginal for V_1 and V_2 and 100-120% ETc for V_3 and V_4, beyond that yield losses are insupportable.

Introduction

Onion is considered as one of the most important spice and vegetable crop grown in Bangladesh. It is grown extensively during winter season in Bangladesh, occupying the second position both in area and production (BBS, 2013) next to chilli. Though it is grown more or less in all the districts of the country, the dominant areas are the greater districts of Faridpur, Rajshahi, Jessore, Pabna and Kushtia. Land area under onion cultivation in Bangladesh was 0.33 million ha during 2000-2001 and within a span of 12 years, it has increased four- fold to 1.32 million ha (BBS, 2013).

However, the bulb yield of onion (8.6 t ha-1) in Bangladesh is less than many other onion producing countries. It is about half of the world average (17 t ha-1) and four fold lower than those achieved in the European Union (30-35 t ha-1) (FAOSTAT 2010). On an average, the total annual requirement of onion in Bangladesh stands at 2200 thousand metric tons whereas the total production is about 1168 thousand metric tons and thereby, there is a shortage of 1030 thousand

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metric tons per annum. To meet this shortage, Bangladesh has to import onion every year at the cost of its hard earned foreign currency. The reasons for the lower productivity of onion in Bangladesh are many including inadequate management practices, short day length during the growing season, low organic carbon content of the soil, shorter (3–4 months) growing period, as well as poor water management. However, to increase the productivity, the grower must have prior knowledge of the crop yield responses to deficit irrigation. Many investigations have been carried out worldwide regarding the effects of deficit irrigation on yield of mainly horticultural crops (Olalla et al. 2004; Bazza and Tayaa, 1999; Faberio et al. 2003 and Sezen et al. 2008). Other experiments with onion (Bekle et al., 2007) showed that deficit irrigation throughout the growing season of onion as 50 and 75% of ETc reduced yields from full irrigation and resulted in the highest water saving and crop water use efficiency. Kumar et al. (2007) also investigated the impact of deficit irrigation strategies on onion yield and water savings. They reported that applying 80 and 60% of crop water requirements resulted in yield decreases of 14 and 38% and saved 18 and 33% of irrigation water compared to full irrigation, respectively.

The evaluation of stress associated with the yield due to soil water deficit during the crop growing season can be obtained by the estimation of the yield response factor (Ky) that represents the relationship between a relative yield decrease (1–Ya/Ym) and a relative evaporation deficit (1–ETa/ETm). Determination of Ky values after adaptive research has been carried out in numerous studies for various crops and under different environments. Results showed a wide range of variations in Ky values and suggest that the within-crop variation in Ky may be as large as that between crops (Stanhill et al., 1985). Moreover, factors other than water such as nutrients, different cultivars, etc. also affect the response to water. Vaux and Pruitt (1983) suggest that it is highly important to know not only the Ky values from the literature but also those determined for a particular crop species under specific climatic and soil conditions. In fact, adjustments for site-specific conditions would be needed if greater accuracy is sought This is because Ky may be affected by other factors besides soil water deficiency, viz. soil properties, climate, growing season length and growing technology. Water deficit effect on crops yield can be presented in two ways, for individual growth periods or for the total growing season. Kobossi and Kaveh (2010) suggested Ky values for the total growing period instead for individual growth stages as the decrease in yield due to water stress during specific periods, such as vegetative and ripening periods, is relatively small compared with the yield formation period, which is relatively large.

Both variety and water management practices play a major role in increasing the productivity of crops. The crops having higher yield potential and higher yield response to water have a wide range of water productivity. Onion crop needs adequate management practices especially proper irrigation management to contribute potential yield. The principle and pervasive reasons of low productivity of onion in our country is due to lack of high yielding varieties and proper irrigation management practices. Improved variety contributes substantially to enhance crop yield (Shaikh et. al., 2002). Recently, some private seed companies have released few high yielding winter onion varieties and those are cultivating by farmers with same irrigation practices they follow for BARI onion-1. As water management may vary with the crop varieties and their yield response to water, so farmers are not getting good harvest as expected. However, to increase the productivity, the grower must have prior knowledge of the crop yield responses to deficit irrigation. Hence, it is warranted to test the water requirement of the commercial varieties and its yield potential compared to BARI onion -1. Therefore, the objective of this study was to find out the proper irrigation scheduling of commercial onion varieties and their yield response to water compared to local variety.

Materials and Methods

The field experiment was conducted during the winter season of 2018- 2019, between the months of December and March, at the research field of Irrigation and Water Management Division, Bangladesh Agricultural Research Institute (BARI) (Latitude 24.00^{o} N, Longitude 90.25^{o}E and altitude 8.40 m msl), Gazipur. The average temperature, relative humidity, wind speed and pan evaporation rate during the crop growing season ranged from 14.5 to 26.4 ^{0}C, 56–89%, 0.76–10.87

km h^{-1} and 1.6–3.5 mm d^{-1}, respectively. Total rainfall occurred during crop growing season was recorded as 91 mm and 53 mm in which only 21 mm and 35 mm were effective in the first and second seasons. The percentage of sand, silt and clay in the experimental soil were 36.5, 35.4 and 28.1, respectively. Field capacity, wilting point and bulk density of top 30 cm of the soil were 28.5%, 13.72% and 1.46 g cm^{-3}. The concentrations (kg ha^{-1}) of N, $P_2O_5$and K_2O were 51.1, 12.5 and 265.6, respectively. The soil had an organic matter content of 1.04%.

The experiment was set up in a split-plot design with three onion varieties and five different irrigation treatments that were replicated thrice. Sprinkler irrigation with five different water levels were applied compensating crop coefficient (Kc) and potential evapotranspiration (ETo) based predicted evapotranspiration loss (ETc). Each of the onion varieties experienced five levels of sprinkler irrigation as follows:

Onion varieties

V_1= BARI Piaj-1

V_2= Taherpuri Super (Metal)

V_3= Taherpuri King (Lal Teer)

V_4= BARI Piaj-4

Irrigation levels

I_1= Sprinkler irrigation at 60% ET_c

I_2= Sprinkler irrigation at 80% ET_c

I_3= Sprinkler irrigation at 100% ET_c

I_4= Sprinkler irrigation at 120% ET_c

I_5= Sprinkler irrigation at 140% ET_c

Onion varieties were kept in the main plots and irrigation levels in the sub-plots. The treatments with the same irrigation regime were arranged in a line covering all four varieties for better management of irrigation. Since, the characteristics of the experimental land were homogeneous, there was little possibility of variation in results for such arrangements of the treatments. Each plot was of 4 m × 3.75 m size surrounded by 1.5 m wide buffer strip to restrict lateral seepage of water in-between adjoining plots. Forty days old seedlings of onions (cv. BARI Piaz- 1, Taherpuri Super, Taherpuri King and BARI Piaj-4)) were planted at 15 cm × 10 cm spacing on 30 December 2018 and 25 December 2019. During land preparation, farm yard manure @ 5 t/ha was properly mixed with the soil. Fertilizers were applied @ 115 kg N, 60 kg P and 60 kg K per hectare. Half of the nitrogen and potassium and the full dose of phosphorus were applied at planting and the rest half of the nitrogen and potassium was applied in two equal splits at 25 and 50 days after planting.

Just after transplanting, a common irrigation was applied to all plots for establishing the plants. Thereafter, irrigation treatments started at 12 DAT and subsequent applications were applied according to the treatments design. Irrigation was applied through sprinkler system based on crop evapotranspiration (ETc). Reference evapotranspiration (ETo) was calculated on a daily basis from daily meteorological data by Penman–Monteith's equation using CROPWAT computer programme. Daily meteorological data required for CROPWAT model including maximum and minimum air temperature, relative humidity, wind speed at 2 m height and sun shine hour were collected from a weather station about 1.0 km away from the study site. The actual crop evapotranspiration was computed by multiplying the reference evapotranspiration (ETo) with crop coefficient (Kc) for different growth stages of the crop. The daily irrigation requirement for the crop was calculated by subtracting the effective rainfall from the computed ETa. Time of operation of sprinkler system was calculated for different levels of irrigation dividing water requirement of the crop over irrigation intervals (6 d) by discharge of a sprinkler nozzle. The duration of operation was controlled with gate valves provided at the inlet of each lateral. Soil water content measurements were made from 0-15, 15-30 and 30-45 cm depths before and after each irrigation as well as at transplanting and at harvest and after each rainfall event by gravimetric method. Crop water use (evapotranspiration, ETc) was estimated using the water balance method (Walker and Skogerboe, 1987) as:

$$ET = I + P - D - R \pm \Delta SWS \quad \text{..............................(1)}$$

where P is precipitation (mm), I is irrigation (mm), D is the drainage (mm), R the run-off and ΔSWS is the variation in water content of the soil profile. The change in soil water contents at 30–45 cm soil layer was considered to be deep percolation. Run-off was taken to be zero since it did not occur with the use of micro-sprinkler irrigation system.

The recommended plant protection measures were adopted as and when required. Irrigation was stopped 15 days before harvesting in all treatments. Ten plants from each plot were selected randomly and tagged for recording growth parameters viz., plant height, number of leaves and neck girth at 70 DAT. Leaf area and above ground dry matter were also recorded on 10 plants at different phenological stages. Yield parameters viz., bulb diameter, bulb length, bulb unit weight were recorded from the plants used for recording observations. The bulbs were harvested at full maturity stage on 27 March 2019 and 25 March 2020. Yield of onions were measured after naturally drying the bulbs for seven days. The bulb yield per hectare was calculated based on the plot yield.

The yield response factor (Ky) of onion was estimated using the following relationship given by Doorenbos and Kassam (1979).

$$\left(1-\frac{Ya}{Ym}\right) = Ky\left(1-\frac{ETa}{ETm}\right) \quad \text{...........................(2)}$$

where,

Ya = the actual harvested yield (kg ha^{-1}),

Ym = the maximum harvested yield (kg ha^{-1}),

Ky = the yield response factor,

ETa = the actual evapotranspiration (mm) corresponding to Ya,

ETm = the maximum evapotranspiration (mm) corresponding to Ym,

(1–ETa/ETm) = the relative evapotranspiration deficit, and

(1–Ya/Ym) = the relative yield decrease

The data collected during the experimental period were subjected to statistical analysis using MSTAT computer program to interpret the results. Whenever treatment effects were significant, Least Significance Differences (LSD) test was done using analysis of variance technique as described by Gomez and Gomez (1984).

Results and Discussion

Plant height

The height of onion plant was not much affected by the irrigation regimes but significantly by the variety (Table 1). In general, application of water with higher regime produced taller plant, but it was insignificant compared to lower water regime. The plant height, on average, ranged from 58.38 to 65.98 cm with the shortest and tallest plant was observed from treatment receiving 60% and 140% ETc, respectively. However, variety V_3 and V_4 produced the taller plant than the varieties V_1 and V_2, with V_1 had the shortest height and V_4 the tallest. Variation in plant height with the changing in irrigation regimes was found greater in the variety V_3 and V_4 than other two varieties. On average over the years, it ranged from 60.32 to 68.85 cm for V_3, 61.45 to 68.99 cm for V_4, 56.27 to 63.23 cm for V_2 and from 55.50 to 61.30 for V_1 with the lowest value for 60% and the highest value either for 120% ETc or for 140% Etc. The increasing of plant height with adequate soil moisture application is related to water in maintaining the turgid pressure of the plant cells which is the main reason for the growth (Fabeiro et al., 2002). On the contrary the shortening of plant height under soil moisture stress may be associated with the closure of stomata to reduce crop evapotranspiration, which leads to reduce uptake of CO_2 and nutrient. Therefore, photosynthesis and other biochemical reactions are hindered that eventually affecting plant growth. This finding is in line with the result that has been obtained by Fabeiro et al., 2003, indicated that soil water supply is directly proportional with plant height growth.

Leaf number

Irrigation regimes had significant effect on leaves number increased from 7.45 to 8.74 with corresponding increment of water regime from 60% ETc to 140% ETc. Obviously, the lowest value was obtained from 60% ETc and the highest was from 140% Etc. The highest number of leaves at 140% ETc with corresponding values being 8.55, 9.50, 8.60 and 8.38, respectively, for V1, V2, V3 and V4. Treatment receiving 60% ETc had significantly lower number of leaves than treatment receiving 120-140% ETc. Over the varieties, number of leaves gradually increased with the increased in water regime from 7.45 for 60% ETc to 8.74 for 140% ETc. Number of leaves per plant under 80% and 100% Etc water regimes were identical. Similarly, no significant difference was observed in leaves number between 120% ETc and 140% ETc water regimes. Among the varieties, V_2 had the highest leaf number closely followed by V_3 and V_1 while V_4 had the lowest number of leaves per plant. On average over the years, number of leaves were significantly lower in V_4 than other three varieties V_1, V_3 and V_4 which were at per with each other. With the increasing in irrigation regime from 60% to 140% ETc, the leaf number increased from 7.07 to 8.55 for V_1, 7.80 to 9.50 for V_2, 7.42 to 8.60 for V_3 and from 7.50 to 8.38 for V_4, respectively (Table 1a and 1b). Similar increments in leaf number with the increase of irrigation regimes have earlier been reported by Wakchaure et al. 2018.

Bulb length and diameter

The application of deficit irrigation affected the size of onion bulb. The highest bulb length and diameter was recorded from the wettest treatment 120-140% ETc non-significantly followed by 100% ETc. The least bulb length and diameter was recorded from treatment receiving 60% ETc and this was significantly different to treatment receiving higher irrigation regimes. In general, bulb diameter was greater than bulb length for all varieties studied, except variety V_4. Bulb length and diameter of the variety V_1 and V_2 were identical and significantly lower than variety V_3 and V_4. Like the bulb size, unit bulb weight was found higher for wetter treatments than for drier treatments. Variety V_4 produced the bigger size bulbs with higher unit weight (56.10 g) than other three varieties. The second highest unit weight was recorded as 50.15 g for variety V_3 while the lowest was recorded as 40.63 g for V_1. Like the bulb size, unit weight of V_2 (40.90 g) was comparable to V_1. In general, unit bulb weight gradually increased with the increasing of irrigation regimes. This result is in agreement with that of a study conducted by Sezen et al. (2008), high amount of soil moisture application leads to large photosynthesis area (plant height and large number of leaves), results to large bulb size and weight as well.

Onion bulb and biomass yield

Like yield contributing characters, variation in the amount of the applied water caused a significant ($P \leq 0.05$) variation in bulb and biomass yield of onion (Table 1). Irrespective of variety, bulb yield was found the highest when irrigation was applied on the basis of 120% ETc, while the least amount of applied water (60% ETc) resulted in the lowest bulb yield. Application of increasing amount of water per irrigation from 0.6 ETc to 1.2 ETc resulted in significant increase in bulb yield. The increase in yield per unit of applied water decreased with the increasing amount of applied water. The rate of increment was 24.32% from 0.6ETc to 0.8ETc, 14.23% from 0.8 ETc to 1.0 ETc, and only 11.87% from 1.0ETc to 1.2ETc. Bulb yield increased significantly at each irrigation level from 60% ETc to 100% ETc; however from 100% to 120% ETc the increase in BY was insignificant, which is consistent with the findings reported by Kang et al. (2002) and further increase in water regime from 120% to 140% failed to increase BY of onion rather yield was decreased. Thus water can be saved without significant reduction in yield by irrigating the crop at the level of 1.0 ETc and 1.2 Etc. In case of 0.8 ETc water regime, plant felt stress between two consecutive irrigations and that was the probable reason for lower BY as compared to 80% ETc and higher water regimes. Onions have been shown to be productive under frequent irrigations that allow little soil water depletion (Shock et al., 1998).

Table-1a. Yield and yield contributing parameters of onions under sprinkler irrigation with different water regimes during 2018 - 2019

Treatment	Plant ht, cm	Leaves/plant (no)	Stem dia(mm)	Bulb length(mm)	Bulb dia(mm)	Unit bulb wt,g	Yield, t/ha	ADM (kg/ha)
Irrigation								
I_1	56.32	7.79	4.33	42.83	43.22	42.67	12.75	794.54
I_2	57.88	8.06	4.80	44.77	44.40	45.86	15.86	895.13
I_3	59.17	8.41	4.67	45.65	45.48	46.71	18.11	981.42
I_4	60.24	8.48	4.78	46.88	47.40	51.09	20.22	1016.00
I_5	60.16	8.55	4.72	46.98	46.67	48.38	18.36	1006.04
CV (%)	5.28	7.14	6.88	4.77	4.70	8.48	7.54	8.36
$LSD_{0.05}$	3.32	1.56	1.10	3.22	4.16	3.66	2.59	42.46
Variety								
V_1	55.19	7.90	4.39	41.43	42.65	40.63	14.55	842.93
V_2	61.50	8.10	4.59	41.93	42.92	40.90	15.45	893.50
V_3	56.65	8.56	4.72	45.73	47.91	50.15	18.04	993.00
V_4	61.66	8.47	4.95	52.60	48.25	56.10	20.20	1024.80
CV (%)	5.23	4.78	6.04	6.36	6.54	7.28	5.44	9.26
$LSD_{0.05}$	3.88	2.56	1.02	4.82	4.12	3.65	1.52	36.68
Irrigation x Variety								
V_1I_1	53.47	7.33	4.13	39.53	40.80	38.19	11.34	705.67
V_1I_2	55.17	7.77	4.53	40.27	42.00	39.96	14.17	784.50
V_1I_3	55.93	7.90	4.80	41.47	42.73	41.25	15.74	917.67
V_1I_4	55.73	8.27	4.40	42.53	43.80	43.00	16.57	872.83
V_1I_5	55.67	8.23	4.07	43.33	43.93	40.76	14.91	934.00
V_2I_1	53.93	7.73	4.27	43.13	45.80	46.85	13.15	737.33
V_2I_2	55.03	8.17	5.13	44.93	47.53	50.54	16.39	877.33
V_2I_3	57.17	9.10	4.73	45.67	47.73	49.73	19.44	945.00
V_2I_4	58.60	8.67	4.33	47.60	50.07	53.00	22.04	1006.50
V_2I_5	58.53	9.13	5.13	47.33	48.40	50.62	19.17	902.33
V_3I_1	58.90	7.90	4.20	39.07	40.40	37.32	12.04	859.50
V_3I_2	60.90	7.97	4.80	41.67	42.07	39.88	14.77	950.67
V_3I_3	61.40	8.13	4.40	42.40	44.00	41.15	16.02	994.17
V_3I_4	63.77	8.30	5.20	43.67	44.40	44.62	17.73	1067.17
V_3I_5	62.53	8.40	4.33	42.87	43.73	41.52	16.71	1093.83
V_4I_1	58.97	8.20	4.73	49.60	45.87	48.34	14.49	875.67
V_4I_2	60.40	8.33	4.73	52.20	46.00	53.07	18.10	968.00
V_4I_3	62.17	8.50	4.73	53.07	47.47	54.73	21.25	1068.83
V_4I_4	62.87	8.67	5.20	53.73	51.33	63.75	24.53	1117.50
V_4I_5	63.90	8.63	5.33	54.40	50.60	60.63	22.64	1094.00
CV (%)	5.23	4.78	6.04	6.36	6.54	7.28	5.44	9.26
$LSD_{0.05}$	4.12	3.02	1.18	4.66	4.98	7.75	2.04	63.22

Another possible reason is continuous availability of moisture enhanced the availability and uptake of nutrients throughout the cropping period which resulted in better growth and bulb development.

In case of variety, the highest bulb yield was obtained from V4 followed by V3 while variety V1 gave the lowest yield that was identical with V2. Bulb yield of onion ranged from 14.49 to 24.53 t/ha for V4, from 13.15 to 22.04 t/ha for V3, 12.03 to 17.73 t/ha for V2 and from 11.34 to 16.57 t/ha for V1 in first season and in the second season, it ranged from 21.17 to 34.07 t/ha for V4, from 19.20 to 31.02 t/ha for V3, 15.68 to 25.97 t/ha for V2 and from 15.94 to 24.60 t/ha for V1 with minimum in treatment 60% ETc and maximum value in treatment 120% ETc.

Table-1b. Yield and yield contributing parameters of onions under sprinkler irrigation with different water regimes during 2019 - 2020

Treatment	Plant ht, cm	Leaves/ plant (no)	Stem girth (mm)	Bulb length (mm)	Bulb dia (mm)	Unit bulb wt,g	Yield, t/ha
I_1	60.44d	7.10c	10.63	42.99c	43.98d	42.78	18.00d
I_2	65.64c	7.78b	11.70	47.81b	49.69c	50.56	22.24c
I_3	68.48b	7.92b	13.43	50.18a	52.90b	55.08	25.93b
I_4	70.15ab	8.63a	14.50	51.58a	54.74a	57.86	28.92a
I_5	71.80a	8.92a	15.12	51.78a	54.86a	57.02	27.45ab
$LSD_{0.05}$	1.78	0.621	0.873	1.68	1.31	3.72	1.55
CV (%)	4.32	8.64	7.86	5.08	3.78	7.26	6.44
V_1	63.42b	8.83a	12.21	40.62c	50.86a	46.19	20.93b
V_2	63.63ab	8.89bc	13.67	43.47d	53.29ab	51.54	22.12b
V_3	70.15a	8.15b	13.88	52.53ba	52.78a	55.26	26.16ab
V_4	69.81a	7.41c	12.43	58.93	48.01b	57.88	28.81a
$LSD_{0.05}$	5.86	0.5039	1.11	3.09	3.73	15.78	5.01
CV (%)	3.19	9.26	8.06	4.12	3.08	8.14	7.39
V_1I_1	57.53	6.80	10.00	36.47	43.17	40.92	15.94
V_1I_2	62.27	7.53	10.87	38.87	48.57	43.63	19.49
V_1I_3	64.67	7.40	12.93	42.17	53.00	46.64	22.3
V_1I_4	65.73	8.53	13.33	42.97	54.63	50.43	24.6
V_1I_5	66.93	8.87	13.93	42.60	54.93	49.31	22.32
V_2I_1	58.60	7.87	11.27	36.43	44.10	41.30	15.68
V_2I_2	61.00	8.60	12.47	42.17	51.90	46.53	20.53
V_2I_3	65.13	8.40	13.67	46.47	56.43	55.64	23.49
V_2I_4	65.47	9.73	15.07	46.00	56.17	58.37	25.97
V_2I_5	67.93	9.87	15.87	46.27	57.83	55.86	24.94
V_3I_1	61.73	6.93	10.80	46.37	45.73	43.48	19.2
V_3I_2	69.54	7.73	11.93	52.30	52.37	53.40	23.47
V_3I_3	71.27	8.53	15.07	52.90	53.73	58.00	27.75
V_3I_4	73.93	8.73	16.00	56.03	56.37	61.03	31.02
V_3I_5	74.27	8.80	15.60	55.03	55.70	60.39	29.35
V_4I_1	63.93	6.80	10.47	52.67	42.93	45.41	21.17
V_4I_2	66.73	7.27	11.53	57.90	45.93	58.69	25.45
V_4I_3	72.87	7.33	12.07	59.20	48.43	60.04	30.19
V_4I_4	71.47	7.53	13.00	61.67	51.80	62.72	34.07
V_4I_5	74.07	8.13	15.07	63.20	50.97	62.53	33.18
$LSD_{0.05}$	3.57	1.24	1.74	3.36	2.62	7.45	5.01
CV (%)	3.19	9.26	8.06	4.12	3.08	8.14	7.39

In the present study, the increased yield in sprinkler irrigation system was mostly due to the favorable effect of available soil moisture, uniform distribution of irrigation water during entire growth period. However, the yield of onion at 100% and 120% ETc was found to be non-significant which was probably due to the fact that irrigation at 100% ETc was adequate to provide sufficient soil moisture for optimum onion production. Effect of irrigation regimes on above-ground biomass yield followed almost similar trend like that of bulb yield (Table 1b). Unlike bulb yield, the highest biomass yield was recorded under wettest treatment of 120% and 140% ETc and the least amount of applied water (0.6ETc) resulted in the lowest above ground biomass yield.

Leaf area and above-ground dry matter

Leaf area (LA) was positively affected by increasing level of water regimes. Irrespective of variety, application of water with higher water regimes (120% and 140%ETc) significantly increased the leaf area of onion compared with lower water regime (60%ETc). Application of water at 60%ETc produced the lowest leaf area while water at 120% or 140%ETc regime produced the highest LA (Figure 1a and 1b) at different days after transplanting (DAT). Starting from 35 DAP, increment of LA was almost linear up to 60 DAP, thereafter LA started to decrease. After the maximum leaf area was reached at 60 DAP, the following stage lasted around 15 days, thereafter it started to decrease with drying.

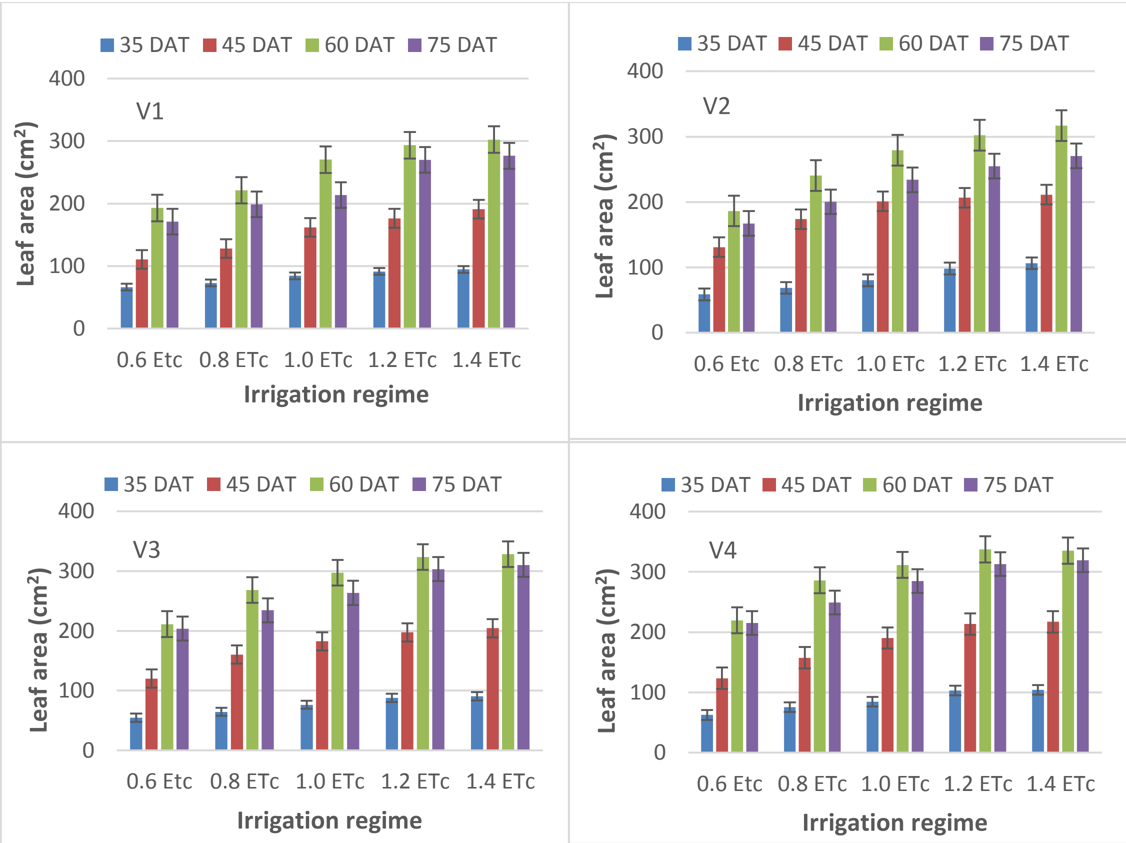

Fig-1a. Leaf area of onion varieties affected by water regimes at different days after planting (DAP).

Increasing rate was faster in early stage than mid stage and at the later stage it decreased as the leaves started to die. Irrespective of variety, in general, leaf area peaked at 60 DAT with corresponding values being 202, 254, 289, 314 and 320 cm2 for 60%, 80%, 100%, 120% and 140% ETc, respectively, in the first season, while in the second season corresponding values of leaf area per plant were 251, 284, 327, 389 and 392 cm2. Leaf area at 60 DAT was 302, 316, 328 and 335 cm2 for V1, V2, V3 and V4, respectively, in the first season and was 376, 380, 397 and 414 cm2 at the wettest regime 140%ETc in the second season. Across the variety, about 94% increment in LA was recorded from 35 to 45 DAP and from 45 to 60 DAP, it was only about 63%.

Rate of increment in LA was somewhat different in magnitude among the varieties. On average over water regimes, it ranged between 66% and 87% for the variety V1, between 53% and 93% for the variety V2, between 67% and 105% for the variety V3 and between 67% and 90% for the variety V4 with maximum values at early stage (from 35 to 45 DAP) and minimum values at mid stage (from 45 to 60 DAP). Among the varieties, V3 and V4 had significantly higher LAs at all water regimes than the varieties V2 and V1 which had the lowest LA. The highest value of leaf area per plant at 140% ETc was 300 for V1, 350 for V2, 360 for V3 and 365 cm2 for V4. The differences in LA between V1 and V2 were very marginal and insignificant and so as to between V3 and V4. The difference in LA among the water regimes was observed to be higher for V3 and V4 than other two varieties, indicating that the variety V3 and V4 were much sensitive to water.

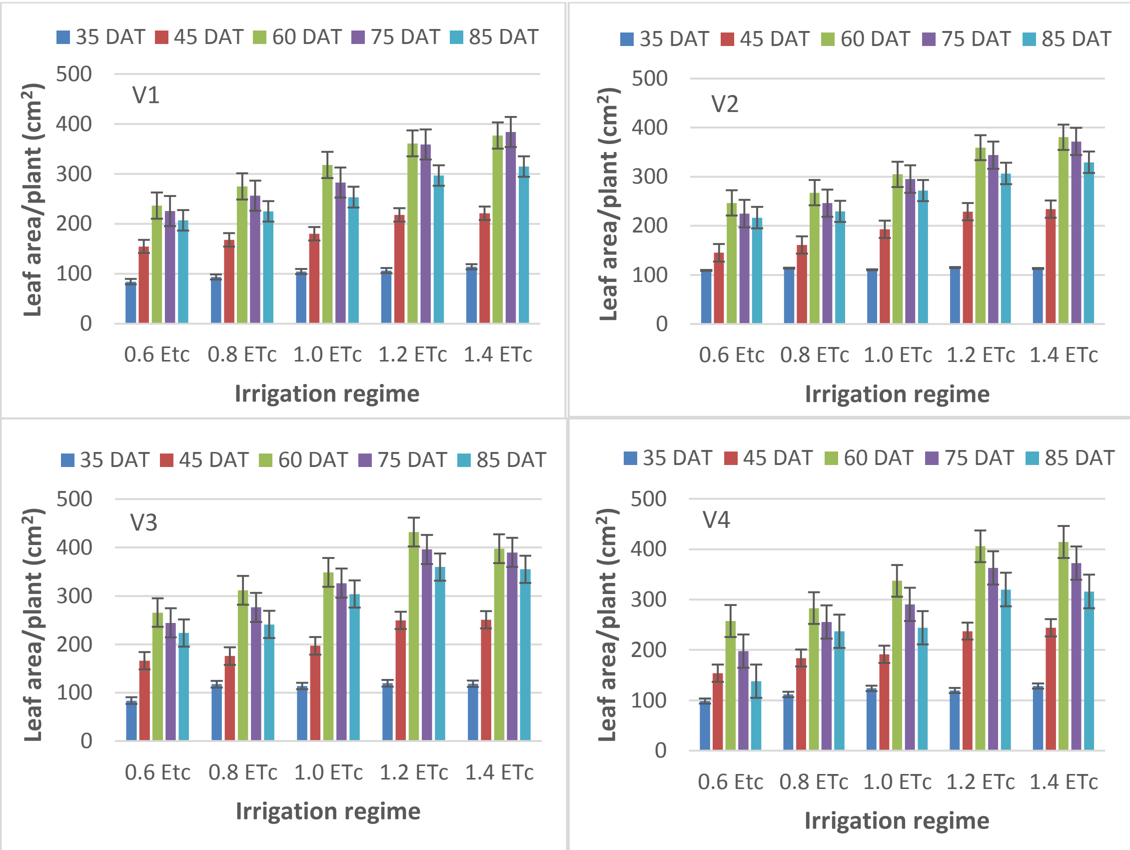

Fig-1b. Leaf area of onion varieties affected by water regimes at different days after transplanting (DAT).

Unlike LA, the above-ground dry matter, ADM, of onion increased gradually during the initial growth stage (35 – 45 DAT) and rapidly during the mid-stage to attain the peak at 60 DAT (Fig. 2); thereafter it maintained a plateau up to 75 DAT and then started to decrease. Dry matter accumulation was found faster during mid-stage (45 – 60 DAT) than during early stage (35 – 45 DAT). ADM decreased at the later stage due to bulb formation and senescence of the plants. That is, after 60 DAT, dry matter accumulated in the plants translocated and contributed much to the formation of onion bulb and thereby ADM gradually decreased. Like LA, hereto, ADM per plant was found higher in wet regime 120 – 140% ETc and lower in dry water regime of 60%ETc. At all levels of water regimes, significantly higher ADM was recorded in V_4 and V_3 compared to V_2 and V_1. The value of ADM per plant ranged from 1.98 to 3.71 g, 1.56 to 3.65 g, 1.99 to 4.22 g, and 1.78 to 4.49 g for V_1, V_2, V_3 and V_4, respectively, either at 120% ETc or at 140% Etc. On average, ADM increased at a faster rate of 135% at the mid stage and at a slower rate of 48% at the early stage.

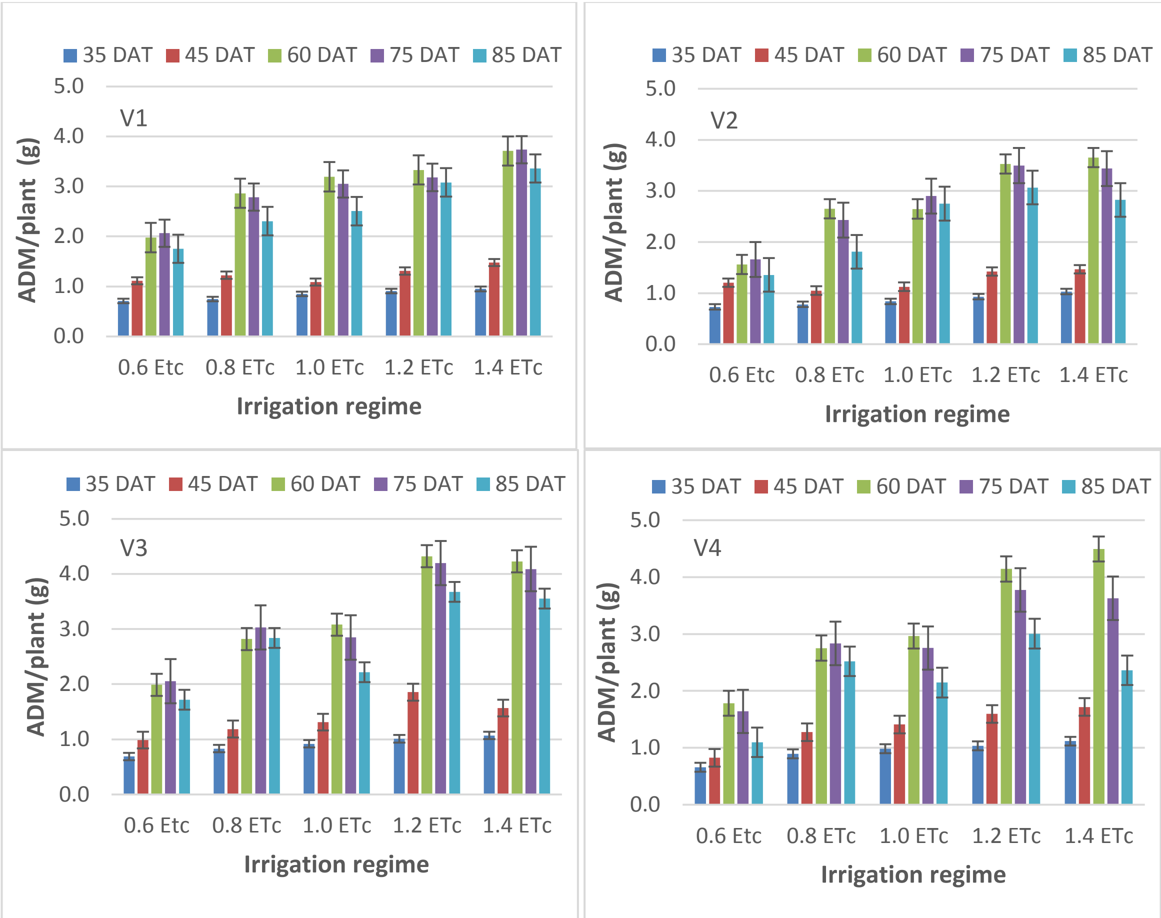

Fig-2. Leaf area of onion varieties affected by water regimes at different days after transplanting (DAT).

Yield response factor (Ky)

The relationship between evapotranspiration deficit (1- ETa/ETm) and yield depression (1 – Ya/Ym) is always linear (Doorenbos and Kassam, 1979), with a slope called the yield response factor (Ky). Crop yield response factor (Ky) for different onion varieties showed statistically significant linear relationship between the decrease in relative evapotranspiration deficit and the decrease in relative yield (Figure 2).The Ky values for total onion growing season ranged between 0.90 to 1.13, the lowest and the highest being for V_1 and V_3/V_4 variety, respectively ((Figure 3). Ky value for V_2 is 0.92 which is comparable to V_1 while Ky value for V_3 is 1.13 which is very close to the value for V_4. The greater Ky value of V_3 and V_4 than other two varieties indicates that the variety V_3 and V_4 are more responsive to irrigation, that is relative decrease in evapotranspiration resulted in more reduction in yield.

The determined Ky values are very close to 1.10 that reported by Doorenbos and Kassam (1986) and Kadayifci et al. (2005). These findings revealed that onion is very sensitive to soil water stress during the total growing season and hence onion should be grown with adequate irrigation for obtaining a good yield. For variety V_1 and V_2, Ky values were less than unity indicated that these varieties can tolerate a mild stress without a considerable yield loss. The higher Ky values for V_3 and V_4 indicate that the crop will have a greater yield loss when the crop water requirements are not met. Therefore, DI practices should be avoided for Ky values that are more than unity. This conclusion is in line with a statement given by Doorenbos and Kassam (1986) who underline that Ky >1.0 indicates the decrease in yield is proportionally greater with increase in water deficit. Considering Ky as a limiting factor, 80% ETc application was a marginal for V_1

and V_2 and 100% ETc for V_3 and V_4, beyond that yield losses are unbearable. These Ky values for onion could be used for planning, design and operation of irrigation projects which allows quantifications of water supply and water use in terms of crop yield and total production for the project area.

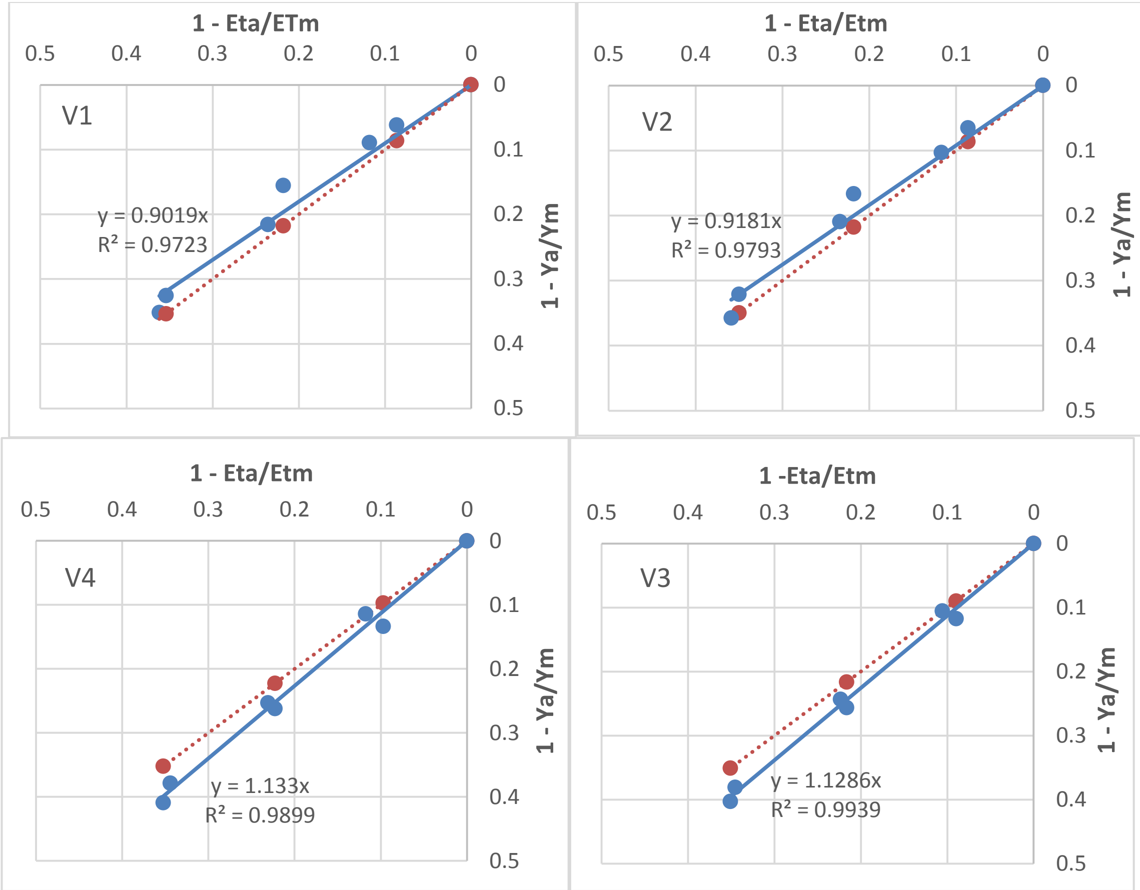

Fig-3. Relationship between relative yield decrease and relative crop evapotranspiration decrease for onion (full line) and reported by Doorenbos and Kassam (dotted line). (Average over two years).

Seasonal water use and water productivity

Total water used by the crop was equal to the applied irrigation water, effective rainfall plus contribution by soil water during the growing season. Irrespective of variety, the amount of water applied to the crop ranged from 121 and 256 mm with minimum in the 60% ETc treatment and maximum in the wettest treatment of 140% ETc (Table 2). Seasonal evapo-transpiration (SET) varied, to a greater extent, with the variation in amount of water application and, to a lesser extent, with the varieties. Though all varieties received same amount of irrigation water, water productivity varied remarkably as variety V_3 and V_4 produced significantly higher yield than other two varieties. Seasonal evapotranspiration was increased with the applied irrigation water and on average it ranged from 157 to 256 mm and for V_1, from 159 to 258 mm for V_2, from 161 to 262 mm for V_3 and from 160 to 264 mm at 60% ETc and 120% ETc treatments, respectively.

In the present study, under different sprinkler irrigation regimes, water productivity ranged from 5.82 to 7.47 kg/m^3 for V_1 and from 6.48 to 7.75 kg/m^3 for V_2 in the first season and the corresponding value in the second season ranged from 8.32 to 10.06 kg/m^3 and from 9.22 to 10.59 kg/m^3 with maximum value in 80% ETc and minimum value in 140% ETc. Unlike V_1 and V_2, the highest WP in the first and second seasons ranging from 9.90 to 13.62 kg/m^3 for V_4 and from 8.97 to 12.61 kg/m^3 for V_3 were obtained from 120% ETc and 140%ETc, respectively, rather than deficit irrigation treatment 80% ETc. This indicates that variety V_3 and V_4 are more responsive to irrigation even at higher water regime. In this case, the greater increase in bulb yield than that of

SET was responsible for the higher magnitude of WP than other two varieties. In case of V_1 and V_2, WP increased up to 80% Etc; thereafter it decreased with further increasing of irrigation regime. But for V_3 and V_4, WP was still on increasing trend with the increasing in irrigation regime and attained the highest level under 120% ETc. This was due to the fact that, for V_1 and V_2, up to 80% ETc the relative increment of bulb yield was greater than the relative increment of SET. For variety V_3 and V_4, relative increment in yield was always higher than relative increment of SET. However, for all levels of irrigation regimes, variety V_4 had the higher water productivity closely followed by V_3 while the other two varieties had the lower WPs due to the greater decrease in bulb yield than that of SET.

Table-2a. Water productivity of onion varieties under different irrigation regimes during 2018-19

Treatment	Irrigation for plant estb. (mm)	Irrigation after plant estb. (mm)	Effective rainfall (mm)	SMC (mm)	Drainage (mm)	SET (mm)	Yield (t/ha)	WP (kg/m^3)
Variety:V_1 (BARI Piaj-1)								
I_1	20	121.16	21	22	0	164.16	11.34	6.90
I_2	20	155.6	21	13	0	189.6	14.17	7.47
I_3	20	188.6	21	12	0	221.6	15.54	7.01
I_4	20	221.72	21	9	9	242.72	16.57	6.83
I_5	20	256.04	21	3	24	256.04	14.91	5.82
Variety: V_2 (Taherpuri Super, Metal)								
I_1	20	121.16	21	23	0	165.16	12.04	7.28
I_2	20	155.6	21	14	0	190.6	14.77	7.75
I_3	20	188.6	21	13	0	222.6	16.58	7.45
I_4	20	221.72	21	8	7	243.72	17.73	7.27
I_5	20	256.04	21	4	23	258.04	16.71	6.48
Variety: V_3 (Taherpuri King, Lal Teer)								
I_1	20	121.16	21	25	0	167.16	13.15	7.86
I_2	20	155.6	21	16	0	192.6	16.39	8.51
I_3	20	188.6	21	14	0	223.6	19.44	8.69
I_4	20	221.72	21	10	7	245.72	22.04	8.97
I_5	20	256.04	21	7	22	262.04	19.17	7.32
Variety: V_4 (BARI Piaj-4)								
I_1	20	121.16	21	23	0	165.16	14.49	8.77
I_2	20	155.6	21	15	0	191.6	18.10	9.45
I_3	20	188.6	21	15	0	224.6	21.25	9.46
I_4	20	221.72	21	11	6	247.72	24.53	9.90
I_5	20	256.04	21	8	21	264.04	22.64	8.57

Table-2b. Water productivity of onion varieties under different irrigation regimes during 2019-20

Treatment	Irrigation for plant estb. (mm)	Irrigation after plant estb. (mm)	Effective rainfall (mm)	SMC	Drainage (mm)	SET (mm)	Yield (t/ha)	WP (kg/m^3)
Variety:V_1 (BARI Piaj-1)								
I_1	20	113.59	35	15	0	163.59	15.94	9.74
I_2	20	144.79	35	14	0	193.80	19.49	10.06
I_3	20	176.0	35	12	0	223.00	22.30	10.00
I_4	20	207.18	35	10	4	248.18	24.60	9.91
I_5	20	238.38	35	7	12	268.39	22.32	8.32
Variety: V_2 (Taherpuri Super, Metal)								
I_1	20	113.59	35	16	0	164.59	15.68	9.53
I_2	20	144.79	35	14	0	193.80	20.53	10.59
I_3	20	176.0	35	13	0	224.00	23.49	10.49
I_4	20	207.18	35	11	4	249.18	25.97	10.42
I_5	20	238.38	35	8	11	270.39	24.94	9.22
Variety: V_3 (Taherpuri King, Lal Teer)								
I_1	20	113.59	35	19	0	167.59	19.20	11.96
I_2	20	144.79	35	17	0	196.80	23.47	12.30
I_3	20	176.0	35	15	0	226.00	27.75	12.61
I_4	20	207.18	35	12	2	252.18	31.02	12.50
I_5	20	238.38	35	8	9	272.39	29.35	10.66
Variety: V_4 (BARI Piaj-4)								
I_1	20	113.59	35	18	0	166.59	21.17	12.71
I_2	20	144.79	35	16	0	195.80	25.45	13.00
I_3	20	176.0	35	13	0	224.00	30.19	13.48
I_4	20	207.18	35	11	3	250.18	34.07	13.62
I_5	20	238.38	35	9	10	272.39	33.18	12.18

Changes in soil moisture storage

Changes in soil moisture storage during the growing period were always higher under lower regime than under higher regime irrigation treatments (Fig. 3). The least amount of irrigation under lowest irrigation regime of 0.6 ETc may be the reason for the higher changes in soil moisture storage. Under lower irrigation regimes, the water depletion from the first layer (0–15 cm) was maximum (12 mm). When the surface layer (0–15 cm) became dry, the 15– 30 cm layer was the primary source of water used by the plant, due either to upward movement of water to the roots, or by direct water uptake by the roots within this depth. In wetter regime treatments, pattern was almost same as of drier regime treatments with difference in magnitude. But under driest irrigation regime (60% ETc), the highest changes occurred in the mid layer (15–30 cm) followed by that obtained in the 0–15 cm layer. This may be due to the fact that under this irrigation treatments a small amount of water was applied at each irrigation, which caused soil wetness down to 15 cm depth, leaving mid layer soil (15–30 cm) drier. As a result, moisture depletion was more in this layer than top layer. Difference in soil water storage between these two layers increased from winter wetter to drier irrigation regimes (120% ETc to 60% ETc) due to decrease in amount of water applied at each irrigation.

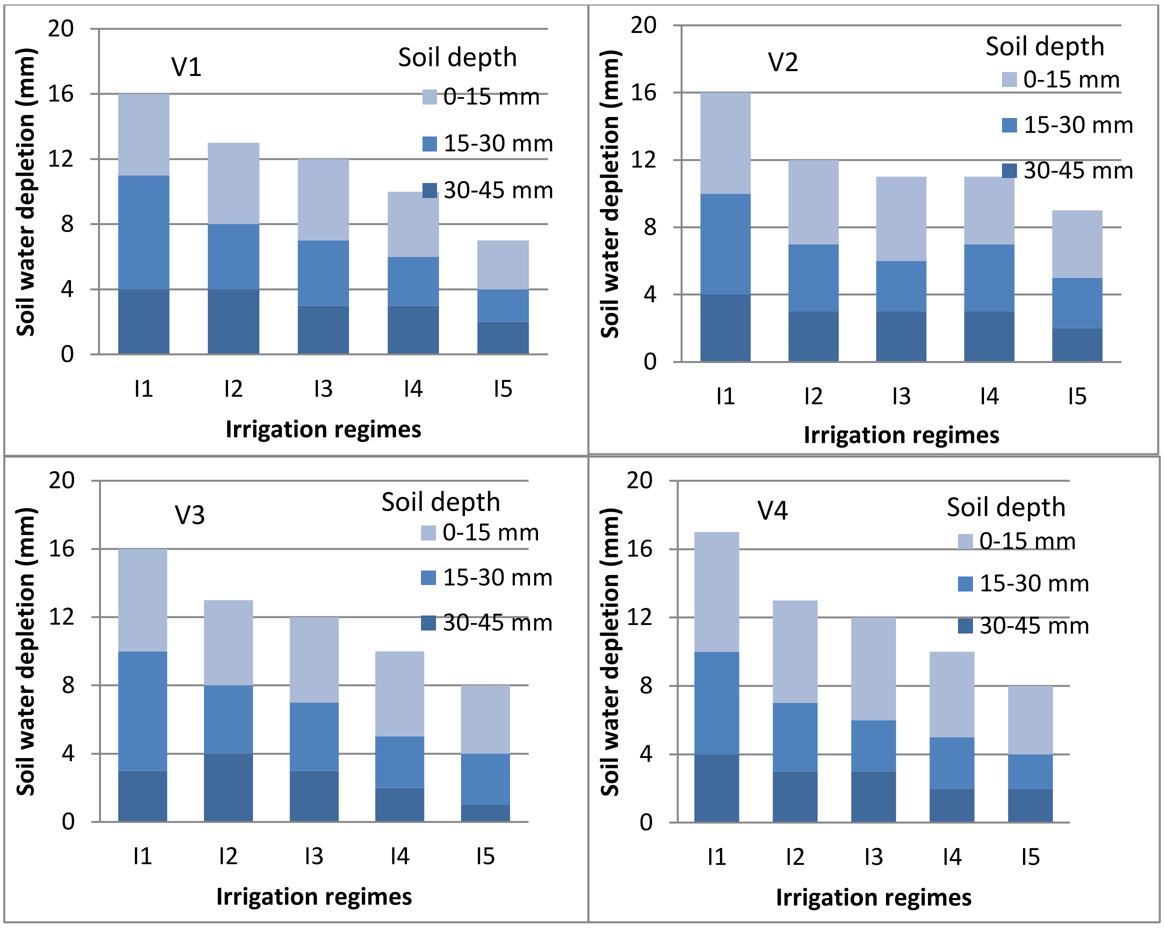

Fig-3. Soil water depletion pattern by soil depth under different water regimes.

Conclusions

Sprinkler irrigation with different water regimes had a significant effect on the growth and bulb yield of onion. Onion bulb yield under sprinkler irrigation with higher water regimes was significantly higher than the yield recorded under lower irrigation regimes. For all varieties, bulb yield of onion increased gradually with increasing of water regime from 60% to 120% ETc. For V_1 and V_2, application of water beyond 100% ETc water regime increased the yield insignificantly, but it was significant for the variety V_3 and V_4. The yield obtained from V_3 and V_4 was always higher under all levels of irrigation regimes than that obtained from V_1 and V_2. Bulb yield obtained from V_4 and V_3 were identical and so does that obtained from V_1 and V_2. The amounts of water used for evapotranspiration varied little among varieties and much (157 – 272 mm) among irrigation regimes with minimum at 60% ETc and maximum at 140% ETc water regime. In case of V_1 and V_2, application of water helped to increase the WP up to 80% ETc; thereafter it started to decrease, while for the variety V_3 and V_4 it continued to increase even at higher water regime of 120% ETc. Values of Ky determined for the whole growing season was found higher for V_3 (Ky 1.12) and V_4 (1.13) than other two varieties (0.90 for V_1 and 0.92 for V_2). The higher WP and Ky indicate that variety V_3 and V_4 are highly responsive to irrigation. The values of Ky and WP can be a good basis for onion growers in relation to the optimum irrigation water use and utilization of irrigation systems, and also for improving the production technology of the crop.

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EFFECT OF FERTILIZER AND IRRIGATION FREQUENCY ON THE YIELD AND QUALITY OF EXPORT AND PROCESSING POTATO

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Abstract

*Fertilization and irrigation play a crucial role in enhancing system productivity of potato. To achieve improvement in maximizing dry matter (DM) and quality of potato tuber in relation to combined fertilization and irrigation, are needed. We hypothesized that fertilization and irrigation frequency influence growth patterns, distribution of dry matter in different parts of potato plants and quality of potato tubers. To test this hypothesis, an experiment was conducted at the research field of Irrigation and Water Management Division of the Bangladesh Agricultural Research Institute, Gazipur, and evaluated dry matter partitioning, tuber yields, water use and water productivity and quality of two export and processing potato varieties of BARI Alu-25 (V_1) and BARI Alu-29 (V_2) in different fertilization and irrigation treatments. The treatments consisted of nine combinations of three fertilizers levels and three irrigation levels. Three fertilizer levels were **(i)** F_1: FRG 2018 (Split 2 times: N, K) (ii) F_2: FRG 2018 with combination of SOP (Split 3 times: N, SOP, Mg), (iii) F_3: FRG 2018 with combination of SOP (20% Additional) (Split 2 times: P, 3 times: N, SOP, Mg. Three irrigation frequency were (i) I_1: 3 irrigation (20-25 DAP, 40-45 DAP, 60-65 DAP), (ii) I_2: 4 Irrigation (18-20 DAP, 40-42 DAP, 55-60 DAP, 70-75 DAP) and (iii) I_3: 5 Irrigation (17-20 DAP, 32-35 DAP, 50-52 DAP, 62-65 DAP, 78-80 DAP). The results indicated that fresh tuber yields of potatoes (V_1 and V_2) were not significantly different among the treatments. The treatment F_2 produced greater tuber yield of both the varieties, V_1(30.32 t/ha) and V_2(28.60 t/ha) compared to F_1(V1=25.14 t/ha and V2= 25.3t/ha) and F_3(V1=23.39t/ha and V2=24.2 t/ha.). The interaction of fertilizer and irrigation produced no significant difference on total dry matter (tdm) of potato in V_1 and V_2. At harvesting stage, there was greater tdm per plant in F_2 than F_1 and F_3. In I_2 treatment, there was also higher tdm per plant in V_1 and V_2 compared to those in I_1 and I_3. Dry matter partitioning in root, stem, leaf and tuber of potato plants were influenced by treatments at different growth stages. At harvesting stage, the interactive effect of F_2 and I_2 produced greater tuber dry matter per plant than the interactive effect of F_1I_2 and F_3I_2 in V_1 and V_2. Water productivity varied among the treatments from 7.2 to 13.15 kgm^{-3}. The combination of F_2 and I_2 noticeably resulted in the highest WP in both the varieties than any other interactive treatment combinations.* The quality parameters of potato tubers (TSS, reducing sugar content, starch content, firmness, color, crispness) were not reported due to incomplete analysis. *These results are of considerable importance to export and processing potato growers to achieve more efficient use of fertilizer and water by processing potato grown in availability environments of Bangladesh.*

Introduction

Potato is a tuber crop that plays an important role in feeding people of the world and consumed daily by millions of people from diverse cultural backgrounds (Ahmadi et al., 2014). Potatoes are processed into a great variety of products, including cooked products, par-fried potatoes, French fries, potato chips, potato starch etc. Worldwide, potato is the most important agricultural food crop after cereals like wheat, rice and maize but it is a high yielding crop. It is also a cheap source

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of energy due to its large carbohydrate content (13 to 23%) (Haase, 2003; Ahmadi et al., 2014), as well as containing vitamins B and C and minerals. Moreover, potato is also used in many industries like textile and alcohol production (Abdeldagir et al., 2003). Exporting potato by increasing its yield and quality may keep an important role on economic development of Bangladesh. Water is a basic requirement for early plant growth and tuber development. It is also related to dry matter content of the tuber. Harvesting time or maturity also directly affects dry matter content. So, it is necessary to find out the optimum irrigation scheduling and harvesting time in order to maximize the economic return from exporting as well as processing. Dry matter content is important for both fresh markets and processing. Tubers with dry matter above 18-20% tend to be more susceptible to bruising and tubers disintegrate more readily when cooked. However, for processing high dry matter content is required to achieve a good fry color and often 20-25% is specified. Nitrogen, potassium and magnesium all have influences on tuber dry matter content (Sarker et al., 2019). Potassium is essential for synthesis of sugars and starch and for translocation of carbohydrates (Singh et al., 1996). It also plays an important role for maintaining vigor of the plants. Other crop management practices influencing dry matter content are selecting the right variety to meet dry matter production needs, selecting quality seed with less risk of disease, avoiding fields with adverse factors such as poor drainage or low water holding capabilities ensuring blight spray programs, scheduling irrigation to maximize quality characteristics, and harvesting early, thereby minimizing late disease ingress or tuber deterioration.

The specific objectives were:

- To find out the fertilizer dose for optimum yield, dry matter and quality of processing potato;
- To find out the appropriate irrigation frequency and date for optimum yield, dry matter and quality of processing potato.

Materials and Methods

The study was conducted at the research field of Irrigation and Water Management (IWM) Division of Bangladesh Agricultural Research Institute (BARI) in Gazipur during the dry season (November-February) in 2020. The soil was silt clay loam with an average gravimetric field capacity (FC) of 28.4% (weight basis) and mean bulk density of 1.47 g cm^{-3} over 0-45 cm soil profile. The experiment was laid out in randomized complete block design (RCBD) with nine treatments replicated three.

The treatments consisted of nine combinations of three fertilizer levels and three irrigation levels. Three fertilizer levels were **(i)** F_1: FRG 2018 (Split 2 times: N, K) (ii) F_2: FRG 2018 with combination of SOP (Split 3 times: N, SOP, Mg), (iii) F_3: FRG 2018 with combination of SOP (20% Additional) (Split 2 times: P, 3 times: N, SOP, Mg. Three irrigation frequency were (i) I_1: 3 irrigation (20-25 DAP, 40-45 DAP, 60-65 DAP), (ii) I_2: 4 Irrigation (18-20 DAP, 40-42 DAP, 55-60 DAP, 70-75 DAP) and (iii) I_3: 5 Irrigation (17-20 DAP, 32-35 DAP, 50-52 DAP, 62-65 DAP, 78-80 DAP). At each irrigation event, water was applied up to 100% of field capacity (estimated at weight basis). The unit plot size was 18 square meter (3 m × 6 m). Two processing potato varieties, 'BARI Alu-25 (V_1) and BARI Alu-29 (V_2) (cv. 'Asterix' and Courage, respectively), were used in this study.

Potatoes were planted on 26 November in 2019, with the row to row 60 cm and plant to plant 25 cm. Potato tubers were planted by hand. At the time of plant establishment, the same amount of irrigation water was applied in every furrow in all treatments and the irrigation treatments were initiated after plant establishment. The recommended doses of fertilizers were nitrogen (N) at 120, phosphorus (P) at 30, potassium (K) at 100, sulfur (S) at 15, zinc (Zn) at 4, and boron (B) at 1.4 kg ha^{-1} and applied in the form of urea, triple super phosphate, muriate of potash, gypsum, zinc sulfate and borax, respectively (FRG, 2018). Decomposed cow dung was applied @ 4 t ha^{-1} before land preparation. Some of fertilizers were applied as basal dose during land preparation 4 days before planting. Remaining fertilizers were applied as side-dressing during earthing up operation followed by irrigation. Adequate plant protection measures were taken whenever required. Gravimetric soil moisture content was determined before each irrigation event. The soils were sampled from both the center of the raised beds and bottom of the furrows from 0-15, 15-30 and 30-45 cm soil depths at the time of planting to harvest. The irrigation water requirement was estimated by the following formula (Michael, 1978; Majumdar, 2004; Sarker et al., 2016; 2019):

$$\mathrm{I} = \sum_{n=i}^{n} \frac{P_{wi}}{100} \times B_{ai} \times D_i \qquad (1)$$

$P_w = FC - RL$

where, I is depth of irrigation water to be applied within one irrigation cycle (mm); B_{ai} is apparent specific gravity of the i^{th} layer of the soil; D_i is depth of the i^{th} layer of the soil profile within the root zone to be irrigated (mm); FC is mean soil moisture content at field capacity on weight basis (%,); RL is the residual gravimetric soil moisture level before each irrigation in the i^{th} layer of soil profile (%); n is number of soil layers (n=3) in the root zone depth.

The root zone depth was considered 45 cm with 15 cm depth increment from the soil surface. The calculated amount of irrigation water was measured by volumetric method and supplied to the experimental plot using a polyethene hose pipe connected to a water flow meter. Seasonal crop water use (CWU) and the change in soil water contribution before planting and final harvest was estimated by the soil water balance approach (Micheal 1978; Sarker et al., 2019; 2020). Dry matter of potato with partitioned to root, stem, leaf and tubers were measured at different intervals during the crop growing season. Three plants were randomly collected from each treatment at 25-27, 44-45, 64-65 and 90 DAP during 2020. The roots and tubers were collected and cleaned and washed with clean water. The roots, stems, leaves and tubers were dried in the oven at 60^0 C until a constant weight was reached and expressed in g $plant^{-1}$. Three plants from each treatment were randomly chosen to measure the number of tubers per plant. The number of tubers/plant and tuber yield (t ha^{-1}) were measured from the fresh weight from the plants harvested from each plot. The potato was manually harvested on February 25 in 2020. Crop water productivity (WP) was calculated as the ratio of economic tuber yield (t ha^{-1}) and CWU, and expressed as kg m^{-3}. The quality parameters of potato tubers (TSS, reducing sugar content, starch content, firmness, color (L, a & b), crispness) will be determined from the laboratory of Post-Harvest Technology Division of BARI, Gazipur (Data is not included in this report). Data on tuber yield and yield attributes and dry matter of potato were statistically analyzed to test the effects of fertilizer and irrigation levels on these parameters using R statistical software version 3.5.0 developed by the R Foundation for Statistical Computing Platform (2018). All the treatment means were subjected to analysis of variance (ANOVA) and compared for any significant differences using R-statistical models at $P < 0.05$.

Results and Discussion

Fresh tuber yield of export and processing potato

Table 1 illustrates the fresh tuber yield and yield contributing characters of export and processing potato varieties (V1 and V2) at the harvest. Table 1 shows that fresh tuber yields of potatoes (V1 and V2) were not significantly ($P < 0.05$) different among the fertilizer and irrigation treatments. The small letters show the ANOVA among the fertilizer and irrigation treatments in potato cultivars (V1 and V2). Although there were no significant differences among the treatments, there were around 25% and 12% greater tuber yield in cultivar V1 and V2, respectively in the treatment, F2 compared with the control treatment of F1. In this study, the treatment F2 produced greater tuber yield of both cultivars V1 and V2 relative to F1 and F3. The interaction of fertilizer and irrigation had no significant differences, although F2 and I2 produced greater tuber yield in both the varieties, V1 and V2 that should have been favorable for tuber yield. Plants in treatment F2 had insignificant tuber numbers per plant in both V1 and V2 with different diameters (Table **1**).

Table- 1. Tuber yield and yield contributing characters of processing potato variety of BARI Alu-25 (V_1) and BARI Alu 29 (V_2) under different fertilizers and irrigation frequency levels during 2019-20

Treatments effect		Tuber no.		Diameter, mm		Length, mm		Tuber fresh weight, TFW, g plant^{-1}		Tuber yield, TY, t ha^{-1}	
		V1	V2	V1	V2	V1	V2	V1	V2	V1	V2
Effect of fertilizer (F)											
F_1		8.4b	9.2b	31a	34.5a	51.8a	41.9a	377.2 a	379.5ab	25.14a	25.3ab
F_2		10.7a	10.1a	30.9a	35.7a	52.2a	46.4a	454.8a	429.5a	30.32a	28.6a
F_3		9.7ab	7.8c	30.3a	33.4a	47.4a	44.7a	350.8a	363.7b	23.39a	24.2b
CV (%)		16.79	4.99	10.73	9.21	11.17	8.83	28.13	12.43	28.11	12.43
Effect of irrigation frequency (IF)											
I_1		9.1a	7.4b	30.6a	36.6a	52.2a	44.2ab	381.7a	354.5b	25.45a	23.6b
I_2		9.6a	8.0b	32.2a	34.8a	53.4a	48.2a	434.3a	420.4a	28.96a	28.0a
I_3		10.1a	11.7a	29.5a	32.2b	45.7b	40.6b	366.7a	397.9ab	24.45a	26.5ab
CV (%)		17.83	38.85	9.33	6.63	11.17	13.59	20.64	16.13	20.64	16.14
Effect of interaction (F × IF)											
F_1	I_1	7.7bc	6bc	32.4abc	38.6ab	56.9a	46b	361.2bc	335.6bc	24.08bc	22.37bc
	I_2	8bc	8.7abc	33.2ab	30.2e	53.3ab	41.8b	433.2abc	403.7ab	28.88abc	26.91ab
	I_3	9.7bc	13a	27.cd5	34.8bcd	45.0bc	37.9b	337.1bc	399.4abc	22.48bc	26.62abc
F_2	I_1	10.7ab	10.7abc	32.8ab	35.2bcd	51.9ab	41.7b	471.8ab	438.1ab	31.45ab	29.20ab
	I_2	13.7a	7.7abc	28.9bcd	41.3a	52.6ab	58.7a	538.6a	464.1a	35.9a	30.94a
	I_3	7.7bc	12.0ab	30.9abcd	30.6e	52ab	38.9b	354.2bc	386.5abc	23.61	25.76abc
F_3	I_1	9bc	5.7c	26.5d	36.1bc	47.8abc	44.9b	312.2c	289.7c	20.81c	19.32c
	I_2	7c	7.7abc	34.4a	32.8cde	54.3ab	44b	331.2bc	393.5abc	22.08bc	26.23abc
	I_3	13a	10abc	30.1abcd	31.3de	40.1c	45.1b	408.9abc	408.0ab	27.27abc	27.20ab

Mean values within the treatments by different letters (a-d) are significantly different at the level of 5% ($P<0.05$).

Total dry matter of potato

The total dry matter (tdm) of potato plants as influenced by treatments at different growth stages are presented in Fig. 1 (a, b, c). There was no significant effect of fertilizer on tdm in V1 at different growth stages of potato (Fig. 1a. A, B, C, D). Similarly, there was no significant effect of fertilizer on tdm at different growth stages of potato variety, V2, except at harvesting stage. (Fig. 1a. A, B, C, D). The Fig. 1a (D) shows that the F2 significantly produced greater tdm in V2 at harvesting stage. At the harvesting stage, there was 19% and 31% greater tdm per plant in treatment F2 than F1 and F3, respectively.

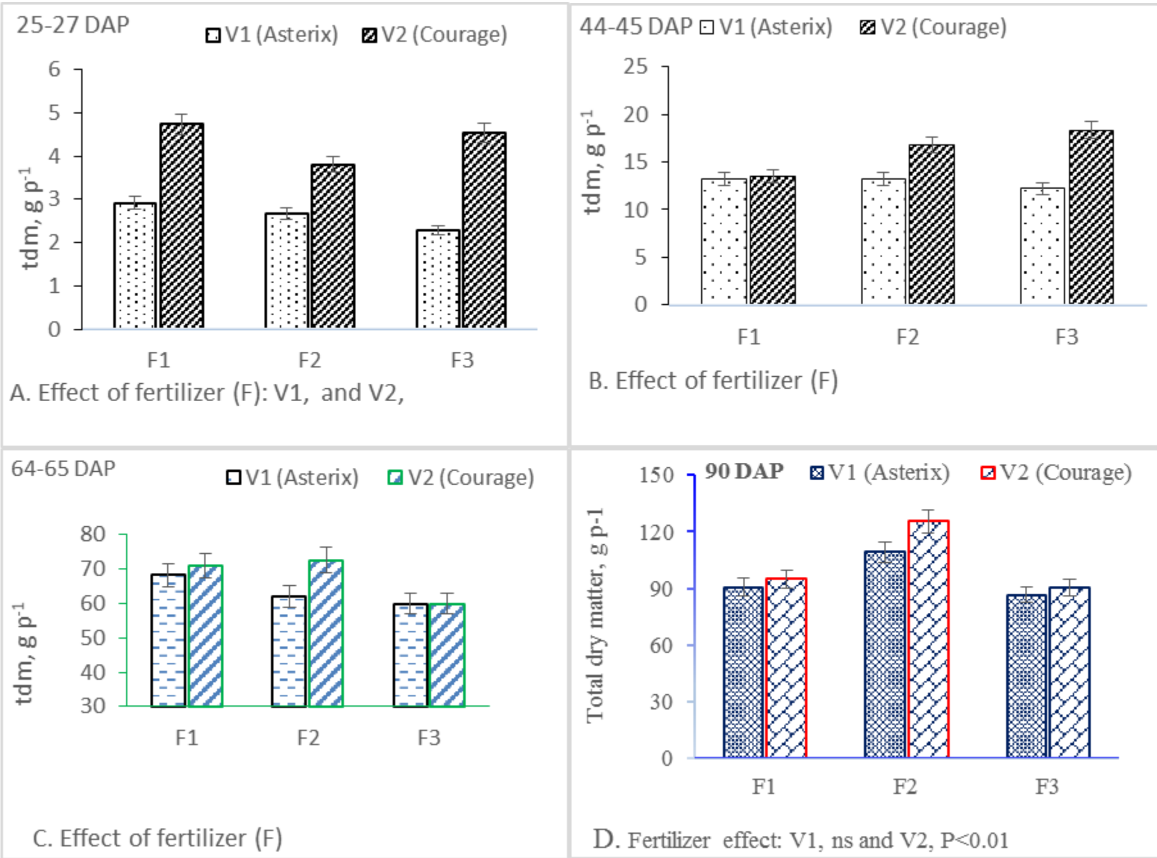

Figure 1 (a). Effect of fertilizer on total dry matter (tdm, g p^{-1}) at different growth stages (days after planting, DAP) of potato (V_1 and V_2).

The effect of irrigation had no significant effect on tdm at different growth stages of potato in V_1 (Fig. 1b. A, B, C, D) except at 44 DAP (Fig. 1b. B). For irrigation frequency, there was no significant effect on tdm at different growth stages of potato variety, V_2, except at harvesting stage (Fig. 1b. D). In the I2 treatment, there was also 5% and 14.% greater tdm per plant in V_1 and 11% and 12% greater tdm per plant than I_1 and I_3, respectively, in V_2.

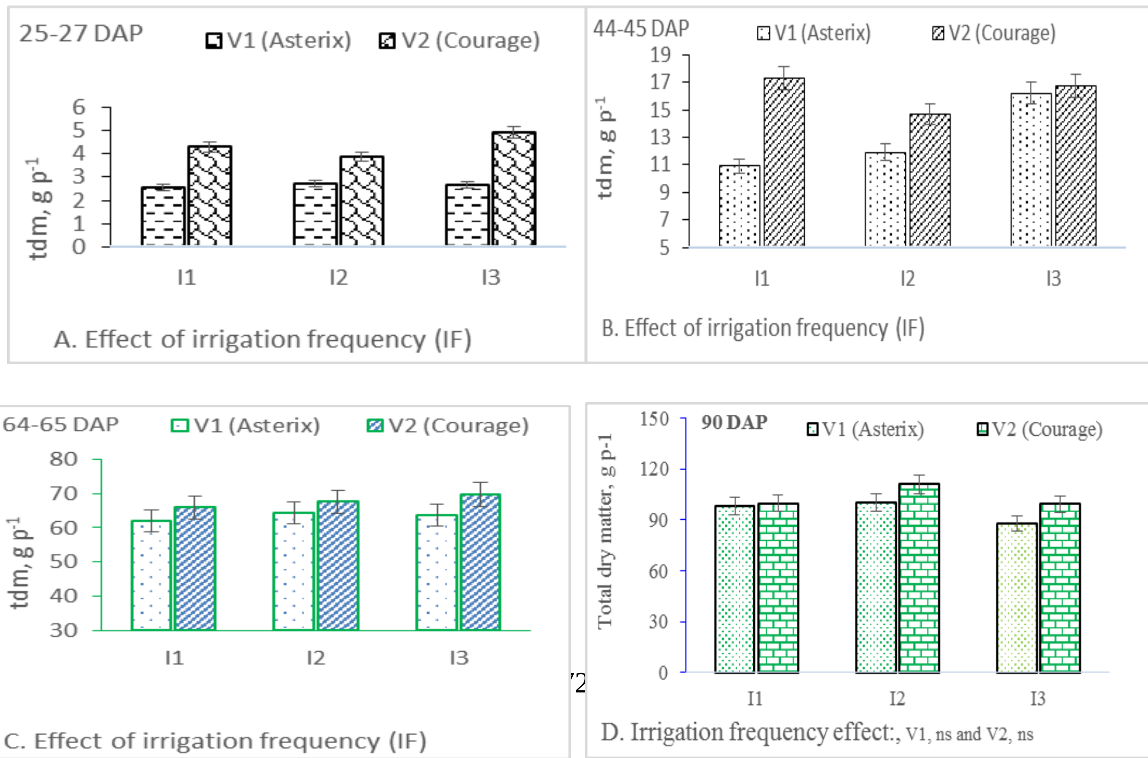

Figure 1 (b). Effect of irrigation frequency on total dry matter (tdm) at different growth stages (days after planting, DAP) of potato (V_1 and V_2).

The interaction effect of fertilizer and irrigation frequency had no significant difference on tdm at different growth stages of potato (V_1 and V_2) (**Fig.** 1c. A, B, C, D) except V_1 at 44 DAP (**Fig.**1c.B). At harvesting stage, the figure (1 a. D) indicates that F2 produced better tdm than F1 and F3 fertilizer treatments. At harvesting stage, there was 22% and 35% higher tdm per plant in treatment F_2I_2 than interaction effect of F_1I_2 and F_3I_2, respectively, in V_1 and 43% and 41% greater tdm per plant than the interaction effect of F_1I_2 and F_3I_2, respectively, in V_2.

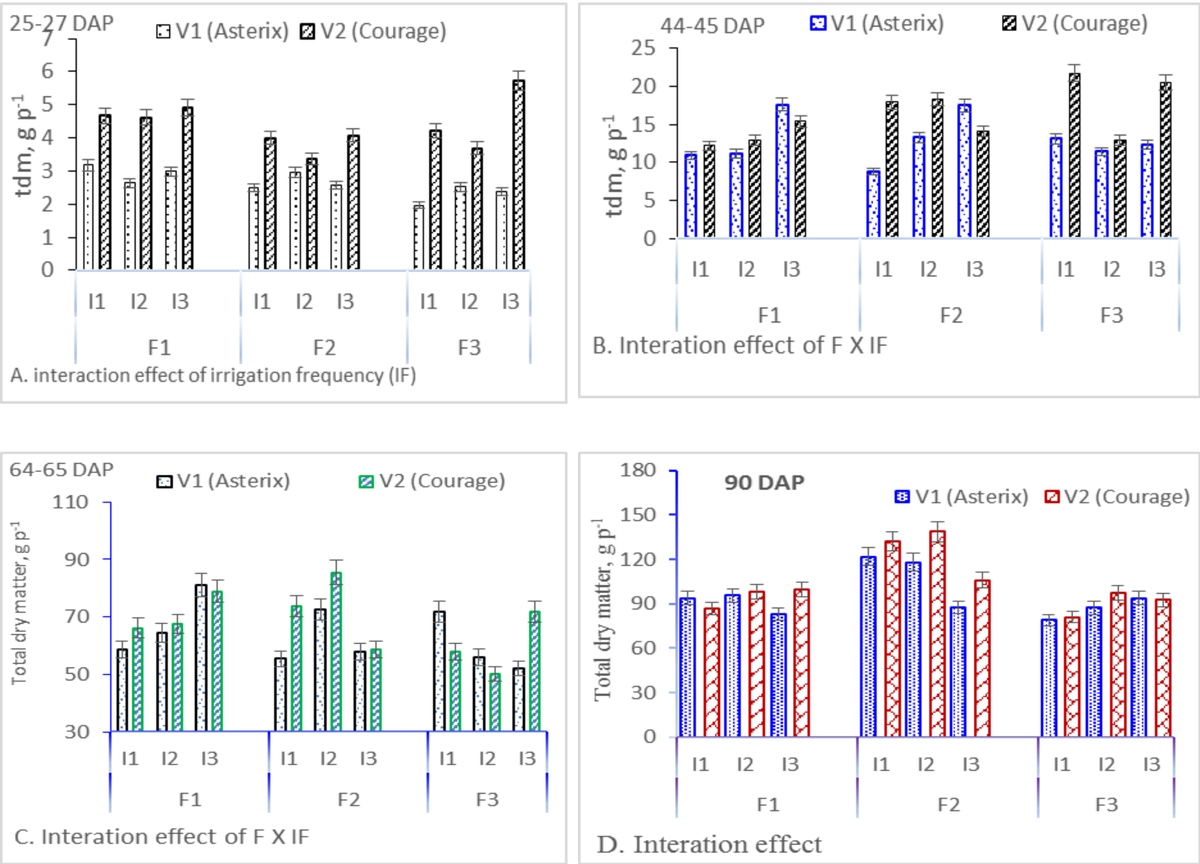

Figure 1 (c). Interaction effect of fertilizer and irrigation frequency on total dry matter (tdm) at different growth stages (days after planting, DAP) of potato (V_1 and V_2).

Dry matter portioning of potato

Dry matter partitioning in root, stem, leaf and tuber of potato plants as influenced by treatments at different growth stages are illustrated in Table 2-5. At the initial growth stage, there was no significant effect of fertilizer and irrigation frequency on dry matter partitioning in root, stem and leaf of potato plants of V_1 and V_2 (Table 2). There was no significant differences among the treatments.

Table- 2. Dry matter partitioning in root, stem and leaf of potato plants at initial growth stage (25-28 days after planting, DAP) of potato variety of V_1: BARI Alu 25 (Asterix) and V_2: BARI Alu 29 (Courage) during 2019-20

Treatments		Dry matter (g plant^{-1}) at initial (stolonization) growth stage (25-28 DAP)							
		Leave number		Root		Stem		Leaf	
		V_1	V_2	V_1	V_2	V_1	V_2	V_1	V_2
Fertilizer (F)									
F_1		18.3a	36.44a	0.93a	0.79	1.17a	1.91	0.82a	2.03
F_2		16.1a	32.11a	0.81a	0.62	1.01ab	1.69	0.85a	1.60
F_3		11.9b	34.78a	0.80a	0.87	0.86b	1.82	0.62b	1.68
CV (%)		16.99	22.51	51.71	66.45	14.62	46.35	11.16	45.47
Irrigation frequency (IF)									
I_1		15.4a	34.4a	0.72a	0.67ab	1.0a	1.91a	0.81a	1.72ab
I_2		16.0a	34.3a	0.96a	0.62b	0.98a	1.56a	0.76a	1.66b
I_3		14.9a	34.6a	0.86a	0.99a	1.06a	1.96a	0.73a	1.94a
CV (%)		18.4	13.18	40.97	44.95	26.27	26.02	22.32	14.16
Interactive treatments (F×IF) mean values									
F_1	I_1	20.7a	35.7abc	0.95	0.74b	1.22a	1.95ab	0.99a	1.98abc
	I_2	16.0abc	40.7a	0.87	0.79b	1.08a	1.78ab	0.67bc	2.003ab
	I_{3s}	18.3ab	33abcd	0.97	0.82b	1.21a	1.99ab	0.79abc	2.10a
F_2	I_1	14.3bcd	38.3ab	0.66	0.75b	1.04a	2.11ab	0.79abc	1.58cd
	I_2	18.4ab	27.3d	1.11	0.45b	0.88a	1.34b	0.96ab	1.52d
	I_3	15.7abcd	30.7bcd	0.65	0.66b	1.11a	1.65ab	0.81abc	1.71abcd
F_3	I_1	11.3cd	29.3cd	0.56	0.52b	0.77a	1.67ab	0.63c	1.60bcd
	I_2	13.7bcd	35abcd	0.91	0.60b	0.97a	1.56ab	0.64c	11.44d
	I_3	10.7d	40a	0.94	1.49a	0.85a	2.24a	0.59c	1.99abc

Mean values within the treatments by different letters (a-d) are significantly different at the level of 5% ($P<0.05$).

At tuberization growth stage, there was no significant effect of fertilizer on dry matter partitioning in root, stem and leaf of potato plants of V_1 and V_2 (Table 3). The effect of irrigation frequency had significant effect on dry matter partitioning in V_1 but there was no significant differences in V_2. The interaction effect of fertilizer and irrigation frequency had no significant difference on DM partitioning in root, stem, leaf and tuber of potato plants (V_1 and V_2) at different growth stages (days after planting, DAP) (Table 3).

Table- 3. Dry matter partitioning in root, stem, leaf and tuber of potato plants at tubarization growth stage (41-42 days after planting, DAP) of potato variety of V_1: BARI Alu-25 (Asterix) and V_2: BARI Alu-29 (Courage) during 2019-20

Treatments	Dry matter (g plant^{-1}) at vegetative growth stage (41-42 DAP)													
	Leaf number		SN		TN		RDM		SDM		LDM		TDM	
	V1	V2	V1	V2	V1	V2	V1	V2	V1	V2	V1	V2	V1	V2
Fertilizer (F)														
F_1	93.2a	45.7b	7.8a	4.2a	13.1a	11.2a	1.12b	0.79a	10.84a	1.91a	6.57a	2.04a	2.04a	2.13b
F_2	80.8a	45.9b	8.78a	4.3a	14a.	10.8a	1.08b	0.62a	9.86a	1.69a	5.64a	1.6 a	2.87a	6.39a
F_3	82.6a	53.9a	8.8a	4.7a	123a	11a	1.65a	0.87a	8.2a	1.82a	5.3a	1.68a	1.81a	6.16a
CV	18.16	9.85	34.4	24.89	41.06	32.92	28.84	66.46	41.2	46.35	23.67	45.47	53.1	62.45
Irrigation (I)														
I_1	88.1a	44.8b	7.7b	4.1a	12.3b	12.3a	1.06b	0.67ab	9.9a	1.91a	5.25b	1.72ab	1.83b	6.69a
I_2	83.4a	46.9b	8.1ab	4.7a	12.1b	11.6a	1.29ab	0.62b	9.8a	1.56a	5.28b	1.66b	1.99b	3.69b
I_3	85a	53.7b	9.6a	4.4a	15a	9.1a	1.50a	0.99a	9.2a	1.96a	7.19a	1.94a	3.03a	4.3ab
CV (%)	19.61	13.31	17.87	30.09	18.16	20.45	30.98	44.95	18.44	26.02	21.14	14.16	41.1	54.63
Interactive treatments (F × I)														
F_1 I_1	102.7a	43.7cd	6.67c	4.0a	14ab	12a	0.75c	0.73b	11.4a	1.95ab	5.83bc	1.98abc	1.17c	1.68c
I_2	95a	45.7bcd	8abc	4.0a	11.7ab	12.3a	1.06bc	0.79b	11.2a	1.78ab	5.36bc	2.03ab	1.89bc	1.81c
I_3	82a	47.6abcd	8.7abc	4.7a	13.7ab	9.3a	1.56ab	0.82b	9.9ab	1.99ab	8.5a	2.1a	3.05ab	2.89bc
F_2 I_1	76.3a	39d	7.7abc	4.0a	12ab	13a	0.75c	0.75b	9.9ab	2.11ab	4.1c	1.58cd	1.67bc	8.56a
I_2	76a	42.7cd	9abc	4.3a	14.3ab	10.3a	1.48ab	0.45b	9.8ab	1.34b	5.53bc	1.52d	2.68abc	6.87ab
I_3	90a	56ab	9.7ab	4.6a	15.7a	9a	1.02bc	0.65b	9.8ab	1.65ab	7.3ab	1.7abcd	4.26a	3.74bc
F_3 I_1	85.3a	51.7abc	8.7abc	4.3a	11.0b	12a	1.68ab	0.52b	8.7ab	1.67ab	5.86bc	1.6bcd	2.64abc	9.82a
I_2	79.3a	52.3abc	7.3bc	5.7a	10.3b	12a	1.31bc	0.60b	8.3ab	1.56ab	4.96c	1.44d	1.42bc	2.4bc
I_3	83a	57.6a	10.3a	4.0a	15.7a	9a	2.13a	1.49a	7.8b	2.24a	4.99bc	1.99abc	1.16c	6.27abc

Mean values within the treatments by different letters (a-d) are significantly different at the level of 5% (P<0.05

At tuber development stage, there was no significant effect of fertilizer on dry matter partitioning in root, stem and leaf of potato plants of V_1 and V_2 (Table 4). The effect of irrigation frequency had also insignificant effect on dry matter partitioning in in root, stem, leaf and tuber of potato in V_1 and V_2. The interaction effect of fertilizer and irrigation frequency had no significant difference on DM partitioning in root, stem, leaf and tuber of potato plants (V_1 and V_2) at different growth stages (days after planting, DAP) (Table 4) but the F_2 and I_2 treatment produced greater potato tuber dry matter than other fertilizer and irrigation treatment.

The response of dry matter partitioning in tuber of potato plants as influenced by the treatments of fertilizer at harvesting stage is illustrated in Table 5. At final growth stage, there was no significant effect of fertilizer on dry matter partitioning in root, leaf and tuber dry matter of potato plants of V_1 and V_2 except shoot dry matter in V_1 and tuber dry matter in V_2 (Table 5). The table 5 shows that the F_2 insignificantly produced 20% and 27% greater tuber dry matter than F_1 and F_3, respectively, in V_1. Similarly, F_2 produced 40% and 47% greater tuber dry matter than F_1 and F_3, respectively, in V_2. The effect of irrigation had no significant effect on tuber dry matter at harvesting stage of potato in V_1 and V_2 except leaf dry matter in V_1 (Table 5). In the I_2 treatment, there was 6.6% and 12.7% greater tuber dry matter per plant in V_1 and 18% and 13% greater tuber dry matter per plant in V_2 than I_1 and I_3, respectively V_2. The interaction effect of fertilizer and irrigation frequency had no significant difference on tuber dry matter at harvesting stage of potato plants (V_1 and V_2) (Table 5). At harvesting stage, the interactive effect of F_2I_2 found higher tuber dry matter per plant than the interaction effect of F_1I_2 and F_3I_2 in V_1 and V_2.

Table- 4. Dry matter partitioning in root, stem, leaf and tuber of potato plants at tuber development growth stage (62-63 days after planting, DAP) of potato variety of V_1: BARI Alu 25 (Asterix) and V_2: BARI Alu 29 (Courage) during 2019-20

Treatments		Dry matter (g plant^{-1}) at tuber development stage (62-63 DAP)													
		LN		SN		TN		RDM		SDM		LDM		TDM	
		V1	V2	V1	V2	V1	V2	V1	V2	V1	V2	V1	V2	V1	V2
Fertilizer (F)															
F_1		93.2a	60a	7.8a	5.2a	13.1a	14a	1.74a	1.38a	10.8a	8.5a	13.5a	11.95a	42.1a	49.1ab
F_2		80.8a	57.7a	8.8a	4.8a	14a	14.1a	1.31a	1.80a	9.86a	6.97a	13.3a	12a	37.6a	51.8a
F_3		82.6a	51.7a	8.8a	5.1a	12.3a	13.2a	1.84a	1.42a	8.2a	6.6a	12.7a	11.7a	37.2a	40.1b
CV		18.18	27.3	34.4	43.56	41.01	29.38	48.26	34.02	41.2	32.74	33.29	42.27	39.84	18.14
Irrigation (I)															
I_1		88.1a	58.3a	7.7b	5.56a	12.3b	13a	1.57ab	1.60a	9.99a	7.7a	13.9a	12.9a	36.5a	43.7a
I_2		83.4a	50.6a	8.1ab	4.3a	12.1b	13.7a	1.87a	1.54a	9.77a	7.2a	13.99a	10.85a	38.8a	48.1a
I_3		85a	60.4a	9.6a	5.2a	15a	14.7a	1.45b	1.45a	9.18a	7.2a	11.6a	11.9a	41.5a	49.1a
CV (%)		19.61	20.54	17.87	28.1	18.16	27.01	22.87	38.85	18.4	27.23	29.29	32.4	30.74	27.17
Interaction treatments (F × I) mean values															
F_1	I_1	102.7a	65.7a	6.67c	5.7a	14ab	13.7a	1.65b	1.62a	11.4a	8.5ab	13.7a	14.5	32.1b	41.6bc
	I_2	95a	56.3ab	8abc	4.3a	11.7ab	13.7a	1.81ab	1.16a	11.2a	9.2a	13.9a	10.8 a	37.7ab	46.3abc
	I_3	82a	58ab	8.7abc	5.7a	13.7ab	14.7a	1.76ab	1.35a	9.92ab	7.8ab	12.9a	10.5a	56.5a	59.3ab
F_2	I_1	76.3a	56ab	7.7abc	5.7a	12ab	13.3a	1.27b	1.68a	9.91ab	7.4ab	13.4a	13.6a	30.83b	51.1abc
	I_2	76a	54.7ab	9abc	4.3a	14.3ab	16a	1.47b	2.03a	9.83ab	7.2ab	15.2a	10.6a	46.1ab	65.7a
	I_3	90a	62.3a	9.7ab	4.3a	15.7a	13a	1.19b	1.68a	9.82ab	6.4ab	10.6a	11.8a	35.8ab	38.7bc
F_3	I_1	85.3a	53.3a	8.7a	5.3	11b	12a	1.79a	1.50a	8.67	7.1ab	14.7a	10.7a	46.7a	38.4b

			b	bc	a			b		ab				b	c
	I_2	79.3a	40.7b	7.3bc	4.3a	10.3b	11.3a	2.32a	1.44a	8.26ab	5.3b	12.9a	11.1a	32.5b	32.3c
	I_3	83a	61ab	10.3a	5.7a	15.7a	16.3a	1.40b	1.32a	7.8b	7.5ab	10.6a	13.4a	32.3b	49.6abc

Table- 5. Dry matter partitioning in root, stem, leaf and tuber of potato plants at harvesting stage (90 days after planting, DAP) of potato variety of V_1: BARI Alu 25 (Asterix) and V_2: BARI Alu 29 (Courage) during 2019-20

. Treatments		Dry matter (g plant^{-1}) at harvesting stage (90 DAP)											
		SN		LN		RDM		SDM		LDM		TDM	
		V1	V2	V1	V2	V1	V2	V1	V2	V1	V2	V1	V2
Fertilizer (F)													
F_1		3.7a	5a	19.4a	27.7a	0.66a	0.59a	4.83b	5.36ab	4.13a	6.08a	81.04a	82.8b
F_2		5a	4.1b	29.7a	24.3a	0.74a	0.78a	5.11a	4.35b	5.87a	4.35b	97.3a	116.0a
F_3		4.4a	4.1b	26.3a	22.1a	0.66a	0.59a	4.53c	6.0a	4.91a	5.1ab	76.5a	78.54b
CV		41.7	14.8	60.8	20	32.88	32.6	3.74	21.58	35.99	21.2	21.31	10.97
Irrigation (I)													
I_1		4.9a	4.2a	33.7a	23.6a	0.69a	0.63a	5.33a	5.75a	6.18a	4.7a	85.9a	88.9a
I_2		4.1b	3.9a	17.1b	25.4a	0.69a	0.63a	4.33a	4.56a	3.63b	5.89a	91.6a	100.2a
I_3		4.1b	5.1a	24.7b	25.1a	0.68a	0.69a	4.81a	5.4a	5.11ab	4.91a	77.4a	88.4a
CV (%)		12.8	49.1	33.8	29.74	37.59	30.3	33.03	23.49	30.34	27.89	18.98	13.79
Interactive treatments (F × I)													
F_1	I_1	4.3cd	3.7a	27.3bc	26abc	0.71a	0.45bc	5.93a	5.05b	5.8abc	5.18b	81.3ab	76.2bc
	I_2	3.3e	3a	14.7c	28abc	0.54a	0.58bc	3.47a	5.36ab	2.46d	8.39a	89.1ab	83.5bc
	I_3	3.3e	5.7a	16.3c	29ab	0.73a	0.74ab	5.08a	5.36ab	4.13bcd	4.67b	72.7b	88.8bc
F_2	I_1	6.7a	4.7a	47.7a	22.7abc	0.89a	1.08a	4.95a	5.67ab	7.71a	3.48b	108.1a	122.8a
	I_2	3.7de	4.3a	15c	32.7a	0.64a	0.63bc	5.07a	4.11b	3.36cd	5.29b	108.9a	128.7a
	I_3	4.7bc	3.3a	26.3bc	17.7bc	0.69a	0.62bc	5.32a	4.27b	6.55ab	4.28b	74.9b	96.6b
F_3	I_1	3.7de	4.3a	26bc	22abc	0.47a	0.34c	5.11a	7.54a	5.02bcd	5.54b	68.2b	67.6c
	I_2	5.3b	4.3a	21.7bc	15.7c	0.91a	0.68bc	4.44a	4.21b	5.06abcd	3.99b	76.8b	88.3bc
	I_3	4.3cd	6.3a	31.3b	28.7abc	0.61a	0.74ab	4.04a	6.27ab	4.66bcd	5.8b	84.5ab	79.8bc

Mean values within the treatments by different letters (a-d) are significantly different at the level of 5% ($P<0.05$).

Soil water content, crop water use and water productivity

Soil water content (Fig. 2) crop water use (CWU) and WP (Table 6) varied among the treatments due to the variation of irrigation water applied. SWC varied from 266 to 284 mm. In this study, the WP varied from 7.2 to 13.15 kg m^{-3} (Table 6) which is consistent to other studies (Sarker et al., 2019; Jovanovic et al., 2010; Ahmadi et al., 2010). The results indicate that I_2 irrigation strategy produced the greater WP as compared to I_1 and I_3. The combination of F_2 and I_2 system noticeably resulted in the highest WP but this technique also produced highest tuber yield in both varieties than other interactive treatments. The reduced WP in I_1 and I_3 is mainly due to lower fresh tuber yield and high amount of water lost in potato cultivation. This study revealed that proper fertilizer and timely irrigation strategy is required to improve water productivity of potato (V_1 and V_2).

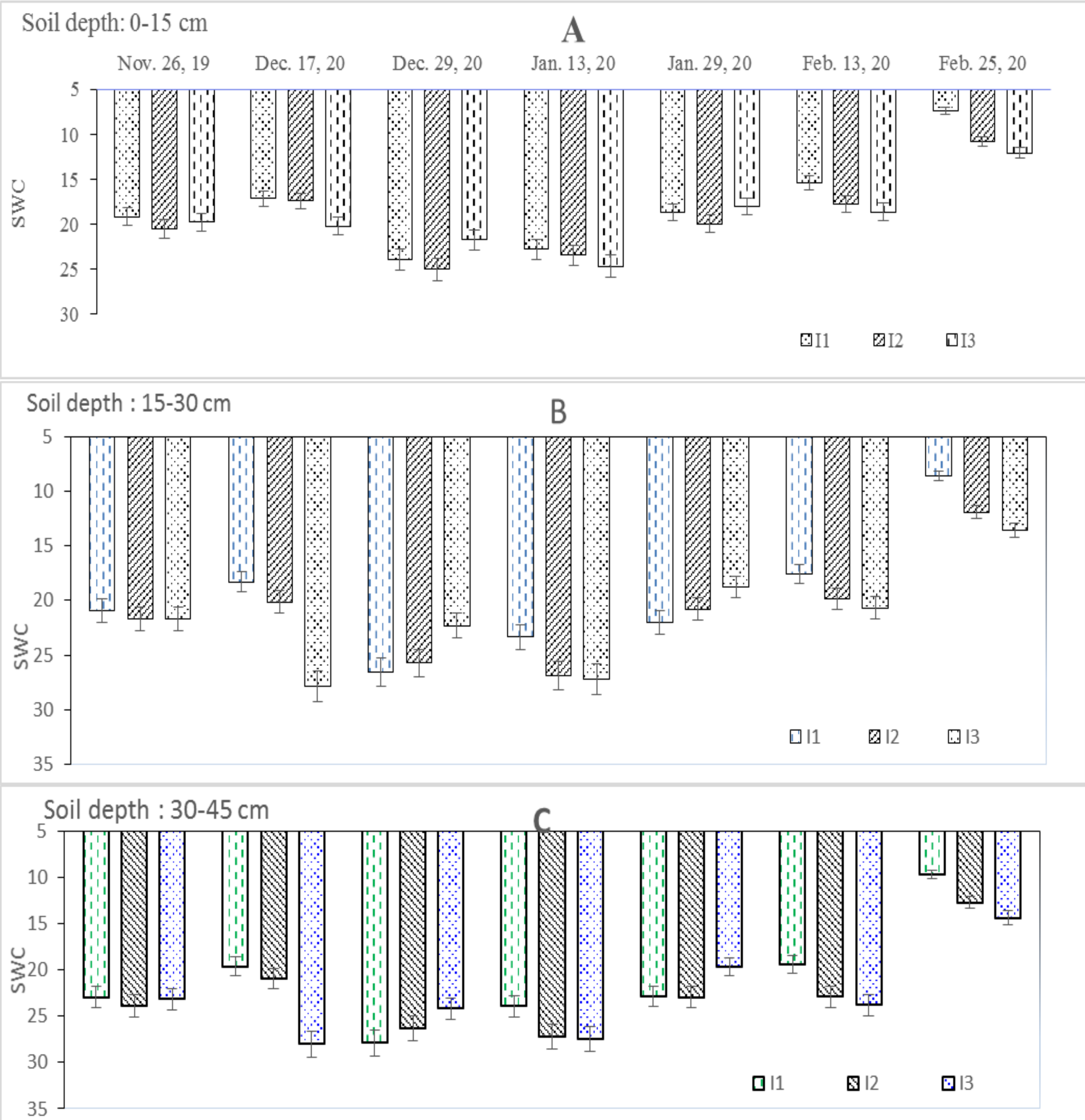

Figure 2. Effect of irrigation frequency on soil water content (SWC) at the soil depth of 0-45 cm with 15 cm increments (A, B, C) from planting to harvesting of potato (V_1 and V_2) in 2019-20. Here, vertical bars indicate the error percentage (5%).

Table- 6. Number of irrigation event, amount of applied irrigation water, crop water use (CWU) and water productivity (WP) of export and processing potato (V_1 and V_2) cultivation under three fertilizer and irrigation frequency during 2019-20

Treatment		Irrigation water (mm)	ΔSWC (mm)	Effective rainfall, R_e mm	CWU (mm)	Water productivity (kg m^{-3})	
Fertilizer level	IR level					V_1	V_2
F_1	I_1	156	84	26	266	9.05bc	8.41bc
	I_2	179	68	26	273	10.58abc	9.86abc
	I_3	203	55	26	284	8.71c	9.37abc
F_2	I_1	156	84	26	266	11.82ab	10.98ab
	I_2	179	68	26	273	13.15a	11.33 a
	I_3	203	55	26	284	8.31bc	9.07abc
F_3	I_1	156	84	26	266	7.82c	7.26c
	I_2	179	68	26	273	8.09c	9.61abc
	I_3	203	55	26	284	9.6bc	9.58abc

Mean values within the treatments and the mean values of water productivity (WP) within the treatments by different letters (a-d) are significantly different at the level of 5% (P<0.05)..

Conclusion

Based on this first year study, it was observed that total dry matter and yield of potato were influenced by the combination of fertilizer with irrigation strategies. Our study demonstrates that there was a significant effect of fertilizer and irrigation on potato dry matter, yield and WP. The combined treatments based on fertilizer level, F_2 and irrigation level, I_2 proved to be the best combination to increase DM, tuber yield and WP. Fresh yields of potato tubers were statistically different between these techniques with F_2 fertilizer and I_2 irrigation strategies. There are two important novel findings from the present study. In both varieties (V_1: BARI Alu-25 and V_2: BARI Alu-29), F_2 and I_2 produced better tuber yield, tuber dry matter and other attributing growth and quality factors of potato that could be favorable for export and processing. The technique has the potential for application in a dry environment with limited water. Three repeated studies are required to understand the fertilizer levels with various irrigation for improving the dry matter, size, yield, water productivity and tuber quality in Bangladesh. Appropriate fertilizer and irrigation management for production of export quality potato will be known and the growers would be able to grow their produces as per demand to get higher prices of their products.

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POTENTIALITY OF BIOCHAR TO ENHANCE PRODUCTIVITY OF TOMATO UNDER DEFICIT IRRIGATION

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Abstract

This study was conducted at the research field of Irrigation and water Management Division (IWM) of Bangladesh Agricultural Research Institute (BARI), Gazipur during 2017-2018, 2018-2019, and 2019-2020 to examine the potentiality of biochar in improving productivity of tomato cultivated under deficit irrigation regimes, and the effects of biochar on some soil properties. BARI Tomato-14 cultivar was used for the experiment. There were six different irrigation treatments comprising three levels of irrigations with (T_1 to T_3) and without (T_4 to T_6) biochar application. It was observed that plant height at different growth stages was lower in deficit irrigation (sequence: full irrigation > 75% irrigation > 50% irrigation). However, plant height was significantly higher in treatments with biochar compared to the non-biochar treatments (T_1>T_4, T_2>T_5 and T_3>T_6). In contrast to the plant height, root length was found higher in non-biochar treatments (T_4, T_5, T_6) than that of their parallel biochar treatments (T_1, T_2, T_3). Again, both wet and dry biomass weights were found highest in T_1, where the lowest values of both of these attributes were found in T_6. Moreover, the number of fruits per plant, unit fruit weight and the marketable yield in different treatments followed the usual trend, higher in biochar treatments, and significantly lower in non-biochar treatments. These parameters were also found lower in treatments where lesser amount of irrigation was applied. About 3-4%, 6-7% and 9-10% higher marketable yield of tomato was observed in T_1, T_2 and T_3 compared to T_4, T_5 and T_6, respectively. As less amount of irrigation water was applied to deficit irrigation treatments, water productivity (WP) showed an increasing trend with the increase in irrigation deficiency. Nonetheless, an improvement of WP by around 4-6%, 8-11% and 11-12% were observed in T_1, T_2 and T_3 over T_4, T_5 and T_6, respectively. It was also observed that the soil moisture content dropped sharply in non-biochar treatments under deficit irrigation regimes compared to the treatments with biochar. Thus, the biochar addition in the soil helped improve the growth and yield of tomato grown under deficit irrigation regimes, as well as the water holding capacity, N-status and heterotrophic respiration of the soil.

Introduction

Biochar, which is produced by the pyrolysis of agricultural leftovers has got the attention of many scientists in recent years due to its numerous sustainability feats comprising enhancements of soil and plant growth, energy production, and carbon sequestration (Cao and Harris 2010; Hu et al. 2013; Deenik and Cooney 2016). The direct benefit of application of biochar in soil is that it supplies mineral nutrients such as P, Mg, K, Cs, S, etc. to the plants; whereas, indirect benefits consists of improvement of soil chemical, physical and biological properties (Suman and Gautam 2017; Caroline et al. 2013; Amin et al. 2016).

Biochar has high cation exchange capacity (CEC) and specific surface area, therefore, has significant adsorption capacity that can remediate wide range of potentially toxic materials, including heavy metals from the contaminated soils (Lehmann and Joseph 2015; Tan et al. 2015; Lawrinenko and Laird 2015). Moreover, accumulation of biochar into cultivated soils has ability to mitigate climate change by improving crop yield per area, increasing soil carbon (C) storage and decreasing nitrous oxide (N2O) emissions (Lorenz and Lal 2014; Zhang et al. 2013). Research

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findings also suggest that some biochar have the ability to absorb variety of salts (Akhtar et al. 2015; Muegue et al. 2017), however, the concept is still debatable due to lack of in-depth research.

Although wide range of researches have been done so far to demonstrate the potential of different methods such as mulching, use of bio-organic fertilizer, soil replacement, subsurface drainage, etc. to improve the condition of the soil for crop cultivation; potentiality of biochar has not been explored to that extent. The influence of biochar on crop productivity, crop quality and different soil characteristics are, however, highly variable depending on the properties of the biochar and the soil, plant species, irrigation methods and environmental conditions. Therefore, a two-year experiment has been conducted at the research field of Irrigation and water Management Division (IWM) of Bangladesh Agricultural Research Institute (BARI), Gazipur with the following views:

- Observation of the potentiality of biochar on enhancing the growth, yield and quality of tomato cultivated under deficit irrigation regimes.
- Examine the effects of biochar on different soil physical and chemical properties.

Materials and Methods

The experiment was set-up at the research field of Irrigation and Water Management Division (IWM), Bangladesh Agricultural Research Institute (BARI), Gazipur during the rabi season of 2017-2018 (Year-1), 2018-2019 (Year-2) and 2019-2020 (Year-3). BARI Tomato-14 cultivar was used for this experiment. Six irrigation treatments were used, where each treatment was replicated thrice following randomized complete block design (RCBD). The treatments were as follows:

T_1 = Full irrigation (FI) with biochar at a rate of 10 t/ha

T_2 = Deficit irrigation (75% of FI) with biochar at a rate of 10 t/ha

T_3 = Deficit irrigation (50% of FI) with biochar at a rate of 10 t/ha

T_4 = Full irrigation with no biochar

T_5 = Deficit irrigation (75% of FI) with no biochar

T_6 = Deficit irrigation (50% of FI) with no biochar

** All the treatments were under drip irrigation applied at 3-5 days interval.

The soil was sandy clay loam with pH 6.44, field capacity 28.6%, wilting point 14.3% (by weight basis) and bulk density 1.51 g/cc. The weather of the experimental site during the crop growing season was colder, where maximum temperature was recorded in April (33.6^{0}C) and minimum temperature was in January (13.16^{0}C). The average relative humidity was recorded highest in the month of December and gradually decreased afterwards. A total rainfall of 106 mm, 127 mm and 87 mm was recorded during crop season in Year-1, Year-2, and Year-3, respectively. A summary of the weather information of the experimental location for both seasons is given in the Table-1.

The unit plot size was 1.8 m × 4 m, where the experimental blocks were separated by 2 m and the plots in each block were separated by a buffer distance of 1 m. In Year-1, tomato plants of 28 days were transplanted on 11 December 2017, where they were transplanted on 03 December 2018 in Year-2 and 01 December in Year-3. Plant to plant distance was kept 40 cm and line to line distance was maintained 55 cm. Biochar, which was made through the pyrolysis of Mahogany (*Swietenia mahagoni*) wood, was collected from the *Christian Commission for Development in Bangladesh (CCDB)*. The basic chemical properties of the applied biochar is presented in Table-2. It was then mixed with compost at a ratio of 1:1, maintained adequate moisture and left for a week before application in the plot as suggested by Blackwell and others (2009). Finally, inoculated biochar was evenly mixed with the top soil of the treatment plots (T_1, T_2 and T_3) during final land preparation. Fertilizers were applied in the form of urea, TSP, MP, gypsum, borax, and zinc sulphate (@$N_{100}P_{55}K_{120}Zn_4B_1Mg_4$ kg/ha and cowdung 10 t/ha) following the Fertilizer Recommendation Guide (FRG), 2012. Where, N and K in the form of Urea and MP, respectively, were applied into four splits with irrigation water. The entire quantity of P in the form of TSP, other micronutrients and composts were applied during final land preparation.

Table-1. Monthly weather data during the crop growing period in Year-1, Year-2, and Year-3

Month	T_{max} (°C)	T_{min} (°C)	RH (%)	Wind Speed (Km/h)	Sunshine hour	Rainfall (mm)	ET_0 (mm)
Year-1 (2017-2018)							
*December	26.9	14.1	81	66	5.8	0	2.0
January	27.8	13.2	76	103	6.4	0	2.3
February	28.9	15.3	70	98	6.8	17	3.3
March	33.2	19.5	68	174	7.2	39	3.7
*April	33.6	21.5	76	167	6.5	50	4.4
Year-2 (2018-2019)							
Month	T_{max} (°C)	T_{min} (°C)	RH (%)	Wind Speed (Km/h)	Sunshine hour	Rainfall (mm)	ET_0 (mm)
*December	25.5	14.6	73	62	5.9	0	1.9
January	27.1	13.2	69	84	6.3	0	2.1
February	29.4	15.4	72	91	6.5	45	3.2
March	32.0	19.4	77	195	7.0	70	3.9
*April	33.5	22.3	81	184	6.8	12	4.1
Year-3 (2019-2020)							
Month	T_{max} (°C)	T_{min} (°C)	RH (%)	Wind Speed (Km/h)	Sunshine hour	Rainfall (mm)	ET_0 (mm)
*December	26.6	13.8	80	59	5.9	0	2.0
January	23.9	13.1	84	86	6.5	35	2.0
February	27.3	14.6	79	107	6.7	6	2.9
March	31.2	19.9	75	168	7.2	24	4.0
*April	33.3	21.7	83	191	6.7	22	4.1

**In December and April, only the crop growing days were considered to calculate average monthly weather components*

Table-2. Basic chemical properties of collected biochar from CCDB

pH	OC %	Ca	Mg	K	Total N %	P	S	Cu	Fe	Mn	Zn
		meq/100 ml				µg/ml					
9.4	41.9	3.79	2.23	1.18	1.40	0.15	0.03	0.05	0.08	0.03	0.01

Irrigation was applied by drip method keeping 3-5 days interval (to meet the demand of crop ET) and the amount of water in each irrigation event was determined following the individual treatments. A 200-litres water tank (0.5 m height) placed on an iron stand of 1 m height was used as the water source to the drip system of each treatment. Admire and Bavistin were applied few times to control white fly and fungus. Weeding was done according to necessity. When the fruits got matured, harvesting were done from 12 March to 10 April in Year-1, 08 March to 04 April in Year-2, and 05 March to 05 April in Year-3.

The soil moisture content up to root-zone depth (45 cm) in each plot was monitored by using the gravimetric method at seven-day interval starting from sowing and ending up to harvest. The seasonal crop water use was estimated for each treatment by the following equation (Michael 2008):

$$SWU = NIR + R_f + \sum \frac{n\,(Mb_i - Me_i)}{100} \times As_i \times D_i$$

Where, SWU = Seasonal water use (mm); NIR = Total irrigation water applied during the crop season (mm); R_f = Seasonal effective rainfall (mm) [seasonal effective rainfall is calculated as the 80% of the seasonal total rainfall (Dastane 1974)]; Mb_i = Percent moisture content at the beginning of the season of i^{th} layer of the soil; Me_i = Percent moisture content at the end of the season of i^{th} layer of the soil; n = Number of soil layers considered within the root zone depth (this was considered 0-30, 30-60 and 60-90 cm); D_i = Depth of the i^{th} layer of soil within the root zone (mm); Asi = Apparent specific gravity of i^{th} layer of the soil.

Finally, water productivity (WP) was calculated as the ratio of fruit yield and total seasonal water use (SWU).

Both NH_4-N and NO_3-N were extracted from the soils during the crop growing period to determine the available N in the soil sample (Jackson 2005). Microbial respiration from the soil in different treatments were also assessed periodically by trapping emitted CO_2 in NaOH (Anderson 1982). All assays were performed in triplicate. The trapped CO_2 was measured by adding 15 mL of 10% w/v $BaCl_2$ to the NaOH to precipitate $BaCO_3$. The remaining NaOH was then back titrated against 1M HCl to the phenolphthalein to neutralize NaOH. Finally, more HCl was added to the methyl orange to dissolve $BaCO_3$.

Data on the yield attributing characters of tomato (plant height, number of branches per plant, number of marketable and cull fruit per plant, fruit length, fruit diameter, unit weight of the fruits, weight of marketable and cull fruit per plant, and marketable and cull yield) were collected during the crop growing season as well as after the harvesting was done. After the raw data were collected from field and the lab, all were then sorted to the standard units to make suitable for the analysis. Finally, data analysis was done using Statistix 10 software and tabulated according to the desired format.

Results and Discussion

Effect of deficit irrigation and biochar on growth and yield parameters

Different growth attributes of tomato as influenced by the combined effect of biochar and deficit irrigation are presented in the Table-3. The tabulated results suggest that the plant height at various crop growing stages (25 DAT, 50 DAT, 75 DAT and at harvest) varied significantly among the irrigation treatments during both the crop growing season.

At 25 days after sowing (DAT), highest plant height was found in T_1 followed by T_4, whereas, the lowest was observed in T_6 followed by T_3. Similar trend of plant height was also observed at 50 DAT and 75 DAT, where maximum was in T_1 and minimum was in T_6. During harvest plant height went to its peak for every treatment, however, maintained the trend observed at 25 DAT, 50 DAT and 75 DAT. From the obtained plant height values at different growth stages it is clear that the plant height dropped significantly due to deficit irrigation (highest in full irrigation > 75% irrigation > lowest in 50% irrigation); whereas, biochar application improved the plant heights in the similar irrigation treatments ($T_1 > T_4$, $T_2 > T_5$ and $T_3 > T_6$).

Another growth parameter, the number of branches per plant did show statistically significant variation among the treatments. Completely opposite trend than that of the trend found in plant height was observed in case of root length. This suggests that as the non-biochar treatments lacked soil moisture under deficit irrigation conditions, plant stressed its root deeper into the soil in search for water. The non-biochar treatments (T_4, T_5, T_6) had higher root length than those of their correspondingbiochar treatments (T_1, T_2, T_3). Moreover, the observed data showed that the root length increased as the water deficiency increased ($T_1 < T_2 < T_3$ or $T_4 < T_5 < T_6$). Again, both the wet biomass and dry biomass weights were found highest in treatment with biochar and full irrigation (T_1), whereas the lowest values of both attributes were found in T_6. The observed data from both the crop years suggest that the amount of irrigation water played a significant role in defining the growth attributes of tomato, where biochar improved the growth attributes, particularly under deficit irrigation.

Table-4 represents the effects of biochar application and deficit irrigation on yield attributes and yield of tomato. The result showed that the full irrigation plus biochar treatment (T_1)

had the highest number of fresh fruit per plant in both years, whereas, the lowest number of fresh fruit per plant was observed in 50% irrigation in non-biochar irrigation treatment (T_6). However, the number of fresh fruits per plant in each treatment increased over the years (Years-3 > Year-2 > Year-1). In case of fruit height and fruit diameter, no distinct pattern was observed in all three years. In Year-3, highest fruit height was observed in T_2, it was found highest in T_5 and T_4 in Year-2 and Year-1, respectively. On the other hand, T_1 maintained the highest fruit diameter over the years, whereas the lowest values varied among other treatments.

Table-3. Growth attributes of tomato in different irrigation treatments

Treatment	Plant height (cm)				No. of Branches/ Plant	Root Length (cm)	Wet Biomass weight/ Plant (g)	Dry Biomass weight/ Plant (g)
	25 DAT*	50 DAT	75 DAT	At Harvest				
Year-1 (2017-2018)								
T_1	79.93	102.15	125.40	134.63	4.33	26.10	689.68	80.94
T_2	78.23	100.38	125.30	133.17	4.20	26.93	676.74	79.03
T_3	75.00	96.55	122.53	127.93	4.20	27.03	610.07	76.25
T_4	77.60	99.80	125.03	132.83	4.47	26.83	656.52	80.03
T_5	74.10	95.13	122.13	129.10	4.17	26.87	620.98	78.72
T_6	72.73	93.25	121.23	126.97	4.27	28.43	598.35	77.90
CV	1.68	1.75	1.82	1.81	5.05	4.78	3.39	4.11
$LSD_{0.05}$	2.31	3.11	4.10	4.30	0.39	2.34	39.50	5.90
Year-2 (2018-2019)								
T_1	69.24	98.30	117.70	129.60	4.14	29.66	633.99	76.14
T_2	68.88	96.75	115.71	126.96	4.12	30.29	620.18	75.18
T_3	67.80	90.86	113.10	124.38	4.14	31.50	606.26	73.30
T_4	68.77	95.36	116.76	127.16	4.14	29.75	621.27	76.02
T_5	66.80	91.95	112.50	124.56	4.10	31.92	607.56	73.88
T_6	65.23	89.45	112.12	122.07	4.10	32.18	582.55	72.25
CV	1.06	1.62	0.67	0.86	1.41	3.29	1.59	1.67
$LSD_{0.05}$	1.30	2.76	1.40	1.97	0.11	1.85	17.65	2.27
Year-3 (2019-2020)								
T_1	77.26	101.19	124.22	133.37	4.29	26.24	675.76	79.74
T_2	75.90	99.47	122.15	131.61	4.18	27.77	662.60	78.07
T_3	72.45	95.13	119.42	127.05	4.19	28.90	609.12	75.51
T_4	75.39	98.69	122.96	131.41	4.39	26.81	647.71	79.02
T_5	70.78	94.34	120.48	127.97	4.15	28.13	610.12	77.51
T_6	69.36	92.30	118.95	125.74	4.22	29.37	594.40	76.49
CV	1.37	1.56	1.39	1.32	3.82	3.55	2.64	3.31
$LSD_{0.05}$	1.84	2.74	3.06	3.12	0.29	1.80	30.37	4.68

**DAT: days after transplanting*

Nonetheless, effect of biochar and deficit irrigation was significant for unit fruit weight and marketable yield of tomato. The unit fruit weight was found the highest in T_1, while the lowest was found in T_6 in each year. Also, it followed the similar trend that was observed in case of plant height, a gradual decrease from T_1 to T_3 and T_4 to T_6. The marketable yield among different treatments followed the usual trend, highest in T_1 and lowest in T_6. Marketable yield was about 3-4% and 5-6% less in T_2 and T_3, respectively, than that of T_1. Again, the corresponding yield losses in T_5 and T_6 were around 6% and 11% compared to that in T_3. Therefore, it is obvious that yield of tomato reduced significantly with decreasing amount of irrigation water. On the other hand, about 3-4%, 6-7% and 9-10% higher marketable yield of tomato was observed in T_1, T_2 and T_3 compared to T_4, T_5 and T_6, respectively. This suggests that the biochar application in soil potentially improved the yield of tomato. Moreover, the increased yields in lesser irrigation treatments prove that the benefit of mixing biochar in soil is more useful under deficit irrigation regimes.

Table-4. Yield attributes and yield of tomato in different irrigation treatments

Treatment	Number of fresh fruit/ plant	Fruit length (cm)	Fruit diameter (cm)	Unit fruit weight (g)	Marketable yield (t/ha)	Cull yield (t/ha)
Year-1 (2017-2018)						
T_1	34.65	49.26	56.70	82.50	70.57	7.04
T_2	33.11	49.32	56.50	79.36	67.81	5.48
T_3	31.77	48.95	55.69	78.83	66.07	5.81
T_4	34.27	49.47	56.51	82.18	67.96	7.20
T_5	32.93	49.23	55.38	78.40	63.77	7.35
T_6	30.96	49.03	55.58	75.19	60.83	6.12
CV	8.16	2.99	2.05	4.05	5.86	22.56
$LSD_{0.05}$	4.89	2.68	2.08	5.86	7.05	2.67
Year-2 (2018-2019)						
T_1	43.70	46.61	58.10	75.21	80.56	6.28
T_2	42.04	46.52	57.74	74.62	78.10	5.66
T_3	40.50	46.52	57.16	73.86	76.51	5.93
T_4	42.00	46.62	56.52	73.92	78.02	6.36
T_5	38.67	46.64	56.34	72.99	73.06	5.84
T_6	38.14	46.56	56.15	72.46	69.52	5.69
CV	3.83	0.64	0.37	0.71	2.25	15.98
$LSD_{0.05}$	2.85	0.54	0.39	0.96	3.11	1.73
Year-3 (2019-2020)						
T_1	45.77	48.39	55.42	79.71	85.50	7.04
T_2	43.84	48.40	55.25	77.38	82.41	5.73
T_3	42.14	47.99	54.67	76.78	80.45	6.05
T_4	44.81	48.39	55.29	79.09	82.50	7.18
T_5	42.41	47.93	53.78	76.22	77.36	6.25
T_6	40.55	47.75	54.61	75.86	73.72	7.07
CV	6.36	1.97	1.57	2.97	3.54	19.53
$LSD_{0.05}$	5.01	1.73	1.57	4.17	5.17	2.33

Seasonal water use and water productivity

Each of the treatments received a total of 22-25 numbers of irrigation in each cropping season; however, the total amount of irrigation water varied according to the experimental design (Table-5). T_1 and T_4 received highest amount of irrigation, T_3 and T_6 received the lowest. Effective rainfall for the crop growing period was calculated as 85 mm, 120 mm and 70 mm in Year-1, Year-2 and Year-3, respectively. Soil moisture contribution (SMC) was found lower in treatments with biochar compared to the non-biochar treatments, while SMC increased as the amount of irrigation water reduced.

Reasonably, the seasonal water use (SWU) was lower in deficit irrigation treatments than that of the full irrigation. A significant reduction of seasonal water use was also observed in treatments with biochar compared to the similar non-biochar irrigation treatments. The higher fruit yield and lower seasonal water use in treatments with biochar finally produced significantly higher water productivity (WP). An improvement of WP by around 4-6%, 8-11% and 11-12% were found in T_1, T_2 and T_3 over T_4, T_5 and T_6, respectively. While in both biochar and non-biochar treatments, water productivity increased as the amount of irrigation water decreased (full irrigation < 75% irrigation < 50% irrigation).

Table-5. Water use and water productivity of tomato in different treatments

Treatment	Amount of irrigation water (mm)	Effective rainfall (mm)	Soil water contribution (mm)	Seasonal water use (mm)	Yield (t/ha)	Water productivity (kg/m^3)
Year-1 (2017-2018)						
T_1	407	85	3.10	495.51	70.57	14.24
T_2	306	85	5.54	396.10	67.81	17.12
T_3	204	85	18.92	307.62	66.07	21.48
T_4	407	85	12.55	504.96	67.96	13.46
T_5	306	85	24.33	414.89	63.77	15.37
T_6	204	85	28.18	316.88	60.83	19.19
Year-2 (2018-2019)						
T_1	479	102	-1.20	579.97	80.56	13.89
T_2	359	102	8.15	469.53	78.10	16.63
T_3	240	102	14.74	356.32	76.51	21.47
T_4	479	102	5.67	586.84	78.02	13.30
T_5	359	102	15.00	476.38	73.06	15.34
T_6	240	102	19.12	360.70	69.52	19.27
Year-3 (2019-2020)						
T_1	460.00	70.00	2.87	532.87	85.50	16.05
T_2	345.00	70.00	9.10	424.10	82.41	19.43
T_3	230.00	70.00	13.45	313.45	80.45	25.66
T_4	460.00	70.00	4.89	534.89	82.50	15.42
T_5	345.00	70.00	15.80	430.80	77.36	17.96
T_6	230.00	70.00	18.56	318.56	73.72	23.14

Effect of deficit irrigation and biochar on soil-moisture content

Figure 1 (a, b, c) illustrates the soil-moisture status (%) of different treatments throughout the entire crop growing period during Year-1, Year-2 and Year-3, respectively. Soil of each plot was properly watered before the planting was done, therefore, soil moisture at sowing was found very similar in all the treatments. In general, the soil-moisture depleted in every plot as the crop growing season advanced unless there was irrigation or rainfall event(s) immediate before the data collection day. From the graphs, it is observed that during the dry tenures (between the irrigation events) soil moisture dropped sharply in non-biochar treatments (T_4, T_5, T_6) compared to the treatments with biochar (T_1, T_2, T_3). For example, in 50% deficit irrigation with biochar treatment (T_3), the difference between the peak and base soil-moisture content values was only around 7%, whereas the same difference was around 11% in T_6 (50% deficit irrigation without biochar). The findings prove the ability of biochar to preserve the soil moisture content at comparatively persistent level, especially under deficit irrigation conditions.

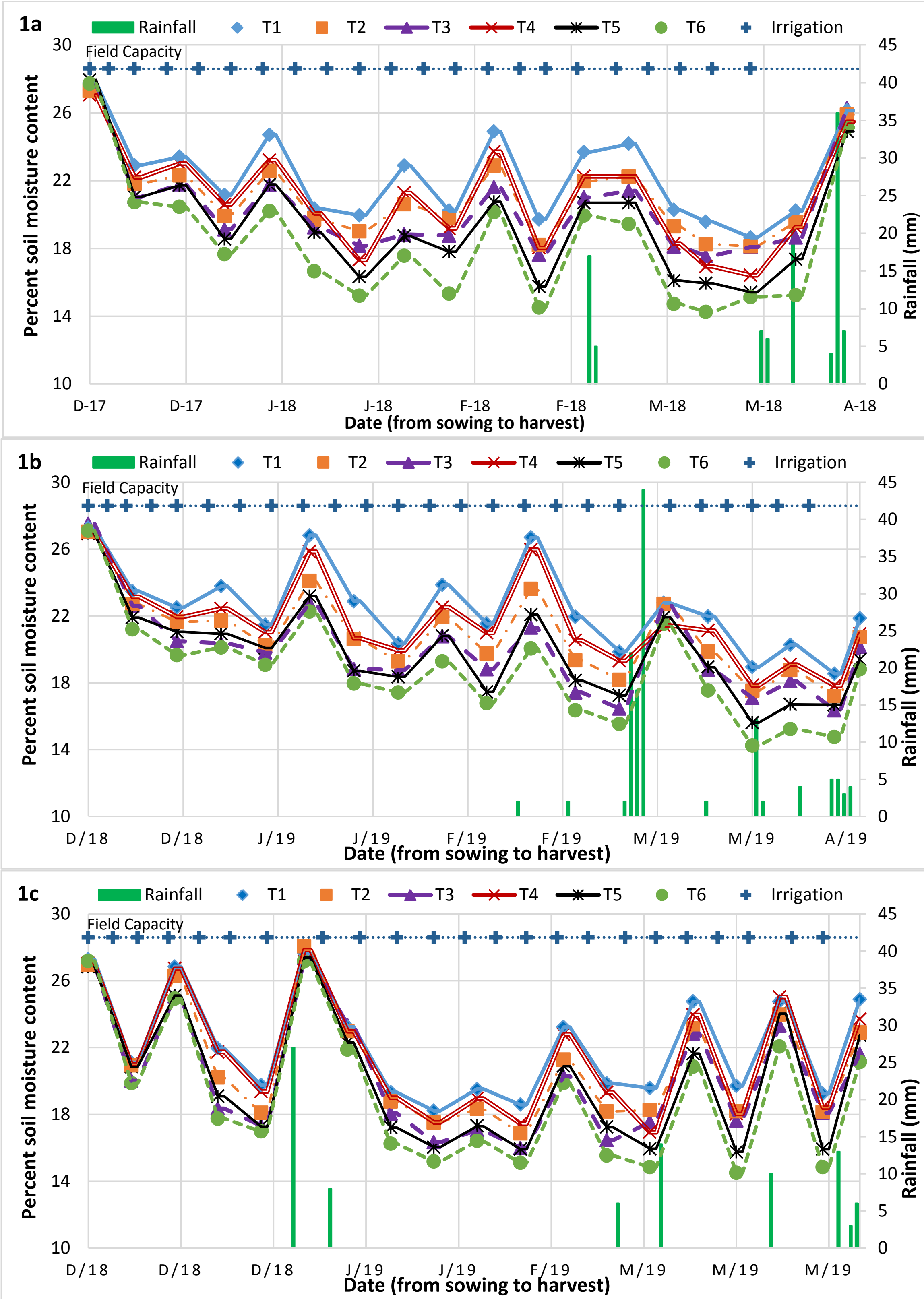

Figure 1(a, b, c). Soil-moisture content in different treatments in Year-1, Year-2, and Year-3.

Effect on soil heterotrophic respiration

The application of biochar in combination with different levels of irrigation to soils for tomato cultivation influenced emission of CO_2 synthesized by heterotrophic respiration. In Year-1, Biochar (at a rate of 10 t/ha) with 75% of FI (T_2) emitted the highest amount of CO_2 up to 60 DAT, while biochar with FI (T_1) had increased emission after 60 DAT (Figure 2a). Biochar with 50% of FI (T_3) had lower emission relative to Biochar with FI (T_1) and 75% of FI (T_2). The FI (T_4) and 75% FI (T_5) without biochar amendment had lower emission up to 51 DAT which reached T_1 and T_2 after 51 DAT. However, the lowest emission was recorded in 50% FI without biochar amendment treatment (T_6). The higher CO_2 emission recorded with the biochar amended treatment with FI and 75% FI might be due to having water soluble C in biochar which upon receiving enough water went under microbial decomposition (Wang et al. 2016; Ding et al. 2016).

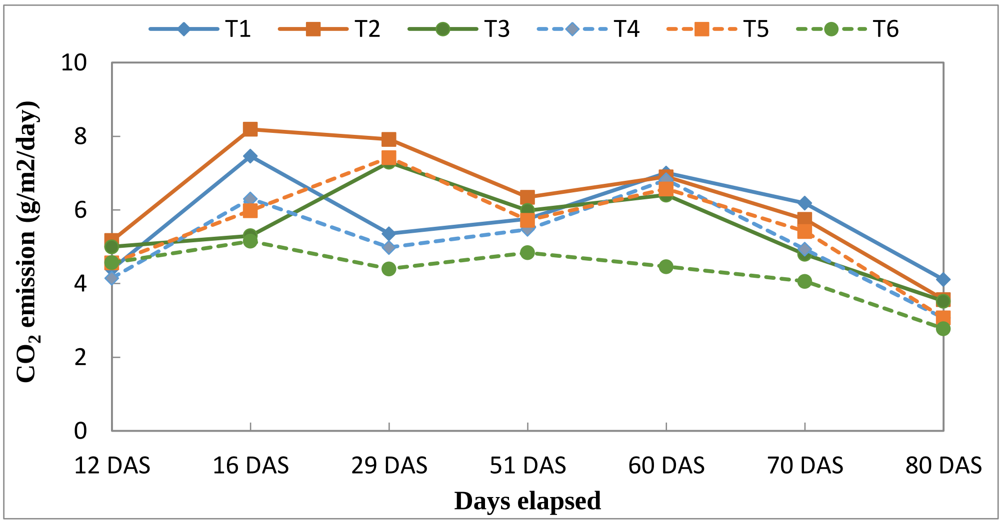

Figure 2a. Effect of biochar amendment and irrigation on CO_2 emission as heterotrophic respiration output in soils under tomato cultivation in Year-1.

On the other hand, in 2018-2019, the application of biochar in combination with different level of irrigation to soils for tomato cultivationp caused variation of CO_2 emissions synthesized by heterotrophic respiration (Figure 2b). Initially with increased water content, biochar applied at 10 t/ha and full irrigation, CO_2 emission by heterotrophic respiration was slow which was increased later. Up to 69 DAT, CO2 emission was higher under biochar application with full and 75% FI treatments. After 69 DAT, the emission slowed down at a rate lower than non-biochar applied treatments. Increased amount of water soluble C of the biochar treated soils might cause the increased emission. Full irrigation had higher emissions than deficit irrigation which suggested that full irrigation at or around field capacity emits increased CO_2 irrespective of C source applied. Biochar applied @ 10 t/ha with full and 75% of FI (T_2) emitted the highest amount of CO_2 up to 55 DAT, while Biochar with FI (T_1) had increased emission after 60 DAT. Biochar with 50% of FI (T_3) had lower emission relative to Biochar with FI (T_1) and 75% of FI (T_2). The FI (T_4) and 75% FI (T_5) without biochar amendment had lower emission up to 55 DAT and 69 DAT than with biochar treatments, respectively, which reached T_1 and T_2 after 69 DAT. However, the lowest emission was recorded in 50% FI without biochar amendment treatment (T_6) (Figure 2b).

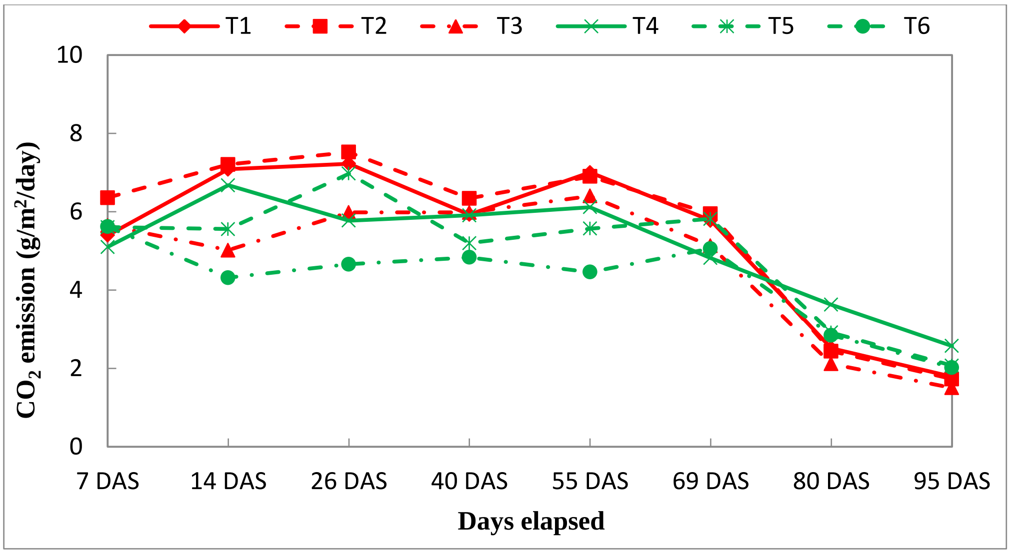

Figure 2b. Effect of biochar amendment and irrigation on CO_2 emission as heterotrophic respiration output in soils under tomato cultivation in Year-2.

The emission of CO_2 due the hetero-trophic respiration in soils under biochar and irrigation treatments was almost similar to the previous years results. In 2019-2020, the emission of CO_2 from soils under tomato crop varied due to the combined application of biochar and irrigation at different levels (Figure 2c).

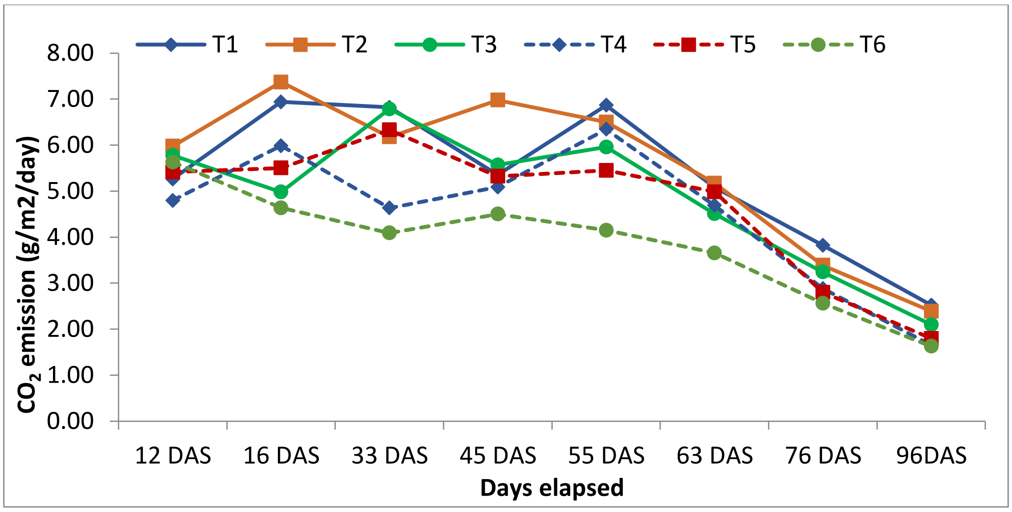

Figure 2c. Effect of biochar amendment and irrigation on CO2 emission as heterotrophic respiration output in soils under tomato cultivation in Year-3.

Initially with increased water content, biochar applied at 10 t/ha and full irrigation, CO_2 emission by heterotrophic respiration was slow which was then increased. Biochar application with full and 75% FI treatments had higher CO_2 emission up until 55 DAT which was then slowed down at a rate at par with non-biochar applied treatments. There were peaks and dives in the trend lines of CO_2 emissions up until 55 DAT that indicated the fluctuations in the availability of water and N source that influenced the activities of microorganisms. Increased amount of water soluble C of the biochar treated soils might cause the increased emission at the initial stage of crop growth. Full irrigation and 75 % FI had higher emissions than further deficit irrigations, suggesting that full irrigation at or around field capacity emits increased CO_2 irrespective of C source applied. Biochar applied @ 10 t/ha with full and 75% of FI (T_2) emitted the highest amount of CO_2 up to 55 DAT, while Biochar with FI (T_1) had increased emission after 63 DAT. Biochar with 50% of FI (T_3) had lower emission relative to Biochar with FI (T_1) and 75% of FI (T_2). The FI (T_4) and 75% FI (T_5) without biochar amendment had lower emission up to 55 DAT and 63 DAT than with biochar treatments, respectively, which reached T_1 and T_2 after 63 DAT. However, the lowest emission was recorded in 50% FI without biochar amendment treatment (T_6).

Effect on available nitrogen (N)

Combination of biochar application and deficit irrigation had significant effect on nitrogen availability in the soil. Biochar with FI (T_1) had the highest available NH_4-N over the season, followed by biochar with 75 % FI (T_2). The availability of NH_4-N in soils with FI without biochar (T_4) was also higher than that of the treatment with low water without biochar amendment (T_5 and T_6). The higher NH_4-N recorded in soils with higher water and biochar amendment can be attributed to increased water level. In Year-1, NH4-N was higher in treatments (full irrigation with or without biochar) where moisture content was higher (Figure 3a). However, it was conspicuous that the NH_4-N concentration was regulated by biochar application by influencing the in-season turnover of NH_4-N. The availability data of NH4-N reflected and matched with moisture data. The lowest NH_4-N concentration was recorded in treatment of 50% deficit irrigation with or without biochar.

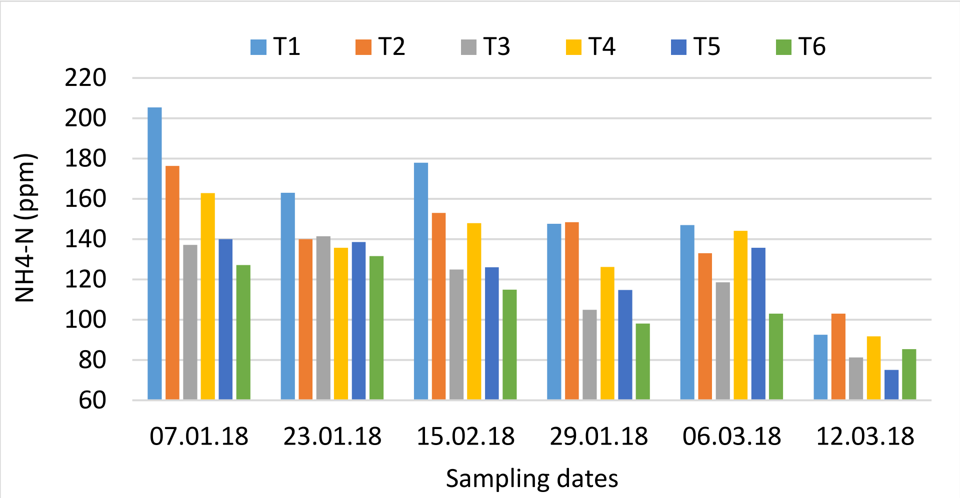

Figure 3a. NH_4-N availability in different treatments during Year-1.

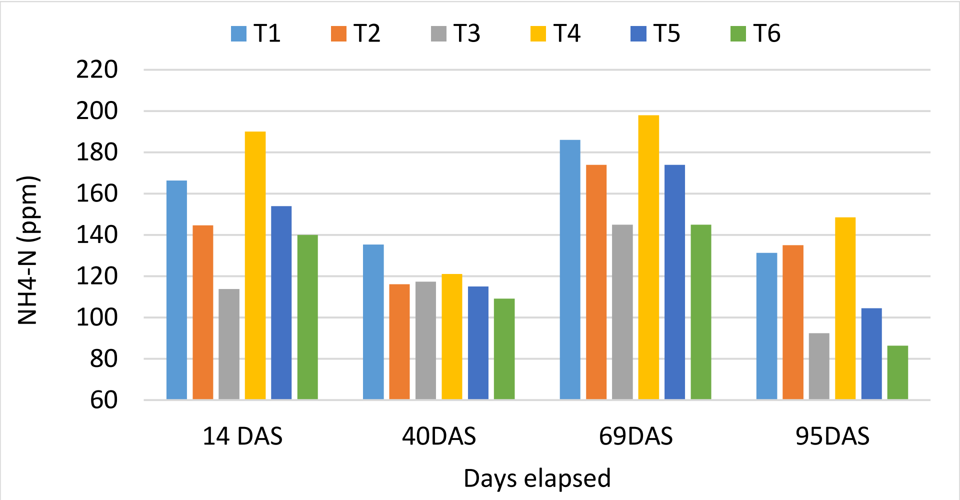

Figure 3b. NH_4-N availability in different treatments during Year-2.

On the other hand, biochar amendment with different levels of irrigation also varied NO_3-N levels in soils. Overall, biochar with 75% FI (T_2) had increased level of NO_3-N, while 50% FI without biochar (T_6) had the lowest available NO_3-N. The conversion of NH_4-N to NO_3-N under lower water available condition might be the cause of increased NO_3-N level under water stress condition.

In 2018-2019, the concentration of NO_3-N was higher in treatments of full irrigation with or without biochar. Initially the available NO_3-N was higher in treatments of full irrigation without biochar but at the later stage (40DAS, 69 DAS and 95 DAS), biochar with full/deficit irrigation had higher NO_3-N (Figure 4b). The results reflected that the NO_3-N concentration was regulated by biochar application by slowing the in-season turnover of NO_3-N which helped keep the nutrient available for a long time. The availability data of NO_3-N reflected and matched with moisture data. The lowest NO_3-N concentration was recorded in treatment of 50% deficit irrigation with or without biochar.

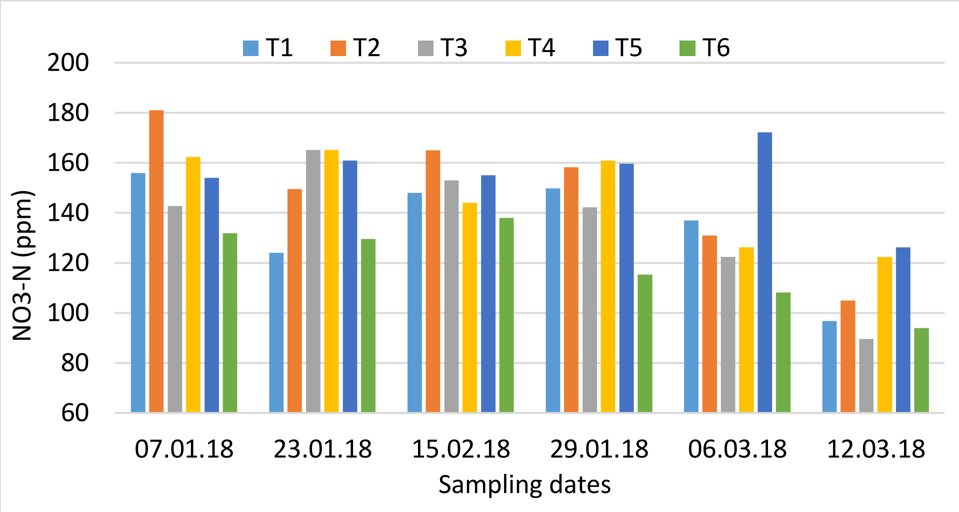

Figure 4a. NO_3-N availability in different treatments during Year-1.

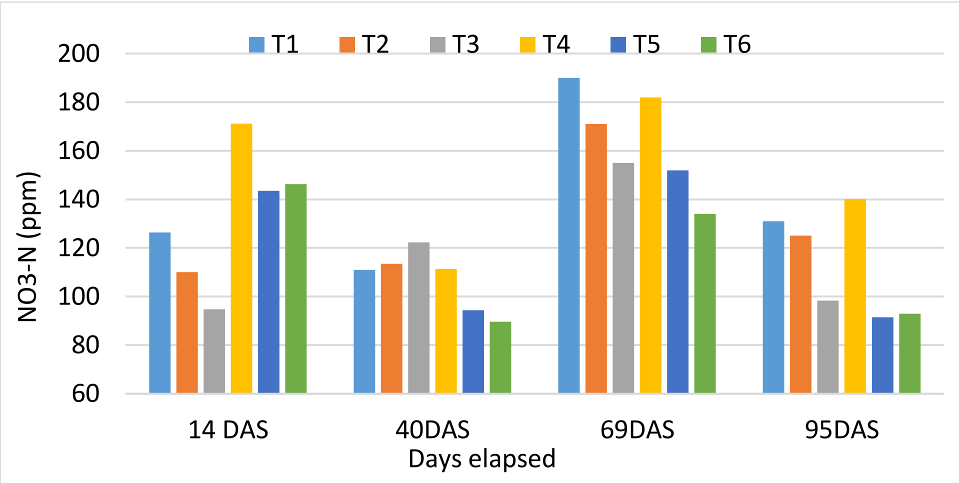

Figure 4b. NO_3-N availability in different treatments during Year-2.

Unfortunately, we could not test available N in the Year-3 because of the faults in the N analyser.

Conclusion

This study was conducted in an attempt to observe the potentiality of biochar to improve the growth and production of tomato cultivated under different irrigation regimes. From the two-year study, it has been observed that addition of biochar in the soil significantly improved different growth attributes of tomato, consequently it also increased the marketable yield of tomato. The impact was more apparent under deficit irrigation regimes. The comparatively better soil-water content, heterotrophic respiration (CO_2 emission) and available nitrogen (N) status in treatments with biochar indicated that biochar also has potential to improve the soil health. The combination of improved soil water holding capacity and N availability may be the reason behind increased productivity of tomato in biochar-added soil. The ability of biochar to significantly increase the fruit yield, therefore increase water productivity under deficit irrigation regimes suggests that it can be a great option for farming in water scarce regions. However, detailed study should be done to reveal the impact of biochar on soil physicochemical properties, and growth and yield of other crops. This study should be continued to study the long term impact of biochar on soil properties.

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EFFECT OF IRRIGATION ON GROWTH, FLOWERING AND CORM PRODUCTION OF GLADIOLUS IN WINTER SEASON

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Abstract

The experiment was conducted in the experimental field of IWM Division, BARI, Gazipur during 2018 -2019 and 2019-20 to evaluate the effect of different irrigation systems and scheduling on the performance of gladiolus. Nine treatments were designed for the experiment with four replications. Treatments were T_1 = Drip irrigation at 3-days interval with recommended N doses, T_2 = Drip irrigation at 3-days interval with 20% less N than recommended doses, T_3 = Drip irrigation at 3-days interval with 40% less N than recommended doses, T_4 = Shower irrigation at 7days interval meeting 100% of FC, T_5 = Shower irrigation at 7-days interval with 80% of FC, T_6 = Shower irrigation at 7-days interval with 60% of FC, T_7 = Flood irrigation at 10-days interval, T_8 = Flood irrigation at 15-days interval, T_9 = Flood irrigation at 20days interval. Results of this study revealed that the drip system of irrigation i.e. (T_1, T_2 & T_3) showed better performance than either of the shower (T_4, T_5 & T_6) or flood irrigation (T_7, T_8 & T_9) systems. Spike yield (22.42 t/ha, 22.55 t/ha), weight of single spike (84.07 gm, 85.08 gm), spike length (104.67 cm (2nd highest), 104.83 cm), rachis length (54.46 cm, 54.03 cm) in both the years were found the maximum with gravity drip irrigation at 20% less N than recommended doses. These were competitive with other two drip irrigation treatments with shower irrigation having 100% of FC and 80% of FC at 7-days interval. Maximum yield of corms (1.04 t/ha) and cormels (0.94 t/ha, 1.09 t/ha), number of cormels per plant (33.50, 41.25) and weight of cormels per plant (12.33 gm, 11.82 gm) were obtained in both the years. The weight of a single corm (43.71 gm), diameter of corm (6.2 cm) in 2018-19 were found with gravity drip irrigation at recommended N doses at 3 days interval which was competitive with drip irrigation at 20% less N than recommended doses along with shower irrigation with 100% of FC and 80% of FC. Whereas, the minimum plant growth, spike yield attributes, corm and cormel yield parameters were achieved with shower irrigation having 60% of FC along with flood irrigation at 10-days, 15-days and 20-days interval. The results of the study showed that the lowest irrigation water use, highest water productivity, and water and N savings through drip irrigation system, or shower irrigation with 100% of FC and 80% of FC promotes flower growth and quality characters and corm production of gladiolus in comparison with optimal, or scarce water applied through shower or flood irrigation system.

Introduction

Gladiolus (Gladiolus grandiflorus L.) is an important commercial bulbous flower crop which is extensively cultivated in many countries of the world including Bangladesh. Cut spikes of gladiolus remain fresh at least for a week and are in great demand for presentations and interior decoration. Gladiolus occupies prestigious position among the bulbous cut flower crops. Productivity of gladiolus (florets, corms and cormels) depends to a large extent on irrigation system. Optimizing use of irrigation water is an important step for effective water management in order to determine the effects of water on the growth period of ornamental plants as well as their visual quality (Carvalho et al., 2005; Lin et al., 2011). The optimum use of irrigation can be scheduled based on the rooting area, and at the same time, taking care of avoiding the leaching of nutrients into deeper soil layers (Raina et al., 1999, 2002, 2011). The seepage system of irrigation showed the best performance than sprinkler and flood irrigation system for gladiolus in India (Puvinder Gupta, June 2007). The highest water use efficiency and maximum soil water storage

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for gladiolus flower was obtained in gravity drip irrigation in comparison with surface irrigation (Khanam and Patra, 2015). In Bangladesh, gladiolus is gaining importance day by day for it's demand and commercial value. Most of the farmers use flood irrigation in commercial gladiolus flower production which waste a huge amount of water. But still there is a lack of standardize research work on irrigation and water management to produce quality spikes. Hence, an attempt was made to find out the best irrigation scheduling and suitable irrigation method for profitable production of gladiolus.

Objectives:

1. To find out the optimum irrigation scheduling for Gladiolus production
2. To investigate the performance of gladiolus under different irrigation method

Materials and Methods

The experiment was conducted during the winter season of 2018-2019 and 2019-20 at the experimental field of IWM Division, BARI, Gazipur. The soils were silty clay loam with field capacity (28.5-29%), and bulk density (1.44-1.48) gm/cc. The experiment was laid out in a RCBD design with four replications. Nine treatments were designed for the experiment as stated below:

T_1 = Drip irrigation at 3 days interval with recommended N doses

T_2 = Drip irrigation at 3 days interval with 20% less N than recommended doses

T_3 = Drip irrigation at 3 days interval with 40% less N than recommended doses

T_4 = Shower irrigation at 7 days interval with 100% of FC

T_5 = Shower irrigation at 7 days interval with 80% of FC

T_6 = Shower irrigation at 7 days interval with 60% of FC

T_7 = Flood irrigation at 10 days interval

T_8 = Flood irrigation at 15 days interval

T_9 = Flood irrigation at 20 days interval

The unit plot size was 3 m × 1.5 m, with 1.5m wide buffer strip between plots to restrict seepage from neighboring plots. Recommended dose of fertilizers were applied @ 300 kg N, 375 kg P, 300 kg K, 30 kg S, 8 kg Zn, 12 kg B per hectare and cow-dung 1t/ha. During land preparation, full doses of P, K, S, Zn, B and cow-dung were properly mixed with the soil. Half of the nitrogen was applied at 25 days after planting and the rest half of the nitrogen was applied at flower initiation period. Irrigations were done in drip, shower and flood irrigation methods as per treatments. Corms were sown on 20 November, 2018 and 2019 at a spacing of 15 cm plant to plant and 25 cm line to line. Soil moisture at every 10 days interval was measured. Measured amount of water was applied to each plot as per treatment to maintain the soil moisture content in the root zone depth. Ten plants were selected randomly and tagged in each plot for analysis of growth, flower and corm yield characters viz. length of plant, length of leaves, number of spikes, length of spike, number of corm and cormel, diameter and weight of corms and weight of cormels and various other similar characters. Data of the investigation is presented in the Table 1.

The experimental plots of treatment T_1, T_2 and T_3 were irrigated by drip irrigation with fertilizer (fertigation) as per treatment. The drippers having a discharge of 4 l h^{-1} at a pressure of 0.1 MPa on laterals were located 25 cm apart. The laterals were arranged in such a way that every ridge had five laterals with 25 cm intervals. The amount of irrigation water applied in the treatments was controlled by using a gauge on the main pipeline and valves located on each lateral. The irrigation water to be applied was calculated by the equation given below.

$$I = Pc \times Epan \times A \times P \quad (1)$$

where, I is the irrigation water (mm), Pc is the pan coefficient, Epan is the cumulative pan evaporation (mm), A is the plot area (m^2) and P is the wetted area percentage (%). The wetted area was taken as 100% assuming that lateral interval is equal to the spaces between drippers.

Undesirable plants were rouged out. Flower spikes at color break stage (viz. basal floret showing color) were cut with a sharp knife by giving a slanting cut from plants grown in the experimental plots keeping two leaves at the both side of the spike. Flowers were harvested from 14 February to 28 February, and corms and cormels were harvested from 05 May to 07 May at both the years.

Estimation of irrigation water

Irrigation water was applied to bring the soil moisture content at the root zone to field capacity taking into account the effective root zone depth. Irrigation water was calculated using the following equation (Michael, 1985):

$$d = \frac{Fc - Mci}{100} \times As \times D$$

where, d = Depth of water applied (cm))

Fc = Field capacity of soil (%)

Mci = Moisture content of the soil at the time of irrigation (%)

As = Apparent specific gravity of the soil

D = Depth of root zone (cm)

Results

Effect of irrigation on growth of gladiolus

The bar charts (Fig. 1a and 1b) illustrate changes in root length and biomass resulted from applying different amount of irrigation with different irrigation methods. It is shown from the charts root length varied at different times with different treatments in both the two years. In 2018-19, the highest root length (23.00 cm) was found in treatment T_8 at 50 DAS.

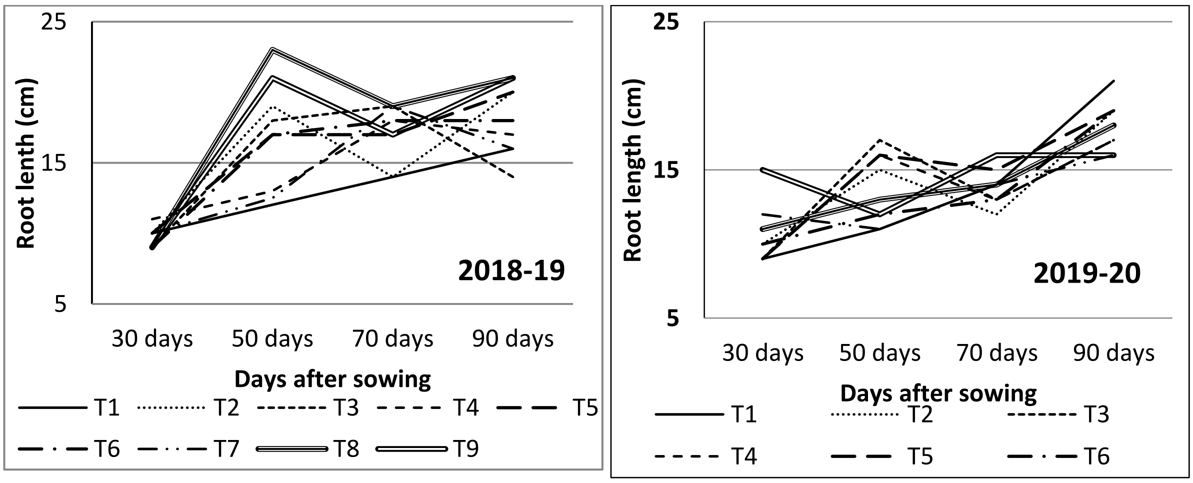

Fig. 1. Effect of different irrigation treatments on root length at different days after sowing at Gazipur during 2018-19 and 2019-20.

After that it dropped by 4 cm and again slightly increased to 21 cm at 90 days after sowing (Fig. 1a), while the lowest root length (9 cm) was found in treatment T_3, T_6, T_8 and T_9. However, in the year 2019-20, the highest root length (21 cm) was found in treatment T_1 at 90 DAS. During this year, root length increased for all treatments at 90 Days after sowing and the lowest root length (9 cm) was reported for the treatments T_1, T_3, T_4 and T_5.

It is seen in the fig. 2 that biomass production was gradually increased up to 90 DAS. In the year 2018-19, the maximum biomass was found of about 20.94 gm/plant in treatment T_5 at 90 days followed by treatments T_1. During the year 2019-20 the maximum biomass was recorded of about 16.84 gm/plant in treatment T_3, followed by treatments T_2, T_5 and T_7 at 90 DAS. It is also seen that treatment T_6 produced comparatively less biomass than other treatments in both the years.

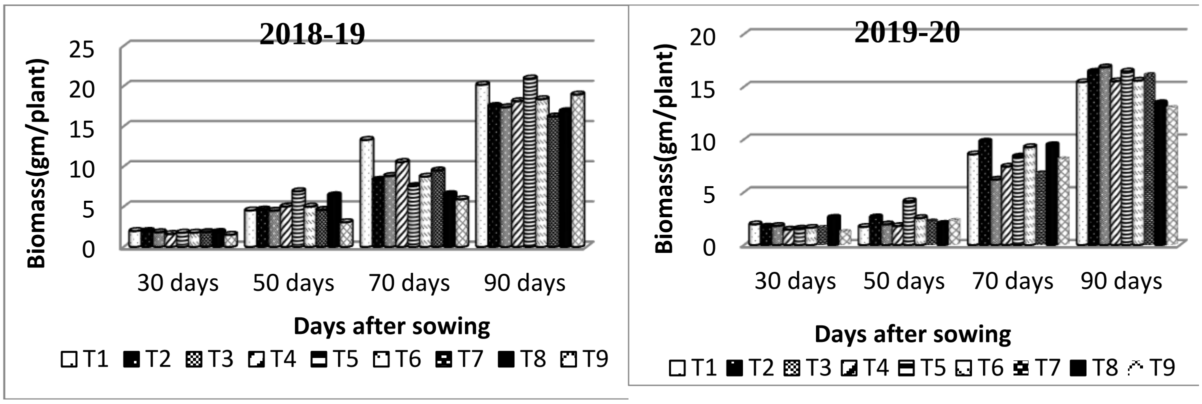

Fig. 2. Effect of different irrigation treatments on biomass production at different days after sowing at Gazipur during 2018-19 and 2019-20.

Plant growth, floral characters and Yield

The growth and flower quality characteristics of gladiolus such as spike length, rachis length, spike yield, weight of cormel were significantly ($p<0.01$) influenced by the drip irrigation with nitrogen variation at a fixed interval (3 days), shower irrigation at a fixed interval (7 days) and conventional surface irrigation with different time scheduling. Table 1.a. revealed that the maximum spike yield (22.42 t/ha) was achieved with the treatment (T_2) (drip irrigation with 20% less N than recommended doses) and and the minimum spike yield (18.91 t/ha) was in treatment (T_6) (shower irrigation at 7 days interval with 60% of FC).

Table 1.a. Effect of irrigation levels on yield and yield contributing characters of gladiolus during 2018-19 at Gazipur

Treatment	Plant height (cm)	No. of leaves	Spike length (cm)	Rachis length (cm)	Spike wt. (gm)	No. of florets	Yield (t/ha)
T_1	58.55	9.33	101.9	53.75	80.04	14.87	21.34
T_2	58.66	9.29	104.67	54.46	84.07	14.79	22.42
T_3	58.37	9.29	105.1	53.55	82.20	14.56	21.94
T_4	59.49	9.11	99.73	49.79	78.93	14.82	21.05
T_5	57.37	8.88	100.98	51.48	80.33	14.79	21.42
T_6	55.94	9.30	95.13	48.14	70.91	14.30	18.91
T_7	58.19	9.44	95.91	47.33	76.52	14.23	20.41
T_8	57.89	9.17	99.00	48.86	74.11	14.23	19.76
T_9	58.34	9.42	98.77	48.56	75.03	14.38	20.01
CV(%)	2.76	3.92	2.93	3.90	5.86	4.35	5.86
LSD(0.05)	NS	NS	5.09	3.42	NS	NS	2.11

The highest spike length (105.10 cm) was recorded for treatment T_3 followed by treatment T_2, T_1 and T_5. But there was statistically significant difference among those treatments. While the shortest spike length was recorded for the treatment (T_6) (shower irrigation at 7 days interval with 60% of FC), was statistically comparable with the treatments T_7 (95.91 cm), T_9 (98.77 cm), T_8 (99.00 cm) and T_4 (99.73 cm). The treatment T_1 (53.75 cm), treatment T_2 (54.46 cm) and Treatment T_3 (53.55 cm) exhibited better performance for rachis length followed by treatment (T_5), which were at par with each other. However, the lowest rachis length was determined in treatment (T_7) (47.33 cm), was comparable with the treatments T_6 (48.14 cm), T_9 (48.56 cm), T_8 (48.86 cm) and T_4 (49.79 cm). The weight of single spike was non-significant (p=0.05) and the highest spike weight was 84.07 gm resulted from treatment T_2 followed by treatments T_1, T_3 and T_5. Whereas, the lowest spike weight (70.91 cm) was obtained from treatment T_6 that was statistically significant with the highest one. The results were found to be statistically at par with all the treatments for plant height, no. of leaves and no. of florets.

Table 1.b. revealed that the maximum spike yield (22.54 t/ha) was achieved with the treatment (T_2) (drip irrigation with 20% less N than recommended doses) which was significantly at par with the treatment (T_1) (22.47 t/ha) and the minimum spike yield (19.31 t/ha) was obtained from the treatment (T_8) (flood irrigation at 15 days interval) along with the treatment (T_6) (19.34 t/ha). The treatment T_1 (103.34 cm), treatment T_2 (104.84 cm) and Treatment T_3 (104.67 cm) exhibited better performance for spike length followed by treatment (T_4), which were statistically equal with each other. However, the lowest spike length was determined in treatment (T_8) (90.25 cm), was comparable with the treatments (T_6) (92.13 cm). The highest rachis length (54.03 cm) was recorded for treatment T_2, was comparable with the treatment (T_3) (53.24 cm) and treatment (T_4) (52.86 cm), while the shortest rachis length (47.29 cm) was recorded for the treatment (T_9) (flood irrigation at 20 days interval), was statistically equal to the treatment (T_8) (47.33 cm), followed by treatment (T_6) (48.07 cm). The highest spike weight was 85.08 gm resulted from treatment T_2, was statistically at par with the treatment (T_1). Whereas, the lowest spike weight (72.81 cm) was obtained from treatment T_6 that was statistically equal to the treatment T_8. The highest plant height and no. of florets were obtained from the treatment (T_2) and the lowest plant height and no. of florets were obtained from the treatment (T_8). Number of leaves were found to be statistically similar with all the treatments except treatment (T_2) and treatment (T_6).

Table 1.b. Effect of irrigation levels on yield and yield contributing characters of gladiolus during 2019-20 at Gazipur

Treatment	Plant height (cm)	No. of leaves	Spike length (cm)	Rachis length (cm)	Spike wt. (gm)	No. of florets	Yield (t/ha)
T_1	59.36	9.21	103.34	52.22	84.96	14.12	21.47
T_2	62.32	8.97	104.83	54.03	85.08	15.07	22.55
T_3	59.91	9.42	104.67	53.24	83.24	14.16	22.15
T_4	60.70	9.34	102.13	52.86	81.96	14.58	21.63
T_5	59.95	9.38	100.25	50.70	83.39	14.46	21.80
T_6	57.21	8.85	92.13	48.07	72.81	13.63	19.34
T_7	58.29	9.36	97.25	49.25	77.39	14.22	20.51
T_8	56.50	9.25	90.25	47.33	72.86	12.09	19.31
T_9	56.77	9.29	93.83	47. 29	75.22	13.42	19.89
CV(%)	2.72	1.74	1.92	1.90	0.32	1.96	0.88
LSD(0.05)	2.34	0.23	2.77	1.40	0.37	0.40	0.27

Floral characters like days to spike initiation and vase life were greatly influenced by the treatments. From the analyzed data in the table 2. It is evident that the plants under different treatments took 74-75 days in 2018-19 and 72-74 days in 2019-20 for 50 % spike initiation that was significantly equal.

Table 2. Effect of irrigation levels on spike initiation and vase life of gladiolus during 2018-19 and 2019-20 at Gazipur

Treatments	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9
Days to reach 50% spike initiation at 2018-19	74	75	74	74	74	75	75	75	75
Days to reach 50% spike initiation at 2019-20	73	72	74	72	73	73	73	73	73
Vase life (days) in 2018-19	5.98	6.5	6.01	4.67	5.95	4.90	5.33	5.12	4.73
Vase life (days) in 2019-20	6.01	6.3	5.97	5.99	5.64	4.86	5.40	4.65	4.72

Table 3.a. delineates that the maximum yield of corms (1.04 t/ha) and cormel (0.94 t/ha), weight of single corm per plant (43.71 gm), diameter of corm (6.2 cm), number of cormels per plant (33.50) and weight of cormels per plant (12.33 gm) were achieved from the treatment T_1 (drip irrigation with recommended N doses), whereas, the lowest corm yield (0.70 t/ha) and cormel yield (0.27 t/ha)|, weight of corm (28.82 gm), diameter of corm (5.47 cm), no. of cormel per plant (20.07) and weight of cormel (5.00 gm)) were resulted from shower irrigation at 7days interval with 60% of FC (treatment T_6). However, the treatment T_1 in respect of cormel yield was statistically comparable with the treatments T_2, T_3, T_5 and significant with each treatment of T_6 and T_9 where rest of the treatments were statistically at par with each other. The variation observed in corm yield among the treatments was almost similar and treatment T_1 was significant to treatment T_6 and T_9 each other. Treatment T_1, in terms of weight of cormel/plant was statistically comparable with the treatments T_2 and T_3 and significant with the treatments T_6 and T_9. Number of corm was almost similar for all the treatments which was non-significant, but the highest one was obtained from treatment (T_7) (flood irrigation with 10days interval). Tripathi el al. (2001) reported the same observation that flood irrigation is the best for the highest number of corms.

Table 3.a. Effect of irrigation levels on yield and yield contributing characters of corm and cormel of gladiolus during 2018-19 at Gazipur

Treatment	No. of corm	Wt. of corm (gm)	Dia of corm Cm	No. of cormel/plant	Wt. of cormel /plant gm	Corm yield (t/ha)	Cormel yield (t/ha)
T_1	10.67	43.71	6.20	33.50	12.33	1.04	0.94
T_2	10.67	38.45	5.82	31.30	11.22	0.91	0.84
T_3	10.67	39.47	5.67	30.90	11.23	0.93	0.78
T_4	10.33	34.86	5.62	25.30	9.63	0.90	0.56
T_5	11.67	40.68	5.94	25.53	9.67	0.93	0.62
T_6	11.00	28.82	5.47	20.07	5.00	0.70	0.27
T_7	11.33	34.82	5.52	24.63	8.07	0.86	0.44
T_8	11.00	33.42	5.72	23.37	7.35	0.81	0.40
T_9	10.33	33.81	5.77	19.30	6.83	0.77	0.34
CV (%)	10.90	17.65	5.78	13.42	13.99	13.53	13.42
LSD (0.05)	NS	NS	NS	54.76	19.98	NS	238.6

Table 3.b. delineated that the maximum yield of corms (1.04 t/ha) and cormel (1.09 t/ha), number of corms per plant (12.00), number of cormels per plant (41.25) and weight of cormels per plant (11.82 gm) were achieved with the treatment (T_1) (drip irrigation with recommended N doses). Whereas, the maximum weight of single corm per plant (41.68 gm), diameter of corm (5.93 cm) were recorded for treatment T_2. However, the lowest corm yield (0.69 t/ha) and cormel yield (0.45 t/ha), no. of cormel per plant (25.73) and weight of cormel per plant (7.56 gm)) were resulted from shower irrigation at 7days interval with 60% of FC (treatment T_6). The lowest weight of single corm (29.66 gm), diameter of corm (3.92 cm) were resulted from flood irrigation with 20 days interval (treatment T_9). The lowest number of corm was obtained from treatment T_3. However, the highest yielded treatment T_1 in respect of corm yield was statistically equal to the treatment T_2 which was comparable with the treatments T_3, T_4 and in respect of cormel yield was

significantly par with the treatments of T_2, T_4 and T_5 And , the lowest yielded treatment T_6 in respect of corm yield was statistically comparable with the treatments T_7, T_8 and T_9 and in respect of cormel yield was significantly par with the treatment T_8, was comparable with the treatments T_3 and T_9 .

Table 3.b. Effect of irrigation levels on yield and yield contributing characters of corm and cormel of gladiolus during 2019-20 at Gazipur

Treatment	No. of corm	Wt. of single corm (gm)	Dia of corm Cm	No. of cormel/plant	Wt. of cormel /plant (gm)|	Corm yield (t/ha)	Cormel yield (t/ha)
T_1	12.00	38.74	4.72	41.25	11.82	1.04	1.09
T_2	10.75	41.68	5.93	39.55	11.40	1.00	1.00
T_3	10.00	40.26	5.12	33.48	9.66	0.90	0.72
T_4	10.75	37.86	5.47	40.15	11.15	0.90	0.99
T_5	12.00	32.07	5.06	39.25	10.74	0.85	0.94
T_6	10.50	29.68	3.95	25.73	7.56	0.69	0.45
T_7	11.75	31.08	4.29	36.63	9.20	0.76	0.75
T_8	10.75	30.99	4.19	28.95	7.99	0.74	0.49
T_9	11.25	29.66	3.92	28.48	8.50	0.74	0.54
CV (%)	10.82	0.62	2.98	10.82	2.45	11.37	16.83
LSD (0.05)	NS	0.31	2.06	5.50	0.35	0.14	0.19

Amount of irrigation water and water use

In 2018-19 and 2019-20, irrigation water (30 mm and 27 mm) was applied for about 15 days and 16 days at the start of the experiment to all experimental plots to avoid any problems in the germination emergence of the bulbs. After the completion of emergence, irrigation water was applied to the experimental plots according to the designed treatments. The amount of irrigation water based on the treatments was initiated on 13 December 2018 and 15 December 2019, and ended on 25 February 2019 and 03 March 2020. During 2018-19, the applied irrigation water varied between 132.97-380.11 mm for spike yield and 215.14 – 461.02 mm for corm production (Table 4.a) for different treatments. The lowest water use in the study was measured at treatment T_1, T_2 and T_3 (132.97, 133.52, 132.99 mm for spike and 215.14, 215.47, 215.98 mm for corm) for which irrigation water was applied with drip irrigation at 3 days intervals using cumulative pan evaporation and the highest water use was measured at treatment T_4 (380.11 mm for spike and 461.02 mm for corm) where irrigation water was applied with 7 days intervals up to field capacity which was approx.. 3.00 times more than the lowest water treatments for spike yield and approximately 2.00 times more than the lowest water treatments for corm yield. And the second highest water use treatment was T_9 (347.02 mm for spike and 428.8.00 mm for corm), was also approx. 3.00 times higher than the lowest water treatments for spike yield and approx. 2.00 times higher than the lowest water treatments for corm yield Application of the same amount of irrigation water with drip irrigation with different N doses has resulted no significant effect among the treatments (T_1, T_2 and T_3) for yield and yield contributing character of gladiolus during 2018-19.

The highest water use was recorded in the shower irrigation at 100% of FC and flood irrigation at 20 days interval (T_9) and the lowest (215.14 mm) in drip irrigation at 100% of evaporation replenishment with recommended nitrogen doses (Table 4.a). On the contrary, the highest water productivity for spike yield (16.79 kg/m^3) was recorded with drip irrigation with 20% less N than recommended doses, and for corm and cormel yield (0.48, 0.44 kg/m3) was recorded with Drip irrigation with recommended N doses (Table 4.b), whereas the lowest for spike yield (5.54 kg/m3) and cormel yield (0.12 kg/m3) were obtained with shower irrigation at 100% of FC. And the lowest water productivity for corm yield (0.20, 0.18 kg/m3) was achieved with shower irrigation at 100% of FC and flood irrigation at 20 days interval (T_9).

Table 4.a. Irrigation water applied in different treatments during 2018-19

Treatment	Number of Irrigation applied	Dripper discharge (l/h)	Water for plant establishment (mm)	Irrigation water applied (mm)	Effective rainfall for spike yield (mm)	Effective rainfall for corm yield (mm)	Soil moisture contribution for spike yield (mm)	Soil moisture contribution for corm yield (mm)	Total water Use for spike production (mm	Total water Use for corm production (mm)
T_1	23	4	30	89	15	97.8	-1.03	-1.66	132.97	215.14
T_2	23	4	30	89	15	97.8	-0.48	-1.33	133.52	215.47
T_3	23	4	30	89	15	97.8	-1.01	-0.82	132.99	215.98
T_4	11	-	30	335	15	97.8	0.11	-1.78	380.11	461.02
T_5	11	-	30	258	15	97.8	0.06	-1.38	303.06	384.42
T_6	11	-	30	180	15	97.8	1.05	-0.53	226.05	307.27
T_7	7	-	30	234	15	97.8	-0.59	-1.63	278.41	360.17
T_8	5	-	30	208	15	97.8	-0.73	-1.89	252.27	333.91
T_9	4	-	30	303	15	97.8	-0.98	-2.00	347.02	428.8

Table 4.b. Water use and water productivity in different irrigation treatments during 2018-19

Treatment	Total water Use for spike yield (mm)	Total water Use for corm yield (mm)	Spike yield (t/ha)	Corm yield (t/ha)	Cormel yield (t/ha)	Water productivity For spike yield (kg/m^3)	Water productivity for corm yield (kg/m^3)	Water productivity for cormel yield (kg/m^3)
T_1	132.97	215.14	21.34	1.04	0.94	16.05	0.48	0.44
T_2	133.52	215.47	22.42	0.91	0.84	16.79	0.42	0.39
T_3	132.99	215.98	21.94	0.93	0.78	16.50	0.43	0.36
T_4	380.11	461.02	21.05	0.90	0.56	5.54	0.20	0.12
T_5	303.06	384.42	21.42	0.93	0.62	7.07	0.24	0.16
T_6	226.05	307.27	18.91	0.70	0.27	8.37	0.23	0.09
T_7	278.41	360.17	20.41	0.86	0.44	7.33	0.24	0.12
T_8	252.27	333.91	19.76	0.81	0.40	7.83	0.24	0.12
T_9	347.02	428.8	20.01	0.77	0.34	5.77	0.18	0.08

During 2019-20, the irrigation water amounts applied according to the treatments varied between 128.94- 350.54 mm for spike yield and 333.58 – 555.36 mm for corm production (Table 5.a). The lowest water use in the study was measured at treatment T_1, T_2 and T_3 (129.31, 130.08, 128.94 mm for spike and 334.24, 334.09, 333.58 mm for corm) for which irrigation water was applied with drip irrigation at 3 days intervals using cumulative pan evaporation and the highest water use was measured at treatment T_4 (350.54 mm for spike and 555.36 mm for corm) where irrigation water was applied with 7 days intervals up to field capacity which was approx.. 3.00 times higher than the lowest water use treatments for spike yield and approx. 2.00 times higher than the lowest water use treatments for corm yield.

The results of the study showed that the highest (555.36 mm) water use was recorded in the shower irrigation at 100% of FC and the lowest (333.58 mm) in drip irrigation at 100% of evaporation replenishment with recommended nitrogen doses (Table 5.a). On the contrary, the highest water productivity for spike yield (17.34 kg/m^3) was recorded with drip irrigation with 20% less N than recommended doses, and for corm and cormel yield (0.31, 0.33 kg/m3) was recorded with Drip irrigation with recommended N doses (Table 5.b), whereas the lowest for spike yield (6.17 kg/m3) was obtained with shower irrigation at 100% of FC. The lowest water productivity for corm yield (0.15 kg/m3) was achieved with flood irrigation at 20 days interval (T_9), and the lowest water productivity for cormel yield (0.11 kg/m3) was obtained from the treatments T_6, T_8 and T_9.

Table 5.a. Irrigation water applied in different treatments during 2019-20

Treatment	Number of Irrigation applied	Drip per discharge (l/h)	Water for plant establishment (mm)	Irrigation water applied (mm)	Effective rainfall for spike yield (mm)	Effective rainfall for corm yield (mm)	Soil moisture contribution for spike yield (mm)	Soil moisture contribution for corm yield (mm)	Total water Use for spike yield (mm	Total water Use for corm yield (mm)
T_1	21	4	27	85	18	224	-0.69	-1.76	129.31	334.24
T_2	21	4	27	85	18	224	0.08	-1.91	130.08	334.09
T_3	21	4	27	85	18	224	-1.06	-2.42	128.94	333.58
T_4	10	-	27	306	18	224	-0.46	-1.64	350.54	555.36
T_5	10	-	27	252	18	224	-1.02	-1.45	295.98	501.55
T_6	10	-	27	171	18	224	0.25	-2.36	216.25	419.64
T_7	7	-	27	227	18	224	0.92	-1.11	272.92	476.89
T_8	5	-	27	212	18	224	-1.03	-0.95	255.97	462.05
T_9	4	-	27	246	18	224	-0.68	-1.6	290.32	495.4

Table 5.b. Water use and water productivity in different irrigation treatments during 2019-20

Treatment	Total water Use for spike yield (mm)	Total water Use for corm yield (mm)	Spike yield (t/ha)	Corm yield (t/ha)	Cormel yield (t/ha)	Water productivity For spike yield (kg/m^3)	Water productivity for corm yield (kg/m^3)	Water productivity for cormel yield (kg/m^3)
T_1	129.31	334.24	21.47	1.04	1.09	16.60	0.31	0.33
T_2	130.08	334.09	22.55	1	1	17.34	0.30	0.30
T_3	128.94	333.58	22.15	0.9	0.72	17.18	0.27	0.22
T_4	350.54	555.36	21.63	0.9	0.99	6.17	0.16	0.18
T_5	295.98	501.55	21.8	0.85	0.94	7.37	0.17	0.19
T_6	216.25	419.64	19.34	0.69	0.45	8.94	0.16	0.11
T_7	272.92	476.89	20.51	0.76	0.75	7.52	0.16	0.16
T_8	255.97	462.05	19.31	0.74	0.49	7.54	0.16	0.11
T_9	290.32	495.4	19.89	0.74	0.54	6.85	0.15	0.11

Discussions

Table (1, 2, 3, 4, and 5) delineated that the performance of the drip irrigation system was the best for gladiolus cultivation. Whereas, the performance of the flood irrigation system was not so good for gladiolus production. Drip irrigation at 3 days interval with 20% less N than recommended doses was the best treatment for the spike yield. However, Drip irrigation at 3 days interval with recommended doses was the best treatment for the corm and cormel yields. Treatment T_1, T_2, T_3, T_4 and T_5 did well for all the parameters which were statistically comparable with each other for maximum yield and differed significantly with 5% level of other parameters. On the other hand, treatments T_6, T_7, T_8 and T_9 exhibited low performance for all the parameters which were statistically comparable with each other for maximum lowest parameters and differed significantly with 5% level at other parameters.

These clearly indicate that optimal or, marginal deficit application of N with irrigation water through fertigation system on regular basis enhanced the growth and quality promoting characters and flower yield of gladiolus. These also clearly indicate that, lack of N fertilization hampered corm and cormel yield and their quality. Though optimal application of irrigation water (shower irrigation with 100% of FC (T_4)) can enhance flower quality and yield, it needs much water. But, marginal application of irrigation water through shower irrigation with 80% of FC (T_5) can increase flower quality and yield, might be due to ensure adequate amount of water at every critical stages (figure-1). Renata bachin mazzini-guedes et al., 2017 demonstrated that irrigation with 80% FC in gladiolus flower promotes plant growth and quality improvement characters and crop yield. The reduced flower yield and water productivity in shower and flood irrigation as reported in this study might be due to the losses of water and nutrients as a result of deep percolation and evaporation mechanisms beyond the crop root zone (Raina et al., 1999, 2011), or due to water stress at critical period (figure-1) which might have failed to fulfill the water requirement of the plant (Begum et al., 2007). On the other hand, the higher WP under drip could be attributed to precise amount of water delivery in root zone without wetting the area with minimum scope for evaporation and deep percolation losses (Mantell et al., 1985; Raina et al., 2002).

Economic analysis

Table 3 showed economic analysis for the experiment where the highest BCR (2.23 and 2.24) was found in treatment (T_2) during 2018-19 and 2019-20 followed by treatments T_1, T_3, T_4 and T_5. And the lowest BCR (1.93 and 1.97) was founded in treatment T_6 during 2018-19 and 2019-20 followed by treatments T_8 and T_9.

Table 6. Economic analysis for gladiolus cultivation

Year	Treatments	Total cost (Tk.)	Gross return (Tk.ha^{-1})	Gross margin (Tk.ha^{-1})	BCR
2018-19	T_1	856000	1813923	957923	2.12
	T_2	855000	1905721	1050721	2.23
	T_3	854000	1864921	1010921	2.18
	T_4	834000	1789269	955269	2.15
	T_5	834000	1820720	986720	2.18
	T_6	834000	1607363	773363	1.93
	T_7	826000	1734868	908868	2.10
	T_8	822000	1679616	857616	2.04
	T_9	820000	1700866	880866	2.07
2019-20	T_1	855000	1824973	969973	2.13
	T_2	854000	1916774	1062774	2.24
	T_3	853000	1882771	1029771	2.21
	T_4	834000	1838570	1004570	2.20
	T_5	834000	1853019	1019019	2.22
	T_6	834000	1643914	809914	1.97
	T_7	826000	1743366	917366	2.11
	T_8	822000	1641365	819365	2.00
	T_9	820000	1690665	870665	2.06

Conclusion

It was observed that Drip irrigation method was superior over flooding and shower irrigation method and treatment T_2 (Drip irrigation with 20% less N than recommended doses at 3 days interval) was the best for spike yield and treatment T_1 (Drip irrigation with recommended N doses at 3 days interval) was the best for corm and cormel production. If drip irrigation method is unavailable anywhere, then shower irrigation is better than flood irrigation method. Among the shower irrigation treatments, shower irrigation with 80% of FC (T_5) at 7 days interval was the best, as it consumes less water but produce higher yield. Whenever there is lack of drip and shower irrigation method then flood irrigation at 10 days interval (T_7) can be followed.

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EFFECT OF SALINE WATER IRRIGATION WITH DIFFERENT DOSES OF POTASSIUM ON CROP GROWTH AND YIELD OF MUNG BEAN

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Abstract

The experiment was conducted at the shade house of IWM Division, BARI, Gazipur during 2018 - 2019 to evaluate the effect of saline water irrigation with different doses of potassium on crop growth and yield of mung bean. Thirteen treatments were designed for the experiment with four replications. Treatments were T_1= Irrigation by fresh water with 100% potassium, T_2*= Irrigation by saline water (4 ds/m) with 0% potassium,* T_3*= Irrigation by saline water (4 ds/m) with 100% potassium,* T_4*= Irrigation by saline water (4 ds/m) with 125% potassium,* T_5*= Irrigation by saline water (4 ds/m) with 150% potassium,* T_6*= Irrigation by saline water (8 ds/m) with 0% potassium,* T_7*= Irrigation by saline water (8 ds/m) with 100% potassium,* T_8*= Irrigation by saline water (8 ds/m) with 125% potassium,* T_9*= Irrigation by saline water (8 ds/m) with 150% potassium,* T_{10}*= Irrigation by saline water (12 ds/m) with 0% potassium,* T_{11}*= Irrigation by saline water (12 ds/m) with 100% potassium,* T_{12}*= Irrigation by saline water (12 ds/m) with 125% potassium,* T_{13}*= Irrigation by saline water (12 ds/m) with 150% potassium. Results of experimental findings revealed that potassium can eliminate the deleterious effects of salinity on mung bean yield to some extent. Additional K application with saline irrigation water significantly affected plant height, root height, number of leaves, plant fresh weight and dry weight of mung bean.*

Introduction

Climate change is now one of the biggest problems across the globe as its impacts on human being and the environment are very terrible and prolonged. Bangladesh is exposed to be one of the most vulnerable countries of the world to climate change and sea level rise. There are several environmental issues and problems that are hindering the development of Bangladesh. Salinity is such an environmental problem. Salinity has been a threat to agriculture in some parts of the world for over 3000 years; in recent times, the threat has grown (Tim Flowers, 2006). It is estimated that at least 20% of all irrigated lands are salt affected (Pitman and Läuchli, 2002) in whole world and about 53% of the coastal areas are affected by salinity in Bangladesh (Haque, 2006). Agricultural land use in these areas is very poor, which is much lower than country's average cropping intensity. Salinity causes unfavorable environment and hydrological situation that restrict the normal crop production throughout the year. Excessive soil salinity may adversely affect plant growth by increasing the osmotic pressure in the solution, forming toxicity in the plant tissue and changing the plants mineral nutritional characteristics (Michael, 1978). In the face of high salinity, a plant's ability to control water potential and hydraulic conductivity is essential for the maintenance of water levels in tissue (Negrao et al., 2017).

Among the alternatives employed to minimize the deleterious effects caused by the high salt concentrations on plants, K fertilization stands out. Hence, studies have associated the tolerance of crops to salinity with an adequate K nutrition (Blanco et al., 2008; Gurgel et al., 2010). Potassium is essential to plants because it plays a key role in osmotic regulation and promotes the maintenance of turgor in guard cells. By increasing their osmotic potential, potassium allows this cell to absorb more water, and the adjacent cell acts as a counter cation for anion accumulation and electrogenic transport processes and, consequently, generates higher turgor pressure (Langer et al., 2004; Islam et al., 2015).

Besides being an osmoregulator, K creates an osmotic gradient that allows water movement and regulates stomatal opening and closure, playing an essential role in water saving

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and cell turgor, transport of carbohydrates and respiration (Shimazaki et al., 2007). Application of higher level of K improves growth and yield of mung bean under mild level of saline conditions (M. E. Kbir et al.,2004).

The mung bean (*Vigna radiata*), locally known as the *moog or sonamoog*, is a plant *species* in the legume family. It has a distinct advantage of being short-duration and can grow in wide range of soils and environments (as mono or relay legume). It has a high nutrient value with protein, carbohydrate, minerals, pro vitamin A and vitamin B-complex.

Material and Methods

An experiment was conducted at IWM shed house of Bangladesh Agricultural Research Institute, Gazipur. BARI Mung bean -5 was used for the experiment. The experimental design was in randomized blocks, with four replicates, and the treatments consisted of four levels of irrigation water electrical conductivity - ECw (0, 4, 8 and 12 dS m-1) and four K doses (0, 100, 125 and 150% of recommendation). The treatments were

T_1= Irrigation by fresh water with 100% potassium

T_2= Irrigation by saline water (4 ds/m) with 0% potassium

T_3= Irrigation by saline water (4 ds/m) with 100% potassium

T_4= Irrigation by saline water (4 ds/m) with 125% potassium

T_5= Irrigation by saline water (4 ds/m) with 150% potassium

T_6= Irrigation by saline water (8 ds/m) with 0% potassium

T_7= Irrigation by saline water (8 ds/m) with 100% potassium

T_8= Irrigation by saline water (8 ds/m) with 125% potassium

T_9= Irrigation by saline water (8 ds/m) with 150% potassium

T_{10}= Irrigation by saline water (12 ds/m) with 0% potassium

T_{11}= Irrigation by saline water (12 ds/m) with 100% potassium

T_{12}= Irrigation by saline water (12 ds/m) with 125% potassium

T_{13}= Irrigation by saline water (12 ds/m) with 150% potassium

Total fifty-two plastic pots (depth: 34 cm and diameter on an average 30.50 cm) were used in the experiment. Each pot was filled with 24 kg soil collected from IWM experiment field and contained three plants. The bottom of the pot was perforated and filled with the coarse aggregate to drain the excess of water to a plate, in order to analyzed their chemical composition. Direct soil EC meter was used to measure in situ soil salinity. The salinity data were measured at two depths (0-5 cm) and (5-15 cm) for each treatment. Four levels of K in the form of muriate of potash (MOP) were applied as the potassium source. Recommended dose of fertilizer was applied equally to all treatments.

The irrigation waters with the respective ECw values were prepared artificially by mixing raw salt into water using trial and error method in the laboratory to get the expected soil salinity. Before using raw salt, salt analysis was done by Flame photometer to compare the amount of percentage of each component (e.g. Na, K, Ca) of salt with the sea salt, and found that raw salt contains desired amount of NaCl as in sea salt.

Before sowing, equal amount of saline water irrigation was used for developing and maintaining soil salinity to some extent in the pots of different treatments. Pre-soaked purified 10 seeds were sown in each pot and irrigated with fresh water for easy germination. At the 2nd trifoliate leaf stage, three uniform and healthy plants were kept at each pot and other plants were picked out. Fresh water was used for plant establishment up to 2nd trifoliate leaf appeared before applying actual treatments. When the first trifoliate appeared, all the treatments were started and continued till maturity. Soil salinity was measured after each irrigation for different treatments. Amount of irrigation water was applied up to field capacity. Plants were grown up to maturity stage and dry matter yield was recorded. Extra 1 replication was included for growth stage wise sampling.

Table- 1. Physical and chemical characteristics of the studied soil

Soil	Texture	pH	Organic Material (%)	Ca	Mg	K	Total N (%)	P	S
				meq/100ml				μg/ml	
Studied soil	silty clay loam	6.4	1.39	5.2	1.8	0.12	0.074	39.0	19.0

Results and Discussion

Yield and yield components of mung bean

The summary of ANOVA suggested that EC of irrigation waters significantly ($p<0.05$) affected yield and all the other yield components (Table 1) of mung bean. There was significant difference in the relative yield decrease with salinity increase between the lowest and the highest K application rates. The mung bean yield decreased to 0.89 and 1.29 t ha-1, respectively by saline irrigation with variable level of potassium doses when compared to 1.47 t ha-1 in pots treated with non-saline irrigation water and recommended potassium dose. The highest yield of 1.47 t ha-1 was obtained from treatment T_1 (irrigation by fresh water with 100% potassium) and the lowest yield of 0.89 t ha-1 was recorded from treatment T_{10} (irrigation by saline water (12 ds/m) with 0% potassium) (Table 1). Table 1. reveals that the highest yield (1.29 t/ha and 1.28 t/ha) among the saline irrigation treatments were obtained from the treatments (T_5) (Irrigation by saline water (4 ds/m) with 150% potassium) and T_3 (irrigation by saline water (4 ds/m) with 100% potassium) which was significantly comparable with the treatments T_4 (irrigation by saline water (4 ds/m) with 125% potassium), T_9 (irrigation by saline water (8 ds/m) with 150% potassium). M. Salim and M. G. Pitman showed 60 % and 25% reduction of mung bean yield due to addition of 50 mM NaCl and 100 mM NaCl respectively. But in this study, maximum and minimum yield reduction due to 50 mM NaCl and 90 mM NaCl addition were 40 % and 12 % respectively. These results showed that the harmful effects of salinity on the yield of mung bean were minimized to some extent with potassium fertilization.

The growth of the plants was adversely affected by saline irrigation (ECsw = 12 dS m-1) as compared to non-saline water (EC = 0.6) (Table 2).

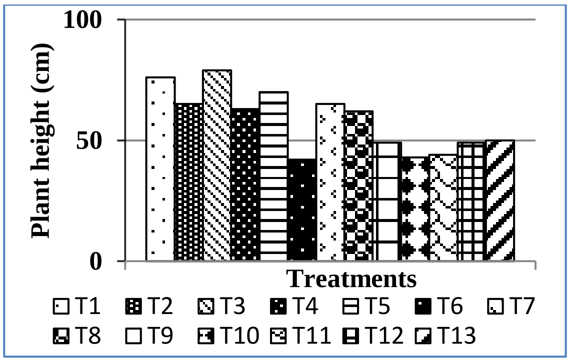
The ECiw x K interaction was significant ($p>0.05$) for all the yield parameters such as number of pod/plant, wt. of seeds/pod, 1000 seed wt. (gm), except pod length and no. of seeds per pod. All the yield parameters decreased with increasing salinity levels, but increased with the increasing potassium level. The highest no. of pods/plant (14.75), pod length (7.54 cm), no. of seeds/pod (9.71), wt. of seeds/pod (0.52 gm), 1000 seed wt. (55.27 gm) were obtained from the fresh water treatment. Among the saline water irrigation treatments, the treatment T_3 (irrigation with 4 ds/m saline water with 100% potassium) and treatment T_8 (irrigation with 8 ds/m saline water with 125% potassium) exhibited better performance for no. of pod/plant (12.00). The highest pod length (9.50 cm) was recorded for treatment T_3 along with treatment $T_{6.}$ While the highest no. of seeds/pod was obtained for the treatment T_2 (irrigation with 4 ds/m saline water with 0% potassium) along with treatment T_5 (irrigation with 4 ds/m saline water with 150% potassium) (9.50). Whereas, the highest wt. of seeds/pod, 1000 seeds wt. and seed yield was resulted from treatment $T_{5.}$ However, the lowest no. of pod/plant (09.75), pod length (6.09 cm), wt. of seeds/pod (0.37 gm) and seed yield (0.89) were found in treatment T_{10} (irrigation with 12 ds/m saline water with 0% potassium). Treatment T_{10} and treatment T_{11} were at par with each other for the lowest wt. of seeds/pod and 1000 seed wt. The lowest no. of seeds/pod (8.46) was resulted from treatment $T_{12.}$

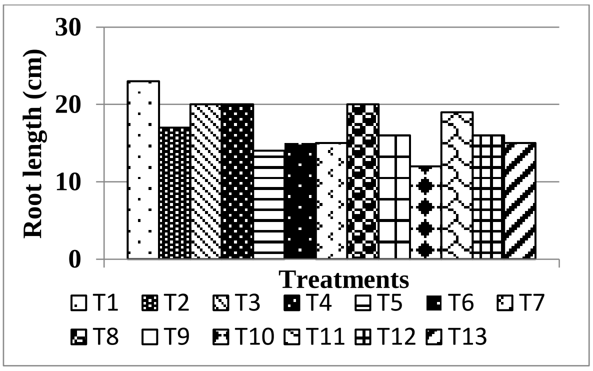
Table- 2. Summary of analysis of variance (ANOVA) for yield and yield components of mung bean as affected by the application of saline water and potassium

Treatments	Number of pod/plant	Pod length(cm)	Number of seeds/pod	Wt. of seeds/pod	1000 seed wt. (gm)	Seed yield t/ha
T_1	14.75	7.54	9.71	0.52	55.27	1.47
T_2	10.75	7.42	9.50	0.42	47.05	1.14
T_3	12	7.46	9.34	0.46	48.85	1.28
T_4	10.75	7.40	9.38	0.47	48.51	1.26
T_5	11.50	7.00	9.50	0.49	50.79	1.29
T_6	11.25	7.46	9.33	0.43	43.65	1.09
T_7	10.50	7.38	9.29	0.43	45.40	1.15
T_8	12.00	7.44	9.25	0.45	45.46	1.18
T_9	11.00	7.06	9.33	0.44	46.00	1.22
T_{10}	9.75	6.09	8.84	0.37	39.38	0.89
T_{11}	10.00	6.86	9.29	0.38	39.21	0.91
T_{12}	10.25	6.96	8.46	0.40	40.21	0.92
T_{13}	10.25	6.88	9.33	0.39	40.75	1.00
CV(0.05)	10.85	8.38	7.76	9.69	6.16	5.40
LSD	1.73	0.86	1.03	0.06	4.04	0.09

Fresh and dry weight of different plant parts at harvesting stage

Plant height, root length, number of leaves, fresh and dry weight of mung bean were significantly affected by different salinity and potassium level (fig:1,2,3). Potassium can slightly reduce the hazardous effect of salinity of mung bean. In presence of different K+ level, the root length, fresh and dry weight of mung bean decreased significantly for all salinity treatments. However, these parameters were not affected by low salinities (4 dS/m) but subsequently, it showed a great response with potassium fertilizers.





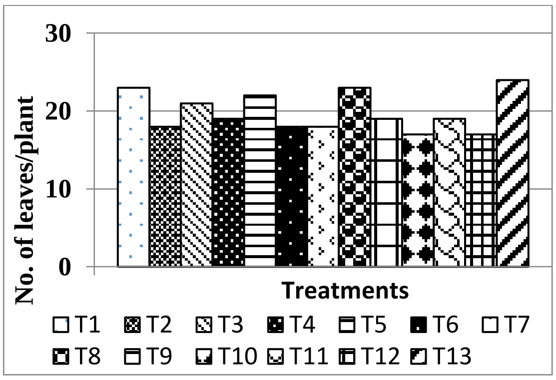


Fig. 1. Effect of salinity and potassium on plant height, root height and number of leaves shoot length at harvesting stage of mung bean.

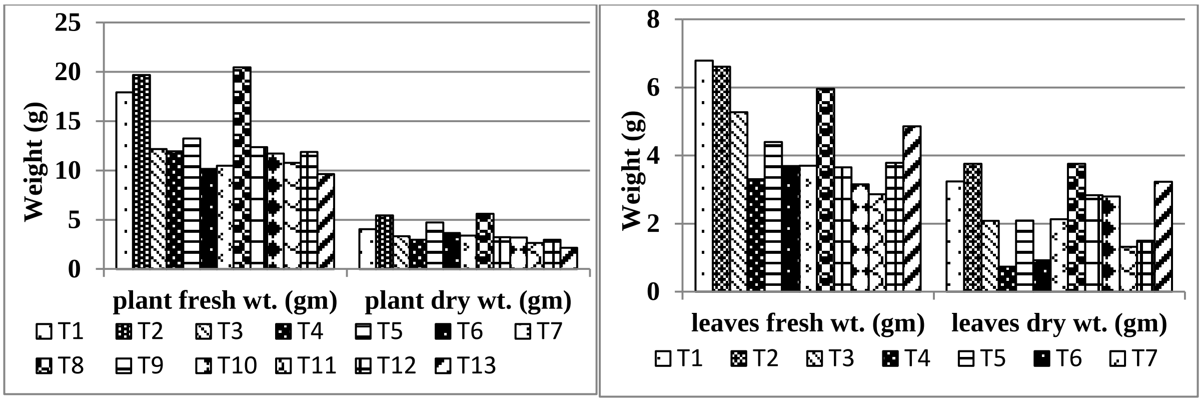


Fig. 2. Effect of salinity and potassium on plant fresh weight and dry weight, leaves fresh weight and dry weight at harvesting stage of mung bean.

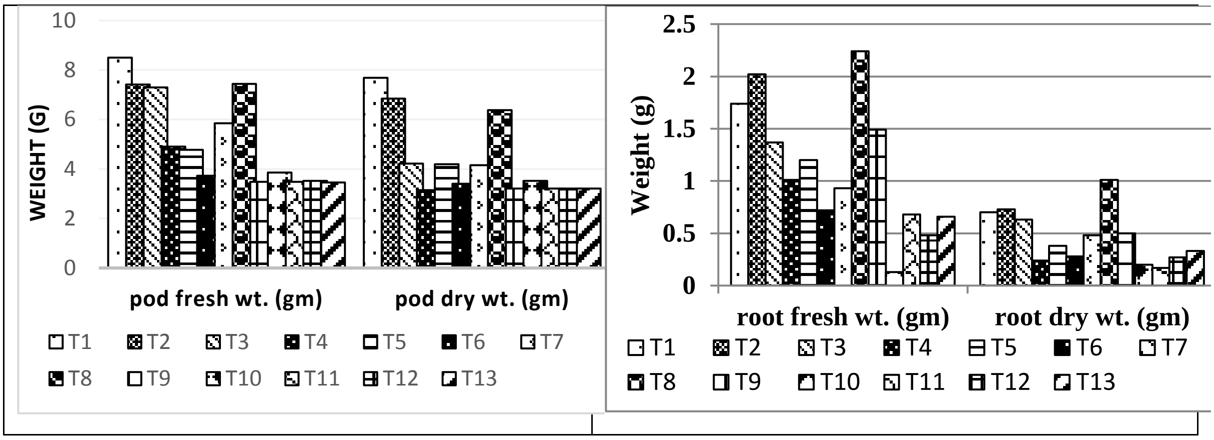


Fig. 3. Effect of salinity and potassium on pod fresh weight and dry weight, root fresh weight and dry weight at harvesting stage of mung bean.

Table- 3. Chemical characteristics of the experimental soil after harvesting of the mung bean

Treatments	EC ds/m		pH	Ca	Mg	K	P	S	B	Zn
	5 cm	15cm		meq/100ml			µg/ml			
T_1	0.54	0.16	6.4	2.28	0.95	0.18	202.0	69.3	1.1	8.8
T_2	5.04	3.98	6.4	3.20	2.13	0.23	193.0	111.7	1.1	10.3
T_3	5.61	4.14	6.5	2.63	1.10	0.28	199.0	79.9	1.3	9.8
T_4	5.29	2.59	6.3	3.33	2.22	0.37	206.0	153.0	1.2	10.1
T_5	5.06	2.59	6.5	3.00	2.00	0.46	249.0	126.2	1.2	11.3
T_6	5.86	3.85	6.4	2.48	1.65	0.24	205.0	111.5	1.1	11.1
T_7	5.74	4.77	6.2	3.41	2.27	0.37	239.0	159.9	0.99	10.3
T_8	6.13	3.43	6.3	3.45	2.30	0.40	249.0	187.2	1.1	11.6
T_9	6.44	4.7	6.4	2.78	1.85	0.42	238.0	182.0	0.98	11.3
T_{10}	8.44	3.52	6.2	3.87	2.58	0.22	257.0	132.6	1.3	10.3
T_{11}	8.12	6.52	6.3	3.11	2.07	0.25	188.0	141.9	1.0	11.3
T_{12}	9.71	5.29	6.3	3.64	2.43	0.34	241.0	197.3	1.2	11.5
T_{13}	8.16	3.44	6.5	3.12	2.08	0.44	257.0	187.0	1.2	10.6

Conclusion

Potassium fertilization can eliminate the deleterious effects of salinity on mung bean yield to some extent. Additional K application with saline irrigation water significantly affected plant height, root height, number of leaves, plant fresh weight and dry weight of mung bean. However, this is only a single year data; therefore, no discreet conclusion can be drawn unless the research runs for few more years.

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EFFECT OF IRRIGATION ON MANGO FRUIT CRACKING IN CHATTOGRAM REGION

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Abstract

The study was conducted at existing HRC Mango Orchard (BARI Aam-4) of Regional Agricultural Research Station, Hathazari, Chattogram during the Rabi season of 2019-20 to explore the optimal period of irrigation to mitigate mango fruit cracking. Five treatments were applied: T_1 (rain-fed i.e. local practice), T_2 (irrigation at flowering stage), T_3 (irrigation at fruiting stage), T_4 (irrigation at flowering and fruiting stages T_5 (irrigation at 2 weeks interval),). The highest yield (76.5Kg plant^{-1}) was found at higher frequency irrigation (T_5). The maximum irrigation (2000 litres plant^{-1}) was applied at two weeks interval irrigation (T_5). In rain-fed condition (T_1), yield was lowest (56.8Kg plant^{-1}). The lowest number of fruits dropping (21no.fruits) was occurred in irrigation at flowering and fruiting stages (T_4). The lowest number of cracking (15no.fruits) as well as the highest sweetness (TSS=24%) occurred irrigation at fruiting stage (T_3) and the benefit-cost ratio was also higher in this treatment.

Introduction

Mango (*Mangifera indica*) is one of the most popular fruits in Bangladesh. Mango belongs to the family Anacardiaceae is a tropical to sub-tropical fruit, originated in the Indian sub-continent (Indo-Burma region) in the prehistoric times. Bangladesh is the world's eighth largest mango producing country as it produces about 1,047,850 tons of mangos every year which accounts for 3.9 percent of the world total mango production.

Mango production increases day by day in Chattogram region e.g. 71459 M.ton.in 2015 and 81112 M.ton in 2016 (BBS, 2017). Irrigation is one of parameters besides nutrition management that increases the yields and improves the quality of mango (W. Spreer et al., 2007). In this region, farmers are still empirically applying water based upon experiences, without technical criteria. As a result, chances are that the mango crop cannot uptake enough water for its development and production due to soil water stress or excess. This kind of irrigation management may also lead to an increase in production costs due to excess amount of water applied that affects the sustainability of water resources. Therefore irrigation management for the mango crop should follow technical criteria, so that water is applied at the right time and at the right amount.

Alam et al. (2017) found that the fruits dropping and cracking of mangoes causes four reasons-diseases, insects, nutrient deficiency, water scarcity in Bangladesh. Mango fruit cracking occurs in Chattogram region during dry season (Nov-March). The cracked fruits lose keeping quality and unsuitable for transportation and consumption. The scarcity of soil moisture and also excess of soil moisture cause fruit cracking (Saran et al., 2008). There is also water scarcity during this period in Chattogram region. So, Optimal stages of irrigation in mango production may save water and boost up quantity and quality (fruit cracking) of mango. The aim of this experiment

- To find out the critical stage of irrigation to mitigate mango fruit cracking of mango.

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Materials and Methods

A field experiment was conducted at existing HRC Mango Orchard (BARI Aam-4, Age 5-7 years), Hathazari, Chattogram during the rabi season of 2019-20. The design of a randomized complete block was performed with three replication and five treatments.

The five irrigation treatments are:

1) Rain fed condition i.e. Local practice (T_1)
2) Irrigation at flowering stage (T_2)
3) Irrigation at fruiting stage (T_3),
4) Irrigation at flowering and fruiting stages (T_4)
5) Irrigation at 2 weeks intervals (T_5)

Fertilizer dose and methods of application were Manure (35 kg/plant), Uea (875 gm/plant), TSP (437 gm/plant), MOP (350 gm/plant), Zn (350 gm/plant), Zn-SO4 (17 gm/plant), and Boric acid (35 gm /plant) (FRG, 2012).

Amount of water to be applied, during each irrigation event, was estimated by measuring soil moisture depletion from the field capacity. The water was applied by hose pipe with ring basin method.

Water content was calculated gravimetrically or volumetrically. Gravimetric soil water content is the mass ofwater divided by the mass of dry soil. It was measured by weighing a mass of wet soil, drying the soil for 24 hours at 105 ^{0}C in Oven, and then reweighing the sample(Waller & Yitayew, 2016).

$$\Theta_{grav}\ (gm/gm) = \frac{Mass\ of\ water (gm)}{Mass\ of\ dry\ soil\ (gm)} = \frac{Mass\ of\ wet\ soil\ (gm) - Mass\ of\ dry\ soil\ (gm)}{Mass\ of\ dry\ soil} \quad (1)$$

$$\Theta_v\ (cm^3/cm^3) = \theta_{grav} \times soil\ bulk\ density\ (gm/cm^3) \quad (2)$$

The depth of irrigation water requirement was estimated with the guideline of Michael (2007) as follows in equation (3).

$$d_{IR} = \frac{(FC - RL) \times A_s \times D}{100} \quad (3)$$

where, d_{IR} = depth of irrigation water requirement (mm), FC= field capacity (%) which measured by ponding water method on the soil surface (Michael, 2007), RL= residual moisture content (%) which measured before irrigation gravimetrically, A_s = apparent specific gravity of soil, D= depth of effective root zone to be irrigated (mm).

The time, required to be irrigation, was calculated following equation (4).

$$t = \frac{d_{IR} \times A}{Q \times 1000} \quad (4)$$

where t = time to be irrigated (min), d_{IR} = depth of irrigation water requirement, A = area of plot (m^2), Q= discharge (m^3/min).

The data were analyzed with "agricolae" R version 4.0.0 software package (Mendiburu, 2020).

Results and Discussions

The highest yield (76.5Kg plant^{-1}) was obtained at two weeks interval irrigation (T_5) and the lowest yield (56.8 Kg plant^{-1}) was in rainfed condition (T_1). The fruit weight per plant was also highest (526 gm/plant) and lowest (355 gm/plant) in irrigation at two weeks interval and rainfed condition respectively. The more frequent irrigation was more response to yield. One irrigation event occurred at both flowering stage and fruiting stage. The fruiting stage irrigation was responsive to yield which was more yield than flowering stage irrigation (Table-1).

The sweetness (TSS) was the lowest (19.3%) in two weeks interval irrigation (T_5) and the highest sweetness (24%) was at fruiting stage irrigation (T_3). Therefore, the more frequent interval irrigation decreased the sweetness of mango. Léchaudel et al. (2005) also showed that the frequent irrigation water supply reduced the sugar or sweetness of mango.

The fruits' cracking at two weeks interval irrigation (T_5**)** was also the highest level (39 no. fruits) than any other treatments. The lowest number of fruits cracking (15 no. fruits) was occurred at fruiting stage irrigation. The results revealed that the less irrigation and excessive irrigation than a certain level may cause more fruit cracking which was similar to Saran et al.(2008) .However, irrigation at fruiting stage was more critical stage of irrigation.

The highest number of fruits' dropping (3 no. Fruits) was obtained at rainfed condition (T_1) which was control treatment in comparison to other treatments. The lowest number of fruit dropping (21 no. fruits) was occurred in irrigation at flowering stage plus fruiting stage (T_4). So, irrigation at both flowing stage and fruiting stage were crucial for reduction of fruits dropping. Spreer et al. (2009) also had evidence that fruits dropping without irrigation were higher.

Table-1. Irrigation effect on Mango production

Treatment	No of fruits per plant	Weight per fruit (gm)	Yield per plant (kg)	No of fruits drop	No of fruit cracks	TSS (%)
T_1	160.0	355.0	56.8	38.3	32.7	23.0
T_2	142.3	410.0	58.4	37.7	25.7	22.3
T_3	147.0	458.3	67.4	24.7	15.0	24.0
T_4	145.7	485.0	70.6	21.0	25.0	21.7
T_5	145.3	526.7	76.5	31.0	39.0	19.3
CV(%)	3.8	2.8	4.3	10.8	11.6	4.3
LSD	10.7	23.8	5.4	6.2	6.0	1.8

Note:*T_1=Rain fed , T_5= Irrigation at 2 weeks interval, T_2= Irrigation at flowering stage, T_3= Irrigation at fruiting stage, T_4= Irrigation at flowering and fruiting stages*

Irrigation at two weeks interval was required more water (2000 liters/plant) than any other irrigation treatments (Table-2). The cost and benefit of this irrigation treatment (T_5) was higher although the benefit-cost ratio was lowest (BCR=1.52). The benefit-cost ratio of irrigation at fruiting stage was highest (BCR=3). Rahman et al. (2019) also found that the benefit-cost ratio of mango production at farmer's level in Bangladeah was 3.00.

However, with respect to economic return and fruits cracking, the irrigation at fruiting stage was the more beneficial and suitable stage of irrigation (T_3).

Table-2. Irrigation event, amount of irrigation, and Profitability analysis of mango production

Treatment	Irrigation no.	Amount of irrigation (Liters/plant)	Effective rainfall (Liters/m2)	Yield per plant (Kg)	Benefit (Tk/plant)	Cost(Tk/plant)	Benefit/Cost Ratio
T_1	0	0	28.7	56.8	2272	780	2.91
T_2	1	1000	28.7	58.4	2336	900	2.60
T_3	1	1200	28.7	67.4	2696	900	3.00
T_4	2	1300	28.7	70.6	2824	1300	2.17
T_5	10	2000	28.7	76.5	3048	2000	1.52

Note: *T_1=Rain fed , T_5= Irrigation at 2 weeks interval, T_2= Irrigation at flowering stage, T_3= Irrigation at fruiting stage, T_4= Irrigation at flowering and fruiting stages*

Conclusion

Irrigation at fruiting stage of mango (T_3) was the more profitable, sweetness, and lower fruits cracking although its yield was lower than the highest frequency irrigation (T_5) at two weeks intervals. This experiment is required to be continued for conformations of findings.

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PERFORMANCE OF FERTIGATION SYSTEM ON BOTTLE GOURD CULTIVATION

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Abstract

An experiment was conducted at the research field of Irrigation and water Management (IWM) Division, Bangladesh Agricultural Research Institute (BARI), Joydebpur, Gazipurduring the rabi season of 2017-18, 2018-2019 and 209-20 to determine the performance of bottle gourd (var. BARI Lau- 3) under fertigation systems. During the rabi season of 2018-19 the experiment was conducted but after two harvest the plants were damaged due to heavy rainfall and wind speed. Six different irrigation treatments T_1= Ring Basin irrigation at 7 days interval with recommended fertilizer doses, T_2= Fertigation at an alternate day with recommended fertilizer doses, T_3= Fertigation at an alternate day with 20% less N and K than recommended doses, T_4= Fertigation at an alternate day with 35% less N and K than recommended doses, T_5= Fertigation at an alternate day with 50% less N and K than recommended doses were selected. From the two years average data the highest yield of 39.3 t/ha was obtained from treatment T_4 by applying 35% less N and K than recommended doses through drip system followed by treatment T_5 (34.7 t/ha) by applying 50% less N and K than recommended doses through drip system. Ring basin method required 404 mm and 313mm of water during the season whereas only 177 mm and 141 mm water was needed in drip method. About 55% water was saved in drip fertigation system than ring basin method. The economic analysis revealed that the highest benefit cost ratio (3.16) was obtained from treatment T_4 by applying 35% less N and K than recommended doses through drip system followed by treatment T_5 (2.81) by applying 50% less N and K than recommended doses through drip system.

Introduction

Global fruit and vegetable production has increased to 1.34 billion MT in 2003, up from 396 million MT in 1961 (FAO, 2005). Vegetable production is usually lucrative compared to staple crops. Therefore, a relatively large body of the literature deals with poverty outcomes for small farmers from opportunities represented through horticultural trade (Dolan and Humphrey, 2000; Henson et al., 2005, Maertens, 2006). Bottle gourd (Lagenariasiceraria L.) belongs to Cucurbitaceae family. It is characterized by trailing growth habit, branched tendril, male flowers appear first, fruits are pepo varying greatly in shapes, sizes and colors. It thrives well in hot and humid conditions. Higher temperature, long day length, and sun light render more male flowers. It can grow over a wide range of soils but sandy loam soil with good natural drainage and pH near 6.5 is desirable. Bottle gourd is very popular vegetable in Bangladesh. It is widely cultivated throughout the country during winter season. Now a day, it is grown in almost all the seasons. But the average yield 10.6 tons per hectare (Anonymous, 2014), which is very low as compared to the other neighboring countries. Variety is an important characteristic that regulates yield and water requirement of crop. For high yielding variety, irrigation is very much essential during winter season to produce better yield in terms of quality and quantity (Bosh et al. 1980). The frequency of irrigation in summer is very important but irrigation may not be necessary at all in summer for the crop if rainfall is well distributed between June and September. The role of irrigation at proper level and stages of plant growth has great significance in improving the yield (Singh et al., 1990). Padem and Alan (1992), Gupta (1990), Bandel et al. (1980), and Thomas et al. (1970) reported that judicious application of fertilizers in conjunction with proper irrigation is the principal factor affecting the crop yield. Modern farming systems have taken advantages of different sophisticated

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techniques of irrigation that are based either on assessment of soil moisture depletion or moisture tension. Irrigation, once in 5 to 6 days, may be necessary depending upon soil, location, temperature etc, and it is very much essential during winter season to produce better yield in terms of quality and quantity (Bosh et al. 1980).

Fertigation is a modern technique and is widely used in many developed countries for horticultural crops. But it is not yet to practice widely in Bangladesh. Furrow and flood irrigation are being widely practiced here for papaya cultivation. The concept of fertigation is to create a continuous method strip along the lines of the plants. It increases the irrigation water and fertilizer use efficiency to a considerable extent and is especially used for high value horticultural crops. This technology saves both water and fertilizer and gives higher yield than any other method (Bresler, 1997). Fertigation in tomato gave encouraging results in terms of yield and economic return (Akandaet al., 2004).

Several studies have been reported on drip irrigation of bottle gourd in different countries of the world (Birbalet al., 1998; Birbalet al., 2003; Suresh and Kumar, 2007; Tan et al., 2009). But, Information regarding drip irrigation of bottle gourd in the context of our country is not available. So, it is important to determine the performance of bottle gourd under fertigation systems in the context of our country for higher yield of bottle gourd. That is why; the present study was undertaken in the field of Irrigation and Water Management Division of Bangladesh Agricultural Research Institute, Joydebpur, Gazipur.

Objectives of the study

- To determine the performance of bottle gourd under fertigation systems in the context of our country for higher yield of bottle gourd
- To study the economics performance of fertigation system

Materials and Methods

The experiment was conducted on bottle gourd (BARI Lau-3) in the field of Irrigation and Water Management Division of Bangladesh Agricultural Research Institute, Joydebpur, Gazipur.during rabi seasons of 2017-2018, 2018-19 and 2019-20. During the rabi season of 2018-19 the experiment was conducted but after two harvest the plants were damaged due to heavy rainfall and wind speed. So, Findings of the results during 2017-18 and 2019-20 were presented in this report. Five treatments including a control were designed for the experiment. Each treatment was replicated thrice. The treatments were:

T_1 = Ring Basin irrigation at 7 days interval with recommended fertilizer doses
T_2 = Fertigation at an alternate day with recommended fertilizer doses
T_3 = Fertigation at an alternate day with 20% less N and K than recommended doses
T_4 = Fertigation at an alternate day with 35% less N and K than recommended doses
T_5 = Fertigation at an alternate day with 50% less N and K than recommended doses

Each plot size was 4.0m × 4.0m. The soil was silty clay loam with an average bulk density of 1.5 gm/cc and field capacity of 28 percent (by weight basis). The experiment was laid out in a randomized complete block design. Seeds were shown on 18 November 2017 and 24 October 2019 to produce seedlings and these were transplanted in experimental plots on 13 December 2017 and 16 November 2019. Fruits were harvested from 11 March 2018 and continued upto 16 April 2018 during 2017-18 but during the year 2019-20, fruits were harvested from 25 February and continued upto 10 April 2020 . The N and K in the form of urea and MP, respectively, were applied with irrigation water as per design of the treatments. The total P in the form of TSP, Gypsum, Borax Zn and Magnesium were applied as the basal dose in the pit. Cow-dung was applied at the rate of 10 kg/pit. Depleted soil moisture was applied to the soil in ring basin irrigation method (control). Soil moisture was determined before each irrigation by gravimetric method for control treatment. Irrigation was applied upto the field capacity of the soil. In drip system, irrigation was applied at every alternate day meeting the demand of crop evapotranspiration. The average dripper discharge was 3.75 litres/hr. Experimental irrigation schedule was started just after plant establishment. In the early stage of crop, the irrigation time was 25 minutes in drip system and in fruiting stage, it was up to 60 minutes depending on crop ET. Data in respect of yield and yield contributing parameters viz. fruit weight, length, breadth, no. of fruits/plant and total yield were recorded.

Fertigation system

Four tank for four fertigation treatments ($T_2 – T_5$) were placed at a height of 1.0 m from the ground surface supported by bamboo structure on one side of the treatments. Each drum had a capacity of 215 litres of water. A water tap was attached to one side of the bottom part of each drum to which fertigation system was connected. The drippers were set according to the plant spacing in the treatments. Each plant received an emitter through which, water was applied to the plant in drips. A schematic diagram of the fertigation system is shown in Fig.1.

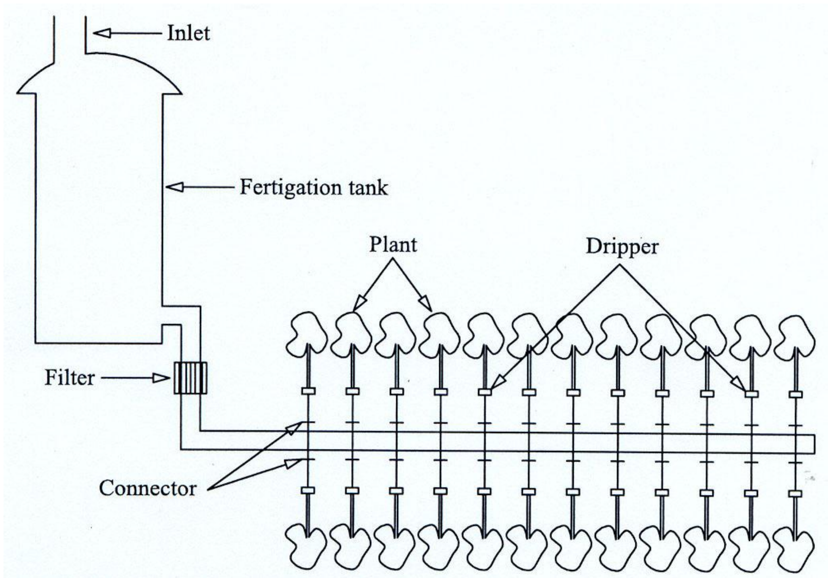

Fig. 1. Schematic diagram of fertigation system.

Results and Discussion

Fertigation effect on yield and yield contributing characters of bottle gourd were analyzed statistically and are presented in Table 1 and 2. The yield and yield contributing characters like no. of fruit/plant, unit fruit weight, yield except fruit length and fruit diameter varied significantly. Referring to Table-1 and 2, the highest yield of 37.20 t/ha and 41.39 t/ha was obtained from treatment T_4 by applying 35% less N and K than recommended doses through drip system followed by treatment T_5 (33.02 t/ha and 36.44 t/ha) by applying 50% less N and K than recommended doses through drip system. Yield difference was not statistically significant during 2017-18 but during 2019-20 it was found statistically significant. The lowest yield was found 24.97 t/ha by applying irrigation in ring basin method at 7 days interval with recommended fertilizer doses (farmer's practice in Table 3 and 4. Referring to Table 3 and 4, it was seen that 404 mm and 363 mm water for ring basin method were needed during the season whereas only 177 mm and 141mm water was needed in drip method during 2017-2018 and 2019-20, respectively. Water can be saved in drip irrig) during year 2017-18 and 2019-20, respectively. Irrigation water applied in different treatments was shown ation method about 55% compared to ring basin method. The effective rainfall during the growing season was 82 mm and 32 mm during 2017-18 and 2019-20, respectively.

Table- 1. Yield and yield contributing characters of bottle gourd during 2017-18

Treatment	Fruit length (cm)	Fruit dia (cm)	Fruits/ plot (no.)	Fruits/ plant (no.)	Unit weight of fruit (kg)	Weight of fruits/plot (kg)	Yield (t/ha)
T_1	32.79	9.86	23.00	5.75	1.74	39.95	24.97
T_2	32.55	10.26	30.67	7.67	1.57	47.97	29.83
T_3	32.16	9.74	26.67	6.67	1.79	47.86	29.91
T_4	32.73	10.87	33.33	8.33	1.76	59.52	37.20
T_5	33.52	10.17	30.00	7.50	1.76	52.84	33.02
CV (%)	2.43	8.12	8.72	8.72	5.66	10.33	10.33
$LSD_{0.05}$	1.49	1.55	4.72	1.18	0.18	9.65	6.03

Table- 2. Yield and yield contributing characters of bottle gourd during 2019-20

Treatment	Fruit length (cm)	Fruit dia (cm)	Fruits/plot (no.)	Fruits/ plant (no.)	Unit weight of fruit (kg)	Yield (t/ha)
T_1	32.77	9.86	25.66	6.41	1.74	24.25
T_2	32.34	10.32	31.66	7.91	1.58	32.96
T_3	32.40	9.75	29.33	7.33	1.70	33.07
T_4	33.00	10.52	37.00	9.25	1.87	41.39
T_5	33.34	10.25	33.40	8.33	1.74	36.44
CV (%)	2.95	3.15	10.78	10.70	4.63	5.54
$LSD_{0.05}$	0.79	0.26	2.76	0.68	0.06	1.52

Table- 3. Irrigation water applied in different treatments during 2017-18

Treatment	Number of Irrigation applied	Dripper discharge (l/h)	Water for plant establishment (mm)	Irrigation water applied (mm)	Effective rainfall (mm)	Total water use (mm)
T_1	12	3.75	12	310	82	404
T_2	22	3.75	12	83	82	177
T_3	22	3.75	12	83	82	177
T_4	22	3.75	12	83	82	177
T_5	22	3.75	12	83	82	177

Table- 4. Irrigation water applied in different treatments during 2019-20

Treatment	Number of Irrigation applied	Dripper discharge (l/h)	Water for plant establishment (mm)	Irrigation water applied (mm)	Effective rainfall (mm)	Total water use (mm)
T_1	11	3.75	5	326	32	363
T_2	28	3.75	5	104	32	141
T_3	28	3.75	5	104	32	141
T_4	28	3.75	5	104	32	141
T_5	28	3.75	5	104	32	141

Economic analysis for fertigation over traditional system for bottle gourd cultivation was done based on two years data and is presented in Table 5. The economic analysis reveals that the benefit cost ratio is the highest of 3.16 was obtained from treatment T_4 by applying 35% less N and K than recommended doses through drip system followed by treatment T_5 (2.81) by applying 50% less N and K than recommended doses through drip system. The lowest BCR was found 1.92 by applying irrigation in ring basin method at 7 days interval with recommended fertilizer doses (farmer's practice). The higher return is also found (Tk. 40322.00) in fertigation (T_4) system by cultivating bottle gourd from only 0.1 ha of land.

Table-5. Economic analysis for fertigation over traditional system for bottle gourd cultivation (for 1000 m^2 of land)

(a). Fixed cost

Item	Quantity	Rate	Cost (Tk.)		
			T_1	Fertigation (T_4)	Fertigation (T_5)
Fertigation tank	4 nos	1000.00	-	4000.00	4000.00
GI fittings and supporting platform	-	LS	-	1000.00	1000.00
1.25 cm dia PVC pipe	300 m	4.00	-	1200.00	1200.00
0.32 m dia micro-tube	750 m	2.50	-	1875.00	1875.00
Total fixed cost, Tk.				**8075.00**	**8075.00**

Expected life of the system = 4 years Fixed cost/year = 2018.00

(b). Variable cost

Item	Cost (Tk.)		
	Ring basin (T_1)	Fertigation (T_4)	Fertigation (T_5)
Seedlings	160.00	160.00	160.00
Pit making	250.00	250.00	250.00
Fertilizer	1915.00	1600.00	1465.00
Trail	12500.00	12500.00	12500.00
Irrigation cost	2000.00	500.00	500.00
Labour	2400.00	1600.00	1600.00
Total variable cost, Tk.	**19225.00**	**16610.00**	**16475.00**

(c). Return

Item	Return, Tk.		
	Ring basin (T_1)	Fertigation (T_4)	Fertigation (T_5)
Yield/1000m^2 (metric ton)	2.46	3.93	3.47
Selling rate (Tk./ton)	15000.00	15000.00	15000.00
Gross return (Tk.)	36915.00	55950.00	52050.00
Total fixed cost/year (Tk.)	-	2018.00	2018.00
Total cost/year (Tk.)	19225.00	18628.00	18493.00
Net return (Tk./ha)	17690.00	40322.00	33557.00
Benefit cost ratio (BCR)	**1.92**	**3.16**	**2.81**

Conclusion

From the two years study, the highest yield of bottle gourd 39.30 t/ha was obtained from treatment T_4 by applying 35% less N and K than recommended doses through drip system followed by treatment T_5 (34.70 t/ha) by applying 50% less N and K than recommended doses through drip system. From the economic point of view, fertigation system was more profitable over traditional irrigation system.

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Project: Cropping System Intensification in the Salt-Affected Coastal Zones of Bangladesh and West Bengal, India (ACIAR)

CONJUNCTIVE USE OF FRESH AND SALINE WATER IN IRRIGATION FOR WHEAT, BARLEY AND MUSTARD IN COASTAL AREAS OF BANGLADESH

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Abstract

Conjunctive use of fresh water (low-saline) and saline water (medium saline) for irrigation is a strategy to irrigate rabi crops in the coastal salt affected areas of Bangladesh where fresh water is not available. In this study, the objectives were to assess the effect of fresh water (FW) and saline water (SW) irrigation on the crop performances, and the scope of fresh and saline water irrigation for rabi crops. Three field experiments were laid out in a randomized complete block design with four irrigation treatments for wheat, barley and mustard, and replicated thrice during 2018-2019 and 2019-2020. These field experiments were conducted in farmers' fields at Sikandorkhali village, Amtali upazila in Barguna and Tildanga village, Dacope upazila in Khulna districts. Standard crop management practices and irrigation scheduling of different crops were followed. Results showed that the use of FW at early growth stages and SW at later growth stages had significant difference. Treatment T4 (FW at early stage and SW at later growth stages of wheat/barley/mustard) produced significantly greater yield at around 2.2, 2.4 and 1.2 t/ha wheat, barley and mustard respectively than other treatments. The effect of location had significant difference on the crops yield. At Amtali, wheat, barley and mustard were found significantly greater yield than Dacope coastal regions. The highest salinity of field soil water (EC_w) and osmotic potential were occurred in mid to end of February 2019 in all treatments in the soil profiles (0-60 cm). The exact soil salinity (EC_e) varied from around 2 to 13 dS/m at Tildanga and 2 to 7 dS/m at Amtali. On average, the osmotic potential was found -200 to -700 kPa at Amtali and -200 to -1300 kPa at Tildanga, Dacope from December 2018 to March 2019 and highest osmotic potential was observed in February 2019 in both locations. Soil water contents substantially decreased in upper soil layers (0-15 cm) at mid February which affected the crop growth. The changes in soil pH occurred 5.5 to 6.5 at Amtali and 6.5 to 8.5 at Dacope. The water salinity of the pond, canal and river ranged from around 1.5, 2 and 5 dS/m (November 2018) to 3.5, 4 and 20 dS/m (April 2019). The irrigation water (low saline) was not available from the pond/canal from mid-February to March during the crop growing season which hampered to the crop production. However, the use of FW (low sanity of: ≤2 dS/m) at early growth stages and SW(2 ≥ salinity ≤ 4 dS/m) at later growth stages of wheat, barley and mustard could be an alternative optioned for intensifying cropping system in the coastal saline zones of Bangladesh.

Introduction

Irrigation influences the plant growth and yield during dry (*rabi* season) environments. Due to scarcity of water, only around 66% of the total area in Bangladesh is irrigated (BBS, 2015). About 30% of the net cultivable area in Bangladesh exists in coastal regions, where fresh water is becoming scarce with time. The effects of salinity depend on the degree of salinity at the critical stages of crop growth, which reduces yield, in severe cases to zero. Therefore, the dominant crop grown in the saline areas is transplanted *aman* rice which is grown during the rainy season using traditional, low yielding varieties. The cropping patterns followed in the coastal areas are mainly Fallow-Fallow-Transplanted *aman*. Cultivation of short duration winter crops, including wheat, maize, sunflower, barley and mustard are very limited in the coastal area due to inadequate fresh

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irrigation water and accumulation of salts in the surface soil. In Bangladesh after rice, wheat is the most important food grain. But recently, the cultivation of a wide range of crops such as wheat, mustard, sunflower and vegetables after the *aman* harvest has been expanding around some surface water sources and shallow wells with low salinity water (Akanda et al., 2015).

Wheat consumption in Bangladesh has increased significantly at 17.5 kg per capita by around 59.4% from the years of 1963 to 2013. In Bangladesh, despite the yield growth, the total domestic wheat production remains more or less static due to the gradual decrease in wheat area (BBS 2018). The wheat area in Bangladesh, however, started declining due to competition with other *rabi* crops, such as hybrid maize, and the area currently reduced to 0.42 million ha in 2017 (BBS 2018). Wheat production in Bangladesh is facing many constraints such as terminal heat stress, drought, salinity, soil acidity, and many diseases. In addition, wheat also competes with different *rabi* crops during the wheat season. On the other hand, barley is another an important cereal crop for the arid and semi-arid Mediterranean environments. (Cammarano, 2019).

The importance of future drought and heat stresses on barley yield will be explored prior sowing, at vegetative and reproductive stages. In addition, in dry environments, where crops rely on soil moisture stored prior sowing, an adequate level of soil available water content is vital to achieve certain yield levels. The patterns of rainfall prior sowing will also be an important determinant of crop yield (Passioura, 2006). Europe produces about 63% of the world's barley with most of it under rainfed conditions (FAOSTAT, 2018). In Bangladesh, barley consumption, marketing and its uses are limited. It is expected that the faster economic growth and speedy urbanization process may further increase the wheat and barley demand in Bangladesh in the future.In the study, we are trying to establish on wheat/barley in the salt-affected areas of Bangladesh in contracts with changing climate. Further studies are needed in coastal saline areas for expansion of wheat, barley and mustard cultivation in moderate saline zones in Bangladesh. A sensible use of saline water requires a better understanding of how plants respond to salinity at different growth stages (Maas *et al*., 1988). There are some sources of saline water like as canal water, pond water in saline prone areas of Bangladesh which can be used for irrigation. In most cases, saline water reduces the yield, but with the careful and appropriate soil-water-plant management practices could be used for crop production in saline areas of Bangladesh (Majid and Hossain, 2013). Most of the coastal areas have many surface water bodies filled with moderately saline to high saline water, whereas some of the areas have limited fresh groundwater sources (Hasan et al., 2013). Some areas also have access to non-saline water river through the dry season. The scarcity of suitable fresh surface and ground water has led the farmers to recommend the conjunctive use of saline and fresh water to irrigate crops (Ma et al., 2007). Judicial use of fresh and saline water for irrigation would not only increase crop production, but also enable to sustainably use of fresh and saline water for better crop production and identify crops respond to salinity (Shahid et al., 2013). At early growth stages, crops are very sensitive to irrigation water salinity. At later growth stages, saline water can be used to irrigate the plants which have better resisting ability (Keterji et al., 2005). Appropriate irrigation scheduling and method are very important for saline water irrigation. Therefore, irrigation scheduling technique is needed to minimize yield reductions and better utilization of surface water sources in coastal regions of Bangladesh. Therefore, this study has been undertaken to identify the salt sensitive stages and better understanding of how crops respond to salinity by applying the conjunctive use of fresh water (low saline) and saline water (medium saline) for irrigation at different growth stages. Keeping this technique in view, the objectives of this study were undertaken: (i) to assess the effect of fresh and saline water irrigation on the crop performances, and (ii) to introduce and transfer the scope of the conjunctive use of fresh and saline water irrigation for *rabi* crops (wheat/barley and mustard) among the farmers.

Materials and Methods

Study area

Three field experiments were conducted in farmers' fields at Sikandorkhali village, Amtali upazila in Barguna and Tildanga village, Dacope upazila in Khulna districts during *rabi* season of 2018-2019. The land situation is medium low land and the soil texture is silty clay loam. Field experiments on wheat, barley and mustard were carried out in two locations. The soils were clay loam and silty-clay loam with an average field capacity of 37.2% (gravimetric water content) and mean bulk density of 1.40 g/cc over the 60 cm soil profile (15 cm soil layers).

Experimental design and treatments

Three field experiments were laid out in a randomized complete block design with four irrigation treatments for wheat, barley and mustard, and replicated thrice. Each experiment was conducted in a farmers' field. The unit plot size was 30 square meter which depended on existing farmers' plot. The irrigation treatments were as follows:

Wheat
T_1 = One IR at CRI stage (17 - 21 DAS) with FW
T_2 = Two IR at CRI with FW and booting stages (55 - 60 DAS) with SW
T_3 = Two IR at CRI and grain filling stages (75 - 80 DAS) with SW
T_4 = Three IR at CRI with FW, booting and grain filling stages (75 - 80 DAS)

Barley
T_1 = One IR at 17 - 21 DAS with FW
T_2 = Two IR at 17-21 DAS with FW and booting stages (55 - 60 DAS) with SW
T_3 = Two IR at 17-21 DAS with FW and grain development stages (75 - 80 DAS) with SW
T_4 = Three IR at 17-21 DAS with FW, booting and grain development stages with SW

Mustard
T_1 = No irrigation
T_2 = One irrigation at preflowering stage (30-35 DAS) with FW
T_3 = One irrigation at siliqua filling stage (45-50 DAS) with SW
T_4 = Two irrigations at preflowering with FW and siliqua filling stages with SW

Crop management

Standard crop management practices and irrigation scheduling of different crops were followed. Different crops with duration under different cropping patterns were considered over two locations. Wheat (BARI Gom-25), a medium salt tolerant variety (optimum yield up to 6-7 dS/m of soil salinity) was sown at 120 kg seed/ha on 8 December 2018 with a row spacing of 60 cm at Amtali and continuous seed sowing 150 kg/ha on 17 December 2018 at Tildanga. Barley (BARI Barley-7), a salt tolerant variety was sown on 9 December 2018 at 120 kg seed/ha with a row spacing of 60 cm at Amtali and continuous seed sowing (broadcasting) on 17 December 2018 at Tildanga. Mustard (BARI Sarisha-14), a low salt tolerant variety (optimum yield up to 3.5 - 4.5 dS/m of soil salinity) was sown on 7 December 2018 at Amtali and 17 December 2018 at Tildanga. Seeds were planted in continuous (Broadcasting) at the rate of 7 kg/ha in both locations. Fertilizer was applied in the forms of urea, triple super phosphate, muriate of potash, gypsum, borax, and zinc sulphate, respectively. Fertilizers were applied for wheat and barley @ N_{120} P_{30} K_{90} S_{15} Mg_6 $Zn_{2.6}$ B_1, with two-thirds of N and all the P, K, S, Mg, Zn and B applied basally. The remaining one-third of N was applied at 17-21 DAS after the first irrigation. Fertilizers were applied for mustard @ N_{75}, P_{20}, K_{45}, S_{15}, $Zn_{1.25}$, and $B_{0.5}$in the form of urea, triple supper phosphate, muriate of potash, gypsum, zinc sulphate and borax, respectively. Two-thirds of N and the total amount of other fertilizers were applied at the time of final land preparation and the remaining N was applied as a top dressing after the first irrigation. Adequate plant protection measures were undertaken at vegetative stages. The crops were sprayed with Rovral-50wp at 0.2%

at 30 DAS for prevention against diseases. Wheat, barley and mustard were harvested on 20 March, 2019, 10 March, 2019 and 28 February 2019, respectively at Amtali and 24 March 2019 (wheat / Barley) at Tildanga. There was no significant pest or disease infestation in the experimental plots except the mustard experiment at Tildanga village in Dacope After germination, the mustard experiment has been damaged.

Monitoring

Crops yield

Crop yields were determined at harvest. The mean yields of each crop were taken from the each plot within one square meter. Plants were harvested manually at the ground level from the corner avoiding the border effect. After manual threshing, the cleaned, dried filled grain yields were recorded at desired moisture (12%) content. The number of spikes, number of grains per spike, 1000 grain weight, and grain yield of wheat and barley were determined at harvest. The sample size of the harvested area was one square meter for determining grain yield. Sub-samples (30 plants) from each plot were randomly selected to determine yield contributing characters. Plant population, number of siliqua per plant, seed per siliqua, 1000 seed weight, and grain yield of mustard were determined at harvest. The size of the harvested area was one square meter for determining grain yield. Sub-samples (10 plants) from each of the plot were randomly selected to determine yield contributing characters. All the treatment mean values were compared following randomized complete block design with three replications.

Soil sampling for soil water content, salinity, osmotic potential and pH

Soil was collected from each treatment to monitor soil moisture and soil salinity,osmotic potential and pH dynamics at different growth stages and soil profiles. Soils were sampled from 0-15, 15-30, 30-45 and 45-60 cm soil depths at the time of sowing to harvest. The Electrical conductivity of $EC_{1:5}$ was determined and converted to actual salinity EC_w of soil water content (dS/m) while using the formula derived from Richards, 1954 and Rengasamy, 2010). Field soil gravimetric moisture content was determined. The soil samples were taken from each plot in 15 cm increments, well-mixed together, subsampled, weighed, dried at 105^{o}C, and reweighed to determine gravimetric moisture content. $EC_{1:5}$ was also converted to osmotic potential (kPa) of field soil solution using the formula derived from Rengasamy, 2010. The soil pHwas also monitored. $EC_{1:5}$ and pH were determined using portable instrument of water and soil conductivity meter with sensor probes ((model: TRI-METER, pH/EC & TEMP-983) that can inserted directly into the soil solution.

Application of irrigation water and water use

Irrigation water was applied based on the pan evaporation method at different crop growth stages. Data on pan evaporation and precipitation (rainfall) were collected from Khulna and Barguna weather station to estimate irrigation water requirement (I, mm) for full irrigation using the following equation.

$$I = E_p \times K_p \times A \qquad (1)$$

where, I is the amount of irrigation water amount (litre), A is the area of the plot (m^2), E_p is the cumulative pan evaporation (mm) and K_p is the pan coefficient and was considered 0.7 (Michael, 1978).

The gravimetric soil moisture contribution was estimated using the standard formula suggested by Micheal (1978) and (Majumdar, 2004).

$$SWC = \sum_{n=i}^{n} \frac{(SMbi - SMei)\ Asi\ Di}{100} \qquad (2)$$

where, SWC is the soil water contribution during crop cycle (mm); Asi is the apparent specific gravity of the ith layer of the soil; Di is the depth of the ith layer of the soil within the root zone to be irrigated (mm); SMbi is the soil moisture content during sowing (%); SMei) is the soil moisture during harvesting period in the ith layer of soil profile (%); and n is the number of soil layers in the root zone depth.

The calculated amount of irrigation water was supplied to the experimental plots using a polyethylene hose pipe. Each experiment plots were separated by a distance of 1.5 m to prevent the lateral movement of water from one to another. Total water use (TWU) was calculated as the sum of total irrigation water applied (I), effective rainfall (P_e) and soil water contribution (SWC) between plantation and final harvest and expressed by the following equation (3). Effective rainfall was estimated by using the USDA Soil Conservation Method (Smith, 1992).

$$\mathrm{TWU} = \mathrm{I} + \mathrm{Pe} \ \pm \mathrm{SWC} \qquad (3)$$

Water productivity (WP) was estimated as a ratio of total crops grain yield to water consumed/TWU to the system, and expressed as kg/m^3 which was expressed by the following equation (4).

$$\mathrm{WP} = \frac{\mathrm{GY} \times 100}{\mathrm{TWU}} \qquad (4)$$

where, WP is the water productivity (kg/m^3), GY is the crops yield (t/ha) and TWU is the amount of total input water use (mm).

Statistical analysis

Data on yield attributes, crop yield and water productivity were statistically analyzed to test the effects of irrigation using R software version 3.5.0. All the treatment means were analyzed and compared for any significant differences using R-statistical models at 5% ($P \leq 0.05$) probability level of significant. It is mentioned that the number of irrigation event, amount of applied irrigation water, total water use (TWU) and water productivity (WP) under different irrigation treatments during 2018-2019 were done but the analysis of water related data were not included in this report.

Results and discussion

Response of wheat yield and yield components to irrigation

The yield and yield contributing characters of wheat at the both location of Dacope and Amtali during 2018-2019 and 2019-20 are presented in Table 1-2 and Fig. 1. There was a significant difference over the locations on the yield and yield contributing parameters of wheat. The effect of irrigation had significant difference among the treatments. Irrigation had a significant positive effect on the growth, yield and yield contributing parameters of wheat (Table 14). The interaction effect of location and treatment had no significant difference on grain yield of wheat. The results showed that total grain yield was significantly higher produced in Amtali by 35% than Dacope region. Among the treatments, treatment T_4 (Three irrigations: FW at early stage and SW at later growth stages of wheat) produced significantly greater yield than other treatments. Similar trends were observed in both locations. The grain yield was found greater by 17% and 25% in T4 than T_2/T_3 and T_1, respectively. On average, the treatment T_4 produced highest yield by 2.53 t/ha at Amtali and 1.78 t/ha at Dacope during 2019 when irrigation water supplied with the technique of fresh water (low saline) at early growth stages and saline water (medium saline) at later growth stages of wheat at Amtali and Dacope. The results also indicated that yield increased with increased number of irrigations with fresh or saline water irrigation and irrigation had an effect on yield in both locations. The response of plant growth and wheat yield to the conjunctive use of fresh water (low saline of canal water: $EC \leq 2$ dS/m) and saline water (canal water: $EC \geq 2$ and $EC \leq 4$ dS/m) could be optioned for developing better irrigation practices at the salt-affected areas in coastal zones of Bangladesh.

Table 1. Effect of fresh and saline water on yield and yield contributing characters of wheat in 2018-19

Parameters		Spike/m2	Plant height, cm	Spike length, cm	Grain/ Spike	Thousand grain weight, g	Grain yield, t/ha
Location							
Dacope		182.2a	56.1b	7.8a	27.19b	40.8b	1.48b
Amtali		116.5a	77.04b	8.3a	31.6a	45.2a	2.26a
Treatments							
	*T_1	127.8b	65.8a	8.0a	27.08b	40.4c	1.605c
	T_2	135.5b	67.6a	8.1a	28.06b	43.23b	1.833b
	T_3	160.1ab	66.5a	8.13a	30.56a	42.67b	1.883b
	T_4	173.8a	66.3a	8.1a	32.0a	45.76a	2.160a
Location × Treatments:							
Dacope	T_1	142.3c	54.9b	7.6b	26.5de	41.0c	1.23e
	T_2	158.3bc	58.3b	8.2ab	25.2e	40.8c	1.39de
	T_3	201.6ab	56.3b	7.9ab	28.2cde	40.4c	1.52d
	T_4	226.3a	54.8b	7.6b	28.7cd	40.7c	1.78c
Amtali	T_1	113.3c	76.7a	8.4ab	27.6de	39.6c	1.98c
	T_2	112.6c	76.83a	8.03ab	30.8bc	45.5b	2.27b
	T_3	118.6c	76.73a	8.3ab	32.8ab	44.8b	2.24b
	T_4	142.3c	77.9a	8.63a	35.3a	50.7a	2.53a

**Mean values within the same columns by different letters (a-c) are significantly different within treatments. Values are mean of three replication of each treatment. Here, four irrigation techniques at different growth stages: T_1: One IR at CRI stage (17 - 21 DAS) with FW; T_2Two IR at CRI with FW and booting stages (55 - 60 DAS) with SW; T3: Two IR at CRI and grain filling stages (75 - 80 DAS) with SW; T_4:Three IR at CRI with FW, booting and grain filling stages (75 - 80 DAS) with SW.*

Wheat at Amtali   Wheat at Dacope

Fig. 1. Photographic view of wheat cultivation using fresh (low saline) and saline water (medium saline) irrigation at Amtali and Dacope in 2018-19.

Table 2. Effect of fresh and saline water on yield and yield characters of wheatin 2019-20

Location	Treatment	Spike/m2	Plant height, cm	Spike length, cm	Grain/ Spike	Thousand grain weight, g	Grain yield, t/ha
Dacope	T_1	165.0	81.1	6.7	37.9	34.9	1.84
	T_2	186.7	82.5	7.5	39.9	39.0	2.47
	T_3	205.7	81.2	7.1	40.2	37.8	2.42
	T_4	189.3	77.2	6.8	41.1	38.0	2.51
Amtali	T_1	84.3	66.3	7.5	23.3	38.3	1.43
	T_2	93.3	68.4	7.7	23.2	41.3	1.62
	T_3	91.7	73.3	8.0	25.7	47.3	1.78
	T_4	95.0	72.4	8.0	26.7	47.0	1.83

**Mean values within the same columns by different letters (a-c) are significantly different within treatments. Values are mean of three replication of each treatment. Here, four irrigation techniques at different growth stages: T_1: One IR at CRI stage (17 - 21 DAS) with FW; T_2Two IR at CRI with FW and booting stages (55 - 60 DAS) with SW; T3: Two IR at CRI and grain filling stages (75 - 80 DAS) with SW; T_4:Three IR at CRI with FW, booting and grain filling stages (75 - 80 DAS) with SW.*

Response of barley to CU of fresh and saline water irrigation

Yield and yield components of barley under different irrigation treatments over two locations is shown in Table 3-4 and Fig. 2. The yield contributing parameters like as, number of grain and grain yield were found highly significant difference among the treatments. There was a highly significant difference over the locations on the yield and yield contributing parameters of barley. The effect of irrigation treatments had also highly significant difference on grain on the growth, yield and yield contributing parameters of barely. The interaction effect of location and treatment had no significant difference on grain yield of barely. The results showed that total grain yield of barley was significantly higher produced in Amtali by 24 % than Dacope region. Among the treatments, treatment T_4 (Three irrigations: FW at early stage and SW at later growth stages of barely) produced significantly greater yield than other treatments. The grain yield was found greater in T_4 by 15 % and 26 % than T_2/T_3 and T_1, respectively. Yield significantly increased with increased number of irrigations in both locations. On average, the treatment T_4 produced highest yield by 2.56 t/ha at Amtali and 2.22 t/ha at Dacope during 2019 when irrigation water supplied with the technique of fresh water (low saline) at early growth stages and saline water (medium saline) at later growth stages of barley at Amtali and Dacope. Waterlogging may cause the physiological stress on plants. The technique of conjunctive use of fresh water (low saline of canal water: ≤ 2 dS/m) and medium saline water (canal water: EC ≥2 and EC ≤ 4 dS/m) could maintain approximately similar trend of grain yield.

Table 3. Effect of fresh (low saline) and saline water (medium saline) on yield and yield contributing characters of barleyover two locations of Dacope and Amtali during 2018-19

Parameters		Spike/m^2	Plant height, cm	Spike length, cm	Grain/ Spike	Thousand grain weight, g	Grain yield, t/ha
Location							
Dacope		115.5b	56.8b	8.22b	30.36b	36.7b	1.77b
Amtali		160.58a	83.8a	10.72a	32.66a	41.1a	2.33a
Treatments							
	T_1	129.6b	68.4b	9.6a	30.26a	38.1a	1.76c
	T_2	131.3b	70.56a	9.5a	31.20a	39.4a	1.97b
	T_3	134.8ab	71.1a	9.4a	3.98a	38.2a	2.07b
	T_4	152.3a	71.3a	9.2a	32.6a	40.1a	2.39a
Location × Treatments							
Dacope	T_1	114.3c	56.9d	8.2b	29.2b	34.8c	1.44e
	T_2	110.3c	57.1d	8.2b	31.06b	35.4c	1.67d
	T_3	113c	57.2d	8.2b	31.5ab	36.03c	1.76d
	T_4	116.3c	56.3d	8.3b	29.6b	40.8ab	2.22bc
Amtali	T_1	145b	79.9c	11.06a	31.3b	41.4ab	2.09c
	T_2	152b	84.02b	10.6a	31.3ab	43.4a	2.28bc
	T_3	156.6b	85.09ab	10.2a	32.4ab	40.3b	2.38ab
	T_4	188.3a	86.41a	10.9a	35.5a	39.4b	2.56a

**Mean values within the same columns by different letters (a-c) are significantly different within treatments. Values are mean of three replication of each treatment. Here, four irrigation techniques at different growth stages: T_1: One IR at CRI stage (17 - 21 DAS) with FW; T_2Two IR at CRI with FW and booting stages (55 - 60 DAS) with SW; T3: Two IR at CRI and grain filling stages (75 - 80 DAS) with SW; T_4 : Three IR at CRI with FW, booting and grain filling stages (75 - 80 DAS) with SW.*

Fig. 2. Photographic view of wheat cultivation using fresh (low saline) and saline water (medium saline) irrigation at Amtali and Dacope in 2018-19.

Table 4. Effect of fresh (low saline) and saline water (medium saline) on yield and yield contributing characters of barleyover two locations of Dacope and Amtali during 2019-20

Location	Treatment	Spike/m2	Plant height, cm	Spike length, cm	Grain/ Spike	Thousand grain weight, g	Grain yield, t/ha
Dacope	T_1	151.7	71.1	6.6	39.9	35.3	1.85
	T_2	200.0	72.6	7.0	42.1	37.5	2.43
	T_3	209.0	75.5	7.0	43.0	37.2	2.47
	T_4	204.7	72.7	7.0	43.1	36.8	2.39
Amtali	T_1	90.3	71.9	7.7	21.3	36.0	1.37
	T_2	94.3	77.0	7.7	24.9	38.7	1.69
	T_3	88.3	75.0	7.9	22.7	39.0	1.66
	T_4	104.3	77.8	8.5	26.5	39.7	1.82

**Mean values within the same columns by different letters (a-c) are significantly different within treatments. Values are mean of three replication of each treatment. Here, four irrigation techniques at different growth stages: T_1: One IR at CRI stage (17 - 21 DAS) with FW; T_2Two IR at CRI with FW and booting stages (55 - 60 DAS) with SW; T3: Two IR at CRI and grain filling stages (75 - 80 DAS) with SW; T_4 : Three IR at CRI with FW, booting and grain filling stages (75 - 80 DAS) with SW.*

Response of mustard to CU of fresh and saline water irrigation

The seed yield and yield components of mustard under different irrigation treatments is presented in Table 5-6 and Fig. 3. The seed yield contributing parameters like as, plant/m^2, plan height, number of siliqua/plant, seed/siliqua and seed yield were found highly significant difference among the treatments. The number of irrigation treatments had significant difference on seed yield of mustard (Table 3). Seed yield significantly increased with increased number of irrigations. There were the effects of irrigation treatment on the performance of mustard, with yield of all treatments around 0.63 to 1.16 t/ha. On average, the treatment T_4 produced highest yield by 1.16 t/ha at Amtali during 2019 when irrigation water supplied with the technique of fresh water (low saline) at early growth stages and saline water (medium saline) at later growth stages of mustard.

Table 5. Effect of fresh (low saline) and saline water (medium saline) on yield and yield contributing characters of mustard in Amtali during 2018-19

Treatment	Plant/m2	Plant height, cm	Siliqua/Plant	Seed/Siliqua	Seed yield, t/ha
T_1	101b	73.09 d	36.8a	21.94 b	0.63 d
T_2	89.3c	82.8 c	32.47b	26.34a	0.69 c
T_3	106b	86.26 b	34.7ab	27.99a	1.07b
T_4	114 a	90.58 a	33.87b	28.37a	1.16a

Mean values within the same columns by different letters (a-c) are significantly different within treatments. Values are mean of three replication of each treatment. Here, four irrigation techniques at different growth stages: T1: No irrigation, T2: One irrigation at preflowering stage (30-35 DAS) with FW, T3: One irrigation at siliqua filling stage (45-50 DAS) with SW, T4:Two irrigations at pre-flowering with FW and siliqua filling stages with SW.

Fig. 3. Photographic view of mustard cultivation using fresh (low saline) and saline water (medium saline) irrigation at Amtali in 2018-19.

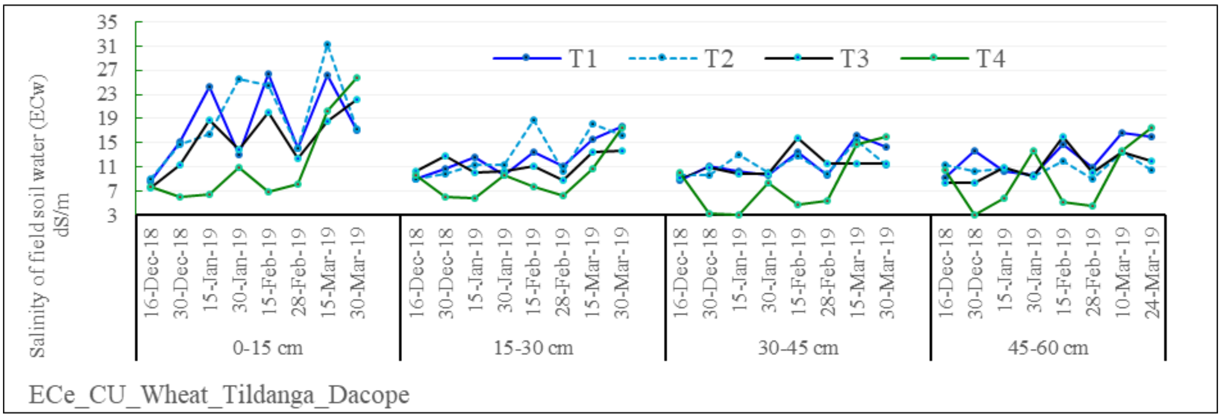
Table 6. Effect of fresh (low saline) and saline water (medium saline) on yield and yield contributing characters of mustard in Amtali during 2019-20

Treatment	Plant/m2	Plant height, cm	Siliqua/Plant	Seed/Siliqua	Seed yield, t/ha
T_1	83	60	27	23.7	0.78
T_2	88	62	30	25.9	0.87
T_3	92	68	30	25.5	0.91
T_4	96	71	32	29.3	0.94

Mean values are mean of three replication of each treatment. Here, four irrigation techniques at different growth stages: T1: No irrigation, T2: One irrigation at preflowering stage (30-35 DAS) with FW, T3: One irrigation at siliqua filling stage (45-50 DAS) with SW, T4:Two irrigations at pre-flowering with FW and siliqua filling stages with SW.

Salinity in field soil

Salinity of field soil water (EC_w) during the growing season for various treatments are in Fig. 4. On average, the changes in salinity of field soil water varied from around 4 dS/m (November 2018) to 25 dS/m (February 2019) in 0-60 cm soil profiles with 15 cm increments at Tildanga, Dacope, Khulna and 4-15 dS/m at Amtali, Barguna. The exact soil salinity (ECe) varied from around 2 to 13 dS/m at Tildanga and 2 to 7 dS/m at Amtali during the crop growing season. The highest salt accumulation was occurred in mid to end of the February 2019in all treatments in soil profiles. The salinity results showed that slightly higher salt accumulation occurred among the treatments within the top soil layer in 0-15 cm depth than lower depth of soil profiles. Due to water uptake and soil evaporation, salt accumulation was generally higher in the soil surface. In treatment T_3, T_4 salt accumulation was slightly higher than the treatment of T_1 due to consequence use of alternative medium saline water (2 to 3.5 dS/m) irrigation from canal to crop. Irrigation with medium saline water (canal water) may cause slightly increase soil salinity. It could be stated that saline water irrigation at later growth stages after fresh water irrigation at early growth stage may produce more salt movement in soil profiles. In this study, the figures indicate that the soil salinity was not substantially greater salt accumulation in soil profiles among the treatments due to medium saline water (2 to 3 dS/m) irrigation and salinity may tolerable for wheat/barley germination to crop yield production in the coastal areas of Bangladesh. Consequently, barley cultivation would be practiced and optioned for intensifying cropping system with salinity and available water scarcity problem in the coastal areas of Bangladesh.



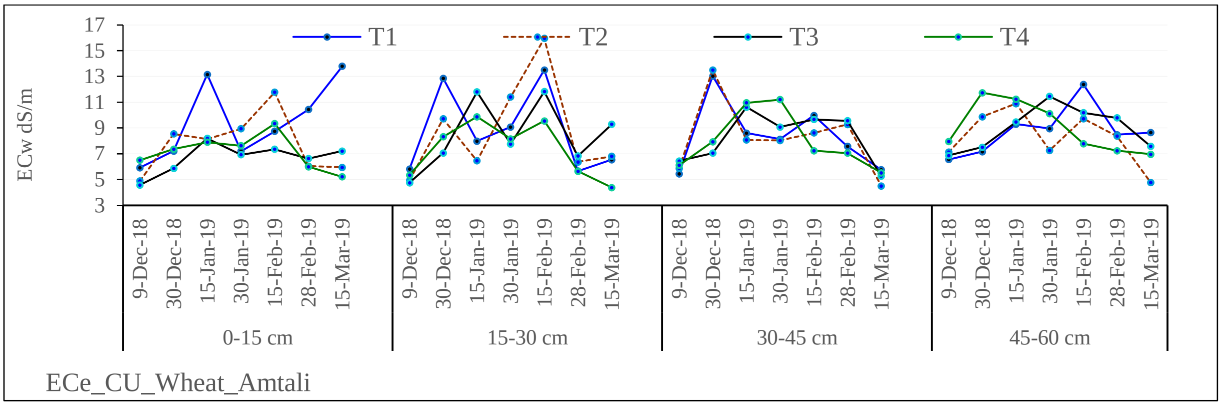


Fig. 4. Variations of soil salinity dynamics expressed as EC_e of soil solution ($EC_{1:5}$) over the soil profile during crop growth season of 2018-2019.

Osmotic potential

The variations of osmotic potential (-kPa) during the growing season for the various treatments are in shown in Fig.5. The osmotic potential among the treatments were similar in trend over the soil profiles with 15 cm increments during the year of 2018-2019. On average, the osmotic potential was found to be -200to -700 kPa at Amtali and -200to -1300 kPa during the growing season from December 2018 to March 2019 and highest osmotic potential observed in February 2019 in both locations. The greater osmotic potential was measured in the treatment of T_1 and T_2 than the treatment of T_4 over two locations. The higher osmotic pressure was found in mid growth stages of the crop due to more soil water uptake and soil moisture evaporation from the soil surface. Generally, plants struggle to take up water when the total potential of the soil solution exceeds -1000 kPa and will permanently wilt at -1500 kPa. In this study, the osmotic potential was reasonable at Amtali with no influence in limiting crop production due to standard irrigation scheduling followed by good crop management practices. But the osmotic potential was not favorable at Tildanga with highly influence in crop production due to more salt accumulation and more salt movement in the upper soil profiles. The results indicated that the osmotic pressure was effected on plant growth and yield at later growth stages of crop because of insufficient soil moisture as well as lack of fresh irrigation water (low salinity) at Tildanga, Dacope.

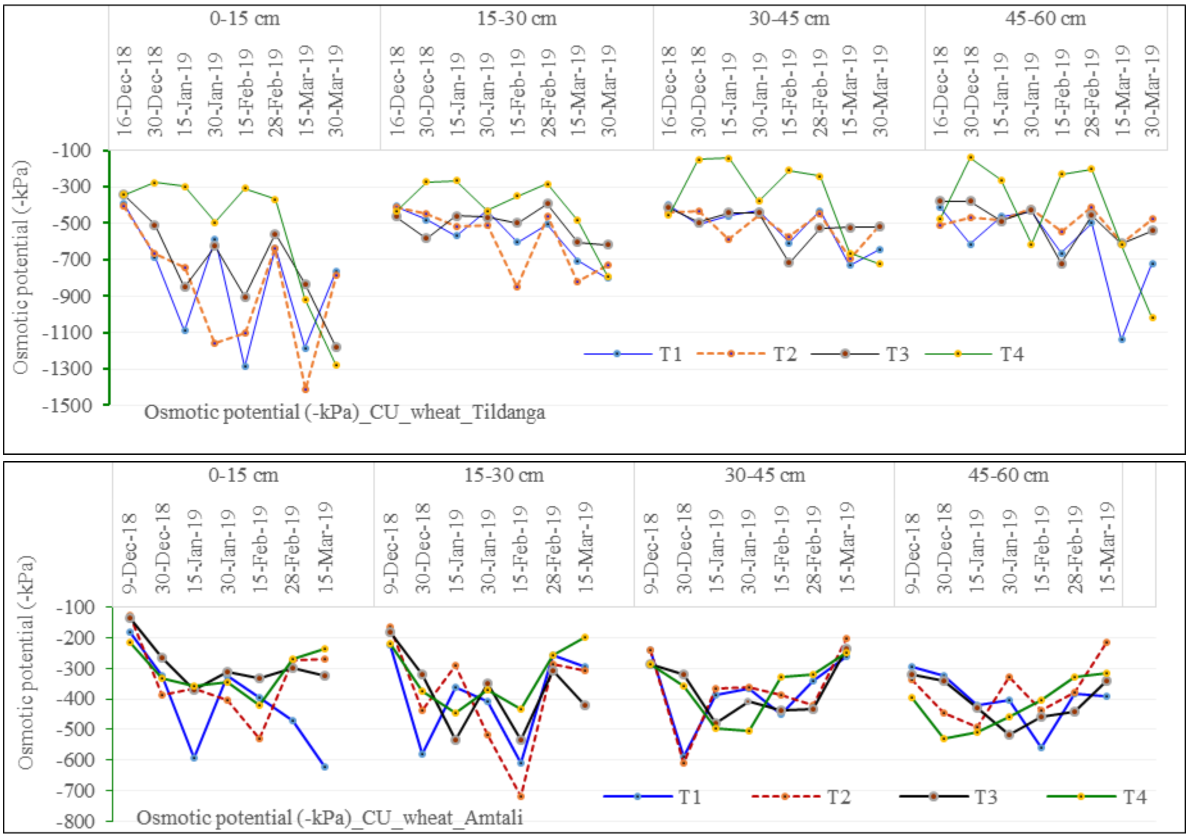


Fig. 5. Variations of osmotic potential dynamics expressed as (-kPa) of soil solution ($EC_{1:5}$) over the soil profiles during crop growth season of 2018-2019.

Soil moisture contents

The variations of gravimetric soil water content in the soil profiles over 0-60 cm soil depth with 15 cm increaments during the growing season of wheat for each different treatments is shown in Fig. 6. An increase or decrease soil water content was observed following irrigation or rainfall. The substantially larger raifall occurred waterlogged at flowering growth stages of wheat/barley during the growing season of 2018-2019, which affected the crop growth and crop yield. Soil water contents (SWC) substantially decreased in upper soil layers (0-15 cm) at mid February 2019 in Dacope which affected the crop development and grain filling stages of crops (Fig. 6). The SWC was found lower in treatment of T_1 and T_2 followed by T_4. The residual soil moisture utilizing technique during sowing could maintain the crop germination and increase the benefits of the crop establishment. Growing short duration T. Aman rice and early drainage could help the soil moisture maintain which help the crop establishment. During sowing at Dacope, initial soil water content among the treatments was close to field capacity at the upper layer of the soil and more than field capacity at lower depth of soil (**Fig. 6**) in both locations. The figures indicate that soil moisture decreased or increased during the growing season, but plants extractable available soil water was not drasticaly reduced at Amtali but soil water was drastically reduced at Tildanga at mid February which affected the plant growth in Dacope region. This stress condition occurred because of insufficieny fresh water (low saline) in the project sites of Dacope (Tildanga) and Amtali (Sikkhandorkhali).

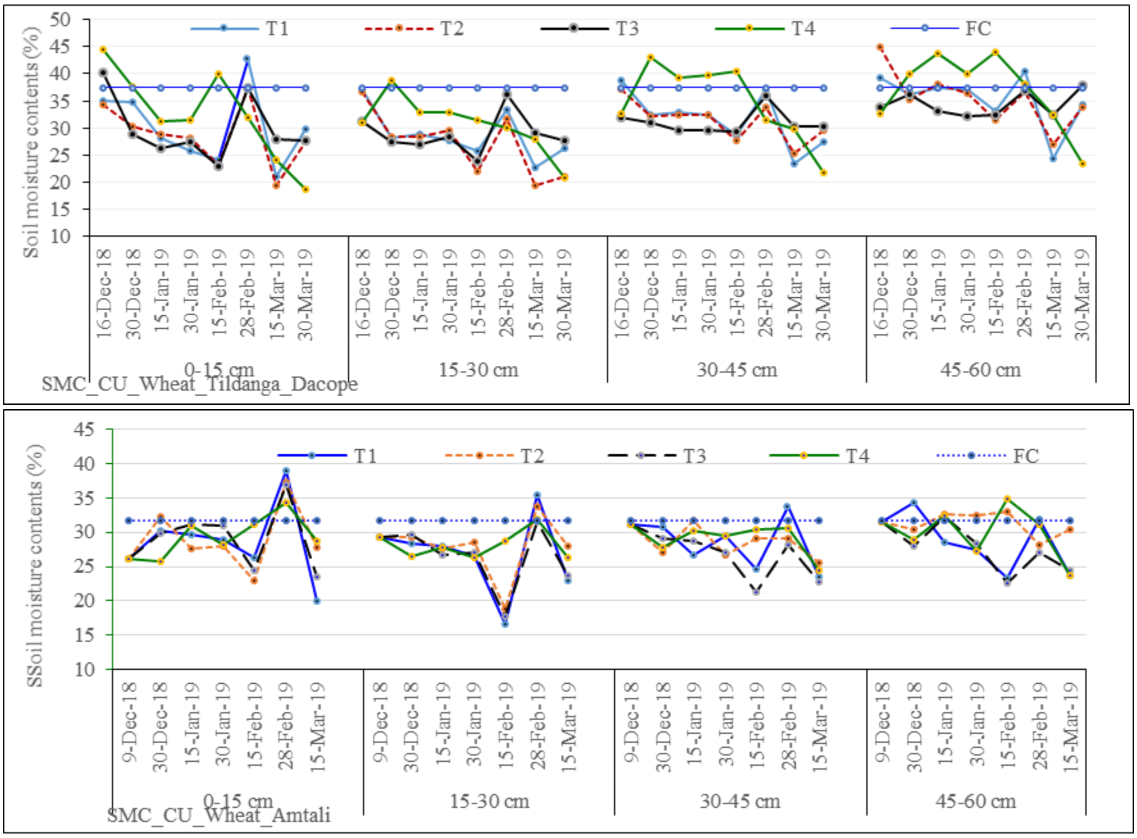
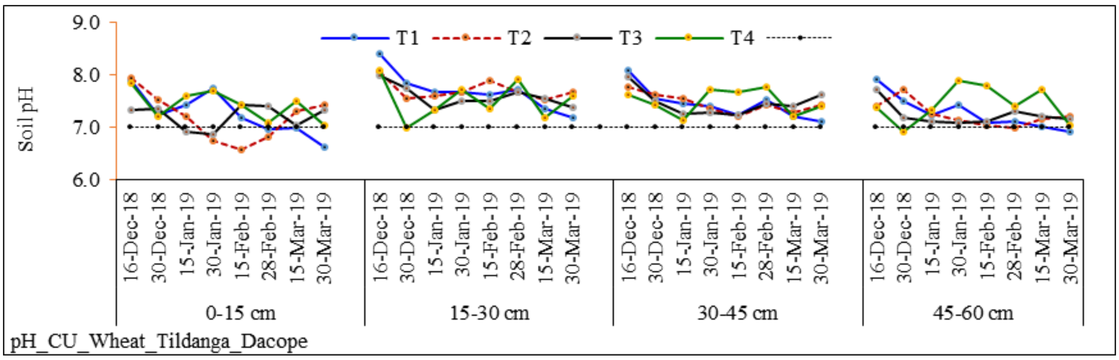


Fig. 6. Variations of gravimetric soil water content at different soil layers with 15 cm increment during crop growth season of 2018-2019.

Soil pH

The variations of soil pH in soil profiles during the crop growing season for various treatments are in **Fig. 7.** Soil pH express the solubility of ions in the soil solution which affect the plant growth. The changes in soil pH occurred averagely 5.5 to 6.5 at Amtali and 6.5 to 8.5 at Tildanga, Dacope in the soil profiles 0-60 cm with 15 cm increments during the growing season of 2018-2019. The results indicated that soil pH was found more than 7 at Dacope and lower than 7 at Amtali. Soil pH is important factor for cation and anion in saline soil soils. In alkaline soil pH (>7) at Tildanga, more contain Ca^{2+}, Mg^{2+}, K^{+} and Na^{+} as exchangeable cations which may affect the root, plant growth and yield for crops production in the selected coastal project areas of Bangladesh.



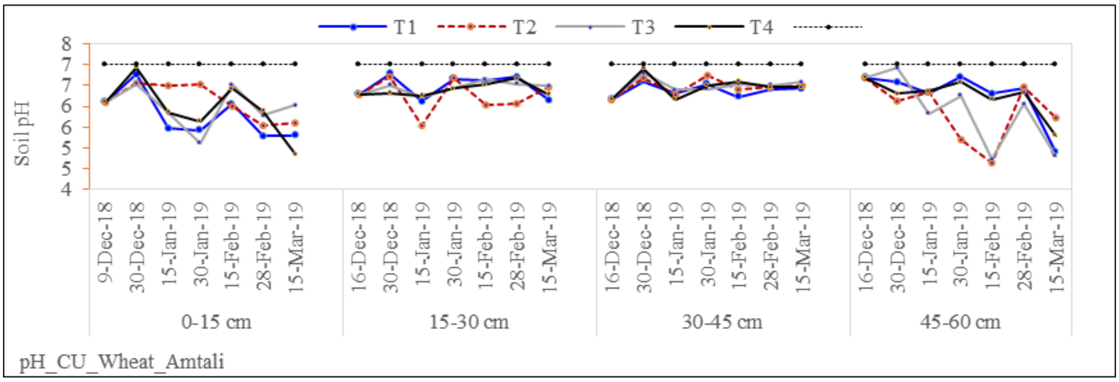


Fig. 7. Variations of soil pH at different soil layers with 15 cm increment during crop growth season of 2018-2019.

Water salinity

Mean values of the water salinity of river, canal, ponds and tube wells at 10 days interval from beginning (November 2018) to the end of the crop growing season (April 2019) are shown in **Fig. 8** in both locations. The water salinity of the pond ranged from around 1.5 (November 2018) to 3.5 dS/m (April 2019) at with an average of 2.7 dS/m at Tildanga, Dacope. The water salinity of the canal ranged from around 2 to 3.8 with an average of 2.9 dS/m at Tildanga, Dacope. The average water salinity of the tubewell was 1.23 dS/m throughout the crop growing season at Amtali, Barguna. River water salinity ranged from around 7(Novemebr 2018) to 11 dS/m (April 2019) with an average of 9.5 dS/m at Amtali and 5 (November 2018) to 20 dS/m (April 2019) with an average of 13 dS/m at Tildanga, Dacope. The water salinity of the canal at Dacope was observed greater compared to Amtali canal due to low and high tide and river water salinity entrance to the canal before protecting the canal for rainwater storage. The water was not available to the canal of Sikhandarkhali, Amtali from mid-February to March during 2019 which hampered to the crop production at the project sites. After protecting the canal, water salinity was observed similar trend in pond water due to protect the low and high tide and protect the entrance water salinity to the canal and increase the rainwater storage in the canal during rain.

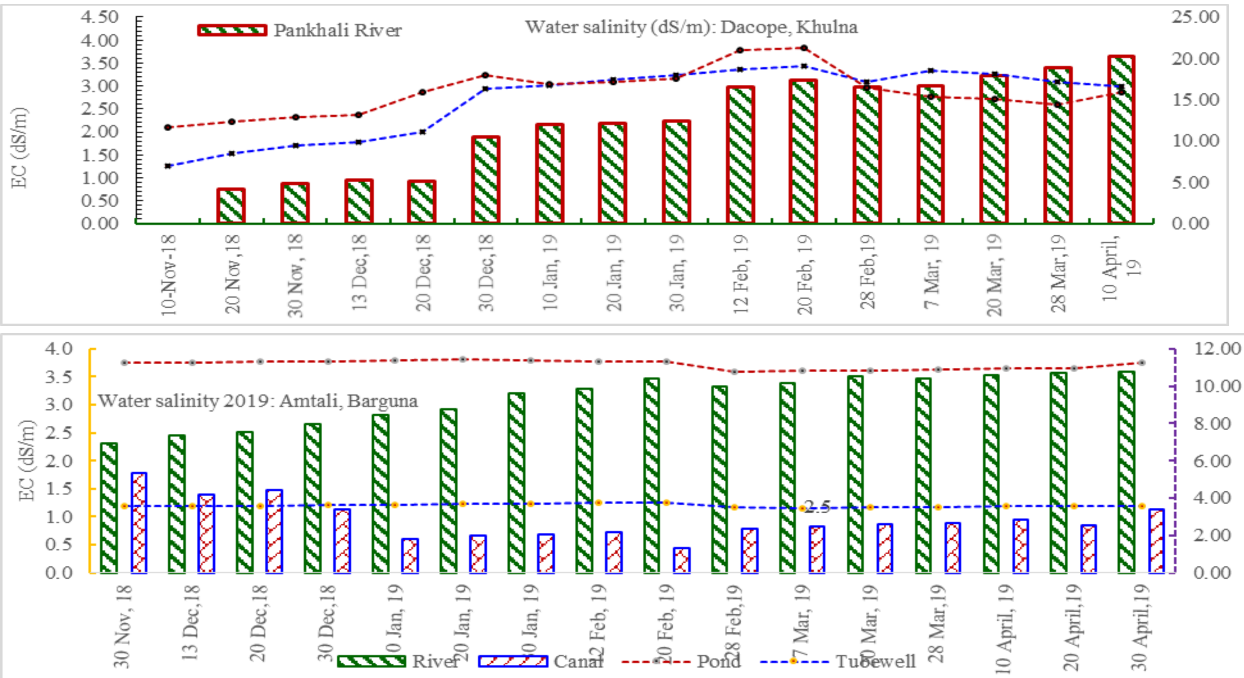


Fig. 8. Variations of water salinity of river, canal, pond and tubewell at 10 days interval during the crop growing periods in both locations of Dacope, Khulna and Amtali, Barguna during 2018-2019.

Conclusions

Based on one year of study, the technique of conjunctive use fresh water (low saline) at early growth stages and saline water (medium saline) at later growth stages of crops have the potential to sustain irrigated agriculture to intensify the cropping system in the coastal salt-affected areas of Bangladesh. Proper irrigation practices can increase crop growth and yield by avoiding water stress and suppressing the buildup of soil salinity. In terms of crop yield and scarcity of available water, this technique could be practiced in preference to the conjunctive use of fresh water (low sanity of: ≤2 dS/m) at early crop growth stages and saline water (2 ≥salinity ≤ 4 dS/m) at later growth stages of *rabi* crops (wheat/barley/mustard) in coastal saline prone areas of Bangladesh. However, further studies are needed to continue and expansion of *rabi* crops in coastal salt affected areas of Bangladesh where fresh water (non-saline) is not available for *rabi* crops cultivation in Bangladesh.

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CONTROLLED MOISTURE AND CRACKS OF SOIL ON SALINITY, CROP GROWTH AND YIELD OF MAIZE AND SUNFLOWER IN NO-TILLED SYSTEMS OF COASTAL SOILS

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Abstract

Crack formation in clay soils presents a major difficulty for movement of water, conserving soil moisture and the accumulation of salts on the soil surface through capillary action from saline groundwater which restricts the crop growth and yield in no-tilled systems of coastal saline soils of Bangladesh. Therefore, the field experiments were conducted at the salt-affected areas of Bangladesh. The objectives of the study were to: (i) evaluate the effect of straw mulching and irrigation frequency on crop growth and yield in maize and sunflower, and (ii) determine the combined effect of straw and irrigation frequency on the salinity, osmotic potential and moisture of soils. The experiment was carried out in farmers' fields with eight treatments and was replicated three times during the dry (rabi) season of 2018-2019. There were two rice straw treatments (with or without straw), and 4 irrigation frequencies (at intervals of 5-7,10-12,15-17 or 20-25 days).Maize and sunflower seeds were sown by dibbling in no-tilled systems. The results showed that rice straw significantly affected the crop growth and yield, increasing the yield of maize and sunflower by 22% and 4.3% compared to treatments of without residue. The irrigation treatments also significantly affected crop yields. There was no interaction between straw levels and irrigation. The causes of these effects appeared to be improved water relations: rice straw and more frequent irrigations both reduced the salinity and osmotic potential of soils compared with treatments without straw while the soil moisture was greater in rice straw treatments and increased with the increased soil layers. It is concluded that straw mulching and irrigation management practice could be used in coastal saline of heavy soils to reduce soil salinity, osmotic potentials thereby increasing crop yields in no-tilled systems.

Introduction

Crack formation in clay soils presents a major difficulty for modeling the flow of water. The penetration of plant roots and microbial processes are strongly affected by the dynamics of continuous macro pores. Clay content, mineralogy and the physical boundary conditions govern the characteristics of a crack network that forms and evolves with decreasing water content. Thereby, a variable network of macro pores is formed, which is highly significant for infiltrating water during rainfall events as well as for water evaporation during dry periods. The grain is mainly used for human consumption while the crop residue is used for various purposes including for construction of huts, as a source of fuel and fodder. Because of these use, virtually no crop residue is left on the soil surface for soil and water management purposes or is incorporated into the soil to maintain the organic matter content. Straw mulch is an effective method in manipulating crop growing environment to better root growth, increase yield and improve product quality by controlling weeds, ameliorating soil temperature, conserving soil moisture, reducing surface runoff, reducing soil erosion, improving soil structure and enhancing organic matter content. Mulching or covering the soil surface with a layer of plant residue is an effective method of conserving water, because it reduces surface run-off and increases infiltration of water into the soil. Mulch also reduces the depletion of water within the root zone because it suppresses evaporation. In addition, mulch decreases crusting of the soil due to rainfall impact, which reduces erosion by absorbing the kinetic energy of the rain drops. Mulching with rice straw significantly increased the infiltration of clay pan soils on sloping land. Straw mulch can be an alternative way to better root growth, increase yield by controlling soil cracking, weeds, ameliorating soil temperature and

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conserving soil moisture. The hypothesis is that irrigation frequency and residue management practice could be used in clay soils to minimize the soil cracking, reduce the amount of water to irrigate crops, mulching the soil for preventing soil moisture by minimizing evaporation, and reduces soil salinity. Therefore, a field experiment was taken to identify the better irrigation intervals with straw mulching to reduce soil cracking, moisture, and salinity and maintain water use efficiency for the cultivation of wheat/maize irrigated with low/moderate saline water in coastal clay soils of Bangladesh. Therefore, the objectives of the study were (i) to evaluate the effect of straw and irrigation frequency on crop growth and yield of maize and sunflower, and (ii) to evaluate the combined effect of straw and irrigation frequency on the salinity, osmotic potential and moisture of soils.

Materials and methods

Study area

Two field experiments were conducted in farmers' fields at Sikandorkhali village, Amtali upazila in Barguna and Tildanga village, Dacope upazila in Khulna districts during rabi season of 2018-2019. The land situation is medium low land and the soil texture is silty clay loam. Field experiments on sunflower at Amtali and maize at Tildanga were carried out in two locations. The soils were clay loam at Amtali with an average field capacity of 33% (gravimetric water content) and silty-clay loam at Tildanga with an average field capacity of 37.2% (gravimetric water content) and mean bulk density of 1.40 g/cc over the 60 cm soil profile with 15 cm increment of soil layers.

Experimental design and treatments

Two field experiments were laid out in a randomized complete block design with eight irrigation treatments for sunflower and maize, and replicated thrice. Each experiment was conducted in a farmers' field. The unit plot size was 25 square meter which depended on existing farmers' block. There were two rice straw treatments (with or without straw), and 4 irrigation frequencies (at intervals of 5-7,10-12,15-17 or 20-25 days).

Crop management

Standard crop management practices and irrigation scheduling of different crops were followed over two locations. Maize (BARI Hybrid maize 13), a medium salt tolerant variety was sown at 20 kg seed/ha on 16 December 2018 with a row spacing of 60 cm (row to row) and 25 cm (plant to plant at Tildanga, Dacope and Sunflower (local hybrid: Hisun-33) seed sowing 12 kg/ha with a row to row and plant to plant spacing was considered as 60 and 30 cm, respectively on 9 December 2018 at Amtali, Barguna in dibbling technique under no-tilled system in both locations. Fertilizer was applied in the forms of urea, triple super phosphate, muriate of potash, gypsum, borax, and zinc sulphate, respectively. Fertilizers were applied for maize @ N_{255} P_{75} K_{120} S_{52} Mg_{15} Zn_4, $B_{1.4}$ kg/ha. One-third of N and K and all of P, K, S, Mg, Zn, Band organic manure (If used) was applied as basal doses below the soil surface as horizontal and vertical separation of seed during planting. Remaining two-third of N and K were applied in two equal splits as top dressing in maize at 30-35 DAS and 50-60 DAS (tasseling stage). For sunflower, fertilizers were applied @ N_{129} P_{32} K_{60} S_{21} Mg_6 $Zn_2B_{1.6}$ kg/ha as basal doses below the soil surface as horizontal and vertical separation of seed during planting and remaining N and K was applied as top dress in two equal splits at 20-25 DAS and 40-45 DAS (before flower initiation stage). In this study, no-tilled system was considered as one of the many types of CT for row crops. Sub-surface placement of band fertilizer was placed. Mixed fertilizers were placed into the sub-soil uniformly and soil packed to minimize fertilizers tie up with manually. Adequate plant protection measures were undertaken at vegetative stages. There was no significant pest or disease infestation in the experimental plots. The crops were sprayed with Rovral-50wp at 0.2% at 30 DAS for prevention against diseases. Maize and sunflower were harvested on 6 April, 2019at Tildanga and 14 April 2019 at Amtali respectively.

Monitoring

Crops yield

Crop yields were determined at harvest. The mean yields of each crop were taken from the each plot within one square meter. Plants were harvested manually at the ground level from the corner avoiding the border effect. After manual threshing, the cleaned, dried filled grain yields were recorded at desired moisture (12%) content. The yield contributing characters and seed yield of sunflower were recorded from the plants during the experimental period. Five plants were randomly chosen to measure the seed yield components from each treatment. Economical seed yield (t/ha) were measured from the plants harvested from the selected two rows of each plot. Seed yield was manually harvested. The yield contributing characters and seed yield of maize were recorded from the plants during the experimental period. Five plants were randomly chosen to measure the seed yield components from each treatment. Economical grain yield (t/ha) were measured from the plants harvested from the selected two rows of each plot. Maize grain yield was manually harvested. All the treatment mean values were compared following randomized complete block design with three replications.

Soil sampling for soil water content, salinity, osmotic potential and pH

Soil was collected from each treatment to monitor soil moisture and soil salinity, osmotic potential and pH dynamics at different growth stages and soil profiles. Soils were sampled from 0-15, 15-30, 30-45 and 45-60 cm soil depths at the time of sowing to harvest. The Electrical conductivity of $EC_{1:5}$ was determined and converted to salinity EC_w of field soil water (dS/m) while using the formula derived from Richards, 1954 and Rengasamy, 2010). Field soil gravimetric moisture content was determined. The soil samples were taken from each plot in 15 cm increments, well-mixed together, subsampled, weighed, dried at 105^{o}C, and reweighed to determine gravimetric moisture content. $EC_{1:5}$ was also converted to osmotic potential (kPa) of field soil solution using the formula derived from Rengasamy, 2010. The soil pH was also monitored. $EC_{1:5}$ and pH were determined using portable instrument of water and soil conductivity meter with sensor probes (model: TRI-METER, pH/EC & TEMP-983) that can inserted directly into the soil solution.

Application of irrigation water and water use

Irrigation water was applied based on the pan evaporation method at different crop growth stages. Data on pan evaporation and precipitation (rainfall) were collected from Khulna and Barguna weather station to estimate irrigation water requirement (I, mm) for full irrigation using the following equation.

$$I = E_p \times K_p \times A \qquad (1)$$

where, I is the amount of irrigation water amount (litre), A is the area of the plot (m^2), E_p is the cumulative pan evaporation (mm) and K_p is the pan coefficient and was considered 0.7 (Michael, 1978).

The gravimetric soil moisture contribution was estimated using the standard formula suggested by Micheal (1978) and (Majumdar, 2004).

$$SWC = \sum_{n=i}^{n} \frac{(SMbi - SMei)\ Asi\ Di}{100} \qquad (2)$$

where, SWC is the soil water contribution during crop cycle (mm); As_i is the apparent specific gravity of the ith layer of the soil; D_i is the depth of the ith layer of the soil within the root zone to be irrigated (mm); SMbi is the soil moisture content during sowing (%); SMei) is the soil moisture during harvesting period in the ith layer of soil profile (%); and n is the number of soil layers in the root zone depth.

The calculated amount of irrigation water was supplied to the experimental plots using a polyethylene hose pipe. Each experiment plots were separated by a distance of 1.5 m to prevent the lateral movement of water from one to another. Total water use (TWU) was calculated as the sum of total irrigation water applied (I), effective rainfall (P_e) and soil water contribution (SWC) between plantation and final harvest and expressed by the following equation (3). Effective rainfall was estimated by using the USDA Soil Conservation Method (Smith, 1992).

$$\mathrm{TWU} = \mathrm{I} + \mathrm{Pe} \ \pm \mathrm{SWC} \qquad (3)$$

Water productivity (WP) was estimated as a ratio of total crops grain yield to water consumed/TWU to the system, and expressed as kg/m^3 which was expressed by the following equation (4).

$$\mathrm{WP} = \frac{\mathrm{GY} \times 100}{\mathrm{TWU}} \qquad (4)$$

where, WP is the water productivity (kg/m^3), GY is the crops yield (t/ha) and TWU is the amount of total input water use (mm).

Statistical analysis

Data on yield attributes, crop yield and water productivity were statistically analyzed to test the effects of irrigation using R software version 3.5.0. All the treatment means were analyzed and compared for any significant differences using R-statistical models at 5% ($P \leq 0.05$) probability level of significant.

It is mentioned that the number of irrigation event, amount of applied irrigation water, total water use (TWU) and water productivity (WP) under different irrigation treatments during 2018-2019 were done but the analysis of water related data were not included in this report.

Results and discussion

Effect of straw and irrigation on sunflower yield

The effect of straw and irrigation frequency on seed yield and yield contributing characters of sunflower at Amtali during 2018-2019 and 2019-20 are presented in Table 1 and 2 and Fig**.** 1. The straw had significantly affected the crop growth and seed yield of sunflower. The results indicated that rice straw increased around 4.5 % seed yield of sunflower compared to the no-residue treatments. The effect of frequent irrigation had significant difference among the treatments but there was no significant difference between treatment of T_2 and T_3. Frequent irrigation had also a significant effect on the growth, yield and yield contributing parameters of sunflower. The results indicated that yield increased with increased number of irrigations. The greater yields were obtained higher irrigation frequencies and lower yields at lower irrigation frequency. On average, the treatment T_1 produced highest seed yield by 1.57 t/ha during 2019 when irrigation water supplied with the technique of irrigation at 5-7 days intervals with straw mulch. The interactive effect of straw and irrigation frequency had no significant different among the treatments. The response of plant growth and yield to frequent irrigation is important for minimizing soil cracks and better crop growth and this technique could be used for better crop cultivation and irrigation practices in coastal areas of Bangladesh.

Sunflower at Amtali using dibbling sowing in no-tilled system

Fig.1. Photographic view of sunflower cultivation under straw and irrigation frequent irrigations in no-tilled system at Amtali during 2018-19.

Table. 1. Effect of straw and irrigation frequency on yield contributing characters and yield of sunflower at Amtali in 2018-19

Parameters		Plant height, cm	Head dia, cm	Seed/ Head	Hundred seed weight, g	Seed yield, t/ha
Straw		96.53a	39.94a	563.2a	7.13a	1.45a
Without straw		95.6a	37.5b	537.8b	6.64b	1.39b
Treatments (Irrigation frequency)						
	T_1	95.6ab	39.53a	565.1a	6.83a	1.52a
	T_2	97.6a	39.15a	570.2a	6.9a	1.45b
	T_3	95.9ab	38.7ab	551.1a	6.8a	1.40b
	T_4	95b	37.5b	515.7b	6.8a	1.33c
Treatments(2 straw level × 4 Irrigation frequency)						
Straw	T_1	95.6b	40.6a	580.9a	7.12a	1.57a
	T_2	98.8a	40.5a	584.4a	7.14a	1.48b
	T_3	95.7b	40.3a	556.3a	7.21a	1.42bc
	T_4	95.9b	38.5ab	531.1bc	7.03a	1.35cd
Without straw	T_1	95.6b	38.4ab	549.3ab	6.53	1.47b
	T_2	98.4ab	37.8b	556ab	6.84a	1.42bc
	T_3	96.2ab	37.1b	545.8ab	6.53a	1.38cd
	T_4	94.2b	36.7b	500.3c	6.65a	1.31d

Note: *Mean values within the same columns by different letters (a-c) are significantly different within treatments. Values are mean of three replication of each treatment. Here,8 treatments (with rice straw and without straw), and 4 irrigation frequencies (T1: Irrigation at intervals of 5-7 days, T2: Irrigation at intervals of 10-12 days, T3: Irrigation at intervals of 15-17 days, T4: Irrigation at intervals of 20-25 days).*

Table 2. Effect of straw and irrigation on yield characters and yield of sunflower at Amtali in 2019-20

Tillage with straw level	Irrigation level	Plant height, cm	Head dia, cm	Seed/head	Hundred seed weight, cm	Seed yield, t/ha
No-till without straw (NTNS)	1	118	12.9	519	7.08	1.90
	2	124	13.3	474	7.03	1.69
	3	128	12.3	366	6.81	1.33
No-till with straw (NTS)	1	140	15.7	638	7.33	2.48
	2	150	16.3	653	7.30	2.54
	3	147	15.0	562	7.17	2.10
No-till without straw with disturb soil (NSD)	1	126	16.0	540	7.98	2.33
	2	133	15.0	511	7.85	2.13
	3	130	13.1	380	7.25	1.45

Mean values within the same columns by different within treatments. Values are mean of three replication of each treatment. Here,8 treatments (with rice straw and without straw), and 4 irrigation frequencies (T1: Irrigation at intervals of 10-12 days, T2: Irrigation at intervals of 15-17 days, T3: Irrigation at intervals of 20-25 days).

Effect of straw and irrigation on maize yield

The grain yield and yield contributing characters of maize at Tiladanga, Daacope during 2018-2019 is presented in Table 3-4 and Fig. 2. The effect of straw had significant difference on the yield and yield contributing parameters of maize. The results indicated that rice straw increased around 20% grain yield of maize compared to the no-residue treatments. The treatment of irrigation frequency had significant difference among the treatments. The results indicated that yield increased with increased number of irrigations. The greater yields were obtained higher irrigation frequencies and lower yields at lower irrigation frequency. On average, the treatment T_1 produced highest grain yield by 5.58 t/ha during 2019 when irrigation water supplied with the technique of 5-7 days interval with straw mulch. The interactive effect of straw and irrigation frequency had no significant different among the treatments (Table 2). The response of plant growth and yield to frequent irrigation is important for minimizing soil cracks and better crop growth and this technique could be used for better crop cultivation and irrigation practices in coastal areas of Bangladesh.

Table 3. Effect of straw and irrigation frequency on yield contributing characters and yield of maize at Tildanga, Dacope during 2018-19

Parameters		Plant height, cm	Cob length, cm	Cob dia, cm	Grain/ Cob	HGW, g	Grain yield/ Cob	Grain yield, t/ha
Treatments								
Straw		152.3a	15.94a	4.87a	365.2a	27.14a	94.5a	5.03 a
Without straw		118.7b	13.38b	4.19b	313.9a	25.57b	79.6b	4.13 b
Treatments (Irrigation frequency)								
	T_1	136.4a	14.8a	4.67a	372.7a	26.1a	97.9a	5.01a
	T_2	135.7a	14.7a	4.68a	353.8a	26.7a	88.6ab	4.79ab
	T_3	135.6a	14.6a	4.53ab	301.3a	26.8a	83.6ab	4.43bc
	T_4	134.3a	14.5a	4.24b	330.3a	25.7a	78.4b	4.09c
Treatments(2 straw level × 4 Irrigation frequency)								
Straw	T_1	152.7a	16.3a	5.0a	391.3a	26.6 abc	103.1a	5.58a
	T_2	156.6a	15.9a	5.04a	385a	27.6ab	94.5ab	5.16a
	T_3	154.3a	15.9a	4.96a	342ab	27.9a	96.17a	5.04ab
	T_4	145.8a	15.7ab	4.46b	342ab	26.4abc	84.2abc	4.36c
Without straw	T_1	120b	13.4c	4.33b	354ab	25.7c	92.8abc	4.44bc
	T_2	114.6b	13.3c	4.31b	322ab	25.9bc	82.7abc	4.42bc
	T_3	117.1b	13.1c	4.12b	260b	25.7c	70.20c	3.83c
	T_4	122.7b	13.7bc	4.02b	318ab	24.9c	72.6bc	3.84c

*Mean values within the same columns by different letters (a-c) are significantly different within treatments. Values are mean of three replication of each treatment. 8 treatments (with rice straw and without straw), and 4 irrigation frequencies (T1: Irrigation at intervals of 5-7 days, T2: Irrigation at intervals of 10-12 days, T3: Irrigation at intervals of 15-17 days, T4: Irrigation at intervals of 20-25 days).

Maize at Dacope using dibbling sowing in no-tilled system

Fig. 2. Photographic view of sunflower cultivation under straw and irrigation frequent irrigations in no-tilled system at Dacope during 2018-19.

Table 4. Effect of straw and irrigation frequency on yield contributing characters and yield of maize at Tildanga, Dacope in 2019-20

Treatment		Plant height, cm	Cob length, cm	Cob perimeter, cm	Grain number /Cob	Thousand grain weight, g	Grain wt / Cob, g	Grain yield, t/ha
Tillage with straw level	Irrigation level							
NTNS	1	195.4	19.2	14.1	609.7	253.3	140.7	8.057
	2	202.4	19.4	14.6	590.6	263.3	138.6	7.864
	3	202.5	18.3	14.3	647.6	273.7	152.8	7.244
NTS	1	199.8	18.3	14.9	631.7	259.0	140.4	8.774
	2	204.9	19.1	14.7	637.1	277.7	138.4	8.649
	3	198.1	18.8	19.9	818.1	266.0	129.8	8.111
DNS	1	201.3	18.4	14.2	644.7	262.7	143.8	9.130
	2	211.8	18.9	15.4	600.7	268.3	140.2	8.926
	3	186.5	18.2	14.3	524.7	259.7	131.5	8.162

Mean values within the same columns by different within treatments. Values are mean of three replication of each treatment. Here,8 treatments (with rice straw and without straw), and 4 irrigation frequencies (T1: Irrigation at intervals of 10-12 days, T2: Irrigation at intervals of 15-17 days, T3: Irrigation at intervals of 20-25 days).

Salinity in field soil

The effect of straw and irrigation frequent on salinity of field soil water (EC_w) in 0-60 cm with 15 cm increments of soil profiles during the growing season for various treatments are in **Fig. 3.** On average, the changes in salinity of field soil water varied from around 2 dS/m (November 2018) to 35 dS/m (mid-February 2019) in 0-60 cm soil profiles with 15 cm increments at Tildanga. The exact soil salinity (ECe) varied from around 2 to 15 dS/m during the crop growing season. The higher salt accumulation was occurred in mid-February 2019in no straw irrigation treatments in 0-60 cm soil profiles. The salinity results indicated that straw mulch with frequent irrigation interval reduced salinity of field soil water averagely around 23% in 0-60 cm soil profiles (0-15 cm soil layers). On other hand, straw with greater irrigation interval of 20-25 days reduces about 40% salinity of field soil water. Due to more crack, water uptake and evaporation from soil surface, accumulation of salt was generally higher on the soil surface through capillary from saline ground water which restricts the crop growth and yield in no-tilled systems of coastal saline soils. Irrigation with medium saline water (canal water) may cause increase soil salinity. In this study, the figures indicate that the soil salinity was substantially greater salt accumulation in soil profiles due to medium saline water (2 to 3.5 dS/m) irrigation and salinity may tolerable for maize germination to crop yield production in the coastal areas of Bangladesh.

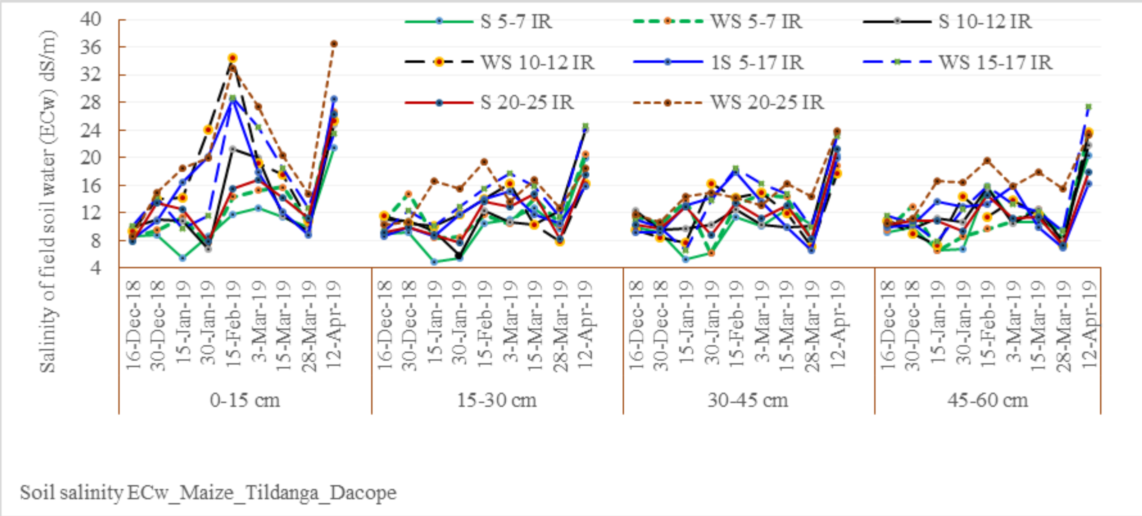

Fig. 3. Effect of straw and irrigation frequency on soil salinity for maize cultivation at Tildanga, Dacope during 2018-2019.

Osmotic potential

The variations of osmotic potential (-kPa) during the growing season for the various treatments are in shown in Fig. 4. On average, the osmotic potential was found around -200 to -1500 kPa during the growing season from December 2018 to April 2019 and highest osmotic potential observed in mid-February 2019. The lower osmotic potential was observed in the treatment of T_1 with straw mulch and irrigation frequent of 5-7 days interval. The greater osmotic potential was measured in the treatment of T_4 with without straw and irrigation interval of 20-25 days than the treatments. The results indicated that straw mulch and more frequent irrigation interval substantially reduces osmotic potential (-kPa) which no influences in limiting crop production. The higher osmotic pressure was found in mid growth stages of the maize due to more soil water uptake and soil moisture evaporation from the soil surfaces. Generally, plants struggle to take up water when the total potential of the soil solution exceeds -1000 kPa and will permanently wilt at -1500 kPa. The results indicated that the osmotic pressure was effected on plant growth and yield at mid and later growth stages of maize because of insufficient soil moisture as well as lack of fresh irrigation water (low salinity) and more salt accumulation in the upper soil profiles.

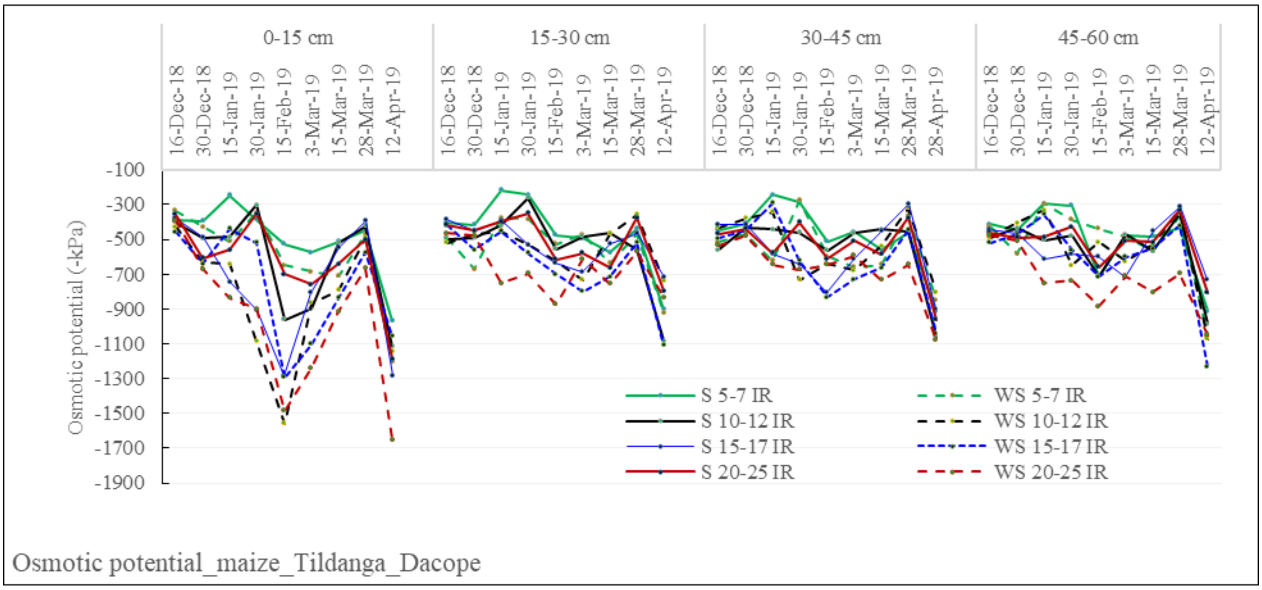

Fig. 4. Effect of straw and irrigation frequency on osmotic potential for maize cultivation at Tildanga, Dacope during 2018-2019.

Soil moisture contents

The variations of gravimetric soil water content in the soil profiles over 0-60 cm soil depth with 15 cm increaments during the growing season of maize in no-tilled system for each treatments is shown in Fig. 5. An increase or decrease soil water content was observed following irrigation or rainfall. The substantially larger raifall occurred waterlogged at silking growth stages of maize, which affected the crop growth and grain yield. Soil water contents (SWC) substantially decreased in upper soil layers (0-15 cm) at mid February 2019 which affected the crop growth (Fig. 3). The SWC was found greater in treatment of T_1 (straw mulch with irrigation interval of 5-7 days) than treatments. The SWC was found lower in treatment of T_4 (no straw mulch with irrigation interval of 20-25 days) than treatments. The residual soil moisture utilizing technique during sowing could maintain the crop germination and increase the benefits of the crop establishment. During sowing at Dacope, initial soil water content among the treatments was close to field capacity at the upper layer of the soil and more than field capacity at lower depth of soil (**Fig. 5**). The figures indicate that soil moisture decreased or increased during the growing season, but plants extractable available soil water was not drasticaly reduced at the treatment of straw mulch but soil water was drastically reduced in no straw mulch treatment at mid February which affected the plant growth. This stress condition occurred because of insufficieny fresh water (low saline) and salt accumulation on the upper soil surface in the project sites of Tildanga village in Dacope.

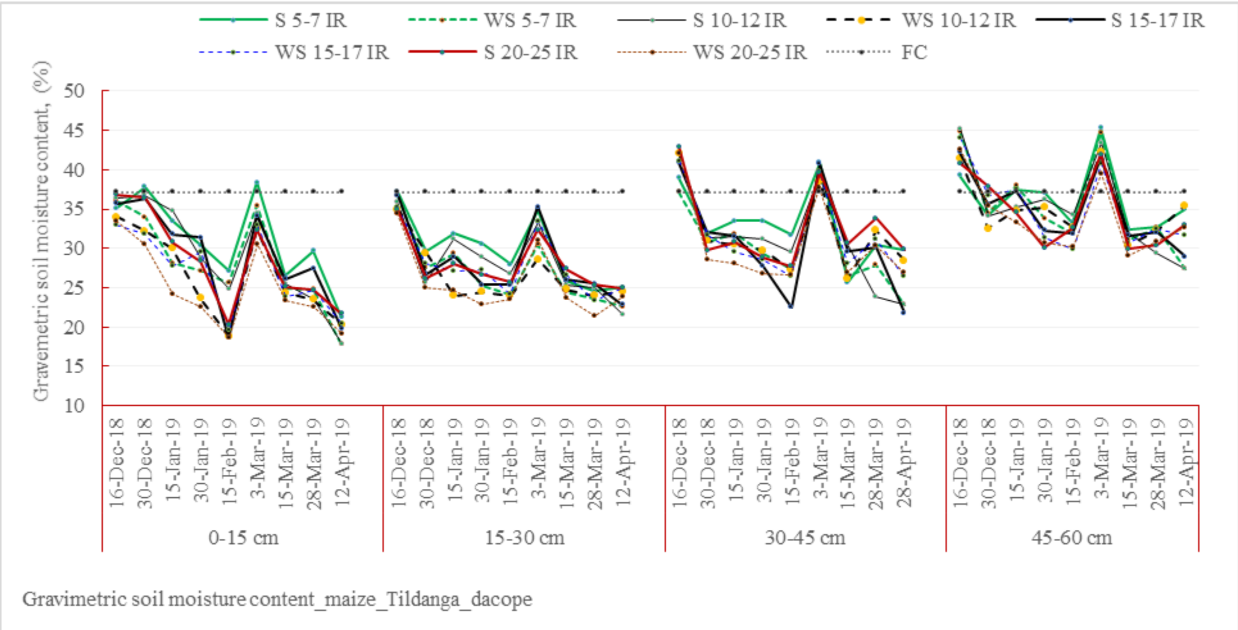

Fig. 5. Effect of straw and irrigation frequency on soil moisture content for maize cultivation at Tildanga, Dacope during 2018-2019.

Conclusions

This is the first year experiment. The conclusion will be drawn after two/three years of crop cycle in no-tilled system of heavy soils of coastal saline areas. However, residue management and frequent irrigation techniques minimize effect of soil moisture, cracks, salinity, osmotic potential and yield reductions by reducing evaporation in coastal eco-system.

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IMPROVING SURFACE DRAINAGE CUM FURROW IRRIGATION TECHNIQUE FOR SUNFLOWER AND MAIZE CULTIVATION IN COASTAL SALINE SOILS

M.A. Hossain[1], K.K. Sarker[2], and S.S.A. Kamar[3]

Abstract

Waterlogging and poor surface drainage are becoming a major constraint to the production of rabi crops in southern coastal saline soils of Bangladesh. Surface drainage is essential for establishment of rabi crops after the harvest of transplanted Aman rice. Hence, two field experiments were investigated to evaluate the rabi crops of sunflower and maize performances at two locations of Dacope and Amtali during 2018-2019 and 2019-2020. The specific objectives of this study were (i) to find out the effect of surface drainage cum furrow irrigation technique on crop growth and yield, (ii) to find out the effect of the surface drainage technique on salinity, osmotic potential and moisture contents of soils during crop growth periods. Four drainage treatments were imposed at all sites with three replications. The 4 treatments consisted of (i) single row raised bed with 30 cm drain, (ii) double row raised bed with 40 cm drain, (iii) triple row raised bed with 40 cm drain, and (iv) random field ditches (scattered)–Pothole in 2018-2019 and one more treatment like four row raised bed with 40 cm drain was ta was included in 2019-2020. Sunflower seed and maize grain yield were ranged from 1.53 t/ha to 2.34 t/ha and 7.16 t/ha to 8.04 t/ha, respectively. The technique of single row raised bed with 30 cm drain greater yield for maize yield than other drainage treatments in both years at Amtali but single row raised bed with 30 cm drain was not greater for sunflower at Tildanga in 2019-2020. The treatment T_1 (single row raised bed with 30 cm drain obtained (8.04 t/ha) significantly greater yield than other drainage treatments. On average, the changes exact salinity (EC_e) of field soil water varied from around 2 to 12 dS/m at Tildanga and 2 to 9 dS/m at Amtali during the crop growing season. The salinity results indicated the salt accumulation was slightly lower in the treatment of single row raised bed planting and drainage technique than the other drainage techniques. The osmotic potential was found around -200 to -1100 kPa at Tildanga and -200 to -800 kPa at Amtali. Soil water contents substantially decreased in upper soil layers (0-15 cm) at later growth stages which affected the crop growth. However, the drainage technique would be optioned for sunflower and maize cultivation in the coastal areas of Bangladesh where salinity and waterlogging problems prevail.

Introduction

Drainage is necessary in the crop fields are to improve the soil condition and create more conducive working conditions for use of farm machinery and as well as non-rice crops establishment. Drainage improves the productivity of poorly drained soils, creating an aerobic zone, enabling faster soil drying and improving the root zone soil layer condition to active functions of crops roots. During rain or irrigation, the fields become wet. The water infiltrates into the soil and is stored in its pores. But the plant roots require air as well as water and most plants cannot withstand saturated soil for long periods (rice is an exception). Besides damage to the crop, a very wet soil makes the use of machinery difficult. Following heavy rainfall, the groundwater table may even reach and saturate part of the root-zone. If this situation lasts too long, the plants may suffer. Excess water may be caused by rainfall or by using too much irrigation water, but may also have other origins such as canal seepage or floods. In very dry areas there is often accumulation of salts in the soil. Most crops do not grow well on salty soil. Salts can be washed out by percolating irrigation water through the root-zone of the crops. But the salty percolation water will cause the water table to rise. The removal of excess water either from the ground surface or from the root-zone, is necessary for drainage. Drainage can be either natural or artificial.

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Many areas have some natural drainage; this means that excess water flows from the farmers' fields to swamps or to lakes and rivers. Natural drainage, however, is often inadequate and artificial or man-made drainage is required. There are two types of artificial drainage: surface drainage and subsurface drainage. Surface drainage is the removal of excess water from the surface of the land. Subsurface drainage is the removal of water from the root-zone. The excess water from the root-zone flows into the open drains. The disadvantage of the subsurface drainage is that it makes the use of machinery difficult. In the subsurface drainage, the installation costs of pipe drains may be higher due to the materials, the equipment and the skilled manpower involved. In surface drainage, open drains require frequent maintenance (weed control, repairs, etc.).All irrigated Rabi crops like as wheat, maize, and sunflower are conventionally planted in narrow spaced rows on the flat or raised bed and is irrigated by flood irrigation or furrow irrigation techniques within bordered basins. Conventional flat planting for Rabi crops have some disadvantages. Traditionally, upland row crops have been conventionally planted on the flat and excess rainfall or flood irrigation causes low water use efficiency. Due to changing climate, irregular excess rainfall causes waterlogged and affects the growth which reduces crops yield. Therefore, the surface drainage has been taken to evaluate the Rabi crops performances in coastal saline soils. The specific objectives of this study were (i) to find out the effect of the type of surface drainage cum furrow irrigation technique on crop growth and yield, (ii) to find out the effect of the surface drainage technique on salinity, osmotic potential and moisture of soils during crop growth periods.

Materials and Methods

Two field experiments were conducted in farmers' fields at Sikandorkhali village, Amtali upazila in Barguna and Tildanga village, Dacope upazila in Khulna districts during *rabi* season of 2018-2019 and 2019-2020. The land situation is medium low land and the soil texture is silty clay loam at Dacope and clay loam at Amtali. Field experiments on sunflower at Tildanga and maize at Amtali were carried out in two locations. The soils were clay loam at Amtali with an average field capacity of 31.8% (gravimetric water content) and silty-clay loam at Tildanga with an average field capacity of 37.2% (gravimetric water content) and mean bulk density of 1.40 g/cc over the 60 cm soil profile with 15 cm increment of soil layers. The rainfall at each location was recorded from the weather stations of Khulna and Amtali, Barguna. The monthly data of the rainfall for the study period are presented in Fig. 1. During the crop growing season 2018-2019, the total rainfalls were 169 mm at Amtali and 343 mm in Khulna than the long-term average, occurred mainly during the crop growing season (Fig. 1).

Two field experiments were laid out in a randomized complete block design with four types of drainage treatments for sunflower and maize, and replicated thrice. The four treatments were (i) single row raised bed with 30 cm drain, (ii) double row raised bed with 40 cm drain, (iii) triple row raised bed with 40 cm drain, and (iv) random field ditches (scattered)–Pothole (3 Pothole/plot) in 2018-19 and one more treatment like four row raised bed with 40 cm drain was taken in 2019-2020. Each experiment was conducted in a farmers' field. The unit plot size was 42 square meter which depended on existing farmers' block. Standard crop management practices and irrigation scheduling of different crops were followed over two locations. Maize (BARI Hybrid Bhutta-9), a medium salt tolerant variety was sown at 20 kg seed/ha on 8 December 2018 with a row spacing of 60 cm (row to row) and 25 cm (plant to plant) at Amtali and sunflower (local hybrid: Hisun-33) seed sowing 12 kg/ha with a row to row and plant to plant spacing was considered as 60 and 30 cm, respectively on 16 December 2018 at Tildanga, Dacope in dibbling technique under no-tilled system at Tildanga and conventional tillage with bed planting system at Amtali. Fertilizer was applied in the forms of urea, triple super phosphate, muriate of potash, gypsum, borax, and zinc sulphate, respectively. Fertilizers were applied for maize @ N_{255} P_{75} K_{120} S_{52} Mg_{15} Zn_4, $B_{1.4}$ kg/ha. One-third of N and K and all of P, K, S, Mg, Zn, Band organic manure (If used) was applied as basal doses below the soil surface as horizontal and vertical separation of seed during planting. Remaining two-third of N and K were applied in two equal splits as top dressing in maize at 30-35 DAS and 50-60 DAS (tasseling stage). For sunflower, fertilizers were applied @ N_{129} P_{32} K_{60} S_{21} Mg_6 $Zn_2B_{1.6}$ kg/ha as basal doses below the soil surface as horizontal and vertical separation of seed during planting and remaining N and K was applied as top dress in two equal splits at 20-25 DAS and 40-45 DAS (before flower initiation stage).

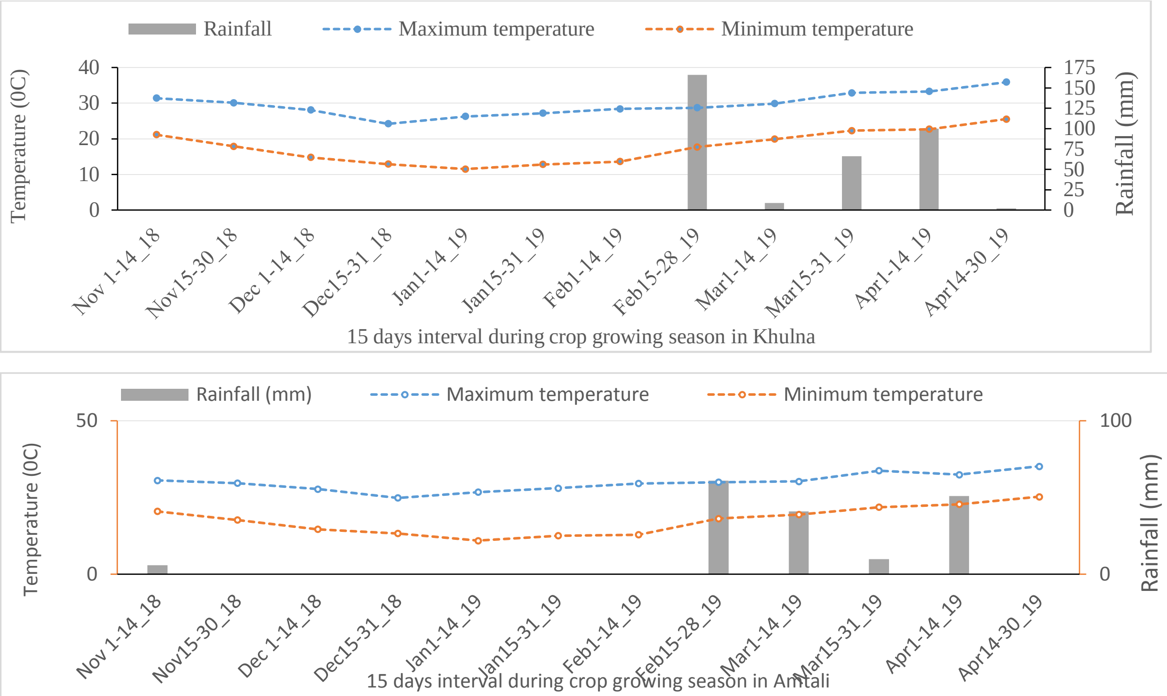


Fig. 1. Maximum and minimum temperature (0C) and rainfall (mm) at Tildanga and Amtali during the crop growing season of 2018-2019.

In this study, no-tilled system was considered as one of the many types of CT for row crops. Sub-surface placement of band fertilizer was placed. Mixed fertilizers were placed into the sub-soil uniformly and soil packed to minimize fertilizers tie up with manually. Adequate plant protection measures were undertaken at vegetative stages. There was no significant pest or disease infestation in the experimental plots. The crops were sprayed with Rovral-50wp at 0.2% at 30 DAS for prevention against diseases. Sunflower and maize were harvested on 3 April at Tildanga and 30 April at Amtali, respectively. Crop yields were determined at harvest. The mean yields of each crop were taken from each plot within one square meter. Plants were harvested manually at the ground level from the corner avoiding the border effect. After manual threshing, the cleaned, dried filled grain yields were recorded at desired moisture (12%) content.

The yield contributing characters and seed yield of sunflower were recorded from the plants during the experimental period. Five plants were randomly chosen to measure the seed yield components from each treatment. Economical seed yield (t/ha) were measured from the plants harvested from the selected two rows of each plot. Seed yield was manually harvested. The yield contributing characters and seed yield of maize were recorded from the plants during the experimental period. Five plants were randomly chosen to measure the seed yield components from each treatment. Economical grain yield (t/ha) were measured from the plants harvested from the selected two rows of each plot. Maize grain yield was manually harvested.

All the treatment mean values were compared following randomized complete block design with three replications. Soil sampling was collected from each treatment to monitor soil moisture and soil salinity, osmotic potential and pH dynamics at different growth stages and soil profiles. Soils were sampled from 0-15, 15-30, 30-45 and 45-60 cm soil depths at the time of sowing to harvest. The Electrical conductivity of $EC_{1:5}$ was determined and converted to salinity EC_w of field soil water (dS/m) while using the formula derived from Richards (1954) and Rengasamy (2010). Field soil gravimetric moisture content was determined. The soil samples were taken from each plot in 15 cm increments, well-mixed together, subsampled, weighed, dried at 105^{o}C, and reweighed to determine gravimetric moisture content. $EC_{1:5}$ was also converted to osmotic potential (kPa) of field soil solution using the formula derived from Rengasamy (2010). $EC_{1:5}$ was determined using portable instrument. Irrigation water was applied based on the pan evaporation method at different crop growth stages. The irrigation scheduling was at early vegetative (30-35 DAE), tasseling/silking (65-70 DAE) and grain development (100-110 DAE) stages for maize and three irrigations at early vegetative, flowering and grain filling stage for sunflower were followed. Data on yield attributes, crop yield and water productivity were statistically analyzed to test the effects of irrigation using R software version 3.5.0. All the treatment means were analyzed and compared for any significant differences using R-statistical models at 5% ($P \leq 0.05$) probability level of significant. The number of irrigation event, amount of applied irrigation water, total water use (TWU) and water productivity (WP) under different irrigation treatments during 2018-2019 were done but the analysis of water related data were not included in this report.

Results and Discussion

Effects of surface drainage systems on sunflower yield

The effect of drainage on yield components and yield of sunflower at Tildanga, Dacope in 2018-2019 is presented in Table 1-2 and photographic view of sunflower cultivation is shown in Fig.2. Seed yields from the surface drainage treatments were from 1.53 t/ha to 2.34 t/ha, respectively. The drainage treatment had no significant difference on the crop growth and seed yield of sunflower but the treatment T_1obtained (2.34 t/ha) greater than other drainage treatments (Table 1). The statistical analysis results showed that increases in seed yield was obtained in treatment T_1 because of improvement in drain discharge. The raised bed planting with saving furrow irrigation techniques using pond/brackish water with EC of ≤4 dS/m) could be option for developing better drainage and saving irrigation water practices for sunflower cultivation in coastal areas of Bangladesh.

Table 1. Effect of drainage on yield components and yield of sunflower at Tildanga, Dacope during 2018-2019

Sunflower	Plant height, cm	Head diameter , cm	Seed/ Head	Seed weight/ Head	Hundred seed weight, g	Seed yield, t/ha
Treatments (4 drainage techniques):						
T_1	81.17a	12.5a	716a	49.65a	6.27 a	2.34 a
T_2	83.7a	10.83a	579a	35.66ab	6.23 a	1.81ab
T_3	79.47a	11.08	544a	34.5ab	6.26 a	1.61 b
T_4	79.59a	11.17a	509a	33.07b	6.36 a	1.53 b

Mean values within the same columns by different letters (a-c) are significantly different at the level of 5% (P<0.05) within treatments. Values are mean of three replication of each treatment. Here, Four drainage techniques at different growth stages: (T1) single row raised bed with 30 cm drain), (T2) double row raised bed with 40 cm drain, (T3) triple row raised bed with 40 cm drain, and (T4) random field ditches (scattered)–Pothole.

Table 2. Effect of drainage on yield components and yield of sunflower at Dacope in 2019-2020

Treatment	Plant height, cm	Head diameter, cm	Seed number/head	Seed weight, g	Hundred seed weight, g	Seed yield, t/ha
T_1	120.53	14.77	559.67	54.07	8.27	1.79
T_2	144.1	15.1	655.3	58.5	8.7	2.71
T_3	141.9	14.7	767.9	59.5	8.1	2.73
T_4	139.9	14.3	716.0	56.8	8.9	2.56
T_5	127.47	13.80	631.40	56.57	8.47	2.14

**Mean values within the same columns by different letters (a-c) are significantly different at the level of 5% (P<0.05) within treatments. Values are mean of three replication of each treatment. Here, Four drainage techniques at different growth stages(T1) single row raised bed with 30 cm drain), (T2) double row raised bed with 40 cm drain, (T3) triple row bed with 40 cm drain, T4: four row bed with 40 cm drain , and T5: random field ditches (scattered)–Pothole.*

Sunflower cultivation using surface drainage technique at Dacope

Fig. 2. Photographic view of sunflower cultivation under surface drainage cum irrigation technique at Tildanga during 2018-2019.

Effects of surface drainage systems on maize yield

The effect of drainage on yield components and yield of maize at Amtali, Barguna during 2018-2019 is shown in Table 3-4 and photographic view of maize is shown in Fig. 3 cultivation**.** Grain yields from the surface drainage treatments were from 7.16 t/ha to 8.04 t/ha, respectively. The effect of surface drainage treatment had significant difference on grain yield of maize but the treatment T_1 and T_2 had no significant difference. The treatment T_1 (single row raised with 15 cm drain) obtained (8.04 t/ha) significantly greater yield than other drainage treatments of T_3 and T_4. The statistical analysis results showed that increases in grain yield was obtained in treatment T_1 because of removing excess water in drain. The single row raised bed planting with furrow irrigation and drainage techniques using pond/brackish water with EC of ≤ 3.5 dS/m) could be option for developing better drainage and saving irrigation techniques for maize cultivation in coastal areas of Bangladesh.

Table 3. Effect of drainage on yield components and yield of maize at Amtali during 2018-2019

Maize	Plant height, cm	Cob length, cm	Cob perimeter, cm	Grain/ Cob	Hundred grain weight, g	Grain yield, t/ha
Treatments						
T_1	177.7a	19.3a	14.1a	475.0a	28.0a	8.04a
T_2	183.9a	18.4ab	13.8a	491.0a	25.0b	7.83 a
T_3	180.6a	18.5ab	13.9a	454.3a	25.3b	7.59 b
T_4	181.8a	18.1b	11.4b	432.7a	22.0c	7.16 c

**Mean values within the same columns by different letters (a-c) are significantly different at the level of 5% (P<0.05) within treatments. Values are mean of three replication of each treatment. Here, Four drainage techniques at different growth stages(T1) single row raised bed with 30 cm drain), (T2) double row raised bed with 40 cm drain, (T3) triple row raised bed with 40 cm drain, and (T4) random field ditches (scattered)–Pothole.*

Fig. 3. Photographic view of maize cultivation under surface drainage cum irrigation technique at Amtali during 2018-2019.

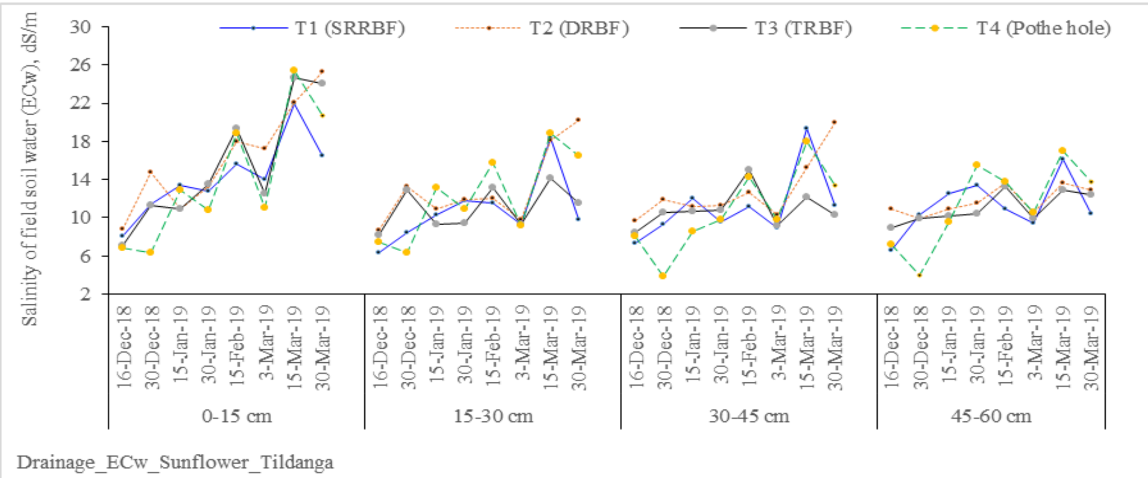
Table 8.4 Effect of drainage on yield components and yield of maize at Amtali in 2019-20

Maize	Plant height, cm	Cob length, cm	Grain/Cob	Hundred grain weight, g	Grain yield, t/ha
T_1	174.4	18.1	475.8	29.4	7.58
T_2	169.2	17.7	471.5	27.3	7.41
T_3	170.7	17.7	443.1	24.9	7.39
T_4	166.5	17.0	424.3	22.0	6.86
T_5	162.5	16.8	453.5	21.8	6.58

*Mean values within the same columns by different letters (a-c) are significantly different at the level of 5% (P<0.05) within treatments. Values are mean of three replication of each treatment. Here, Four drainage techniques at different growth stages(i) single row raised bed with 30 cm drain), (ii) double row raised bed with 40 cm drain, (iii) triple row bed with 40 cm drain, T4: four row bed with 40 cm drain , and T5: random field ditches (scattered)–Pothole.

Effect of the surface drainage on salinity of field soil water

The effect of surface drainage techniques on salinity of field soil water (EC_w) in 0-60 cm with 15 cm increments of soil profiles during the growing season of sunflower and maize are shown in Fig. 4. On average, the changes in salinity (EC_w) of field soil water varied from around 2 dS/m (November 2018) to 26 dS/m (March 2019) in 0-60 cm soil profiles with 15 cm increments at Tildanga, Dacope, Khulna and 5-18 dS/m at Amtali, Barguna.



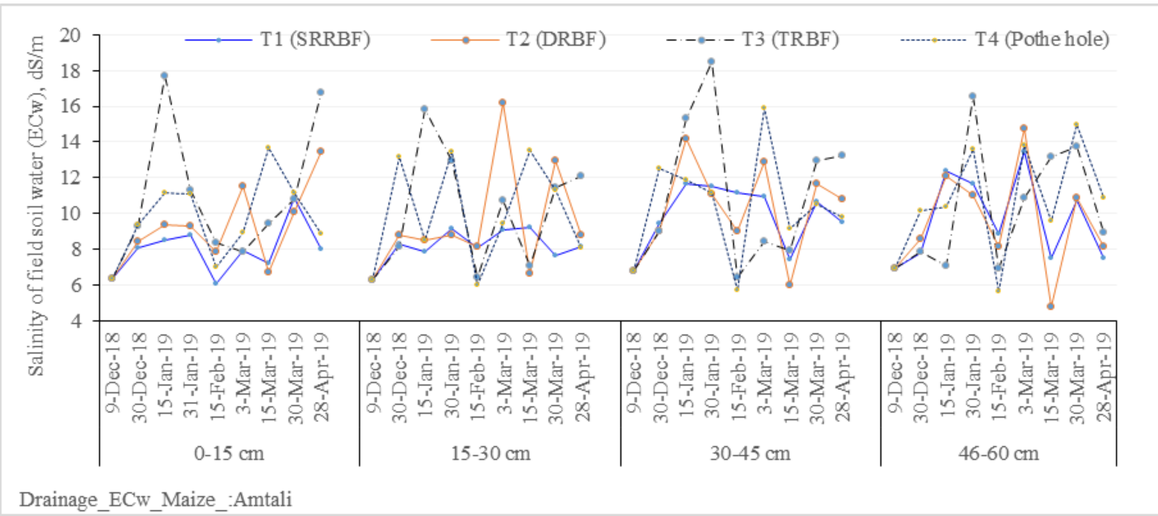


Fig. 4. The effect of the surface drainage treatments on salinity of field soil water at Tildanga and Amtali during 2018-2019.

The exact soil salinity (EC_e) varied from around 2 to 12 dS/m at Tildanga and 2 to 9 dS/m at Amtali during the crop growing season. The higher salt accumulation was occurred at later crop growth stages in 0-60 cm soil profiles. In this study, the figures indicate that the salinity of field soil water was found similar trend and was not substantially greater salt accumulation due to drainage technique. However, single row raised bed planting with drainage technique would be practiced and optioned for sunflower and maize cultivation where salinity and waterlogging problem in the coastal areas of Bangladesh.

Effect of the surface drainage on osmotic potential of soils

The variations of osmotic potential (-kPa) during the growing season for the various drainage treatments are in shown in Fig. 5.

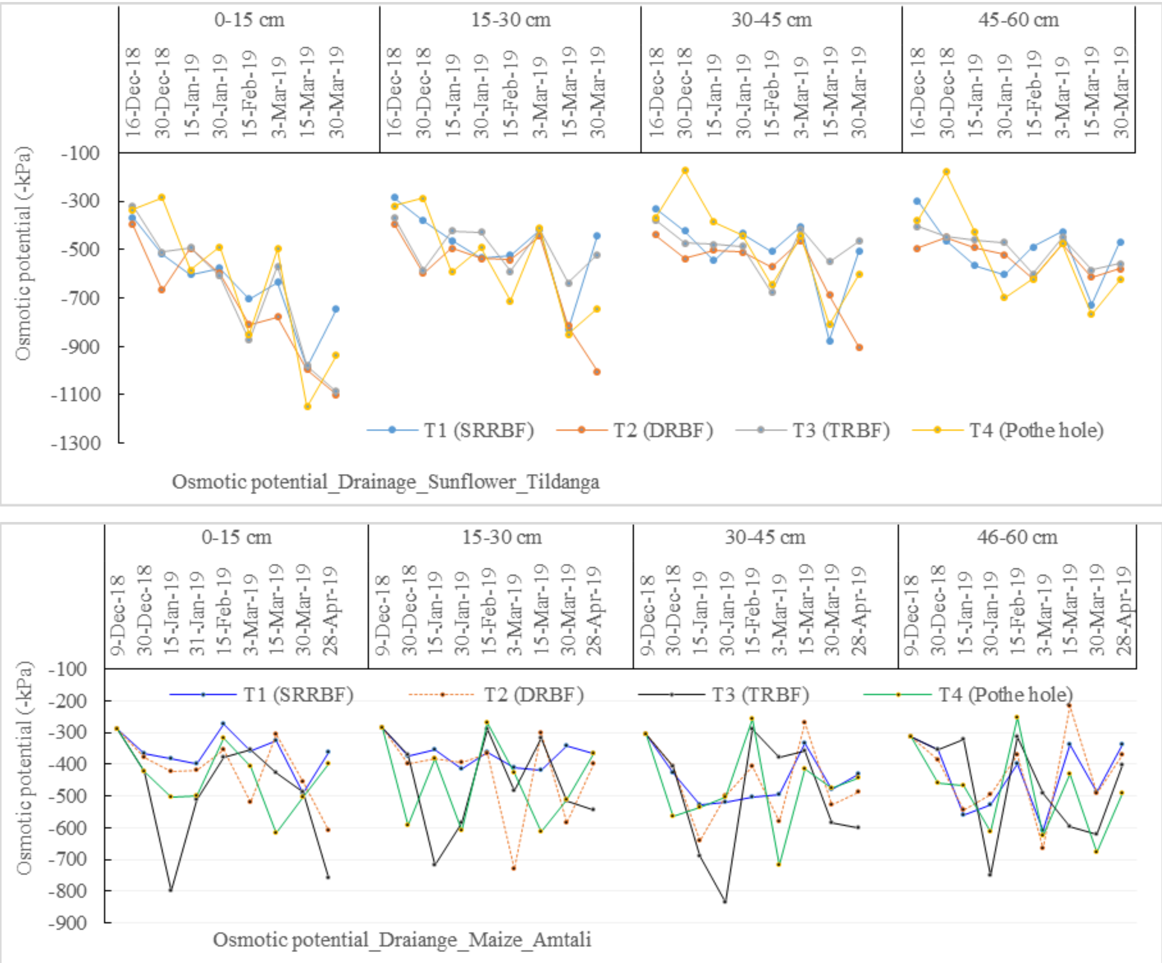


Fig. 5. The effect of the surface drainage treatments on osmotic potential at Tildanga and Amtali during 2018-2019.

On average, the osmotic potential was found around -200 to -1100 kPa at Tildanga and -200 to -800 kPa at Amtali during the growing season from December 2018 to April 2019. The lower osmotic potential was observed in the treatment of T_1 with single row raised bed planting. The results indicated that osmotic potential (-kPa) have no influences in limiting crop production. The higher osmotic pressure was found in mid growth stages of the maize. The results indicated that the osmotic pressure was substantially affected on plant growth and yield at mid and later growth stages of maize and sunflower because of insufficient soil moisture as well as lack of fresh irrigation water (low salinity) and more salt accumulation in the upper soil profiles.

Soil moisture content

The variations of soil moisture content in the soil profiles over 0-60 cm soil depth with 15 cm increaments during the growing season of maize and sunflower for each treatments is shown in Fig. 6. An increase or decrease soil moisture content was observed following irrigation or rainfall. The substantially larger raifall occurred waterlogged at tasseling/silking growth stages of maize at Amtali and flowering stages of sunflower at Tildanga, which affected the grain yield. Soil water contents substantially decreased in upper soil layers (0-15 cm) at later growth stages which affected the crop growth (Fig. 6). The SWC was found greater in treatment of T_1 (single row raised bed with 30 cm drain) than treatments. The figures indicate that soil moisture decreased or increased during the growing season, but plants extractable available soil water was not drasticaly reduced at initial growth stages of crops. This stress condition occurred at later growth stages of because of insufficieny fresh water (low saline) in both locations of the project sites.

Fig. 6. The effect of the surface drainage treatments on soil moisture content at Tildanga and Amtali during 2018-2019.

Conclusions

In coastal heavy soils, the results indicate that the surface drainage system of single row raised bed with 30 cm drain resulted in higher maize yields and three row raised bed with 40 cm drain resulted in better sunflower yields as well as improving soil environment.

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EFFECT OF DRIP IRRIGATION SYSTEM FOR VEGETABLES CULTIVATION IN SALT AFFECTED AREAS OF BANGLADESH

M.A. Hossain[1], K.K. Sarker[2], and S.S.A. Kamar[3]

Abstract

Drip irrigation with mulch has the potential to increase yield with less applied water and fertilizer and controlled salinity by leaching salts from the root zone of the plant. Therefore, two field experiments on drip irrigation system with straw mulch were carried out for the cultivation of vegetables at the project sites of Amtali and Tildanga in coastal saline soils irrigated with low/medium saline water. The specific objectives of this study were (i) to assess the performance of drip irrigation system for vegetables, and (ii) to introduce and transfer the drip irrigation technology among the farmers. The results indicate that the growth of watermelon was observed favourable at the salt-affected area of Dacope but watermelon plants were damaged due to heavy rainfall. Except cauliflower and cabbage, all other vegetables were damaged. However, drip irrigation system may have the opportunity to cultivated the high value crops to irrigation with low/medium saline water in coastal regions of Bangladesh.

Introduction

High value crops production are increasing every year as farmers are getting good returns in coastal areas of Bangladesh. Generally, it is grown in Chattagram, Kumilla, Jashore, Faridpur, Rajshahi, Pabna and Natore districts. Recently, commercially cultivation has also taken place in the coastal zone of Bangladesh. Crops yield in the coastal region is less than that of other areas of Bangladesh. High yielding variety, soil, climate, fertilization, irrigation and other management practices are important for achieving higher yield. Appropriate water management could be used in production systems to reduce soil salinization and maintain crop productivity. Some crops like as watermelon is a shallow rooted crop and requires proper irrigation for maximum yield. Over watering may result in rotting roots or even death of plants and decreased sugar content of the fruits. On the other hand, insufficient irrigation leads to water stress and decrease the productivity. Watermelon requires frequent irrigation. The choice of irrigation method is very important for saline water irrigation. Drip irrigation is a suitable practice to high value crop production systems for irrigation with saline water in coastal regions of Bangladesh. The hypothesis is that drip irrigation could be used to reduce the amount of water to irrigate crops with high water demand of watermelon with mulching the soil, which preserves soil moisture by minimizing evaporation, and reduces soil salinity. For this reason, a field experiment was carried out to identify the better irrigation methods with straw mulching for the cultivation of vegetables in coastal saline soils irrigated with low/moderate saline water. The specific objectives were (i) to assess the performance of drip irrigation system for vegetables, and (ii) to introduce and transfer the drip irrigation technology among the farmers.

Material and Methods

Two field experiments were laid out in a randomized complete block design with drip irrigation system for high value crops like as, tomato, watermelon, cauliflower, cabbage, brinjal and chilli etc. The drip irrigation system was installed of a solar pump with a 130W solar panel capacity supply to 500 litres storage tank for drip irrigation system (204 square meter: 5 decimal) for high value crops like tomato, watermelon, brinjal, chilli, cabbage, cauliflower etc into a pump and then into a holding tank via filters. The drip irrigation system was consisted as a network of a tank (500 litre), disk type filter, one sub main pipe (¾″ dia), sub lateral pipe (½″ dia), and emitters (emitter/each plant). A water tank (500 litres) was set at 2 m height above the ground maintained

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by manually or solar powered system. The treatments were (i) drip irrigation at 3-5 days intervals with straw mulch and conventional/farmers' practices. Local hybrid of cauliflower, cabbage, chilli, watermelon and BARI tomato-14 were planted on 17 December 2018. Total plot size was 5 decimal at each location. Recommended fertilizer doses were used. The N and K were applied into four equal splits at 15, 30, 45 and 60 DAE using drip-fertigation.

Different vegetables cultivation under drip irrigation system at Amtali during 2018-2019

Fig. 1. Effect of drip irrigation system for vegetables cultivation in salt affected area of Amtali and during 2018-2019.

Different vegetables cultivation under drip irrigation system at Tildanga, Dacope during 2018-2019. All vegetables are damaged due to heavy rainfall during February 2019

Fig. 2. Effect of drip irrigation system for vegetables cultivation in salt affected area of Tildanga, Dacope during 2018-2019.

Results and Discussion

Yield of vegetables

Yield of vegetables under the drip irrigation at the salt affected area of Dacope and Amtali is shown in Table 1. Except cauliflower and cabbage, all other vegetables were damaged. The results indicate that drip irrigation system may have opportunity to cultivate the advantage of the cauliflower and cabbage and to some extend to watermelon. The growth of watermelon was observed favourable at the salt-affected area of Tildanga, Dacope but watermelon plants were damaged due to heavy rainfall (Table 1 and Fig. 1).

Table 1. Effect of drip irrigation system for vegetables cultivation in salt affected areas of Amtali and Dacope during 2018-2019

Crop under drip irrigation system	Location	Mean unit weight, g	Total yield weight, t/ha	Unit price, TK	Total price, Tk
Cauliflower	Amtali	330	12	10	700
Cabbage	Amtali	261	6	5	223
others	Amtali	-			
All crops	Tildanga, Dacope	Damaged due to heavy rain			

Watermelon using solar powered drip irrigation

The adaptation of solar powered drip irrigation for watermelon at the salt affected area of Tildanga, Dacope was taken in 2020. The number of fruit and unit fruit weight were better this year using drip irrigation at 3-5 days interval than local farmers' practices. Drip irrigation system produced watermelon by 26.23 t/ha. It reflects the interest of the local farmers for cultivation watermelon. The unit fruit per plant and unit weight per fruit were 2.36 and 4.5 kg, respectively

(Fig. 3). The local price was Tk 15 per one kg of watermelon. The price was low due to the epidemic of COVID-19. The perception and assessment of this techniques may strength on the basis of production of watermelon in future. The results indicates that drip irrigation with the less amount of irrigation water may take the advantage of the physiological response which can maintained greater size as well as yield of watermelon as compared to traditional farmers' practice.

Fig 3. Drip irrigation system for watermelon at salt affected area of Dacope in 2020.

Conclusions

Drip irrigation system may have the opportunity to cultivate the high value crop like watermelon to irrigation with low saline water in coastal regions of Bangladesh.

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MULTI-STEP AHEAD PREDICTION OF GROUNDWATER LEVEL FLUCTUATIONS USING COUPLED WAVELET TRANSFORM AND LONG SHORT-TERM MEMORY NETWORKS

D.K. Roy[1], S.K. Biswas[1], and K.F.I Murad[2]

Abstract

Groundwater level prediction is important for sustainable usage of scarce groundwater reserves of an aquifer to ensure the development of a meaningful groundwater abstraction management strategy. This study evaluated the prediction accuracy and estimation capability of a deep learning algorithm, Long-Short Term Memory (LSTM) network, for multi-step forward forecast of groundwater levels at two observation wells in an aquifer system of the Gazipur Sadar Upazilla, Bangladesh. Model independent partial autocorrelation functions-based feature selection approach was used to recognize appropriate input variables for the prediction models. Root Mean Squared Error (RMSE) criterion was used to calculate the training and test performance of the LSTM models to select the appropriate numbers of hidden layers and hidden neurons within each hidden layer. The prediction accuracy of LSTM network was evaluated using five statistical performance evaluation indices: RMSE, Scatter Index, Maximum Absolute Error, Median Absolute Deviation, and a-20 index. Results revealed that the developed LSTM models were capable of predicting one-, two-, and three-week ahead groundwater levels at the observation wells GT3330001 and GT3330002. In general, the prediction performances of the LSTM models at GT3330001 were better than those at GT3330002. The overall results indicate that the proposed LSTM models could be successfully employed to predict multi-step ahead groundwater levels using previous lagged groundwater levels as inputs. For improving prediction accuracy, wavelet transform based data pre-processing may be adopted.

Introduction

Groundwater aquifers are considered to be the vital sources of world's potable water supplies, and takes the part of an essential role in the sustainability of irrigated agriculture; domestic and industrial water supplies in areas where good quality surface water is inadequate. Human pressure due to population growth, increasing water demand to different sectors and a changing climate have created an enhanced pressure to groundwater resources, and as a consequence, groundwater systems are coming across a rapid degradation. Although human intervention such as over-pumping is considered to be the prime indicator of groundwater level declination, climate change as evidenced by the recent projections, have indicated that the situation will become even worst earlier than was anticipated (Wada and Bierkens, 2014). Excessive abstraction of groundwater resources leads to continuous depletion and variable fluctuations of groundwater level causing a variety of problems such as lowering of the suction heads of pumps, reduction of crop yields due to inadequate irrigation water supplies, decrease in potable water supplies to domestic and industrial purposes, and degradation of water quality, among others. Like many areas in the world, groundwater is the most important usable form of water reserves in Bangladesh, where approximately 80% of the total population depends primarily on the groundwater reserves for their water needs (Hoque and Adhikary, 2020). Therefore, proper management and sustainable utilization of the scanty groundwater reserves in the aquifer in an efficient manner are imperative to secure continuous supplies of groundwater for the future generations. Accurate prediction and forecasting the future scenarios of groundwater level fluctuations may aid in developing such a meaningful groundwater management strategy.

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Numerical simulation models of groundwater flow processes have traditionally been applied in groundwater hydrology to better understand the underlying system processes while predicting the future scenarios of groundwater levels (Doble et al., 2017; Masterson and Garabedian, 2007; Park and Parker, 2008). However, predicting groundwater levels using these physically-based models requires detail understanding of the aquifer properties, as well as expertise and in-depth knowledge of the modeler about the aquifer geometry and modelling techniques. It is often difficult to obtain relevant and good quality data on aquifer properties and on other appropriate prerequisites, i.e. model 'initial and boundary conditions' required for the development of physically-based models. Sometimes unavailable data are substituted by assumptions made on the data based on the prior knowledge of the modeler regarding the model domain. These assumptions and estimations may lead to difficulties in the calibration and validation processes, which are very important in employing the developed model in the prediction purposes. To overcome these unavoidable complexities associated with physically-based numerical modelling approaches, data-driven prediction modelling approaches relying on the machine learning and artificial intelligence have been introduced and applied in hydrology (Fahimi et al., 2017; Govindaraju, 2000a, 2000b; Maier et al., 2010; Sadler et al., 2018; Yang et al., 2017). Data-driven modelling does not require an explicit definition of the parameters of the physical systems being modelled. In data-driven modelling approaches, a direct mapping or correlation between the predictors (inputs) and responses (outputs) of a model is established by way of an iterative learning method of a machine learning algorithm (Solomatine and Ostfeld, 2008). Artificial Neural Networks (ANN)-based data-driven prediction models have been found to be performed as good as or even better than the physically based simulation models in the field of prediction of nonlinear time series data, e.g. groundwater table data (Karandish and Šimůnek, 2016; Mohanty et al., 2013). As such, there have been a growing appreciation that data-driven approaches can be utilized as an alternative modelling approach for capturing nonlinear dynamics of the aquifer responses quite accurately (Adamowski and Chan, 2011; Daliakopoulos et al., 2005; Obergfell et al., 2019; Roshni et al., 2019).

Groundwater level prediction comes into play when it is an indispensable task to evaluate the dynamics of the groundwater system, i.e. how much groundwater is being abstracted from the aquifer system and how much is actually permitted to be abstracted. Adequately precise short- to medium-term groundwater level prediction aids in developing a sustainable and flexible management strategy in areas where climate change induced droughts or human induced over-pumping is a major driving force (Feng et al., 2008; Guzman et al., 2017; Sahoo et al., 2017). Therefore, prediction of groundwater levels has been an interesting topic in hydrological research niche and various data-driven modelling tools are progressively being employed because they require less amount of data and are simple to implement when weighed against traditional hydrogeological modelling approaches (Zhang et al., 2018). A number of approaches has recently been utilized in the research domain of groundwater level predictions. These include machine learning-based prediction modelling (Dong et al., 2018; Guzman et al., 2017; Mohanty et al., 2015; Sahoo et al., 2017), ANNs (Ghorbani et al., 2018; Lee et al., 2019), hybridized wavelet transform – machine learning methods (Adamowski and Chan, 2011; Barzegar et al., 2017; Peng et al., 2017; Raghavendra and Deka, 2015), hybridized ensemble empirical mode decomposition and machine learning-based models (Gong et al., 2018), nonlinear autoregressive with exogenous inputs (NARX) neural networks (Guzman et al., 2017), ARIMA-particle swarm optimization (Boubaker, 2017), ANN – whale algorithm (Banadkooki et al., 2020), integrated linear polynomial and nonlinear system identification models (Makungo and Odiyo, 2017), ANFIS (Nadiri et al., 2019; Nourani and Mousavi, 2016; Raghavendra and Deka, 2015; Wen et al., 2015; Zare and Koch, 2018), wavelet – ANFIS (Moosavi et al., 2013), Support Vector Machine (SVM) (Nadiri et al., 2019; Tang et al., 2019), hybrid SVM-PSO (Wei et al., 2020), Gaussian Process Regression (Raghavendra and Deka, 2015), Facebook's prophet approach of groundwater level forecasting (Aguilera et al., 2019), physics-inspired coupled space-time artificial neural networks (Ghaseminejad and Uddameri, 2020). A detailed review of artificial intelligence-based approaches in modelling groundwater levels is presented in Rajaee et al. (2019). It is clear that a number of different modelling approaches has been employed to predict groundwater level fluctuations with varying degrees of prediction accuracies. It is also evident that it is practically difficult, if not impossible to recommend a particular prediction model for a particular problem for predicting groundwater level fluctuations. Therefore, more advanced approaches of groundwater level prediction are still a requirement for boosting the prediction accuracies of groundwater level fluctuations.

Deep Learning (DL) has recently been recognized as a developed and sophisticated sub-domain of machine learning techniques in the arena of artificial intelligence. The DL-based modelling has gain popularity in the successful application to various domain of science including language processing (Plappert et al., 2018), image classification (Fan et al., 2019), computer vision (Fang et al., 2019), speech recognition (Cummins et al., 2018), and time series prediction (Tien Bui et al., 2020; Xu et al., 2019; Yang and Chen, 2019). The usage of DL has also been observed in developing prediction models in the research niche of groundwater level forecasting (Bowes et al., 2019; Supreetha et al., 2020), and prediction of short-term water quality variable (Barzegar et al., 2020). Recurrent Neural Network (RNN) models are able to preserve a memory of previous network states, and are better suited for predicting groundwater levels through modelling time series of groundwater table data observed at an observation well. For this reason, numerous recent studies related to groundwater modelling (Chang et al., 2016; Daliakopoulos et al., 2005; Guzman et al., 2017) have focused on the successful application of the RNNs. However, the standard RNN architectures cannot properly grab hold of the long-term reliance between variables (Bengio et al., 1994) due mainly to the occurrences of two problems: vanishing and exploding gradients. These are situations where the network weights either reach to zero or turn out to be enormously large during training of the network.

Long Short-Term Memory (LSTM) networks, a variant of typical RNN architectures, is capable of overcoming the training drawbacks (vanishing and exploding gradient problems) of RNNs through retaining valuable information for model development while avoiding unnecessary or redundant information being passed to the subsequent states in the model development process. LSTM has successfully been applied to the research arena of natural language processing, and financial time series prediction (Fischer and Krauss, 2018), traffic congestion and travelling period predictions (Zhao et al., 2017). In spite of wide applicability in various research domains, LSTM models has only recently been utilized for the forecast of hydrologic time series (Hu et al., 2018; Liang et al., 2018; Tian et al., 2018; Zhang et al., 2018). Recently, Jeong et al. (2020) applied LSTM-based modelling to estimate groundwater level using the corrupted data (with outliers and noise) and found that robust training of an LSTM model using a developed cost function ("least trimmed squares with asymmetric weighting and the Whittaker smoother") can adequately model noisy groundwater level data. The prediction ability of an LSTM network was found superior than that of a recurrent neural network in predicting hourly groundwater level values in a coastal city (susceptible to periodic flooding) of Norfolk, Virginia, USA (Bowes et al., 2019). Mouatadid et al. (2019) used a coupled "maximum overlap discrete wavelet transformation" and LSTM for achieving precision and robustness in the forecasting of irrigation flow. Zhang et al. (2018) proposed an LSTM network for predicting depths in water table in agrarian areas and obtained an acceptable prediction result by utilizing simply an uncomplicated data pre-processing technique. Based on their findings, one can argue that an LSTM network does not require a massive data smoothing or pre-processing in producing an acceptable prediction accuracy. The integrated use of gated recurrent unit and convolutional neural network (CNN-GRU) can also be found in recent literature (Pan et al., 2020) for developing water level prediction models in which CNN-GRU outperformed an LSTM model with regard to Nash-Sutcliffe (NS) Efficiency Coefficient, Average Relative Error, and Root Mean Squared Error. The prediction accuracy of a lion algorithm optimized LSTM network was found superior than an ordinary LSTM network for the prediction of groundwater level using the historical groundwater level data obtained from an observation well and rainfall data collected from a weather station located in the Udupi district, India (Supreetha et al., 2020). To the best of our knowledge, this study is the first effort of predicting multi-step ahead groundwater levels at the selected observation wells in the Gazipur Sadar Upazilla, Bangladesh.

Therefore, the key motivation and focus of this study are to delve into the potential of a DL-based prediction model, LSTM in predicting multi-step ahead groundwater level in the selected observation wells.

Materials and Methods

Study area and the data

The study area is situated in the Gazipur Sadar Upazilla having an aerial extent of 446.38 km^2. It is located between 23.88°N and 24.18°N latitudes and between 90.33°E and 92.50°E longitudes. Pumped groundwater appears to be the prime water resource for household usage and crop irrigation. Excessive abstraction of groundwater from the aquifer has been continuing at an increasing rate every year resulting in a gradual declination of groundwater level. To model future scenarios of groundwater table fluctuations in the selected observation wells, especially to provide multi-step ahead forecast of groundwater levels, previous data on groundwater level fluctuations were used in this research. For this, historical weekly data on groundwater level fluctuations were collected from Bangladesh Water Development Board. Collected data at different observation wells were carefully checked and two observation wells, namely GT3330001, and GT3330002 were selected based on the criterion of least amount of missing entries. The observation well GT83330001 is positioned between 23.93˚N latitude and 90.42˚E longitude. The position of the observation well GT3330002 is between 23.96˚N latitude and 90.48˚E longitude. The study area and the positions of the observation wells are shown in Figure 1.

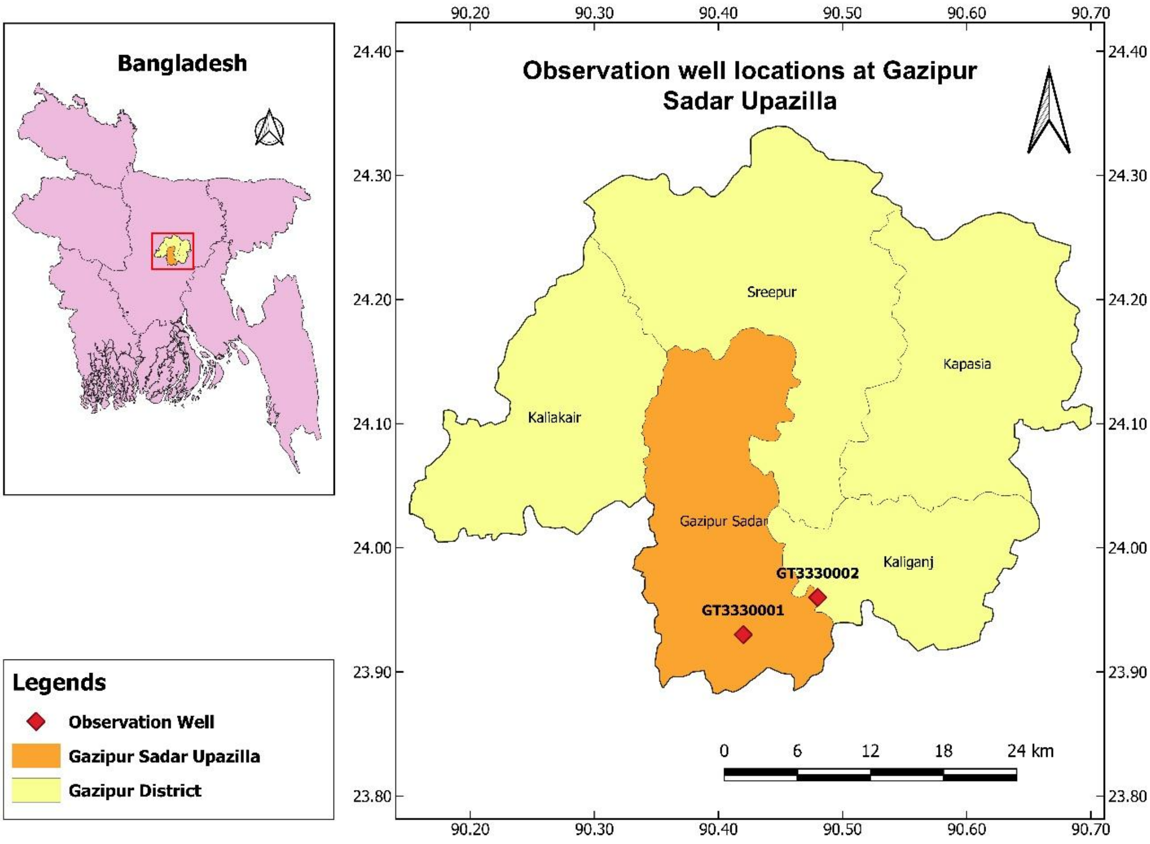
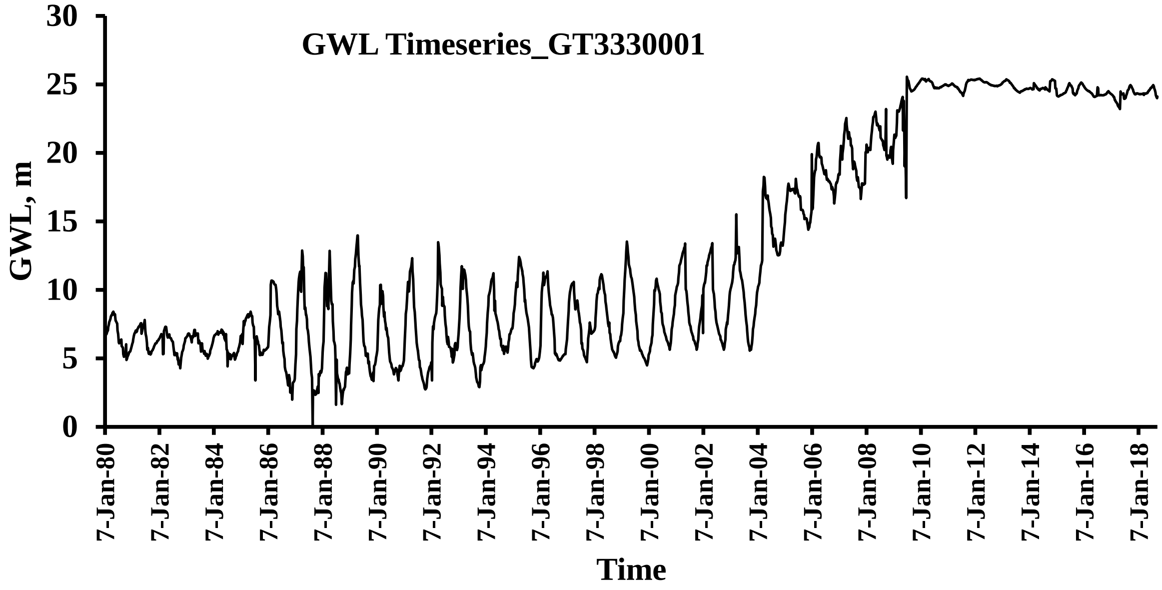


Figure 1. Study area and the locations of the two observation wells.

However, there were some missing values in the groundwater level datasets in the selected observation wells. These missing entries were imputed using the 'moving median' approach of data imputation in which a moving median with a specified window length was used to fill missing numeric data. The observation wells GT3330001 and GT3330002 had 2012 (from 07 January 1980 to 17 September 2018) and 1937 (07 January 1980 to 26 December 2016) weekly groundwater level entries after the imputation of missing entries. Timeseries plots of the groundwater levels at the two observation wells are presented in Figure 2.



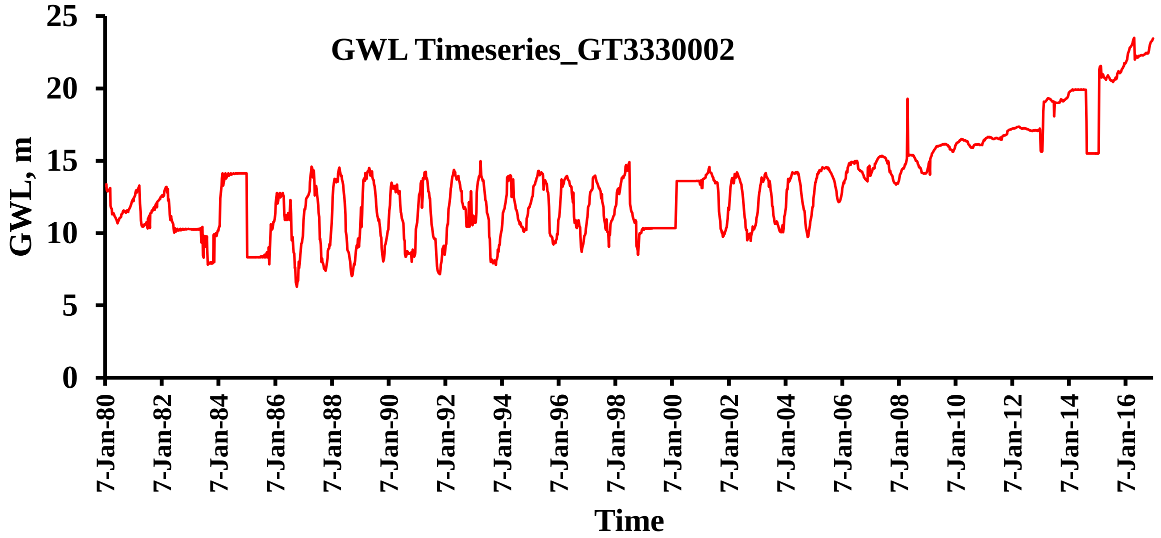


Figure 2. Groundwater level timeseries at the two observation wells GT3330001 and GT3330002.

Table-1 presents few descriptive statistics of the datasets (after imputation of the missing entries) at the selected observation wells. Table 1 reveals that the mean values of groundwater level data range between 12.96 m (at GT3330001) and 13.26 m (at GT3330002) whereas the standard deviation values vary between 3.39 m (at GT3330002) and 7.92 m (at GT3330001). The data at both observation wells possess a longer right tail than the left tail in their distribution as evidenced by the positive (right) skewness values (Table 1). The datasets at observation well GT3330001 showed 'light-tailed' distributions because the kurtosis value was negative at this observation well. On the other hand, the datasets at observation well GT3330002 showed 'heavy-tailed' distributions because the kurtosis value was positive.

Table-1. Measures of the statistical parameter values for the groundwater level data (m) at the observation wells

Obs. wells	Min	Max	Mean	Median	STD	Skewness	Kurtosis
GT3330001	0.10	25.57	12.96	9.83	7.92	0.50	-1.39
GT3330002	6.30	23.50	13.26	13.26	3.39	0.74	0.44

Selection of input variables

The most significant as well as the pertinent aspect in creating machine learning-based prediction models should be the selection of suitable input variables from a list of candidate input variables which may enhance the prediction capability of models. As there exists no explicit approach of determining model inputs for data-driven modelling applications (Deo et al., 2017), several methods were adopted and applied in previous studies by various researchers. It is also noted that useful input variable selection approaches are non-unique and different techniques may result in different combinations of important input variables (Ghaseminejad and Uddameri, 2020). This study adopts preselected lags using PACF for determining the most significant input variables for the multi-step ahead groundwater level predictions.

Partial autocorrelations (PACF)

PACF approach have been utilized to evaluate the patterns that exist in the collected groundwater level data and to perform an initial selection of significant inputs from the groundwater level lags for multi-step (one-, two-, and three-week) ahead groundwater level forecasting. Suppose, $\mathrm{GL_t}$ $(t = 1,2,3,\dots,n)$ denotes the response (output or target variable) and $\mathrm{GL_{t(-1,-2,-3,\dots,-k)}}$ represents the corresponding input variables. If the values of PACF at lags larger than k are within the 95% confidence band, then the input variables to be selected are $\left[-1.96/\sqrt{n}, 1.96/\sqrt{n}\right], \mathrm{GL_{t-1}}, \mathrm{GL_{t-2}}, \mathrm{GL_{t-3}}, \dots, \mathrm{GL_{t-k}}$, respectively. In situations when all the PACF values lie inside the 95% confidence band, the input variables need to be selected with respect to a ‘trial and error’ method through a systematic increment of the numeral of the sequential data (Peng et al., 2017). The following steps (Wang and Zhao, 2009) were followed in calculating the PACF values of the output variable $\mathrm{GL_t}$ $(t = 1,2,3,\dots,n)$:

- **Step 1:** Calculation of the covariance at lag k (γ_k):

$$\gamma_k = \frac{1}{n}\sum_{i=1}^{n-k}(GL_i - \overline{GL}) * (GL_{i+k} - \overline{GL}), k = 0, 1, 2, \dots, M \quad (1)$$

- **Step 2:** Calculation of the autocorrelation coefficient at lag k (ρ_k):

$$\rho_k = \frac{\gamma_k}{\gamma_0}, \qquad \text{where}, \gamma_0 \text{ represents the variance} \quad (2)$$

- **Step 3:** Calculation of the partial autocorrelation coefficient at lag k (α_{kk}):

$$\alpha_{11} = \rho_1$$

$$\alpha_{k+1,k+1} = \frac{\rho_{k+1} - \sum_{k=1}^{k}\rho_{k+1-j}\alpha_{kj}}{1 - \sum_{j=1}^{k}\rho_j\alpha_{kj}} \quad (3)$$

$$\alpha_{k+1,j} = \alpha_{kj} - \alpha_{k+1,k+1}.\alpha_{k,k-j+1}(j = 1,2,3,\dots,k)$$

PACF functions at the selected observation wells were determined to acquire time-lagged statistics from the weekly time series data of groundwater levels (GL). This time-lagged information is used to evaluate the temporal dependencies between GL for a current week ($\mathrm{GL_t}$)

and the GLs at a certain point in an earlier period (i.e. a time lag of $GL_{t-1}, GL_{t-2}, GL_{t-3}, GL_{t-4}$, and GL_{t-5}, etc.). These temporal reliance in the GL time series at the observation wells are evaluated for 50 lags (i.e., from GL_{t-1} to GL_{t-50}) as depicted in Figure 3. In Figure 3, the 95% confidence band is indicated by the blue lines. The relevant inputs and outputs of the prediction models for the GL time series were determined based on the information presented in Figure 3.

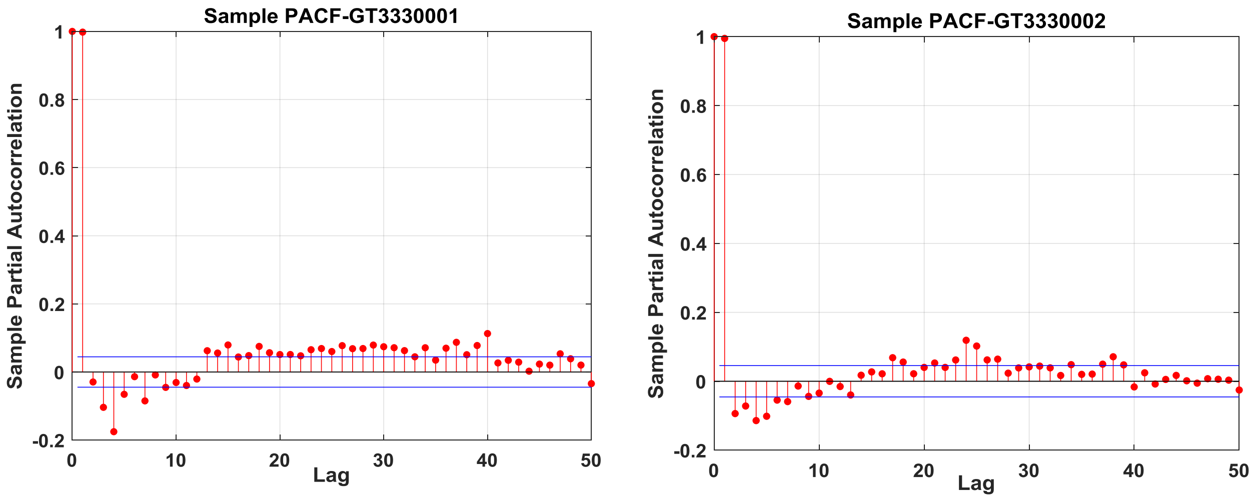


Figure 3. Sample autocorrelation functions for 50 lags.

Based on the sample PACF, the number of input variables selected were 27 and 17 at observation wells GT3330001 and GT3330002, respectively. The input groundwater level lags determined based on the PACF criterion for the observation well GT3330001 included:

$GL_t, GL_{t-1}, GL_{t-3}, GL_{t-4}, GL_{t-5}, GL_{t-7}, GL_{t-13}, GL_{t-14}, GL_{t-15}, GL_{t-18}, GL_{t-19}, GL_{t-23}, GL_{t-24}, GL_{t-25}, GL_{t-26}, GL_{t-27}, GL_{t-28}, GL_{t-29}, GL_{t-30}, GL_{t-31}, GL_{t-32}, GL_{t-34}, GL_{t-36}, GL_{t-37}, GL_{t-39}, GL_{t-40}, GL_{t-47}$

Input variables identified by PACF criterion at GT3330002 were:

$GL_t, GL_{t-1},, GL_{t-2}, GL_{t-3}, GL_{t-4}, GL_{t-5}, GL_{t-6}, GL_{t-7}, GL_{t-17}, GL_{t-18}, GL_{t-21}, GL_{t-23}, GL_{t-24}, GL_{t-25}, GL_{t-26}, GL_{t-27}$, and GL_{t-38}

Standardization of input variables

To eliminate the adverse influence of dimensionality of the data, standardization was performed using the *Z*-Score method (Mathworks, 2020a) in order to scale the data with zero mean and unity standard deviation. For a random variable X with mean μ and standard deviation σ, the z-score of a given value x is given by:

$$z = \frac{(x - \mu)}{\sigma} \tag{4}$$

The z-score of a data point x for the sample data with mean $\bar{X}$ and standard deviation S can be represented by:

$$z = \frac{(x - \bar{X})}{S} \tag{5}$$

The z-score values quantify the distance of a certain data point from the mean in regard to the standard deviation of the dataset. The standardized data thus obtained has the mean value (μ) of 0 and the standard deviation (σ) value of 1. It is also noted that the standardized data holds the shape properties of the actual data, i.e. the standardized data has the same skewness and kurtosis values as the actual data.

Long-Short Term Memory (LSTM) networks

An LSTM neural network is a variant of and improved version of RNNs that is capable of learning long-term reliance amongst the time-steps of a ‘sequence data’. LSTMs are especially suitable for predicting sequence data because they address vanishing and exploding gradient problems of standard RNNs through integrating gating functions and state dynamics (Hochreiter and Schmidhuber, 1997). The architecture of the LSTM network consists of numerous memory blocks linked together through layers, every one of which contains numerous recurrently linked memory cells. An LSTM memory cell comprises of three multiplicative components referred to as gates – such gates are the forget, input, and output gates (Yuan et al., 2018). The major components of a basic LSTM network consist of a sequence input layer that is employed to input a sequence (time series data) to the LSTM network, and an LSTM layer that is used for learning long-term reliance among the time-steps of a sequence (time series) data. To solve a simple regression problem, an LSTM network is comprised of four layers: the network begins with a sequence input layer after that an LSTM layer while the network closes with a completely connected layer followed by a regression output layer. This simple LSTM network can be represented graphically as Figure 4.

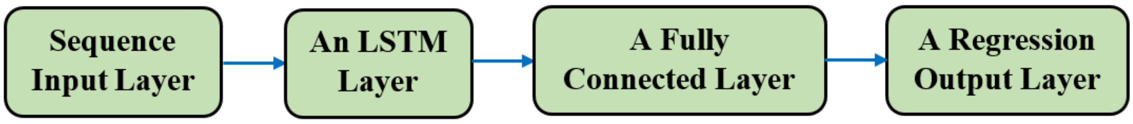


Figure 4. A basic LSTM network architecture for regression problems.

A more complex and deeper LSTM network is created by adding extra LSTM layers into the network. Dropout layers are often inserted right after each additional LSTM layers in order to prevent model overfitting. An LSTM layer architecture illustrating the flow of a time series X having C features (channels) of length S is presented in Figure 5.

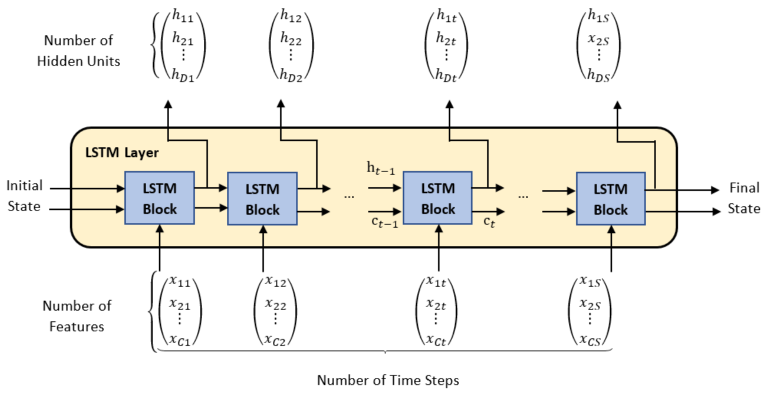


Figure 5. An LSTM layer architecture (Mathworks, 2020b). Here, the cell state and the output (concealed state) at the time step t are denoted by $\mathbf{c}_t$ and $\mathbf{h}_t$, respectively.

The starting LSTM block utilize the networks’ initial state and the starting time-step of the sequence to calculate the first output and the modified cell state. In order to calculate tth time step’s output and the modified cell state $\mathbf{c}_t$, the block employs the networks’ present state $(\mathbf{c}_{t-1}, \mathbf{h}_{t-1})$ and the following time phase of a sequence. There are two types of states in a layer, namely hidden state (also referred to as an output state) and cell state. The purpose of the hidden state is to contain output of an LSTM layer for any particular time step t whereas the cell state stores the evidence acquired from the prior time phases. For every single time phase, an LSTM layer either puts in evidences to or takes away evidences from the cell state. The gates are used as the controlling components of these modifications for any particular LSTM layer. The following four components are employed to regulate the cell and hidden states of an LSTM layer:

a. Input gate (i): Control level of cell state update;
b. Forget gate (f): Control level of cell state reset (forget);
c. Cell candidate (g): Put in information to the cell state;
d. Output gate (o): Control level of cell state added to hidden state.

Figure 6 depicts the mechanism by which the gates forget, update, and produce output of the cell and hidden states.

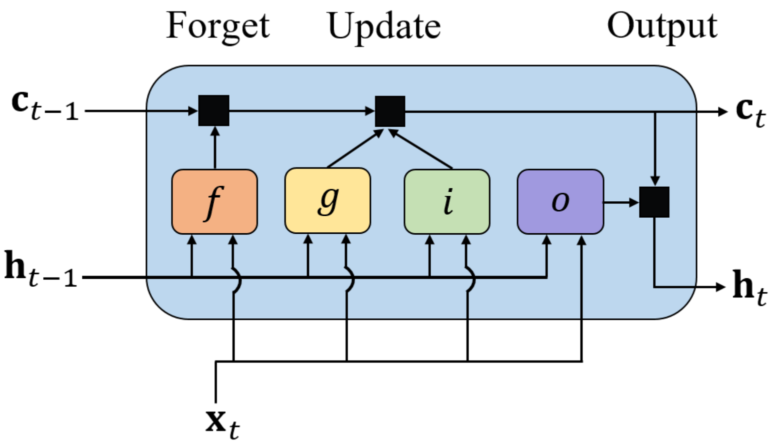


Figure 6. Illustration of the data flow at the time step t.

An LSTM layer has three adjustable parameters, namely the input weights (W), recurrent weights (R), and the bias (b). The matrices of W, R, and b are considered as the concatenations of the input – output weights, and the biases of each component, respectively. The matrices of W, R, and b are concatenated using the following mathematical forms:

$$W = \begin{bmatrix} W_i \\ W_f \\ W_g \\ W_o \end{bmatrix}, R = \begin{bmatrix} R_i \\ R_f \\ R_g \\ R_o \end{bmatrix}, b = \begin{bmatrix} b_i \\ b_f \\ b_g \\ b_o \end{bmatrix}, \tag{6}$$

where, i denote the input gate, f represents the forget gate, g depicts the cell candidate, and o indicate the output gate.

The cell and hidden states at any particular time step t is represented by the following two equations:

$$\mathbf{c}_t = f_t \odot \mathbf{c}_{t-1} + i_t \odot g_t \tag{7}$$

$$\mathbf{h}_t = o_t \odot \sigma_c(\mathbf{c}_t) \tag{8}$$

where, $\odot$ refers to the Hadamard product (also known as the element-wise multiplication of vectors), σ_c symbolizes the 'state activation function'. This 'state activation function' is generally calculated using the hyperbolic tangent function ($\tan h$) (Mathworks, 2020b).

Each of the components of an LSTM layer (input gate (i_t), forget gate (f_t), cell candidate (g_t), and output gate (o_t)) at time step t are described by the following equations:

$$i_t = \sigma_g(W_i\mathbf{x}_t + \mathrm{R}_i\mathbf{h}_{t-1} + b_i) \tag{9}$$

$$f_t = \sigma_g\left(W_f\mathbf{x}_t + \mathrm{R}_f\mathbf{h}_{t-1} + b_f\right) \tag{10}$$

$$g_t = \sigma_c\left(W_g\mathbf{x}_t + \mathrm{R}_g\mathbf{h}_{t-1} + b_g\right) \tag{11}$$

$$o_t = \sigma_g(W_o\mathbf{x}_t + \mathrm{R}_o\mathbf{h}_{t-1} + b_o) \tag{12}$$

where, σ_g designates the gate activation function. A sigmoid function is usually employed to compute σ_g. The sigmoid function can be represented by the following equation:

$$\sigma(x) = (1 + e^{-x})^{-1} \quad (13)$$

Results and Discussions

Training of the LSTM model

The LSTM architecture with multiple hidden units was employed in which the numbers of 'hidden neurons' were decided via conducting several trials through varying the number of 'hidden neurons' in each trial. The other parameters of the LSTM architecture were selected upon conducting several trials, and the optimum parameter sets are presented in Table-2. These optimum parameter values were used for developing the LSTM models for predicting one-, two-, and three-week ahead GWLs at the two observation wells.

Table-2. Optimum combinations of different training options

Options	Corresponding parameters or values
Optimization solver	'adam'
Maximum epochs	1000
Gradient threshold	1
Initial learning rate	0.001
Minimum batch size	150
Sequence length	1000

The entire dataset was separated into two distinct sets – training and testing samples: 80% of the data records was allocated for the training purpose and the left over 20% was allotted for testing of the developed LSTM models. The Root Mean Squared Error (RMSE) criterion was used to train and test the developed models. The RMSE values on the training and test dataset for different numbers of neurons are given in Table 3.

Table 3. Train and Test RMSE values for different combinations of hidden layers and hidden neurons

Hidden neurons	One week ahead prediction		Two weeks ahead prediction		Three weeks ahead prediction	
	Train RMSE, m	Test RMSE, m	Train RMSE, m	Test RMSE, m	Train RMSE, m	Test RMSE, m
GT3330001						
100-50-20	0.454	1.556	0.524	1.257	0.524	1.065
140-120-60	0.620	24.792	1.990	3.651	2.116	24.377
150-100-50	0.666	0.907	**0.885**	**0.910**	**0.915**	**0.975**
160-120-60	0.524	1.913	0.698	5.347	0.899	1.977
180-150-80	**0.737**	**0.827**	0.558	1.220	0.728	1.525
170-140-70	0.403	0.856	0.440	1.536	0.801	22.043
80-60-30	0.784	1.633	0.506	1.012	0.561	0.904
80-60-40-20	0.584	2.295	0.744	2.373	0.626	1.225
100-80-50-20	0.590	1.204	0.669	1.844	0.594	1.546
150-120-80-50	0.594	1.045	0.810	2.167	0.651	18.917
120-100-50-20	0.503	0.707	0.559	1.879	0.636	2.207
GT3330002						
100-50-20	0.339	3.581	0.384	4.115	0.403	13.402
140-120-60	0.913	20.048	**0.403**	**3.623**	0.329	4.081
150-100-50	0.405	18.878	0.546	18.326	1.192	20.412
160-120-60	0.503	17.781	0.537	16.172	1.588	17.441
180-150-80	0.918	18.528	0.657	19.094	0.558	20.288
170-140-70	0.371	16.873	0.493	16.909	0.427	16.389

80-60-30	0.392	4.170	0.383	3.897	0.419	3.815
80-60-40-20	0.426	3.871	0.607	4.781	0.522	3.994
100-80-50-20	0.718	3.925	0.489	3.853	**0.355**	**3.493**
150-120-80-50	**0.337**	**3.466**	0.528	18.194	0.462	19.203
120-100-50-20	0.363	3.480	0.395	3.660	0.434	13.992

It is observed from Table-3 that at GT3330001, the minimum values of the absolute difference between the training and test RMSE were 0.09 (hidden neurons: 180-150-80), 0.03 (hidden neurons: 150-100-50), and 0.06 (hidden neurons: 150-100-50) for one-, two-, and three-week ahead predictions, respectively. On the other hand, at GT3330002, these values were 3.13 (hidden neurons: 150-120-80-50), 3.22 (hidden neurons: 140-120-60), and 3.14 (hidden neurons: 100-80-50-20) for one-, two-, and three-week ahead predictions, respectively. Therefore, the LSTM models with these hidden neurons were selected as the best performing models over others. A set of several statistical performance evaluation indices were then calculated based on this result. The performance evaluation indices were computed on test datasets using the selected LSTM models for the one-, two-, and three-week ahead predictions of groundwater levels. Other than RMSE, scatter index, MAE, MAD, and a-20 index were calculated to evaluate the performances of the LSTM models at the two observation wells. The results are presented in Table-4. It is observed from Table-4 that the performances of the LSTM models for multi-step ahead predictions at GT3330001 were in general better than the performances of the LSTM models developed at GT3330002. However, at both observation wells, the developed LSTM models provided acceptable results.

Table-4. One-, two-, and three-week ahead prediction performance of the developed LSTM model on test dataset

	Performance evaluation indices				
	RMSE, m	Scatter index	MAE, m	MAD, m	a-20 index
GT3330001					
One-week ahead	0.827	0.034	12.480	0.179	0.997
Two-weeks ahead	0.910	0.037	10.237	0.319	0.997
Three-weeks ahead	0.975	0.040	10.754	0.405	0.997
GT3330002					
One-week ahead	3.466	0.188	7.561	1.200	0.589
Two-weeks ahead	3.623	0.196	7.727	1.326	0.531
Three-weeks ahead	3.493	0.189	7.393	1.327	0.573

Conclusions

Precise and robust prediction of groundwater levels can be effectively employed in developing a sustainable and efficient management strategy for groundwater resources. This judicial planning will aid in optimal abstraction and usage of groundwater for agricultural, domestic, and industrial purposes. This study aimed at developing a robust prediction tool for one-, two-, and three-week ahead groundwater level fluctuations using LSTM models. The suitable weekly lag times of groundwater levels were used as inputs to the prediction models while the output from the models was the one-, two-, and three-week ahead groundwater levels. The selection of optimal combination of inputs for the models was executed through careful examination of the PACF functions. The performance comparison of the proposed models was performed by using several statistical performance evaluation indices. Results of the present study indicated that LSTM models could be used to predict multi-step ahead groundwater level fluctuations. However, adopting wavelet-based data pre-processing step could be employed to improve the performance of the developed LSTM models. Therefore, this study should be continued to evaluate the effects of data pre-processing using wavelet transforms on the prediction performances of the proposed LSTM models.

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MONITORING OF GROUND WATER LEVEL AT DIFFERENT BARI STATIONS

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Abstract

This study was conducted at the research fields of Irrigation and water Management Division (IWM) and RARS, Rahmatpur, Barisasl of Bangladesh Agricultural Research Institute (BARI during 2019-2020. Two observation wells were installed at these two locations for regular monitoring of groundwater level fluctuations. In IWM Division research field, a boring depth of 210 ft. with a strainer length 20 ft. was found sufficient for the purpose of groundwater level monitoring. At RARS, Rahmatpur, Barishal, the boring depth was 860 ft with a strainer length of 20 ft It is noted that the boring depth and the strainer length depends on the underlying water bearing strata. The installation of observation wells at other stations is ongoing. The monitoring of groundwater level fluctuations in the installed observation well at IWM Division and RARS, Eahmatpr, Barishal has been continuing.

Introduction

Variations in water storage, including surface water, snow and ice, soil moisture, and groundwater, are essential for understanding a wide range of hydrologic, climatic, and ecologic processes and are important for water resources and agricultural management. Water scarcity is a global concern, with an estimated 1.1 billion people lacking access to clean water (Salman, 2005). Increasing demand for water requires more accurate information needed on water resources. While monitoring networks for precipitation and rivers exist in most regions, monitoring of subsurface water reservoirs (soil moisture and groundwater) is inadequate. However, groundwater represents a much larger fraction (~30%) of global fresh water resources than rivers (~0.006%) (Dingman, 2002). In addition, depletion of groundwater resources has increased substantially in the last several decades, particularly in places where groundwater- based irrigation has expanded (Scanlon et al., 2007). However, monitoring of groundwater storage in Bangladesh is extremely limited. Lack of information on groundwater storage changes inhibits development and execution of effective water management plans. Many countries with severe groundwater depletion problems have limited information on spatial and temporal variability in groundwater storage (Strassberg et al., 2009), as monitoring networks are generally limited and it is difficult to regionalize point-based measurements. To improve water resources management, it is critical to develop monitoring systems that provide accurate and timely information on the status of water reservoirs, including water in soil and aquifers. Therefore, an experiment was proposed with a view to meet the following objectives:

1) Installation of observation well at different BARI stations
2) Regular monitoring of groundwater level at 7 days' interval
3) To determine the depletion of groundwater level

Materials and Methods

The evaluation of groundwater issues and the implementation of management solutions require hydrogeological data that are in part 'baseline' and in part 'time-variant'. The collection of the 'time-variant component' (groundwater level monitoring, groundwater quality monitoring, water

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well abstraction monitoring (direct or indirect), well groundwater level variations, river flow gauging, meteorological observations and satellite land-use surveys) is what is usually considered ‘groundwater monitoring’. Groundwater monitoring thus comprises the collection, analysis and storage of a range of data on a regular basis according to specific objectives. The type and volume of data required will vary considerably with the management issue being addressed, but is also inevitably dependent upon available financial resources. At the heart of all groundwater investigation and monitoring are wells, of the two basic types indicated below. They represent keyholes to aquifers, which allow groundwater pressure and quality measurements to be made and thus furnish information from which the health of the aquifer system can be judged. When water wells are drilled, they provide one-off unique in-situ data on the groundwater resource and its variation with depth and data acquired during drilling (borehole logging) and initial test pumping form key baseline reference information on groundwater quantity and quality, in addition to their value for the determination of abstraction well potential. However, data collected from water wells once operational are normally more difficult to interpret, because groundwater levels are affected by the drawdown-recovery cycle and pumped-sample quality reflects the variable mixing of groundwater from a wide range of aquifer depths and residence times. The observation wells are dedicated monitoring stations, sited and designed to detect potential changes in groundwater flow and quality design parameters include selection of depth for the intake screen, frequency of measurement (if not continuous) and selection of quality parameters. To overcome the widespread presence of depth variation in hydraulic head and/or groundwater quality, nested piezometers or well clusters can be used. Piezometer nests are more cost effective than observation well clusters, but should only be used if proper sealing can be achieved to prevent vertical flow between their screens.

As part of the continuing work, one observation well was installed at the research field of IWM Division, BARI, Gazipur. The another one was installed at the research field of the RARS, Rahmatpur, Barishal. Ground water level fluctuation data at 7 days’ interval have been measuring since the installation of the observation wells.

Results

Installation of an observation well at IWM Division, Gazipur

An observation well was installed at the IWM experimental field, Joydebpur, Gazipur-1701 on January 08, 2020. The observation well is located between 23.99°N latitude and 90.41°E longitude. Aerial map of the study area with the location of the observation well is shown in Figure 1.

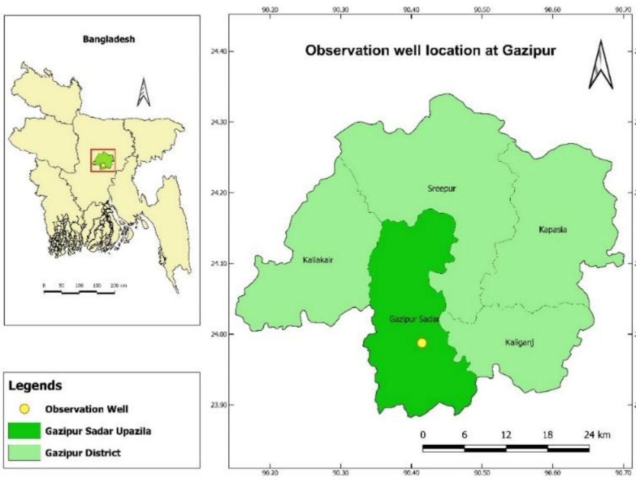

Figure 1. Aerial map and location of the observation well.

The position of the observation well within the IWM research field is presented in Figure 2.

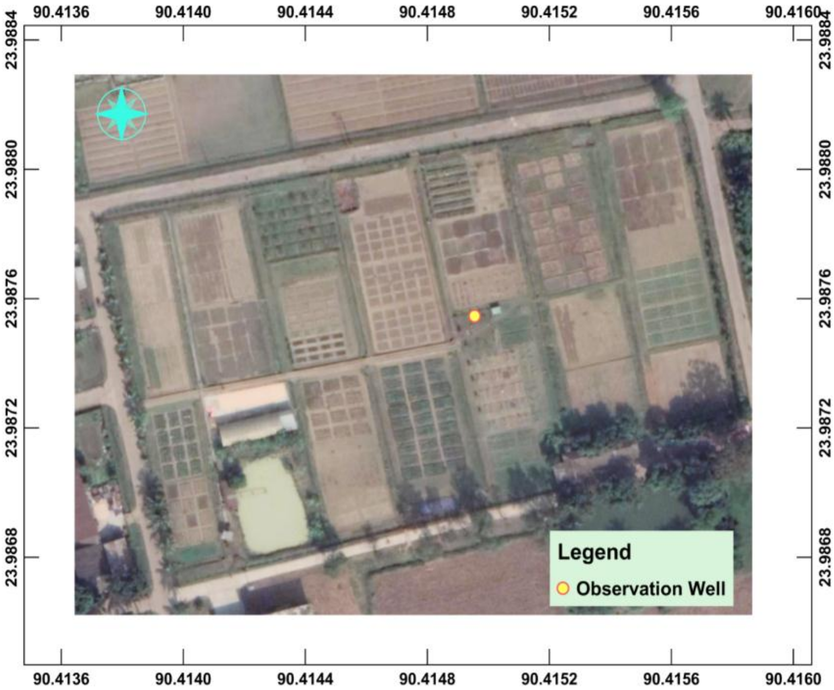

Figure 2. Position of the observation well in the IWM research field.

The installation depth was decided upon careful examination of the water bearing strata during the installation. As such, the depth of boring was 210 ft. including the blind pipe beneath the strainer (5 ft.). The strainer length was 20 ft. A schematic representation of the groundwater observation well is presented in Figure 3.

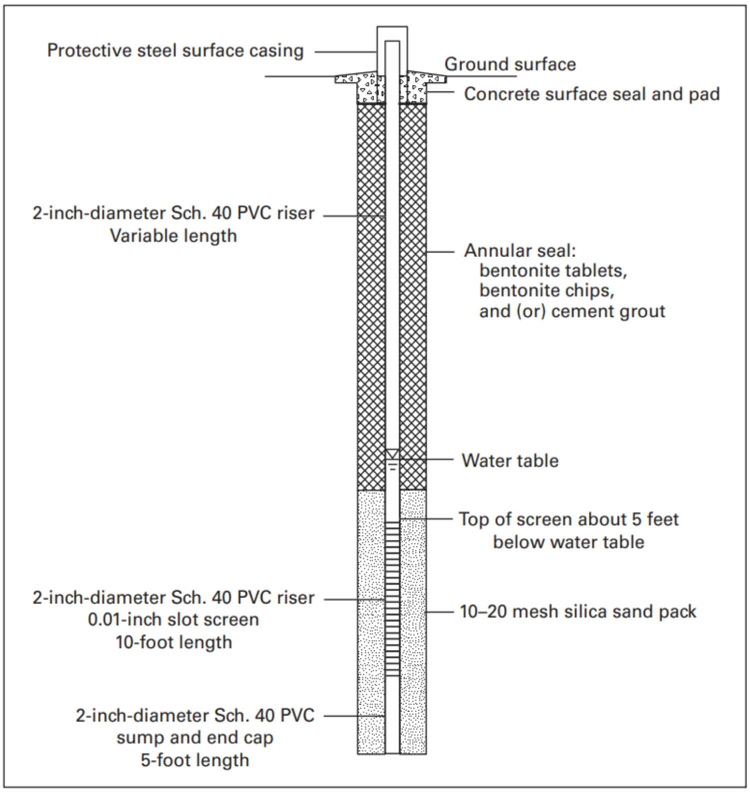

Figure 3. Schematic diagram of groundwater observation well.

After installation, regular monitoring of groundwater level fluctuations at 7 days' interval have been performing. The groundwater level fluctuations at IWM Division, BARI, Gazipur collected thus far are presented in Figure 4.

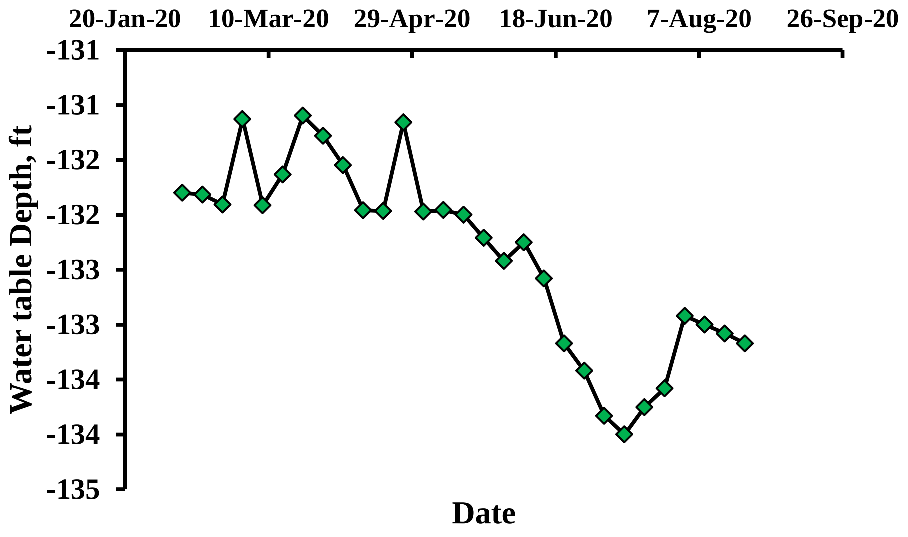

Figure 4. Groundwater level fluctuations during the monitoring period at IWM Division, Gazipur.

Installation of an observation well at RARS, Rahmatpur, Barishal

Another observation well was installed at the RARS, Rahmatpur, Barishal on February 25, 2020. The observation well is located between 22.79°N latitude and 90.29°E longitude. The installation depth was decided upon careful examination of the water bearing strata during the installation. As such, the depth of boring was 860 ft. including the blind pipe beneath the strainer (5 ft.). The strainer length was 20 ft. The measured water level fluctuations are presented in Figure 5.

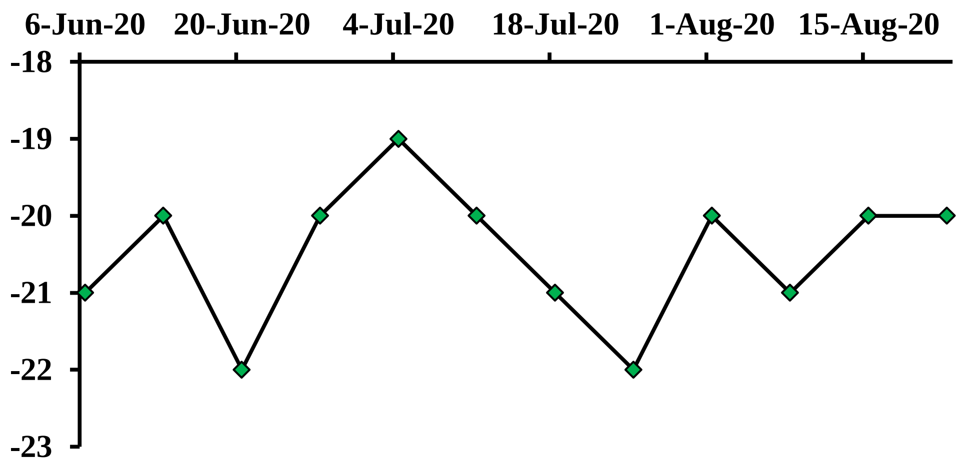

Figure 5. Groundwater level fluctuations during the monitoring period at RARS, Rahmatpur, Barishal.

Conclusions

Two observation wells, one at at IWM Division, BARI, Gazipur while the another one at RARS, Rahmatpur, Barishal were installed thus far. Therefore, the results presented in this report were based on these installed observation wells. The study should be continued for performing the installation of other observation wells at other BARI stations.

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EFFECTS OF FLOATING AGRICULTURE PRACTICE ON THE WATER BODY OF POND AND CANAL

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Abstract

This experiment was conducted at RARS, Rahmatpur, Barishal to determine the change of water quality of canals for cultivating fish and household uses and to determine the change of water quality of ponds for cultivating fish and household uses. The water samples were collected from three selected ponds of RARS, Rahmatpur, Barishal. The selected ponds were mentioned as FL-1 (Floating Agriculture practiced since 2015), FL-2 (Floating Agriculture practiced since 2018) and F (Fresh Pond). The water quality parameters were analyzed from TCL and Soil Lab, BRAC, Gazipur. It was not possible to collect water samples in the months of March, April and May due to lockdown. For all three ponds the water temperature was observed below 31^0C in all months which was good for fish cultivation. The pH level was found high (6.95-8.04) in the months of January and February, 2020 which was little harmful for carp fish cultivation. The pH level higher than 8.5 and lower than 5 is harmful for household uses. It was observed (Table-3) that the (UIA) Un Ionized Ammonia level at all selected ponds were suitable for channel catfish but not suitable for salmonid and craps. The total dissolved solids (TDS) were in desirable limit but in case of floating agriculture practice ponds (FL-1 and FL-2) the TDS level was found higher than fresh pond (F). The Ca levels were in affordable range for only channel fish cultivation (Table-5). The P values (Table-6) were good for plankton/shrimp production but the P value was crossed the limit in floating agriculture practiced ponds for other fish production. According to table-7, it was observed that the nitrate values in the month of January, February and June were in tolerable limit. But in the month of July the nitrate level is exceeding the limit of fish cultivation. Nitrate in excess of 45 mg/L (or in excess of 10 mg/L if reported as nitrate-nitrogen) is of health significance to pregnant women and infants under six months.

Introduction

The southern part of the country consists of coastal lowland and mangrove areas formed by the delta of large river systems. Bangladesh suffers from flooding almost every year to a small or large extent, and in the case of the years with small-scale flooding, the losses have not been assessed properly, but for those years with large-scale flooding, different institutes try to assess the loss from their perspective (Mirza and Ahmad 2005). In some parts of Bangladesh most affected by flood and where water remains for a prolonged period of time, farmers are using their submerged lands for crop production by adopting traditional methods which are similar to hydroponic agriculture practices, i.e. floating agriculture, whereby plants can be grown on the water in a bio-land or floating bed of water hyacinth, algae or other plant residues. The procedure of making the floating bed is usually the same, however the size, shape and local materials vary from region to region (Islam and Atkins 2007; APEIS 2004). The most commonly used material is water hyacinth, but topapana, son ghash, nollghash, wood ash, and dissected coconut fibers are also used (Islam and Atkins 2007: 131). Water hyacinth is utilized not only for the foundation of production system as floating beds during the monsoon season but also for compost especially during the winter cultivation on the ground. Because crops could absorb prime nutrients such as nitrogen, potassium and phosphorus from the floating beds and below water, there is almost no need for fertilizer input. This technique brings many ecological benefits, such as the good use of an

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invasive species like water hyacinth – a very effective way to control this notorious weed; platform residues can be used as organic fertilizer (this practice cuts pollution from chemical fertilizers).The water quality of the canals and ponds used for floating cultivation were going down day by day for decomposition of water hyacinth, topapana, son ghash, nollghash, wood ash and coconut fiber in large scale. So it is needed to analyze the water quality of that canals and ponds for fish cultivation and household use. Objectives of the experiment were given below

- To determine the change of water quality of canals for cultivating fish and household uses and;
- To determine the change of water quality of ponds for cultivating fish and household uses

Materials and Methods

The experimental water samples were collected from Regional Agricultural Research Station, Rahmatpur, Barishal. Three water samples were collected from three selected ponds of Regional Agricultural Research Station, Rahmatpur, Barishal. The two samples were collected from floating agriculture practice ponds and one sample was collected from a fresh pond. The treatments of the experiment were given below

FL-1 = Floating Agriculture Practice as well as fish culture since 2015
FL-2 = Floating Agriculture Practice as well as fish culture since 2018
F = Fresh Pond

The water quality parameters of the collected samples were analyzed at TLC and soil lab of BARDC, Gazipur. The water quality parameters were given below

1. Potassium (k)	2. Sodium (Na)	3. Phosphorus (P)	4. Ammonium (NH_4)	5. Nitrate (No_3)
6. Carbonate (CO_3)	7. Bicarbonate (HCO_3)	8. pH	9. Sulphur (S)	10. Calcium (Ca)
11. Magnesium (Mg)	12. BOD	13. COD	14. DO	

Results and Discussion

Fish do not like any kind of changes in their environment. Anita Bhatnagar and Pooja Devi (2013) stated that any changes add stress to the fish and the larger and faster the changes, the greater the stress. So the maintenance of all the factors becomes very essential for getting maximum yield in a fish pond. Good water quality is characterized by adequate oxygen, proper temperature, transparency, limited levels of metabolites and other environmental factors affecting fish culture. The initial studies of water quality of a fish pond in India were probably conducted by Sewell (1927) and Pruthi (1932). After that many workers have studied the physico-chemical condition of inland waters either in relation to fish mortality or as part of general hydrological survey (Alikunhi *et al*., 1952: Upadhyaya, 1964). The details of various pond ecosystems also have been studied by workers (Mumtazuddin *et al*., 1982: Delince, 1992: Garg and Bhatnagar, 1999: Bhatnagar, 2008). Bhatnagar and Singh (2010) studied the pond fish culture in relation to water quality in Haryana. However, this experiment would provide the basic guidelines, parameter wise for the fish farmers who are interested in floating agriculture practice as well as fish culture in a single pond via maintaining water quality of their ponds.

Temperature is defined as the degree of hotness or coldness in the body of a living organism either in water or on land (Lucinda and Martin, 1999). As fish is a cold blooded animal, its body temperature changes according to that of environment affecting its metabolism and physiology and ultimately affecting the production. Higher temperature increases the rate of bio-chemical activity of the micro biota, plant respiratory rate, and so increase in oxygen demand. It further cause decreased solubility of oxygen and also increased level of ammonia in water. According to Delince (1992) 30-35^0 C is tolerable to fish, Bhatnagar *et al.* (2004) suggested the levels of temperature as 28-32^{0}C good for tropical major carps; <12^{0}C – lethal but good for cold water species; 25-30^{0}C – ideal for *Penaeous monodon* culture; < 20^{0}C – sub lethal for growth and survival for fishes and > 35^{0}C- lethal to maximum number of fish species and according to

Santhosh and Singh (2007) suitable water temperature for carp culture is between 24 and 30^0C. For all selected ponds the average temperature was found < 33^0C. From table 1, it was observed that the temperature of all selected ponds was found good for fish cultivation.

Table-1. Month wise Temperature (^{0}C) values of different ponds

Ponds	January	February	March	April	May	June	July
FL-1	-	30.70	Due to Lockdown the data was not collected			30.40	30.50
FL-2	-	30.60				30.50	30.50
F	-	30.40				30.60	30.40

pH is measured mathematically by, the negative logarithm of hydrogen ions concentration. The pH of natural waters is greatly influenced by the concentration of carbon dioxide which is an acidic gas (Boyd, 1979). Fish have an average blood pH of 7.4, a little deviation from this value, generally between 7.0 to 8.5 is more optimum and conducive to fish life. pH between 7 to 8.5 is ideal for biological productivity, fishes can become stressed in water with a pH ranging from 4.0 to 6.5 and 9.0 to 11.0 and death is almost certain at a pH of less than 4.0 or greater than 11.0 (Ekubo and Abowei, 2011). According to Santhosh and Singh (2007) the suitable pH range for fish culture is between 6.7 and 9.5 and ideal pH level is between 7.5 and 8.5 and above and below this is stressful to the fishes. Ideally, an aquaculture pond should have a pH between 6.5 and 9 (Wurts and Durborow, 1992: Bhatnagar *et al*., 2004). From table 2, it could be stated that the pH range was within the limit of 6.5 to 9 in all ponds. A pH value higher than 8.5 indicates that a significant amount of sodium bicarbonate may be present in the water. So pH level higher than 8.5 and lower than 5 is harmful for household uses.

Table-2. Month wise pH values of different ponds

Ponds	January	February	March	April	May	June	July
FL-1	8.04	7.09	Due to Lockdown the data was not collected			6.68	6.78
FL-2	8.02	7.13				6.82	6.80
F	8.00	6.95				6.98	6.66

Ammonia is produced by animals as a byproduct of protein metabolism. What is measured by chemical analysis (Nessler method) for ammonia is called total ammonia nitrogen (TAN) because it includes two forms of ammonia: ammonia (NH_3), the unionized form, and the ammonium ion (NH_4^+). The unionized ammonia (UIA) is toxic to fish. The temperature and pH of water affects the ratio of (NH_4^+):(NH_3) in water. For salmonid fishes, it is recommended that the concentration of UIA not exceed 0.0125 to 0.02 mg/L to maintain health of the fish, however, the toxic concentrations of UIA (NH_3) for trout are about 0.32 mg/L for rainbow trout, but 1.50-3.10 for channel catfish (Ruffier et al. 1981, cited by Boyd 1990a). Thus, a UIA of 1.7 mg/L, would be a expected to cause mortality of most fish, and it would be stressful for channel catfish. From table 3 it was observed that the unionized ammonia level is suitable for channel catfish but not suitable for salmonid and craps. Table 3 indicates that the UIA levels are in marginal stage for trout and rainbow trout. Bhatnagar *et al*. (2004) suggested 0.01-0.5 ppm is desirable for shrimp; >0.4 ppm is lethal to many fishes & prawn species; 0.05-0.4 ppm has sublethal effect and <0.05 ppm is safe for many tropical fish species and prawns. Bhatnagar and Singh (2010) recommended the level of ammonia (<0.2 mg L-1) suitable for pond fishery.

Table-3. Month wise UIA (PPM) values of different ponds

Ponds	January	February	March	April	May	June	July
FL-1	0.09	0.23	Due to Lockdown the data was not collected			0.25	0.25
FL-2	0.08	0.24				0.23	0.15
F	0.12	0.23				0.24	0.16

The *total dissolved solids*, or *TDS*, includes ionized and non ionized matter but only the former is reflected in the conductivity. Where TDS are high the water may be "saline" and the applicable parameter "Salinity". Salinity is defined as the total concentration of electrically charged ions (cations – Ca++, Mg++, K+, Na+ ; anions – CO3-, HCO3-, SO4-, Cl- and other components such as NO_3^-, NH_4^+ and PO_4^-). Salinity is a major driving factor that affects the density and growth of aquatic organism's population (Jamabo, 2008). Garg and Bhatnagar (1996) have given desirable range 2 ppt for common carp; however, Bhatnagar *et al*. (2004) gave different ideal levels of salinity as 10-20 ppt for *P. monodon*; 10-25 ppt for euryhaline species and 25-28 ppt for *P. indicus*. Barman *et al*. (2005) gave a level of 10 ppt suitable for *Mugil cephalus* and Garg *et al*. (2003) suggested 25 ppt for *Chanos chanos* (Forsskal). From table 4 it was observed that the total dissolved solids were in desirable limit but in case of floating agriculture practice ponds the TDS was found more than fresh pond. Values of less than 500 ppm (mg/L) are satisfactory and up to 1,000 ppm (mg/L) can be tolerated with little effect in household uses.

Table-4. Month wise TDS (PPM) values of different ponds

Ponds	January	February	March	April	May	June	July
FL-1	-	31.00	Due to Lockdown the data was not collected			29.00	28.00
FL-2	-	18.00				17.00	17.00
F	-	9.00				8.00	9.00

Calcium is generally present in soil as carbonate and most important environmental, divalent salt in fish culture water. Fish can absorb calcium either from the water or from food. Wurts and Durborow (1992) recommended range for free calcium in culture waters is 25 to 100 ppm (63 to 250 ppm $CaCO_3$ hardness) and according to them Channel catfish can tolerate minimum level of mineral calcium in their feed but may grow slowly under such conditions. According to table-5, the Ca values were in affordable range for channel fish cultivation.

Table-5. Month wise Ca (PPM) values of different ponds

Ponds	January	February	March	April	May	June	July
FL-1	26.38	28.46	Due to Lockdown the data was not collected			27.70	30.27
FL-2	30.15	26.42				26.95	28.98
F	22.61	26.38				26.16	26.23

Almost all of the phosphorus (P) present in water is in the form of phosphate (PO_4) and in surface water mainly present as bound to living or dead particulate matter and in the soil is found as insoluble $Ca_3(P04)_2$ and adsorbed phosphates on colloids except under highly acid conditions. It is an essential plant nutrient as it is often in limited supply and stimulates plant (algae) growth and its role for increasing the aquatic productivity is well recognized. According to Stone and Thomforde (2004) the phosphate level of 0.06 ppm is desirable for fish culture. Bhatnagar *et al*. (2004) suggested 0.05-0.07 ppm is optimum and productive; 1.0 ppm is good for plankton/shrimp production. From table-6 it was observed that the P values were good for plankton/shrimp production but were above limit for other fish production.

Table-6. Month wise P (PPM) values of different ponds

Ponds	January	February	March	April	May	June	July
FL-1	1.08	0.321	Due to Lockdown the data was not collected			0.723	0.562
FL-2	0.68	0.161				0.241	0.161
F	0.84	0.120				0.161	0.245

Where ammonia and nitrite were toxic to the fish, Nitrate is harmless and is produced by the autotrophic *Nitrobacter* bacteria combining oxygen and nitrite. Nitrate levels are normally stabilized in the 50-100 ppm range. According to Stone and Thomforde (2004) nitrate is relatively nontoxic to fish and not cause any health hazard except at exceedingly high levels (above 90 ppm). However, OATA (2008) recommends that nitrate levels in marine systems never exceed 100 ppm. According to table-7 it was observed that the nitrate values in the month of January, February and June were in tolerable limit. But in the month of July the nitrate level is going high for fish cultivation. Nitrate in excess of 45 mg/L (or in excess of 10 mg/L if reported as nitrate-nitrogen) is of health significance to pregnant women and infants under six months.

Table-7. Month wise NO_3^{-N} (PPM) values of different ponds

Ponds	January	February	March	April	May	June	July
FL-1	22.40	15.40	Due to Lockdown the data was not collected			14.42	75.60
FL-2	24.15	16.40				15.33	60.90
F	21.35	14.00				15.40	99.40

Conclusion

This is the first year experiment. It is needed to continue for next 3 to 4 years for making a concrete result.

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PROJECT: GROUNDWATER RESOURCES MANAGEMENT FOR SUSTAINABLE CROP PRODUCTION IN NORTHWEST HYDROLOGICAL REGION OF BANGLADESH (BARI COMPONENT)

S.K. Biswas[1], D.K. Roy[1], and K.F.I. Murad[2]

Executive Summary

A coordinated project entitled "Groundwater resources management for sustainable crop production in northwest hydrological region of Bangladesh" has been implementing by the different NARS institutes like BARI, BRRI and BINA with BARC as coordinate component with a view to sustainable management of groundwater resources of northwest region through optimizing water demand and supply. Field work was initiated with a base line survey in two study areas: Rajshahi and Joypurhat. For collecting baseline information from the project area, a structured questionnaire was developed and 25 farmers from each specified location were interviewed. The existing farming system, groundwater utilization, pricing system and problems in irrigation scheme, etc. were assessed through the survey work. The specified selected locations were Godagari and Tanore upazila of Rajshahi and Joypurhat sadar and Kalai upazila of Joypurhat district. Based on the survey results, a few location specific promising cropping patterns based field trials with rice and non-rice crops were conducted with adoption of water saving irrigation technologies in respect of the project aim. Selection of site and farmers has been completed and as part of the cropping pattern based experiment, a number of field experiments with T.Aman rice, potato, mustard, wheat, boro have already been conducted in the selected locations. Meanwhile long-term (1980-2018) historical groundwater level data has been collected and prediction model has been developed by using discrete Space-state modeling approach for future forecasting of groundwater level. It is perceived that groundwater level declination in Rajshahi will be more than double (from 17.87 m in 2018 to 37.62 m in 2040) at all the three observation wells for the next 22 years if the present rate of abstraction continues. Groundwater abstraction pattern due to irrigation, domestic and municipal uses has been assessed and it is apparent that total abstraction will increase by 33-35% in Joypurhat area and by 40-45% in Rajshahi area in the next 20 years. So, appropriate measures should be taken to ensure judicious use of water in all sectors especially in agriculture to protect the groundwater resources from being further depleted. The groundwater quality in the study areas has been evaluated for agricultural use. The water quality indices such as SAR, SSP, RSC, KR and WQI were calculated to find out its suitability for irrigation. In respect of all evaluating criteria, groundwater of the study area was found suitable and can safely be used for irrigation purpose. The increased and decreased recharge scenarios were computed using the existing groundwater pumping values in the year 2018. The three recharge scenarios considered was: (i) actual recharge, (ii) 90% of the actual recharge, and (iii) 110% of the actual recharge. The aquifer processes were simulated using a calibrated 3D finite difference based numerical simulation code MODFLOW. The results revealed that the computed groundwater heads at the three observation wells varied noticeably as a result of the changes in the recharge scenarios.

1. Background

The increase of food production with less irrigation water use has been the main policy target in farm management over the recent years, particularly in countries with limited water and land resources (FAO 2002). It has been estimated that if sustainable irrigation water management strategies are not implemented, there will be an estimated loss of agricultural production of 7.8% by 2080 (Cline 2007). Bangladesh is one of the world's most densely populated countries, where food security has been a continuous challenge since its liberation. The expansion of irrigated crop land has probably been the most dramatic development in Bangladesh agriculture during the last

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25 years mainly through groundwater irrigation. In Bangladesh, agriculture is responsible for more than 65 percent of total fresh water withdrawal (Shamsudduha et al. 2011), where nearly 80 percent of this irrigation water comes from groundwater resources due to uncertainty of year-round surface water availability (Rahman & Mahbub 2012). Clearly, the availability of groundwater for irrigation has contributed to manifold increase in crop productivity. Studies found that the contribution of groundwater has increased from 41% in 1982-83 to 77% in 2006-07. The ratio of groundwater to surface water use is much higher in north-western districts of Bangladesh compared to other parts of the country. Climatically, this area belongs to dry humid zone with annual average rainfall vary between 1,400 and 1,900 mm. The seasonal distribution of this amount of rainfall shows that almost 92.7% rainfall occurs during May to October and less than 6% rainfall occurs during the dry season irrigation period of cultivating rice (November to April). All the rivers and canals become dry during the dry season and make the people completely dependent on groundwater (Shahid 2008; Shahid and Behrawan 2008) to meet up the demand of cultivating crops, especially for boro rice.

Though the groundwater dominates the total irrigated area, its sustainability is at risk in terms of quantity in the northwest region (Simonovic 1997; Shahid 2011) through over extraction of this resources. Researchers have revealed that over extraction of groundwater for irrigation due to lack of proper knowledge, cultivation of water intensive crops, irrational irrigation management, indiscriminate installation of pumps and non-availability of modern technologies are the major reasons behind the current crisis (Adhikary et al. 2013; Ali et al. 2012; Shahid & Hazarika 2010). In addition, global climate change effects and reduced water flow in major rivers due to upstream water diversion by India has made the situation worse (Adhikary et al. 2013). Different studies have documented that groundwater table has been declined by at least 10 meters during the last 14 years (Ali et al. 2012; Shahid & Hazarika 2010) in some areas of the Barind tract of northwest region. Decline of groundwater [strong declining trends (0.5 – 1.0 meter/year) in the central part of the country, moderately declining trend (0.1 – 0.5 meter/year) in western, north-western and north-eastern areas during dry season] is a threat of water resources for future if annually not replenished from annual seasonal rainfall. This substantial declination of groundwater level during the last decade causing threat to the sustainability of water use for irrigation in this region and impacting upon other sectors as well (Jahan et al. 2010); as recharge occurs mainly due to rainfall, while the contribution of irrigation (in the winter) is very negligible (Akram, 2009). Frequent shortage of water has had impacts that can be ranged as economic, social and environmental (Islam et al. 2014). If this over-utilization continues, it may result in its exhaustion after few years that may have serious impact on the agriculture-based economy of the country. So, emphasis should be given on the sustainability of these valuable resources.

Although maximizing crop production through greater expansion of irrigated lands is a basic requirement, sustainable utilization of country's limited water resources is also a major concern. The key challenges are now to increase agricultural productivity without deteriorating the groundwater resources (Shahid & Hazarika 2010). This is possible only if safe extraction of groundwater resources, the irrigation water is utilized judicially by implementing apposite irrigation methods, and practicing water saving cropping patterns simultaneously. Rahman and Saha (2008) suggested for wheat, mustard and potato for dry season crops, which can increase the total crop production of the area. Dey et. al. (2013) also suggested for promoting less water demanding crops for sustainability of groundwater use for irrigation in north-west Bangladesh. The overall objective of this study was sustainable management of groundwater resources through optimizing water demand and supply with the following specific objectives:

- To determine aquifer recharge and groundwater utilization pattern
- To assess availability and quality of groundwater for crop irrigation
- To develop various scenarios for sustainable crop production using groundwater models
- To find out optimum management techniques and suitable cropping patterns for sustainable groundwater use

2. Methodology

2.1 Cropping pattern based field trials with rice and non-rice crops

The study was initiated during the rabi season of 2018-2019 after harvesting of T.Aman rice in both Joypurhat and Barind area of Rajshahi. The soil of the study area is loam - clay loam with an average field water-holding capacity of 28.5- 30.5 % and wilting point of 14.12-15.2%. Soil bulk density in the 0 to 60 cm depth ranges from 1.31 to 1.43 g/cc, with a weighted average of 1.39 g/cc. A typical dry climate with comparatively high temperature prevails in Barind area. Temperature ranges from a minimum of 8^{o}C in the winter to a maximum of 44^{o}C in the summer. More than 85% of the total rainfall occurs from mid-June to October and the magnitude of annual rainfall varies from 1300-1500 mm in Rajshahi and 1800- 2000 mm in Joypurhat. Based on an extensive investigation on the existing cropping patterns in the study areas, two/three promising cropping patterns from each study area were selected for project works and the field experiments were conducted following the major cropping patterns of the respective study area. Three/four different cropping patterns with four/five principal crops of that region were selected as rotation crops, including T.Aman, boro, wheat, mustard, and potato. Mungbean, a popular fallow crop, was included in T.Aman-Wheat-Fallow pattern after wheat cultivation. Irrigation schedule of different crops with their sowing/transplanting and harvesting date are presented in Table 1. All crops were grown in the following sequences starting with rabi crops as: T.Aman-Potato-Boro, T.Aman-Mustard-Boro, T.Aman-Wheat-Fallow. Another pattern T.Aman-Fallow-Boro was tested as control treatment.

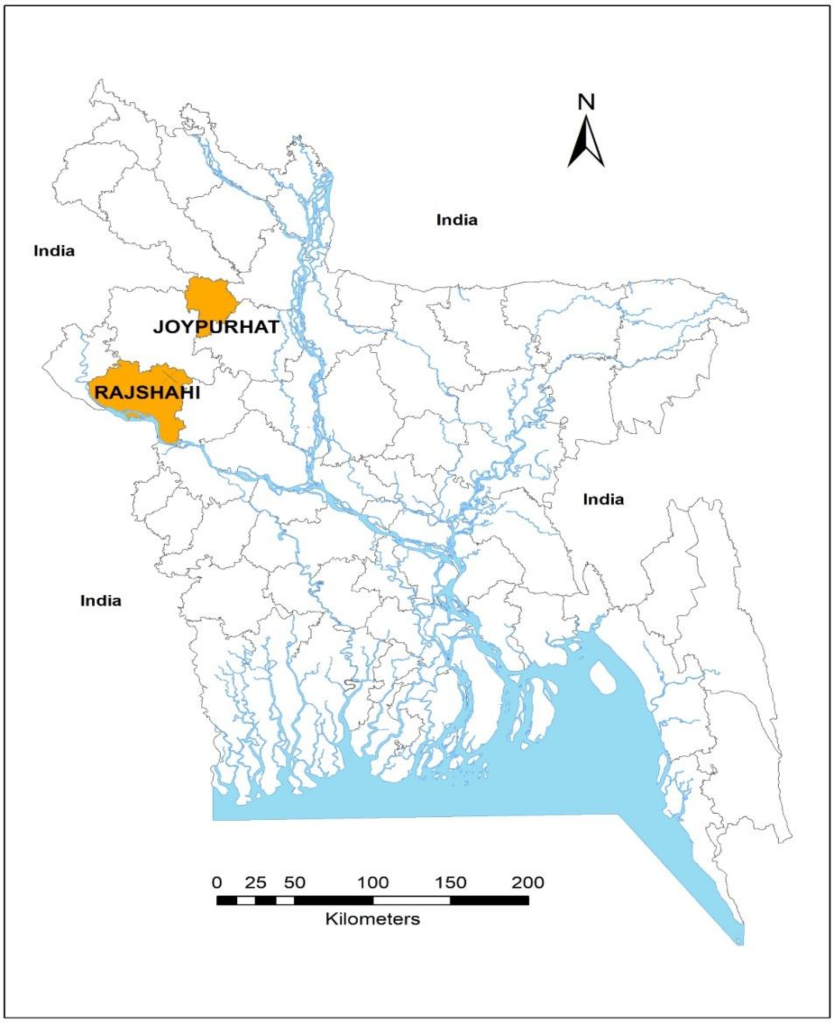


Figure 1. Geographical map showing the study locations.

For each crop, recommended doses of fertilizers were used and standard cultural practices were followed. Crops were sown immediately after harvesting of T. Aman with a view to save water for irrigation with effective utilization of profile soil moisture. Each crop was grown on a 100 m^2 plot with three replications. The growing period for wheat crop was Nov-March, for potato Nov-February, for mustard Oct/Nov-January/Feb and for boro rice December-April. At maturity, all crops were harvested manually to determine grain yield and aboveground biomass. Soil water content was monitored at 20 cm incremental depth up to 60 cm depth for wheat and mustard, and up to 40 cm depth for potato before and after irrigation. Soil moisture content at sowing and at harvest was monitored to find out the amount of profile soil moisture contributing to crops. All cultural practices were done as per recommendations. Important agronomic data and parameters were collected during the cropping season and harvest time.

Yield was estimated by collecting samples from four square meter area of each replication. Harvest wheat/rice was threshed, cleaned and weighed and finally the yield was calculated at 14% moisture content. All weather data of the cropping period influencing crop water use were also collected. Depth of irrigation water applied in each irrigation was duly recorded. Total water use by the wheat, potato and other non-rice crops during the entire cropping period (sowing to harvest) was calculated by using the field water balance equation as:

$$TWU= I + P+ - D - R \pm \Delta SWS$$

where, TWU is the total water use (mm), P is the effective rainfall (mm), I is the irrigation water applied (mm), D is the deep percolation (mm), R the run-off and ΔSWS is the change in water storage in the soil profile. Deep percolation (D) was assumed negligible, since water was applied only to replenish soil moisture in the root zone. Run-off due to irrigation or rainfall was taken to be zero as irrigation/rainfall water was protected by 15 cm height levees.

Table 1. Irrigation schedule of different crops with their sowing/transplanting and harvesting dates

Crops	Treatments	Sowing/ transplanting date	Harvesting date
Wheat (BARI Gom- 30)	T_1= Irrigation at CRI and pre-flowering stages T_2= Irrigation at CRI and grain formation stages T_3= Irrigation at CRI, pre-flowering and grain formation stages (20, 55 and 75 DAS)	20-22/11/2018	13-15/03/2019
Mustard (BARI Sarisha- 14)	T_1= One irrigation at vegetative stage T_2= One irrigation at pre-flowering stage T_3= Two irrigation at vegetative and pod formation stages	18-21/11/2018	11-13/02/2019
Potato (Diamant)	T_1= Farmers' practice (FP) T_2= Irrigation at stolonization, tuberization and bulking stages in furrow system (FI) T_3= Irrigation at stolonization, tuberization and bulking stages in alternate furrow system (AFI)	10-17/11/2018	11-15/02/2019
Boro (BRRI dhan- 28)	T_1= Farmers' practice (ponding up to 3-5 cm) T_2=Irrigation on 3rd day after disappearing of standing water T_3= Irrigation when water level fall 15 cm below ground surface	03-07/01/2018	27-30/04/2019
T.aman (BRRI dhan-56)	T_1= Farmers' practice T_2= AWD with 20 cm depth T_3= AWD with 25 cm depth	21-28 July 2018	24-29 Oct 2019
T.Aus (BRRI dhan-51)	T_1= Farmers' practice T_2= AWD with 20 cm depth T_3= AWD with 25 cm depth	03-09/06/19	11-13/08/19
Maize (BARI Hybrid bhutta-9)	T_1= Irrigation at vegetative and flowering stages (FP) T_2= Irrigation at seedling, vegetative and silking stages by furrow irrigation (FI) T_3= Irrigation at seedling, vegetative and silking stages by alternate furrow irrigation (AFI)	01/12/18	05/05/19
Tomato (Hybrid VL-642)	T_1= Furrow irrigation T_2= Drip irrigation T_3= Alternate furrow irrigation	13-15/09/19	14/11/19-18/12/19

Water productivity was determined as the ratio of yield to total water used by the crop as:

$$WP= Y/TWU$$

where, WP is the water productivity (kg m^{-3}), Y is the crop yield (kg ha^{-1}) and TWU the total water use (m^3 ha^{-1}).

Total water use by rice crop during the entire cropping period (planting to harvest) was calculated by using the following equation:

$$TWU= I + P - R - (S \& P)$$

where TWU is the total water use (mm), I is the irrigation water applied (mm), P is the effective rainfall (mm), R the run-off (mm) and S& P is the seepage and percolation (mm). Run-off was taken to be zero as irrigation water was protected by 30 cm height levees.

Water requirement (WR) for boro rice was determined as irrigation water applied (mm) plus effective rainfall (mm) during the cropping season. And water productivity was determined as the ratio of crop yield to water requirement as:

WP= Y/WR

where, WP is the water productivity (kg/m^3) and Y is the crop yield (kg/ha) and WR the water requirement (m^3/ha).

Water use efficiency (WUE) was calculated by dividing the total water use by water requirement during the cropping season as:

WUE = TWU/WR

where, WUE is the water use efficiency (%), TWU the total water use (mm) and WR is the water requirement (mm)

2.2 Long-term yearly groundwater abstraction pattern

Irrigation Water Requirement

The people of the study area are dependent on groundwater for irrigation and domestic uses. Thus a large portion of groundwater is abstracted to meet up irrigation water requirement while a small portion is abstracted for domestic and municipal water requirements. Irrigation in the study area is provided either by DTWs or STWs or LLPs. Under the present situation, DTWs are of different capacities while STWs are mainly of same capacity. Most of the DTWs (80%) are of 2 cusec and some are of 1 cusec (about 20%), STWs and LLPs are of 0.50 cusec capacity. Abstraction due to irrigation was estimated by the field irrigation water requirement (FIWR) for each crop. FIWR was calculated utilizing evapotranspiration (ET_0), effective rainfall, crop coefficient, crops and cropping patterns of the study areas. Thus, total irrigation water requirement for the entire area is FIWR of crops and area under each crop. Crop coverage under each crop for entire area was estimated from the Upazila wise area weighted average crop coverage.

Domestic and Municipal Water Requirement

In Bangladesh, about 97% of total potable water is met up from groundwater sources. It is understood from the field survey that domestic and municipal water source of the study area is solely based on groundwater. Therefore, assessment of domestic and municipal water requirement is important to see the abstraction effect on groundwater table. Estimation of the present population and projected population is necessary for assessing the present and future domestic and municipal water demand. The Per Capita water demand is the annual average water consumption of one person daily. Thus average daily demand over a year means the annual average daily demand. The total quantity of water required by the community can be computed using the following equation.

$$Q = P \times q$$

where, Q is the present or projected quantity of water required by the community per day, P is the present or projected population and q is the rate of water consumption per capita per day.

The projected population is estimated by the Geometric Progression method (Ahmed et al, 2003):

$$P_p = P_b\,(1 + \mathrm{r})^{\mathrm{n}}$$

where, Pp = projected population in the year n

Pb = Base population

r = rate of natural increase of population per year

n = number of years being considered.

On the basis of population projection by geometric progression method and per capita water demand, the domestic and municipal water requirement was estimated. According to the NWMP report, per capita gross water demand for municipal town and rural areas are 166 lpcd and 30 lpcd respectively. The gross water demand of municipal town includes 119 lpcd net domestic water demand, 20% of it as a system loss, 10% as gross commercial demand and 15% as industrial demand. On the other hand it has 50% returned flow from the commercial demand and 75% returned flow from domestic water demand, thus the net water demand for municipal town becomes 76 lpcd. The gross water demand for rural areas doesn’t include any loss and commercial and industrial demand. Thus the net water demand for rural areas is same as the gross water demand.

2.3 Trend of groundwater level fluctuation in the study area

Secondary data of weekly groundwater level fluctuations at selected observation wells were collected from Bangladesh Water Development Board. Historical weekly groundwater level data from January 1980 to September 2018 of three observation wells of Bangladesh Water Development Board were used. Along with this, a few observation wells were selected in the study areas for collecting groundwater level data directly. Collected data were used to predict the trend of change of groundwater level by using discrete Space-state and MAKSENS modeling approach.

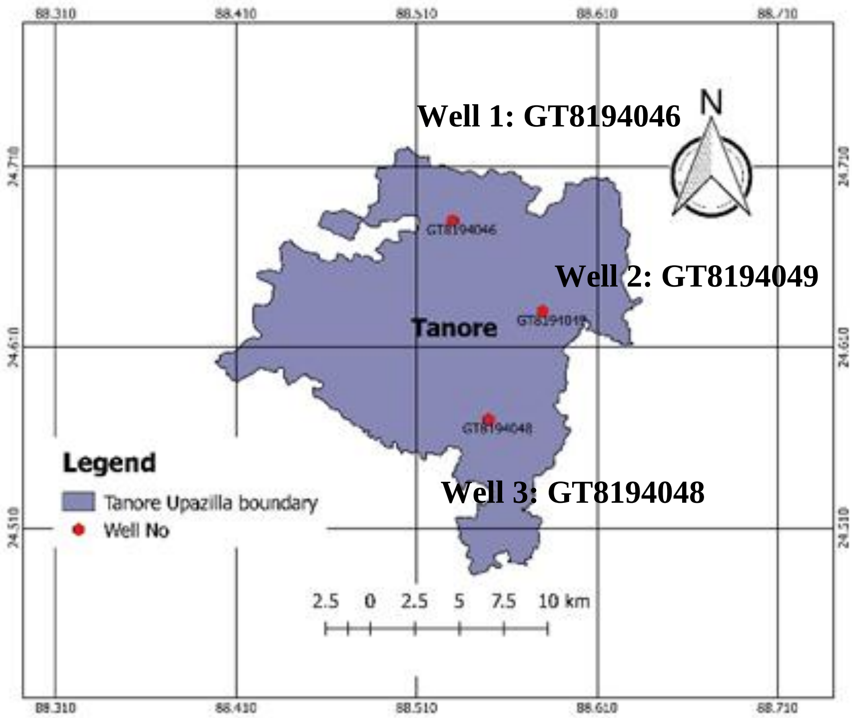


Figure 2. Locations of the observation wells in Tanore of Rajshahi district.

Observation well GT 8194046 is located at 24.68^{0}N latitude and 88.53^{0}E longitude. Observation well GT 8194048 is situated at 24.57^{0}N latitude and 88.55^{0}E longitude whereas the observation well GT 8194049 is located at 24063^{0}N latitude and 88.58^{0}E longitude. Time series water level data of the three observation wells are illustrated in Figure 3 below.

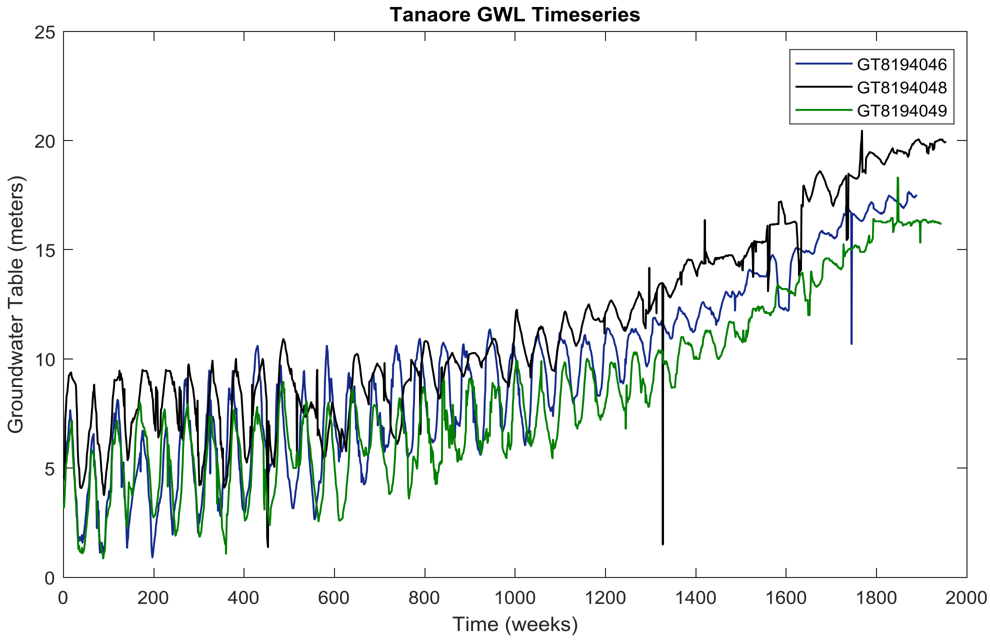


Figure 3. Groundwater level time series data for the three observation wells.

a) Discrete Space-State model

Modelling technique

This study utilizes a discrete Space-State model as a prediction tool for future scenarios of groundwater level forecasting. The groundwater table can be modelled as a state-space system with noise input and measured water table date as output. The measured water table is proportional to the system state, i.e.

$$x_{n+1} = Ax_n + Ke_n \tag{1}$$

$$y_n = Cx_n + e_n \tag{2}$$

where, x_n is the state vector, contains the weekly water table values; y_n is the output from the model; e_n is the noise and A, C, K are to be identified.

In Space-State modeling approach, a model is identified to accurately compute a dynamic system with response to an input. Two different approaches exist to generate an identified model response: (a) Simulation that computes model response using input data and initial conditions, and (b) Prediction that computes the model response at some specified amount of time in the future using the current and past values of measured input and output values, as well as initial conditions. The present study utilizes the prediction focused approach of the system identification process in which the overall goal is to create a realistic dynamic system model that can be used or handed off for an application goal. During the model identification process, a one-step prediction focus is used as it generally produces the best results. By using both input and output measurements, one-step prediction accounts for the nature of the disturbances. Accounting for disturbances provides the most statistically optimal results.

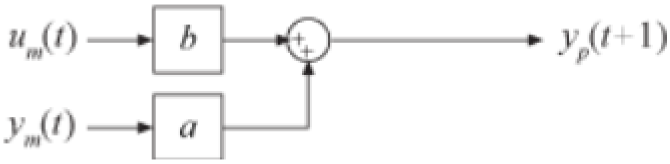
Prediction focused approach

Prediction means projecting the model response k steps ahead into the future using the current and past values of measured input and output values. k is called the prediction horizon, and corresponds to predicting output at time kT_s, where T_s is the sample time. In other words, given measured inputs $u_m\,(t_1, \ldots, t_{N+K})$ and measured outputs $y_m(t_1, \ldots, t_N)$, the prediction generates the final output $y_p(t_{N+K})$.

For example, if the input and output signals of a physical system are $u_m\,(t)$ and $y_m\,(t)$, respectively, then the first order equation of this system can be represented by

$$y_p(t+1) = a y_m(t) + b u_m(t) \tag{3}$$

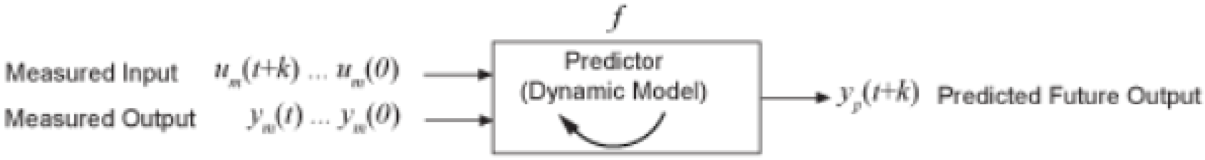
where y is the output and u is the input. The system can be represented by the following block diagram



In general, to predict the model response k steps into the future ($k \geq 1$) from the current time t, one must know the inputs up to time $t+k$ and outputs up to time t such that:

$$y_p(t+k) = f\big(u_m(t+K), u_m(t+k-1), \ldots, u_m(t), u_m(t-1), \ldots, u_m(0), y_m(t), y_m(t-1), y_m(t-2), \ldots, y_m(0)\big) \tag{4}$$

where, $u_m(0)$ and $y_m(0)$ are the initial states. $f(\,)$ represents the predictor, which is a dynamic model whose form depends on the model structure.



A MATLAB command is used to identify a discrete state-space model from the measured data.

Historical weekly time series of water table data for 38 years was used for developing the time series model, which was used for future water level predictions for a period of the next 22 years (up to 2040).

The original time series of groundwater table data is divided into identification (training) and validation data. Eighty percent of the entire time series data is used to train the model whereas the rest 20% is used to validate the developed model. After satisfactory training of the models, the trained and validated models were used for future predictions. Figure 4 presents the partitioning of the time series dataset into training and validation dataset for the three selected observation wells.

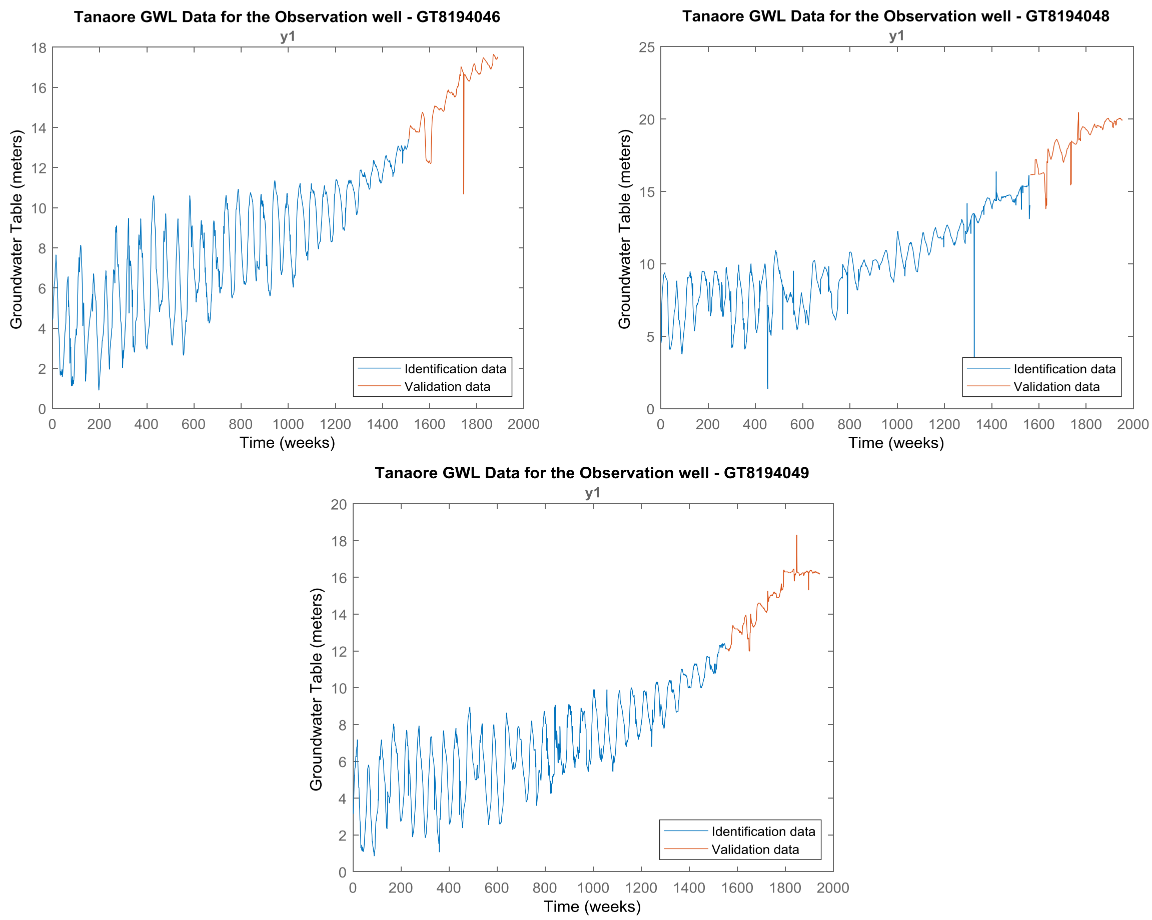


Figure 4. Partitioning of the data into identification and validation datasets.

Performance criteria

Akaike's Final Prediction Error (FPE)

FPE criterion provides a measure of model quality by simulating the situation where the model is tested on a different data set. According to Akaike's theory, the most accurate model has the smallest FPE. Akaike's Final Prediction Error (FPE) is defined by the following equation:

$$FPE = \det\left(\frac{1}{N}\sum_{1}^{N} e\left(t,\hat{\theta}_N\right)\left(e\left(t,\hat{\theta}_N\right)\right)^T\right)\left(\frac{1+{}^{d}/_{N}}{1-{}^{d}/_{N}}\right) \tag{5}$$

where, N is the number of values in the estimation data set, $e(t)$ is a ny-by-1 vector of prediction errors, θ_N represents the estimated parameters, d is the number of estimated parameters. If number of parameters exceeds the number of samples, FPE is not computed when model estimation is performed.

Mean Squared Error (MSE)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Actual_i - Prdicted_i)^2 \tag{6}$$

Model development:

As the first step of the model development, a 1-step ahead prediction is performed for all the three observation well locations. For observation well GT8194046, the system identifies 440 numbers of free coefficients to develop a Space-State model for which estimation data fit is found to be

91.35% (prediction focus). The FPE and MSE values of 0.07358 and 0.06796, respectively is found, which indicates a very good prediction model. The corresponding values of free coefficients, FPE and MSE values of observation wells GT8194048 and GT8194049 are presented in the following Table.

Table 1. Prediction performance of the developed models at observation wells GT8194048 and GT8194049

Observation Well	Free coefficients	Fit to estimation data (prediction focus), %	FPE	MSE
GT8194048	440	81.42	0.292	0.2704
GT8194049	440	89.98	0.07411	0.06861

The identified models minimize the 1-step ahead prediction. Now, the model is validated using a 10 step ahead predictor, i.e., given $y_{0,\dots,}y_n$, the model is used to predict y_{n+10}. Note that the measured and predicted values, $y_0 - \hat{y}_0, \dots, y_n - \hat{y}_n$, were used to make the y_{n+10} prediction. The 10-step ahead prediction results for the identification and the validation data for observation wells GT8194046, GT8194048, and GT8194049 are presented in Figures 5, 6, and 7 respectively.

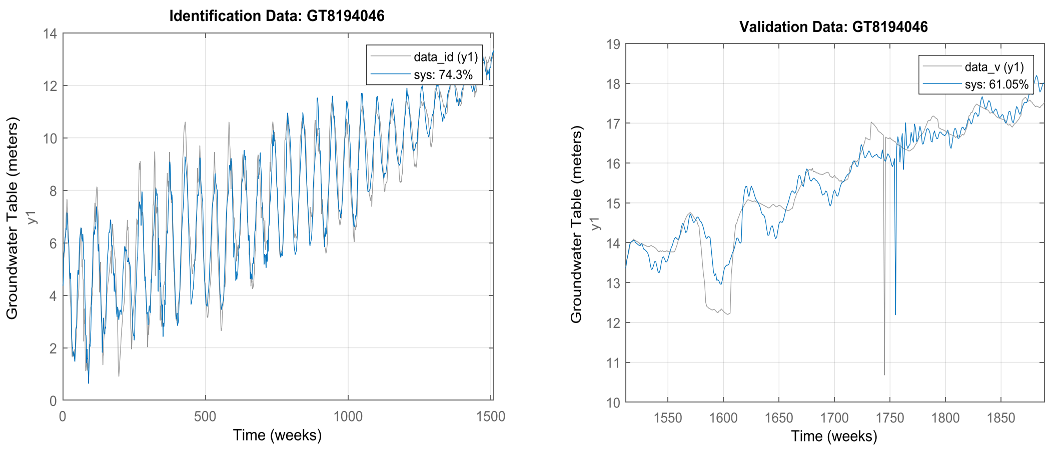


Figure 5. 10-step ahead prediction results for the identification and validation data at observation well GT8194046.

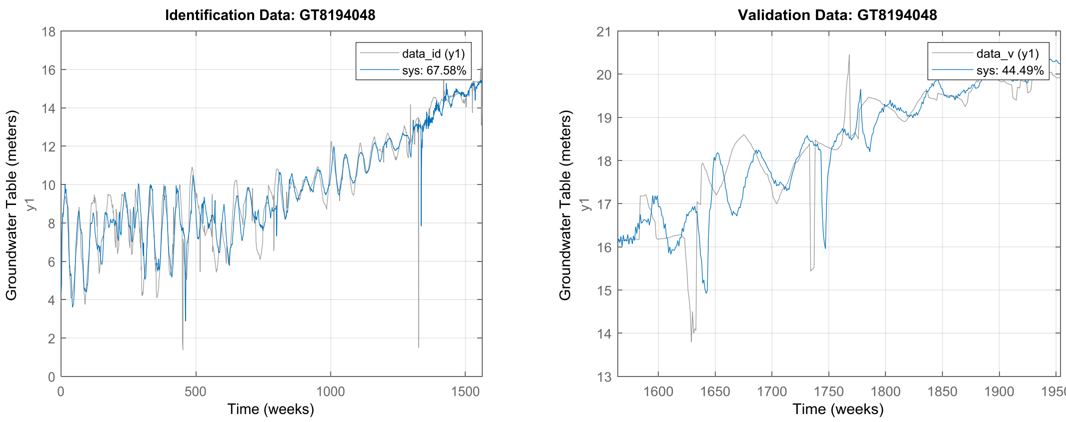


Figure 6. 10-step ahead prediction results for the identification and validation data at observation well GT8194048.

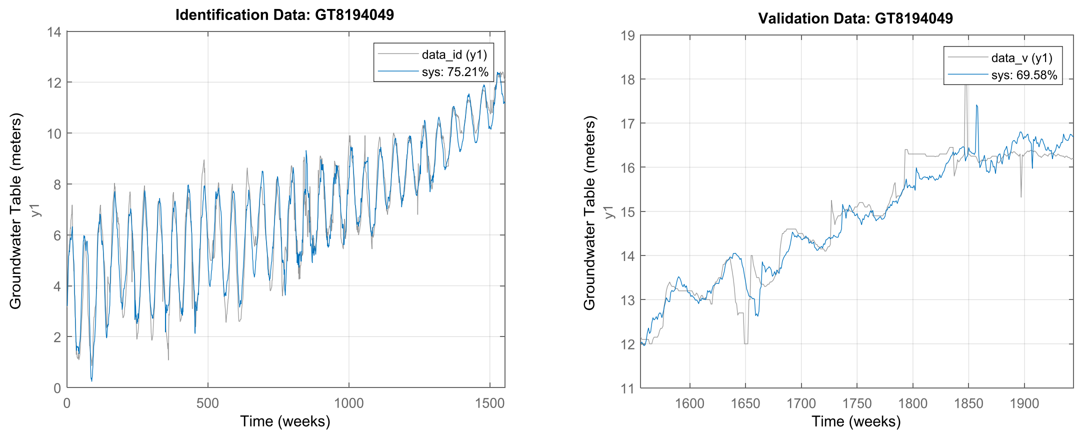


Figure 7. 10-step ahead prediction results for the identification and validation data at observation well GT8194049.

It is observed from Figures 5, 6, and 7 that both identification and validation datasets at all observation wells show that the predictor matches well with the measured data. Now to further verify the developed prediction model, forecasting within the range of the validation data was performed. Forecasting uses the measured data record $y_0, y_1, \dots, y_n - \hat{y}_n$ to compute the model state at time step n. This value is used as initial condition for forecasting the model response for a future time span. We forecast the model response over the time span of the validation data and then compare the two.

b) MAKESENS modeling approach

- MAKESENSE performs two types of statistical analyses.
- First, the presence of a monotonic increasing or decreasing trend is tested with the nonparametric Mann-Kendall test, and
- Secondly, the slope of a linear trend is estimated with the nonparametric Sen's method.
- The Sen's method uses a linear model to estimate the slope of the trend and the variance of the residuals should be constant in time.
- Annual data needs to be used.

Secondary data of weekly groundwater level fluctuations at selected observation wells were collected from Bangladesh Water Development Board. Historical weekly groundwater level data from January 1980 to September 2018 of three observation wells of Bangladesh Water Development Board were used. Along with this, a few observation wells were selected in the study areas for collecting groundwater level data directly. Collected data were used to predict the trend of change of groundwater level by using discrete Space-state and MAKSENS modeling approach

Historical weekly groundwater level data of thirty five years (1984 - 2018) were collected from three observation wells of Bangladesh Water Development Board. (BWDB). The sites differed in hydrologic, climatic and agricultural peculiarities. The collected GWL data were arranged in month wise and then reduced to mean value. The trend of computed monthly GWL was detected and estimated by MAKESENS trend model. It is a computer model, which was developed using Microsoft Excel 97 and the macros were coded with Microsoft Visual Basic (Salami et al., 2002). MAKESENS implements statiscal analyses in two ways. Firstly, the presence of a monotonic increasing or decreasing trend was tested with the non-parametric Mann-Kendal test and, secondly, the slope of a linear trend was estimated with the non-parametric Sen's Method (Gilbert, 1987). The model was used to analyses the trend of change of arranged climatic parameters. The testing was done at the significance level of 0.001, 0.01, 0.05 and 0.10. The changes of groundwater levels were computed based on the trend analysis results as: Groundwater level = B+Q (2018-1984).

where

B = the intercept,

Q = the slope of the trend line

2.4 Optimization of groundwater abstraction by Hydrologic Model

Previous studies in the Bengal Delta modelled a very large area (Faneca Sanchez et al., 2015; Michael and Voss, 2009) by assuming groundwater abstraction per unit area of the model domain. The withdrawals were dispersed based on estimations done for each administrative unit. Of note, it is difficult to show point pumping in the model domain as individual bores because of the large number of unreported wells and the large scale of the study area. Therefore, the exact location of the point pumping was approximated in the present study on the basis of the land-use pattern of the study area. In conformance with the total water abstraction and for simplicity in the model, total water abstraction was distributed among the individual wells during the calibration process. Groundwater abstractions for domestic, industrial, and agricultural water use were discussed earlier in Section 6.2. Total irrigated area in the study area was obtained from the district statistics for Tanore upazilla (Bangladesh Bureau of Statistics (BBS), 2013). The total irrigated area was multiplied by an abstraction rate of 1 m/pumping season/m^2 of irrigated area (Harvey et al., 2006).

The entire model domain was discretized into finite difference grids with a cell size of 300m×300m. The type and thickness of aquifer material layers were chosen in accordance with the lithological data of the study area. As most of the physical processes are occurred in the first few meters of the aquifer, an aquifer thickness of 95 m was chosen. The total thickness of the aquifer was divided into three layers of materials. First layer below the ground surface belongs to silty clay with a thickness of 45 m, followed by a layer of fine to medium sand with 25 m thickness, followed by a soil type of medium to coarse sand with a thickness of 25 m. An average estimate of hydraulic conductivity was assigned to each model layer. The aquifer material within each model layer was assumed homogeneous, only vertical heterogeneity in terms of hydraulic conductivity was considered. The hydraulic conductivity values used in this study were in accordance with previous studies conducted in the Bengal Delta (Faneca Sanchez et al., 2015; Michael and Voss, 2009). A vertical anisotropy of 4 was chosen (GMS user's manual). The 3-D view of the model domain with finite difference grids is shown in Fig. 8.

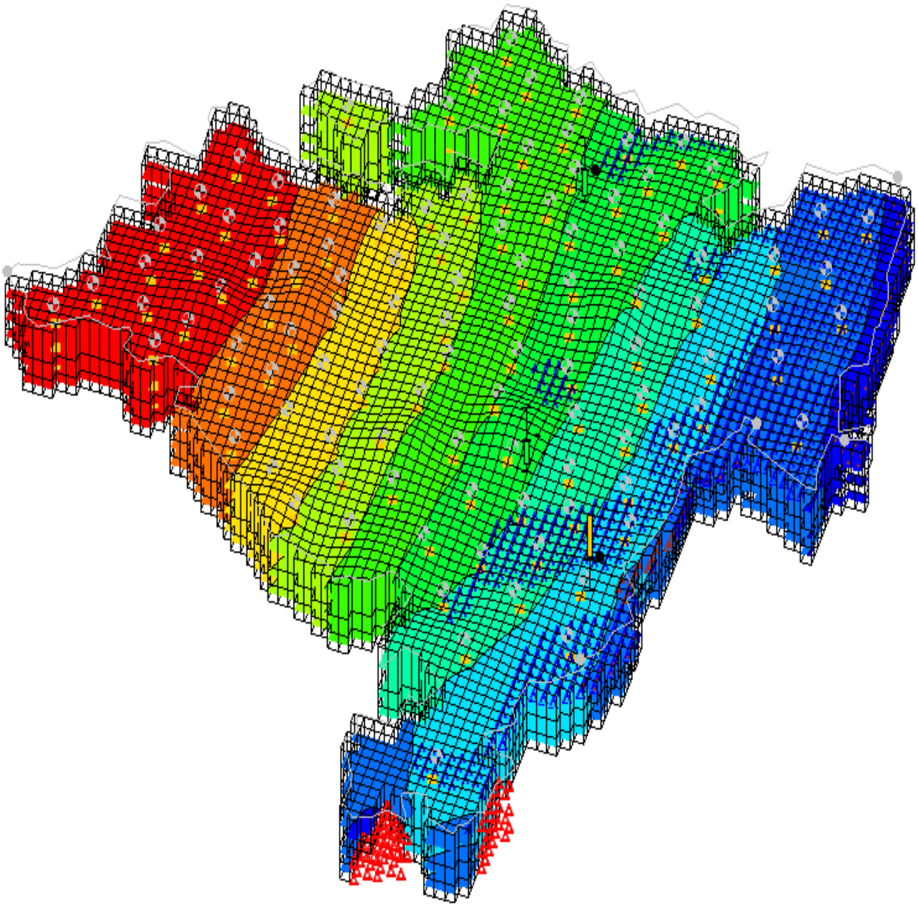


Fig. 8 Three dimensional view of the study area.

A plan view of the study area with boundaries and wells is shown in Fig. 9.

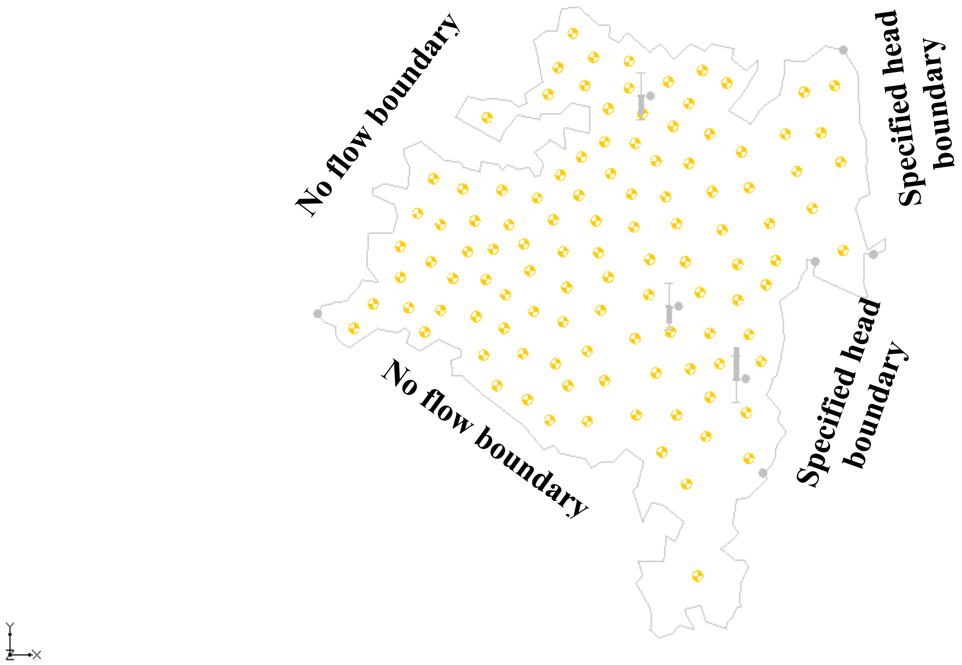


Fig. 9 Plan view of the study area showing the boundaries and wells.

The calibration process was initiated from a steady state condition of the hydraulic heads in the finite difference grids of the model domain. To achieve this condition, the simulation model was run for 80 years. The simulation was performed in stages with an interval of 10 years. An average value of pumping was used during this simulation period. Outputs at the end of the 10th year's simulation were used as initial conditions for the succeeding intervals of 10 years' period. The process was continued until a stable condition with respect to hydraulic head was achieved. These hydraulic head estimates at various grids of the model area were used as initial conditions of the calibration process. At this stage, the actual groundwater abstraction from the study area was used. The calibration was performed for the observed hydraulic heads on September 2018, and the hydraulic heads were monitored at the designated monitoring locations. Recharge and hydraulic conductivity estimates were fine-tuned to achieve the hydraulic heads closer to the actual hydraulic heads in the observation wells GT8194046, GT8194048, and GT8194049. Table 1 presents major parameter values used in the calibrated groundwater simulation model.

Table 2. Parameter values of the calibrated model

Parameters	Values	Units
Hydraulic conductivity in X-direction for soil layer 1	2.5	m/day
Hydraulic conductivity in X-direction for soil layer 2	18	m/day
Hydraulic conductivity in X-direction for soil layer 3	25	m/day
Vertical anisotropy for the soil layers	4	-
Aquifer recharge applied on the top soil layer	0.0004	m/day
Conductance of the specified head boundaries	1.0	$(m^2/day)/m$
Specific yield of Aquifer layer 1	0.01	-
Specific yield of Aquifer layer 2	0.03	-
Specific yield of Aquifer layer 3	0.05	-

2.5 Collection and analysis of water samples

Groundwater samples were collected before starting (November/December, 2018) and at the end (February/March, 2019) of dry season irrigation to examine its suitability for irrigation over the season. The samples were collected from different sources like STWs and DTWs of the study areas. The water samples were collected in white plastic bottles filling up to the brim and immediately sealed to avoid exposure to air. Then the samples were labeled and brought to the laboratory for chemical analysis. The samples were analyzed for different water quality parameters such as pH, EC, $PO_4^{2-,}$ NO_3^{2-}, Cl-, HCO_3^-, Na^+, K^+, Ca^{2+} and Mg^{2+}.The analysis was done in the laboratories of BRAC, Gazipur and Soil Science Division, BARI, Gazipur.

Groundwater suitability for irrigation purpose in this study area was assessed using SAR (Sodium Adsorption Ratio), RSC (Residual Sodium carbonate), SSP (Soluble Sodium percentage) and KR (Kelly's ratio). All determined groundwater concentrations used in assessing these indices were in meq/l.

SAR (Sodium Adsorption Ratio) is a measure of suitability of water for irrigation with respect to the sodium hazard. The SAR values were calculated using the following equation:

$$SAR = \frac{Na^+}{(\sqrt{Ca^{+2}+Mg^{+2}})/2}$$

The residual sodium carbonate is a measure of the hazard involved in the use of high carbonate waters. RSC is calculated as follows:

$$RSC = (CO_3^{\ 2-} + HCO_3^-) - (Ca^{+2} + Mg^{+2})$$

Kelly (1940) and Paliwal (1967) introduced another factor to assess quality and classification of water for irrigation purposes based on the concentration of Na^+ against Ca^{2+} and Mg^{2+}. It can be calculated using the following equation:

$$KR = \frac{Na+}{Ca2++Mg\ 2+}$$

KR > 1 indicates an excess level of Na^+ in waters. Therefore, water with a KI ≤ 1 has been recommended for irrigation, while water with KI ≥ 1 is not recommended for irrigation due to alkali hazards (Ramesh and Elango 2012; Karanth 1987).

To get a comprehensive picture of overall quality of groundwater, the WQI was used. WQI is defined as a rating reflecting the composite influence of different water quality parameters on the overall quality of water. The FAO standard specified for irrigation water was used for the calculation of WQI. The WQI was computed through three steps. First, each of the measured parameters (pH, EC, TDS, Na, Ca, Mg, K, CO_3, HCO_3, Cl, SO_4, NO_3, PO_4, Fe, Zn and B) was assigned a weight (w_i) according to its relative importance in the overall quality of water for irrigation purposes. The maximum weight 5 was assigned to parameters like pH, EC, TDS, Na^+, Cl^-, and SO_4^{2-} due to their importance in water quality assessments. A minimum weight of 1 was assigned to zinc because of its insignificant role. Other parameters were assigned weights between 1 and 5 based on their relative importance in the evaluation of water quality.

In the second step, the relative weight (Wi) of the chemical parameter was computed using the following equation:

$$Wi = wi / \sum_{i=1}^{n} \text{wi}$$

where W_i is the relative weight, w_i is the weight of each parameter, and n is the number of parameters.

In the third step, a quality rating scale (q_i) for each parameter is assigned by dividing its concentration in each water sample by its respective standard according to the guidelines given by FAO, 1997 and the result is multiplied by 100:

$$qi = (Ci/Si) \times 100$$

where q_i is the quality rating, C_i is the concentration of each chemical parameter in each water sample in mg/L, and S_i is the irrigation water standard for each chemical parameter in mg/L.

For computing WQI, the sub index (SI) is first determined for each chemical parameter, as given below:

$$SI = Wi \times qi$$
$$WQI = \sum SIi\text{-}n$$

where SI_i is the sub index of i^{th} parameter; W_i is relative weight of i^{th} parameter; q_i is the rating based on concentration of i^{th} parameter, and n is the number of chemical parameters. The computed WQI values are classified into five categories: excellent water (WQI < 50); good water (WQI = 50–100); poor water (WQI = 100–200); very poor water (WQI = 200–300); and water unsuitable for irrigation (WQI > 300).

3. Results and discussion

Yield, water requirement and water productivity of crops

T. Aman

Yield, water requirement and water productivity of T.Aman rice obtained from the separate experimental fields at four locations during 2018-2019 are presented in Table 3a and 3b. Over the locations, yield varied from 3.41 to 4.17 t/ha in 2018 with minimum in farmers' practice treatment T_1 and maximum in T_2 where AWD with 20 cm depth was used for determining irrigation timing. In Rajshahi, grain yield was significantly lowest in T_1 compared to both AWD treatments T_2 and T_3. In Joypurhat too, highest yield was obtained from T_2 and it was insignificant compared to both T_1 and T_3. This happened because treatment T_2 and T_3 received almost same number and amount of irrigation water. Even treatment T_1 received ample amount of water from rainfall that almost satisfied the water requirement of T. Aman rice.

Table 3a. Yield, water requirement and water productivity of T. Aman rice during 2018

Treat-ment	Applied water (mm)	Eff. rainfall (mm)	WR (mm)	Yield (t/ha)	Water productivity (m^3/kg)	Yield increased (%)
Godagari (cv. BRRI dhan 51)						
T_1	200	328	528	2.65	1.99	
T_2	412	328	740	4.17	1.77	57.36
T_3	384	328	712	3.96	1.80	49.43
Tanore (cv. BRRI dhan 62)						
T_1	210	306	516	2.90	1.78	
T_2	423	306	729	3.98	1.83	37.24
T_3	346	306	652	3.56	1.83	22.76
Kalai (cv: Swarna)						
T_1	207	362	569	3.61	1.58	
T_2	287	362	649	3.77	1.72	4.43
T_3	296	362	658	3.79	1.74	4.99
Joypurhat sadar (cv: Guti Swarna)						
T_1	204	354	558	3.41	1.64	
T_2	294	354	648	3.66	1.77	7.33
T_3	294	354	648	3.63	1.79	6.45

Table 3b. Yield, water requirement and water productivity of T. Aman rice during 2019

Treat-ment	Applied water (mm)	Eff. rainfall (mm)	WR (mm)	Yield (t/ha)	Water productivity (m^3/kg)	Yield increased (%)
Godagari (cv. BRRI dhan 51)						
T_1	155	421	576	4.17	1.29	
T_2	237	421	658	4.77	1.30	13.42
T_3	155	421	576	4.13	1.30	-0.89
Tanore (cv. Sumon Swarna)						
T_1	162	375	537	4.26	1.18	
T_2	241	375	616	4.86	1.19	13.16
T_3	162	375	537	4.32	1.16	1.32
Kalai (cv: Swarna)						
T_1	130	494	624	3.91	1.48	
T_2	192	494	686	4.35	1.48	10.45
T_3	130	494	624	3.87	1.50	-0.95
Joypurhat sadar (cv: Guti Swarna)						
T_1	120	431	551	4.05	1.27	
T_2	178	431	609	4.24	1.34	4.37
T_3	120	431	551	4.03	1.27	-0.46

But in Rajshahi, as number and amount of irrigation were different among treatments, so difference in grain yields were found a significant. In 2019 too, highest yields were obtained from T_2. But yields obtained from T_1 and T_2 were almost same as these treatments received same amount of water from irrigation as well as from rainfall. In 2018, however, WPs were found highest in T_3, except Godagari where highest WP was obtained from T_1. Over the other three locations, WP varied from 1.58 m^3/kg for T_1 to 1.83 m^3/kg for T_3. That is, 1580 to 1830 liters of water was required to produce one kilogram of rice whereas in 2019, 1180 to 1500 litres of water was needed. As yield was found higher in 2019, so does the water productivity. Water requirement was varied from 528 mm to as much as 729 mm in 2018 whereas in 2019 it varied from 537 to 686 mm with minimum in T_1 and maximum in T_2.

Boro

The effects of different irrigation treatments on yield, water requirement and water productivity of boro rice grown in four different upazillas are presented in Table 4a and 4b. Two different rice varieties: BRRI dhan 28 and BRRI dhan 29 were used as test crops. BRRI dhan 29 performed better in terms of yield, but in terms of water requirement and water productivity BRRI dhan 28 performed better under all irrigation regimes. Irrespective of variety, treatment T_1 and/or T_2 produced the highest and identical yield of rice. AWD method with 15 cm depth (T_2) yielded more or less similar yield that obtained by farmers' practice. In some plots, AWD with 15 cm depth performed better while some other plots farmers' practice produced the highest yield. While AWD with 25 cm depth (T_3) produced about 3% less yield than farmers practice treatment T_1. However, water requirement was obviously higher in treatment T_1 as this treatment received irrigation more frequently than AWD treatments. Water productivity was found highest (less water required to produce 1.0 kg of rice) in AWD method with 25 cm depth even though this treatment produced the lowest yield, water use was was more efficient. Water required to produce highest yield was ranged from 1017 to 1096 mm for AWD with 15 cm depth and from 1139 to 1176 mm for farmers' practice with minimum values for BRRI dhan 28 and Maximum values for BRRI dhan 29. The difference in water requirement between these two varieties was due to difference in their growing period varietal potentiality.

Table 4a. Yield, water requirement and water productivity of boro rice during 2019

Treatment	WR (mm)	Yield (t/ha)	Water productivity (m^3/kg)	Yield reduction (%)	Water saved (%)	TWU (mm)	WUE (%)
Godagari (cv. BRRI dhan 28)							
T_1	1128	5.31	2.12	-	-	727	64.45
T_2	1017	5.27	1.93	0.75	9.84	662	65.09
T_3	912	5.06	1.80	2.82	19.15	635	69.63
Tanore (cv. BRRI dhan 29)							
T_1	1176	5.80	2.03	-	-	746	63.44
T_2	1096	5.78	1.90	0.34	6.80	684	62.41
T_3	952	5.56	1.71	3.62	19.05	658	69.12
Kalai (cv: BRRI dhan 29)							
T_1	1149	5.63	2.04	-	-	739	64.32
T_2	1044	5.78	1.81	-2.66	9.14	676	64.75
T_3	958	5.49	1.74	0.71	16.62	662	69.10
Joypurhat sadar (cv: BRRI dhan 28)							
T_1	1139	5.19	2.19		-	718	63.04
T_2	1027	5.16	1.99	0.58	9.83	658	64.07
T_3	908	5.03	1.81	3.08	20.28	636	70.04

Table 4b. Yield, water requirement and water productivity of boro rice during 2020

Treatment	WR (mm)	Yield (t/ha)	Water productivity (m^3/kg)	Yield reduction (%)	Water saved (%)	TWU (mm)	WUE (%)
Godagari (cv. BRRI dhan 28)							
T_1	1088	5.75	1.89			738	67.83
T_2	966	5.69	1.70	1.04	11.21	666	68.94
T_3	858	5.21	1.65	9.39	26.81	608	70.86
Tanore (cv. BRRI dhan 29)							
T_1	1169	6.34	1.84			819	70.06
T_2	1040	6.38	1.63	-0.63	11.04	740	71.15
T_3	901	5.63	1.60	11.20	29.74	641	71.14
Kalai (cv: BRRI dhan 29)							
T_1	1137	6.12	1.86			787	69.22
T_2	1029	6.18	1.67	-0.98	9.50	729	70.85
T_3	906	5.56	1.63	9.15	25.50	646	71.30
Joypurhat sadar (cv: BRRI dhan 28)							
T_1	998	5.47	1.82			648	64.93
T_2	993	5.46	1.82	0.18	0.50	693	69.79
T_3	871	5.13	1.70	6.22	14.58	611	70.15

Wheat

Yield, water requirement and water productivity of wheat obtained from the two separate experimental fields at two locations are presented in Table 5. Highest yields (4.73 t/ha at Godagari and 4.36 t/ha at Tanore) were obtained from T_3 treatment that received three irrigations at CRI, booting and grain filling stage up to field capacity at both locations. Only 3-4% decrease in yields were recorded in treatment T_2 (two irrigation at CRI and booting stages) which were at per with T_3.

Table 5. Yield, water requirement and water productivity of wheat

Treatment	WR (mm)	Yield (t/ha)	Water productivit y (kg/m^3)	Yield increased (%)	Yield decreased (%)	Water saved over T_3 (%)
Godagari (cv. BARI Gom 30)						
T_1	161	4.08	2.53	-	13.74	29.69
T_2	174	4.57	2.63	12.0	3.38	24.01
T_3	229	4.73	2.08	15.93	-	-
Tanore (cv. BARI Gom 30)						
T_1	166	3.90	2.35	-	10.55	30.25
T_2	179	4.18	2.34	7.18	4.12	24.07
T_3	238	4.36	1.83	11.79	-	-

The result revealed that less frequent irrigation can reduce the yield of wheat, but the amount of reduction can significantly be minimized by changing the timing of irrigation application. Therefore, where water is scare, two irrigations at CRI and grain filling stage (T_2) can be suggested rather than irrigation at CRI and booting stage (T_1). A reasonably good yield, though the lowest, was obtained from treatment T_1 received irrigation only at CRI stage. Total water use was highest in irrigation treatment T_3 as it received three number of irrigation. Although the number of irrigation was same for T_1 and T_2, T_2 received slightly more water, because irrigation interval in this treatment was higher and the soil was more dried to receive more amount of irrigation water. WPs were also found highest (2.34-2.63 kg/m^3) in this treatment T_2 with a water saving of about 24% over treatment T_3. So, considering water saving, water productivity and grain yield, two irrigations at CRI and booting stages can be suggested for growing wheat crop in this drought prone and water scarce area.

Potato

Variation in tuber yield, water requirement and water productivity of potato under three different irrigation treatments are presented in Table 6a and 6b. The yield of potato was significantly higher in furrow irrigation compared to the farmers practice in all study areas except in Joypurhat where treatment with farmers' practice and furrow irrigation produced almost same yield while alternate furrow irrigation produced the lowest. In other locations, however, alternate furrow irrigation produced the second highest yields those were at per with furrow irrigation. Compared to farmers' practice, the average yield increased in furrow irrigation and alternate furrow irrigation system was 7.42% and 4.30%, respectively. From the result it is clear that both furrow and alternate furrow irrigation can significantly improve the growth and yield of potato, where the difference in yield between furrow and alternate furrow is marginal. From Table 6, it is seen that significantly higher irrigation water was applied in farmers' practice compared to furrow irrigation and alternate furrow irrigation. Therefore, the total water use was also highest in the farmers' practice, whereas the lowest water use was in alternate furrow irrigation treatments. About 40% water was saved in alternate furrow irrigation treatment compared to the farmers' practice, whereas it was about 15% in furrow irrigation treatments.

Table 6a. Yield, water requirement and water productivity of potato during 2018-19

Treatment	WR (mm)	Yield (t/ha)	Water productivity (kg/m^3)	Water saved (%)	Yield increased over T_1 (%)
Godagari (cv. BARI Alu 7)					
T_1	336	28.65	8.53	-	-
T_2	285	31.28	10.98	15.17	9.18
T_3	196	30.07	15.34	41.66	4.96
Tanore (cv. BARI Alu 7)					
T_1	342	35.56	10.40	-	-
T_2	281	37.18	13.23	17.83	4.56
T_3	203	35.90	17.68	40.64	0.96
Kalai (cv. BARI Alu 8)					
T_1	307	31.76	10.35	-	-
T_2	276	34.47	12.49	15.18	8.53
T_3	186	33.98	18.27	41.67	6.99
Joypurhat sadar (cv. BARI Alu 26)					
T_1	298	26.64	8.94	-	-
T_2	268	26.86	10.02	17.84	0.83
T_3	193	24.33	12.61	40.64	-8.67

Table 6b. Yield, water requirement and water productivity of potato during 2019-20

Treatment	WR (mm)	Yield (t/ha)	Water productivity (kg/m^3)	Water saved (%)	Yield increased over T_1 (%)
Godagari (cv. BARI Alu 7)					
T_1	333	30.76	9.24	-	-
T_2	288	32.58	11.31	13.51	5.92
T_3	201	29.80	14.83	39.64	-3.22
Tanore (cv. BARI Alu 7)					
T_1	326	37.2	11.41	-	-
T_2	284	46.6	15.56	12.88	20.17
T_3	206	44.2	22.62	36.81	18.28
Kalai (cv. BARI Alu 8)					
T_1	315	33.45	10.62	-	-
T_2	279	35.32	12.66	11.43	5.59
T_3	197	33.38	16.94	37.46	-0.21
Joypurhat sadar (cv. BARI Alu 26)					
T_1	292	27.66	9.47	-	-
T_2	257	28.09	10.93	11.99	1.55
T_3	189	26.55	14.05	35.27	-4.18

Water productivity was considerably higher in alternate furrow irrigation and furrow irrigation treatments than that of farmers' practice due to higher yield obtained in these treatments with comparatively lower irrigation water use. Highest water productivity (12.49 – 17.68 kg/m^3) was observed in alternate furrow irrigation followed by furrow irrigation treatment (10.02–13.23 kg/m^3), whereas the lowest (8.53–10.40 kg/m^3) was always in farmers practice. Water productivity was around 65% higher in alternate furrow and around 22% higher in every furrow irrigation compared to the traditional irrigation practice.

Mustard

Yield of mustard differed significantly by the number and timing of irrigation (Table 7a &7b). Grain yield of mustard increased considerably when number of irrigation increased from one to two. But it showed an insignificant yield variation when yield under one irrigation either at vegetative or pre-flowering stage were compared. Though treatments T_1 and T_2 both received one irrigation, yield variation was observed between them due to variation in timing of water application with marginally higher yield in T_2 where water was applied at pre-flowering stage. This result indicate that pre-flowering stage is more responsive than vegetative stage. However, the highest yield (1.56-1.61 t/ha) was obtained from treatment T_3 that received two irrigations at vegetative and pod formation stages. The lowest yield (1.39-1.43 t/ha) was obtained from T_1 when irrigation was applied at vegetative stage. Around 10-15% higher yield was noticed in T_3 compared to T_1, while yield difference between T_1 and T_2 was registered as 2 - 4%. Though treatment T_1 and T_2 both received one irrigation, amount of water requirement was slightly higher in T_2 due to timing of application. Treatment T_2 received irrigation about 10 days later than T_1 when plants were taller with drier field soil, hence more water was needed to fulfill the crop demand. Obviously treatment T_3 that received two irrigations at vegetative and pod formation stages gave the highest yield with low water productivity. As increase in yield was not proportionate to water use, so water productivity was slightly lower in treatment T_3 than other two treatments. A reasonably good yield and water productivity was obtained from treatment T_2 with one irrigation only at pre-flowering stage is preferred to irrigation at vegetative stage, even it is preferred to two irrigations at vegetative and pod formation stages in water scarce situation.

Table 7a. Yield, water requirement and water productivity of mustard during 2018-19

Treatment	WR (mm)	Yield (t/ha)	Water productivity (kg/m^3)	Yield increased (%)	Water saved over T_3 (%)
Godagari (cv. BARI Sarisha 14)					
T_1	139	1.43	1.03		19.19
T_2	142	1.47	1.04	2.16	17.44
T_3	172	1.56	0.91	9.09	-
Tanore (cv. BARI Sarisha 14)					
T_1	143	1.39	0.97		19.66
T_2	149	1.48	0.99	4.20	16.29
T_3	178	1.61	0.90	15.83	-

Table 7b. Yield, water requirement and water productivity of mustard during 2019-20

Treatment	WR (mm)	Yield (t/ha)	Water productivity (kg/m^3)	Yield increased (%)	Water saved over T_3 (%)
Godagari (cv. BARI Sarisha 14)					
T_1	133	1.15	0.91	-	21.30
T_2	145	1.19	0.85	1.65	14.20
T_3	169	1.49	0.80	12.40	-
Tanore (cv. BARI Sarisha 17)					
T_1	136	1.21	0.94	-	21.39
T_2	147	1.25	0.88	1.56	15.03
T_3	173	1.57	0.82	10.16	-

Effect of irrigation on the yield of rabi crops and rice equivalent yield (REY)

Individual crop yield under different cropping sequences are presented in Table 8. It is seen that irrigation had significant effects on the yield of rabi crops wheat, mustard, tomato and potato. Yield of mustard differed significantly when number of irrigation increased from one to two. But it showed an insignificant yield variation when irrigation was applied either at vegetative stage or at flowering stage. Similarly, yield of wheat increased slightly when number of irrigation increased from two to three. The highest yield of wheat was obtained from treatment T_3 that received three irrigations at CRI, booting and flowering stages, non-significantly followed by treatment T_2 that received two irrigation at CRI and grain filling stages. The yield under T_1 was significantly lowest compared to T_3. Though both the treatments, T_1 (farmers' practice) and T_2 received two irrigations, a variation in yield was observed due to difference in timing of irrigation with slightly higher yield was found in treatment T_2 . The result revealed that less frequent irrigation can reduce the yield of wheat, but the amount of reduction can significantly be minimized by changing the timing of irrigation application. Therefore, where water is scare, two irrigations at CRI and grain filling stage (T_2) can be suggested rather than irrigation at CRI and booting stage (T_1). In case of mustard, yield variation was insignificant between treatments T_1 (vegetative) and T_2 (irrigation at pre-flowering stage). A significantly higher yield was obtained from treatment T_3 that received two irrigations at pre-flowering and pod formation stages. This yield under treatment T_1 and T_2 was at per with slightly higher yield was found when irrigation was applied at pre-flowering stage. So, if only one irrigation is applied, pre-flowering stage is preferred to irrigation at vegetative stage, even it is preferred to two irrigations at vegetative and pod formation stages in water scarce situation.

Table 8. Rice equivalent yield (REY) of different cropping patterns of study areas

Pattern	Irrigation treatment	Crop yield (t/ha)				Rice equivalent yield (t/ha)	
		Rabi	Boro	T.aus	T.aman	Rabi	Total
Location: Godagari							
Mustard-Boro-T.Aman	T_1	1.29	5.31		2.65	2.86	10.82
	T_2	1.32	5.27		4.17	2.93	12.37
	T_3	1.56	5.06		3.96	3.46	12.48
Tomato-Boro- T.aus	T_1	45.36	4.8	3.84	-	37.78	46.42
	T_2	52.29	4.06	4.21	-	43.56	51.83
	T_3	48.03	4.51	4.13	-	40.01	48.65
Potato-Boro-T.Aman	T_1	29.7	5.53		3.56	19.81	28.90
	T_2	31.93	5.48		4.62	21.30	31.40
	T_3	29.93	5.13		4.2	19.96	29.29
Maize-T.aus-T.aman	T_1	7.82	4.93	-	2.77	8.68	16.38
	T_2	9.96	5.01	-	3.77	11.06	19.84
	T_3	9.28	4.41	-	3.51	10.30	18.22
Location: Tanore							
Wheat-T.Aus-T.Aman	T_1	4.08	-	3.93	2.71	5.63	12.27
	T_2	4.57	-	4.17	3.48	6.31	13.96
	T_3	4.73	-	4.26	3.57	6.53	14.36
Potato-Boro-T.Aman	T_1	35.56	5.8	-	2.9	23.72	32.42
	T_2	37.18	5.78	-	3.98	24.80	34.56
	T_3	35.9	5.56	-	3.56	23.95	33.07
Potato-T.Aus-T.Aman	T_1	34.64	-	3.62	2.79	23.10	29.51
	T_2	36.49	-	3.87	3.54	24.34	31.75
	T_3	35.2	-	3.36	3.32	23.48	30.16
Location: Kalai							
Potato-Boro-T.Aman	T_1	32.60	5.63	-	3.49	21.75	30.87
	T_2	34.89	5.78	-	3.63	23.27	32.68
	T_3	33.68	5.49	-	3.6	22.46	31.55
Mustard-Boro-T.Aman	T_1	1.1	5.41	-	3.61	0.73	9.75
	T_2	1.11	5.56	-	3.77	0.74	10.07
	T_3	1.39	5.29	-	3.79	0.93	10.01
Location: Joypurhat sadar							
Potato-Boro-T.Aman	T_1	27.15	5.19		3.41	18.11	26.71
	T_2	27.47	5.16		3.66	18.33	27.15
	T_3	25.44	5.03		3.63	16.97	25.63
Mustard-Boro-T.Aman	T_1	1.02	5.41		3.56	0.68	9.65
	T_2	1.08	5.56		3.71	0.72	9.99
	T_3	1.31	5.29		3.65	0.87	9.81

The yield of potato was significantly higher in every furrow irrigation compared to the farmers practice in all study areas except in Joypurhat where treatment with farmers' practice and every furrow irrigation produced almost same yield while alternate furrow irrigation produced the lowest. In other locations, however, alternate furrow irrigation produced the second highest yields those were at per with furrow irrigation. On average over the location, the yield of potato was significantly higher in both every furrow irrigation and alternate furrow irrigation compared to the farmers practice. The average yield increased in furrow irrigation and alternate furrow irrigation than that of the farmers practice was 7.42% and 4.30%, respectively. From the result it is clear that both furrow and alternate furrow irrigation can significantly improve the growth and yield of potato, where the difference in yield between furrow and alternate furrow is marginal.

The yield of tomato was significantly influenced by the different irrigation methods. The highest fruit yields of 52.29 t/ha was obtained from the treatment T_1 which received drip irrigation at 3 days interval produced slightly lower yield than traditional furrow irrigation with a greater saving (about 35%). This was at par with the yield that obtained under traditional furrow irrigation (T_2) at 10 days interval. Alternate furrow irrigation at 10 days interval irrigation water. Drip fertigation not only produced the highest yield, but also offered a greater saving of water (45%) and fertilizer.

The grain yield of maize was found a bit higher in every furrow irrigation than that of the alternate furrow irrigation while farmers' practice treatment had the significantly lowest yield. The difference in yield between the treatment T_2 (furrow) and T_3 (alternate furrow) was insignificant, but the total water use was significantly lower in alternate furrow irrigation treatment (T_3) compared to the every furrow irrigation treatment (T_2), as it received less amount of irrigation water. Thus, alternate furrow irrigation can be a judicious option for maize cultivation in water scarce areas.

As yield of different crops in a particular cropping sequence varied, rice equivalent yield (REY) also varied with different irrigation treatments (Table 8). Among the tested crops, tomato had the highest rice equivalent yield (REY) under T_2 water management practice followed by REY of potato. Accordingly the highest REY of 51.83 t/ha was obtained from Tomato – Boro –T.Aus cropping pattern followed by Potato – Boro – T.Aman cropping patterns under this water regime. These two vegetable crops have high yield potential to give the higher REY compared to other crops like mustard and wheat. However, the lowest yield of mustard resulted in the lowest REY which was even lower than that of boro rice. Though wheat also gave the lower REY, it was higher compared to the yield of boro rice. Thus, most of the rabi crops had the higher REY than boro rice.

Total water use and water productivity of different cropping patterns

Total water use and water productivity of different cropping patterns under different management options are shown in Table 9. Water use and water productivity was widely varied by cropping pattern and irrigation regimes. Total water use was found highest in Tomato-Boro-T.Aus cropping pattern followed by Potato-Boro-T.Aman and Mustard-Boro-T.Aman patterns and the lowest was recorded by Potato-T.Aus-T.Aman closely followed by Wheat-T.Aus-T.Aman and Maize-T.Aus-T.Aman cropping patterns. Though all were three-crop based patterns, TWU by the previous patterns were higher than latter patterns due to inclusion of more water intensive boro rice. Even drip irrigating tomato consumed more water than other rabi crops. So, the highest water consumed pattern was Tomato-Boro-T.Aus and the TWU by this pattern varied from 1906 mm to 2052 mm with minimum in treatment T_3 and mamimum in treatment T_2. In Potato-Boro-T.Aman pattern, TWU varied from 1730 mm for T_3 to 1993 mm for T_1 in Godagari. In other locations, it varied from 1729 mm in T_3 to as high as 2025 mm either in farmers practice T_1 or standard practice T_2. In Tanore, water used by T.Aman under farmers' practice treatment T_1 was much lower than T_2 as farmer applied less number of irrigation. The difference in TWU between these two management options arose from difference in water use by T.Aman rice. In Kalai and Joypurhat sadar, TWU by Potato-Boro-T.aman patterns were higher than that by Mustard-Boro-T.aman patterns. The difference in TWU between these two patterns arose from difference in water use by mustard and potato. On average, TWU was lower in non-rice rabi crops, except maize, than rice and vegetables crops.

Table 9: Cropping pattern based water productivity

Pattern	Irrigation treatment	Water use (mm)				WP (kg/m^3)		
		Rabi	Boro	T.aus	T.aman	TWU (mm)	REY (t/ha/yr)	WP (kg/m^3)
Location: Godagari								
Mustard-Boro-T.Aman	T_1	139	1128	-	528	1795	10.82	0.62
	T_2	142	1017	-	724	1883	12.37	0.67
	T_3	172	912	-	678	1762	12.48	0.71
Tomato-Boro-T.aus	T_1	358	1136	538	-	2032	46.42	2.28
	T_2	293	1019	740	-	2052	51.83	2.52
	T_3	266	917	723	-	1906	48.65	2.55
Potato-Boro-T.Aman	T_1	333	1108	-	552	1993	28.90	1.45
	T_2	288	991	-	699	1978	31.40	1.59
	T_3	201	885	-	644	1730	29.29	1.69
Maize-T.Aus-T.Aman	T_1	296	-	538	533	1367	16.38	1.20
	T_2	348	-	740	728	1816	19.84	1.09
	T_3	266	-	723	714	1703	18.22	1.07
Location: Tanore								
Wheat-T.Aus-T.Aman	T_1	161	-	538	528	1227	12.27	1.00
	T_2	174	-	728	713	1615	13.96	0.86
	T_3	229	-	711	682	1622	14.36	0.89
Potato-Boro-T.Aman	T_1	336	1176		516	2028	32.42	1.60
	T_2	285	1096		729	2110	34.56	1.64
	T_3	196	952		652	1800	33.07	1.84
Potato-T.Aus-T.Aman	T_1	342		542	512	1396	29.51	2.11
	T_2	281		737	721	1739	31.75	1.83
	T_3	203		713	661	1577	30.16	1.91
Location: Kalai								
Potato-Boro-T.Aman	T_1	307	1149		569	2025	30.30	1.50
	T_2	276	1044		649	1969	32.40	1.65
	T_3	186	958		628	1772	31.75	1.79
Mustard-Boro-T.Aman	T_1	110	1146		564	1820	9.75	0.54
	T_2	119	1041		652	1812	10.07	0.56
	T_3	156	953		626	1735	10.01	0.58
Location: Joypurhat sadar								
Potato-Boro-T.Aman	T_1	298	1139		558	1995	26.37	1.32
	T_2	268	1027		648	1943	26.74	1.38
	T_3	193	908		628	1729	24.89	1.44
Mustard-Boro-T.Aman	T_1	107	1129		558	1794	9.65	0.54
	T_2	113	1015		648	1776	9.99	0.56
	T_3	152	902		628	1682	9.81	0.58

Crop water productivity (WP) or water use efficiency (WUE) expressed in kg/m³ is an efficiency term, expressing the amount of marketable product (e.g. kilograms of grain) in relation to the amount of input needed to produce that output (cubic meters of water). Among the cropping patterns, Tomato-Boro-T.Aus had the highest WP ranged from 2.26 to 2.57 kg/m^3 followed by Potato-Boro-T.Aman pattern in which WP ranged from 1.83 to 2.11 kg/m^3 with maximum in T_1 and minimum values in T_2 or T_3 water management practice. Both the crops potato and tomato have the high yield potential and their inclusion in any pattern perceptibly will increase the REY and WP as well. Over the locations, WP varied from 1.32 to 1.84 kg/m^3 for Potato-Boro-T.Aman with minimum in T_1 and maximum in T_3 water management option. The pattern Mustard-Boro-T.Aman had the lowest WP ranging from 0.62 to 0.71 kg/m^3 for Rajshahi and from 0.54 to 0.58 kg/m^3 for Joypurhat. In this pattern too, WP was found highest under T_3 management option. In general, WP was found higher in water management options where water saving technologies were included as a treatment.

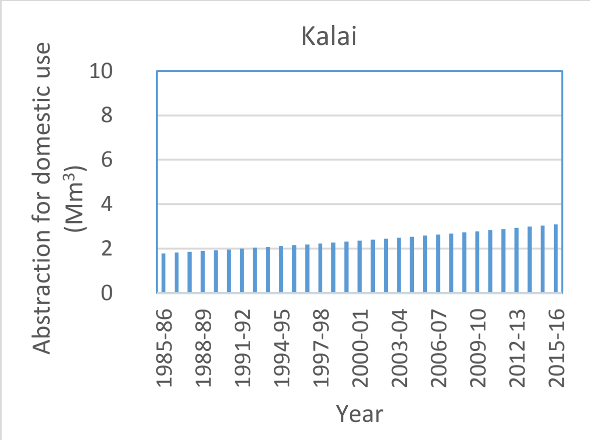
Conclusions

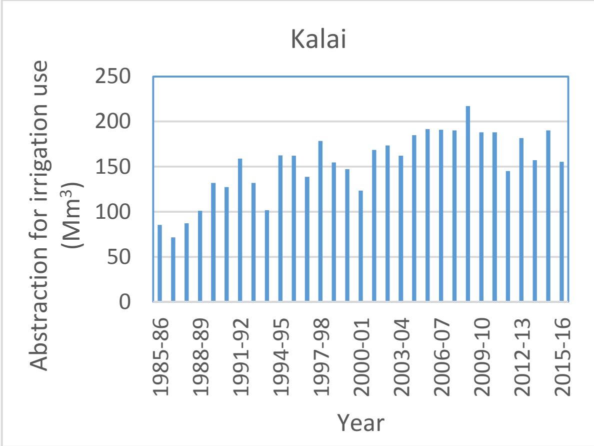
REY, TWU and WP were greatly influenced by the crops in a cropping pattern. Among the tested crops, tomato had the highest rice equivalent yield (REY) under T_2 water management practice followed by REY of potato. Accordingly the highest REY was obtained from Tomato – Boro – T.Aus cropping pattern followed by Potato – Boro – T.Aman cropping patterns under T_2 water management option. These two vegetable crops have high yield potential to give the higher REY compared to other crops like mustard and wheat pattern. Total water use was also found higher in this pattern and ranged from 1906 mm to 2052 mm depending on irrigation management while the lowest water use pattern was Potato–T.Aus–T.Aman with total water use ranged from 1577 – 1800 mm. Implausibly, comparatively higher water use patterns gave the higher WPs due to inclusion of vegetable crops with high yield potential and water saving technology. In general, WP was found higher in water management options where water saving technologies were included as a treatment. Therefore, inclusion of vegetable crops even non-rice rabi crops instead of boro rice and water saving irrigation technologies can significantly reduce the irrigation water requirement in dry season and increase the rice equivalent yield (REY) without having any effect on farm's productivity

7.2 Groundwater abstraction pattern

Abstraction due to irrigation, domestic and municipal water demand

Groundwater abstraction due to irrigation, domestic and municipal requirement are presented in Figure 10, 11, 12 and 13. While future prediction of groundwater abstraction for irrigation, domestic and municipal use in study areas are presented in Figure 14. From figures, it is apparent that abstraction due to domestic uses increasing almost steadily over the years for all study areas. This is because of gradual increase of population and their demand for domestic uses. Whereas abstraction due to irrigation varied over the year with less abstraction in wet (rainfall) year and high in dry year. In dry year, water demand by crops was fully satisfied by groundwater pumping while rainfall partially satisfied the crop water demand in wet year. On average over the year, increasing trend of groundwater abstraction for irrigation was evident and so does the total water abstraction. It is apparent from Figure 12 that groundwater abstraction will continue to increase if the present rate of abstraction continues. As the increasing demand of water is triggering more in Rajshahi than in Joypurhat, so more groundwater need to be abstracted in future from Barind area of Rajshahi. Abstraction will be increasing by 33-35% in Joypurhat study areas while it will be increasing by 40-45% in Rajshahi in the next 20 years. So, appropriate measures should be taken to ensure judicious use of water in all sectors especially in agriculture to protect the groundwater resources from being further depleted.





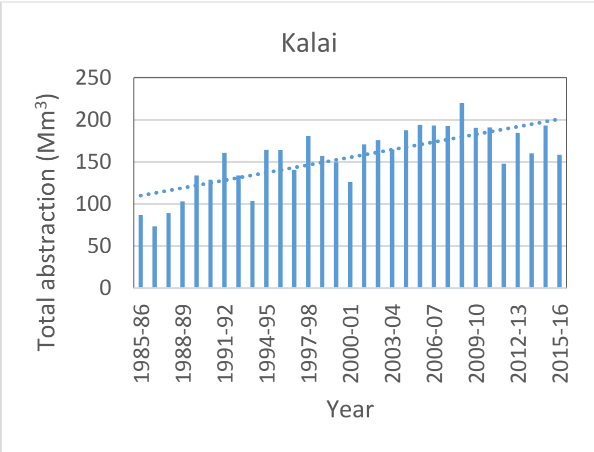
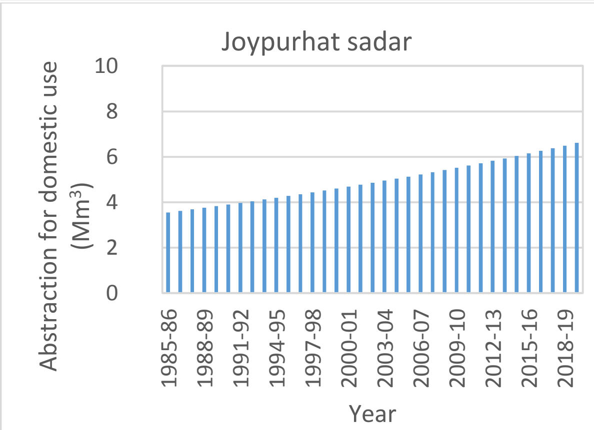
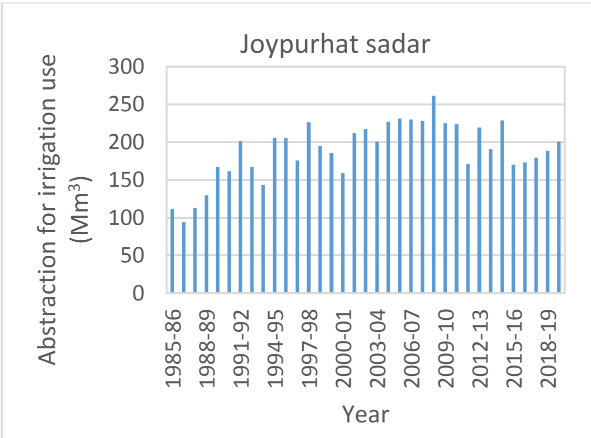


Figure 10. Groundwater abstraction pattern in Kalai upazila.





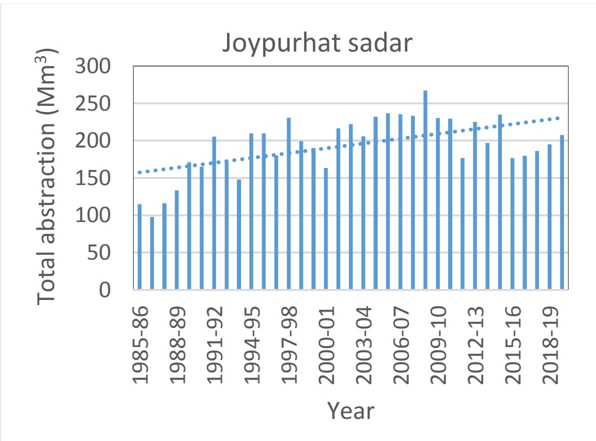
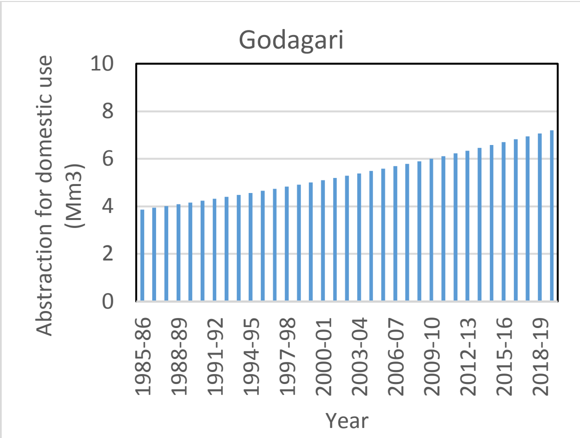
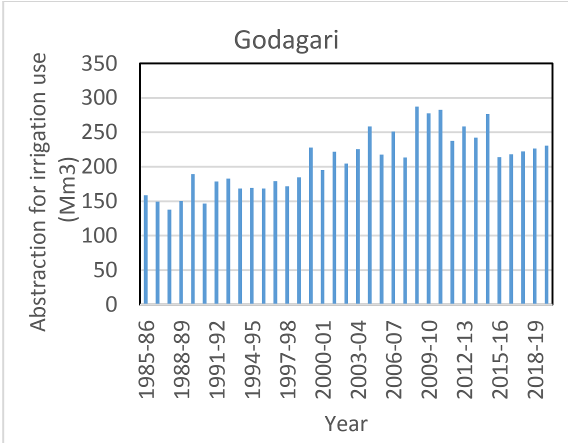


Figure 11. Groundwater abstraction pattern in Joypurhat sadar upazila.





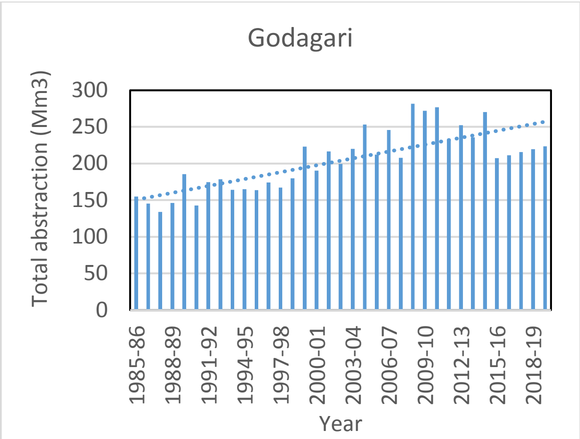
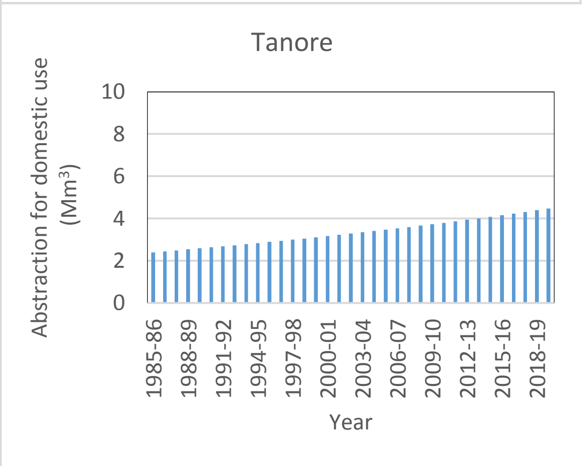
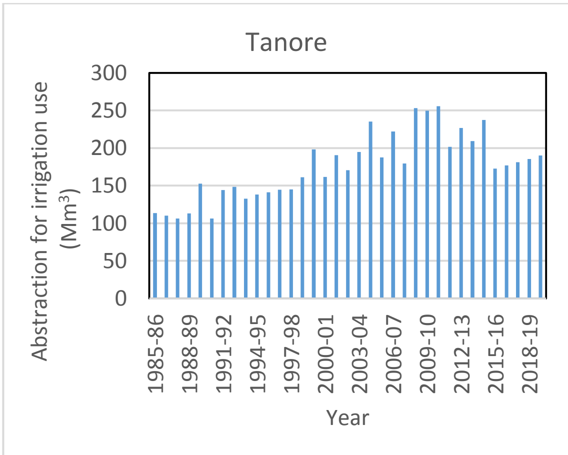


Figure 12. Groundwater abstraction pattern in Godagari upazila.





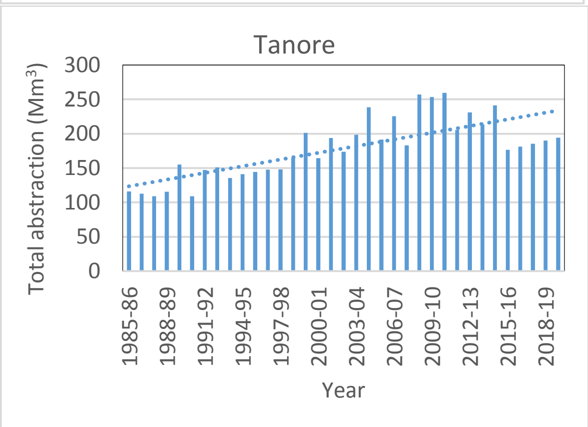


Figure 13. Groundwater abstraction pattern in Tanore upazila.

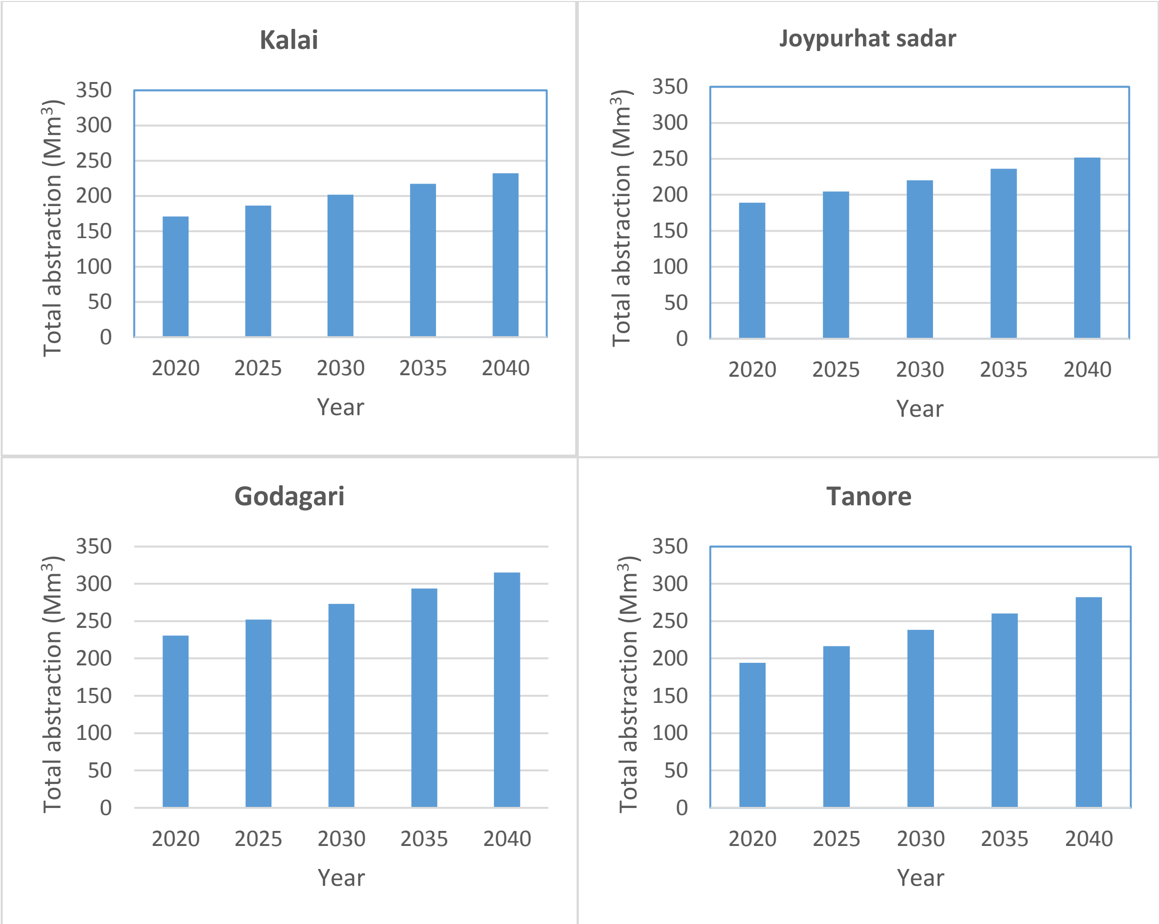


Figure 14. Predicted groundwater abstraction for irrigation, domestic and municipal use in study areas.

7.3 Trends of groundwater levels fluctuation

Predicted response over the validation data's time span at observation well GT8194046 is illustrated in Figure 13. The plot shows that the model response overlaps the measured value for the validation data. The combined prediction and forecasting results indicate that the model represents the measured water level data. Figure 15 shows that there are relatively good agreements between the simulated and observed groundwater level for all the three models. Thus, it is practically possible to develop groundwater forecasting models using this data-driven approach. However, there are discrepancies in matching some of the peak events, where the events may be under predicted or over predicted values.

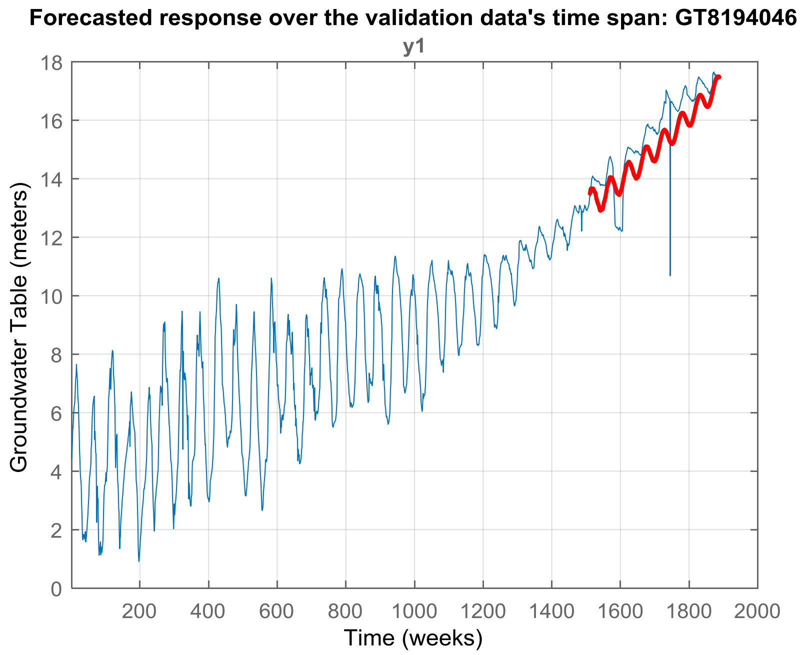


Figure 15. Predicted response over the validation data's time span at observation well GT8194046.

The forecasting results also show that over large horizons the model variance is large and for practical purposes future forecasts should be limited to short horizons. For the water level prediction model, a horizon of 22 years is appropriate given the previous data available is only for 38 years.

Figure 16 and 17 presents the predicted response over the validation data's time span at observation well GT8194048 and GT8194049.

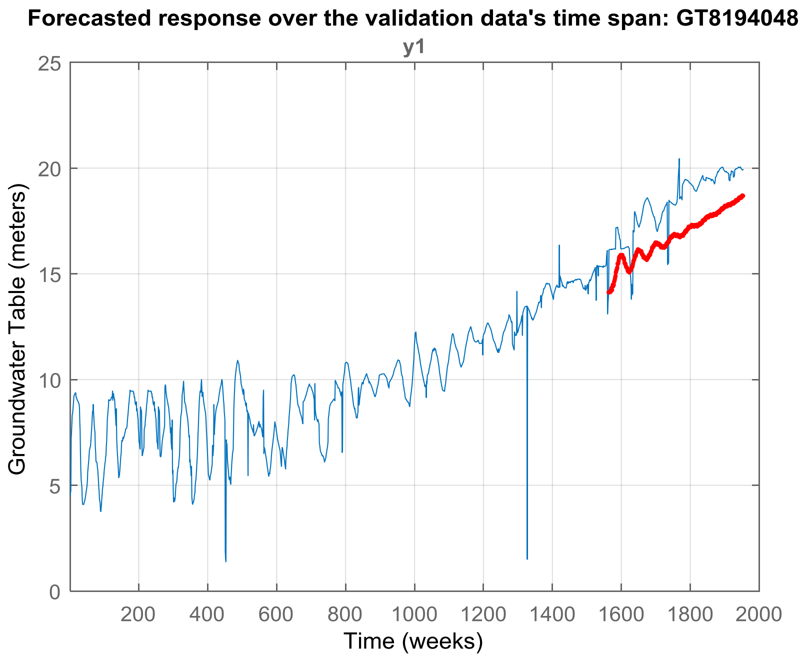


Figure 16. Predicted response over the validation data's time span at observation well GT8194048.

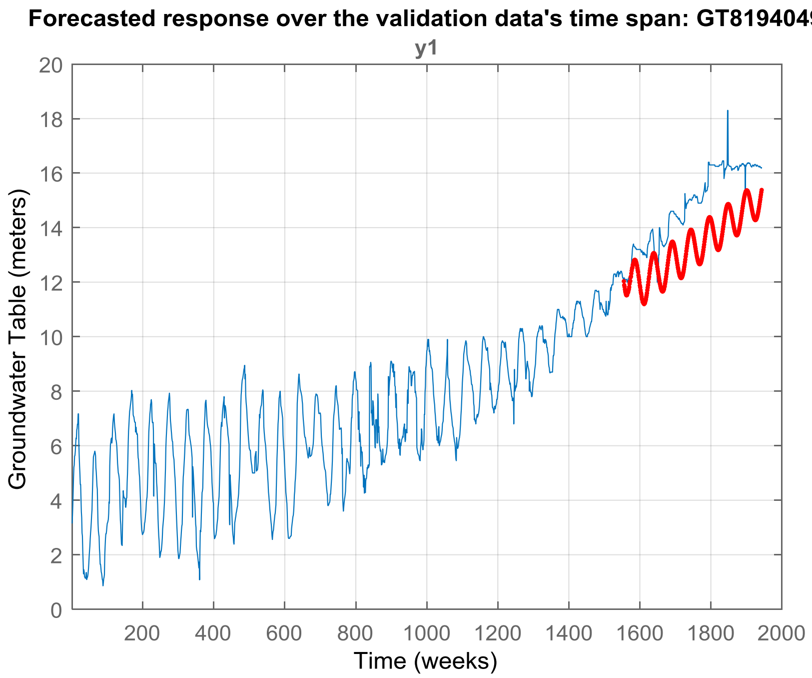


Figure 17. Predicted response over the validation data's time span at observation well GT8194049.

The properly trained and validated models are then used to forecast the response 1105 steps into future for the time span of 22 years (From 25/09/2018 to 24/09/2040). The forecasted results are presented in Figures 18, 19, and 20.

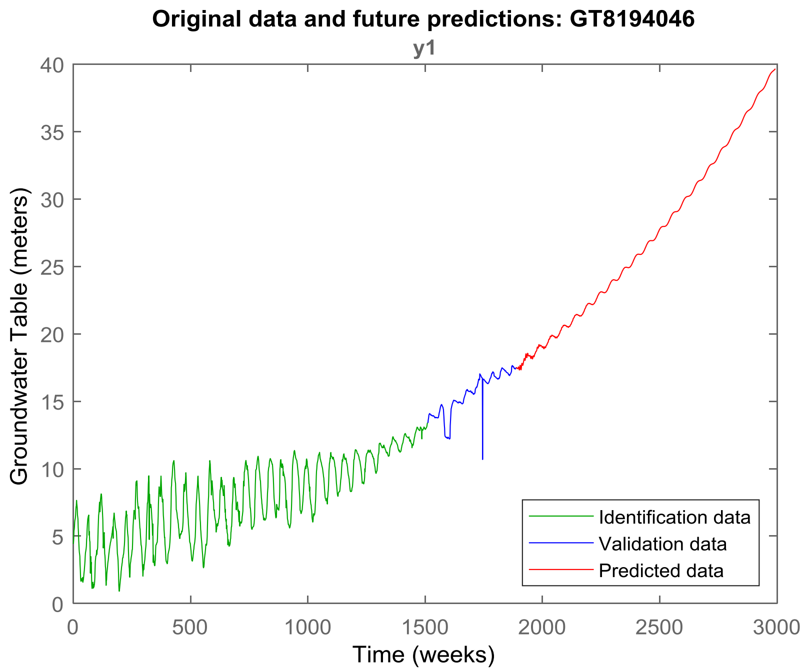


Figure 18. Original and future predicted data at observation well GT8194046.

The green curve shows the measured identification data whereas the blue curve shows the measured validation data that spans over 1-1900 weeks. The red curve is the forecasted response for 1105 weeks beyond the measured data's time range.

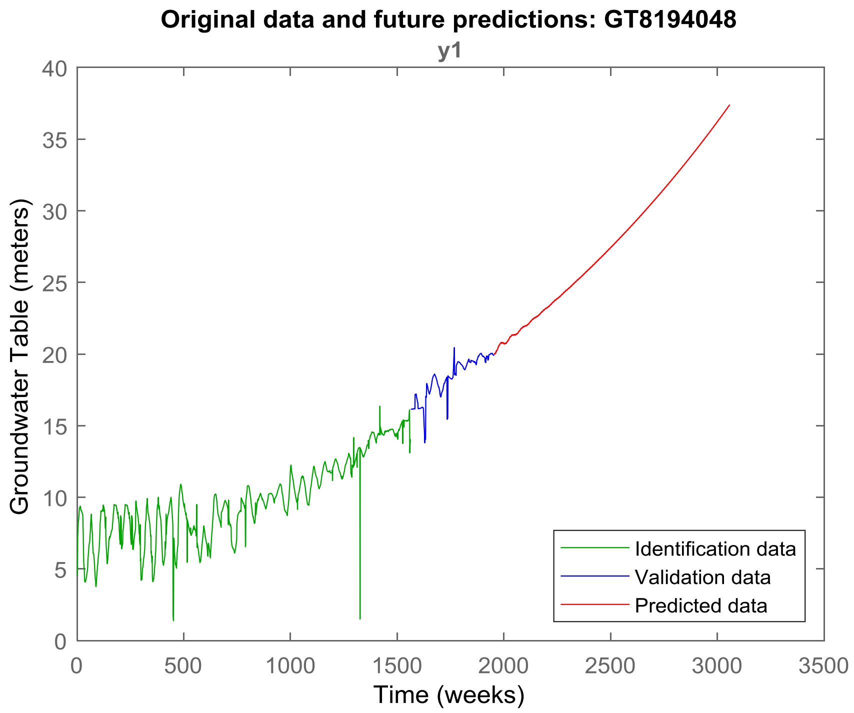


Figure 19. Original and future predicted data at observation well GT8194046.

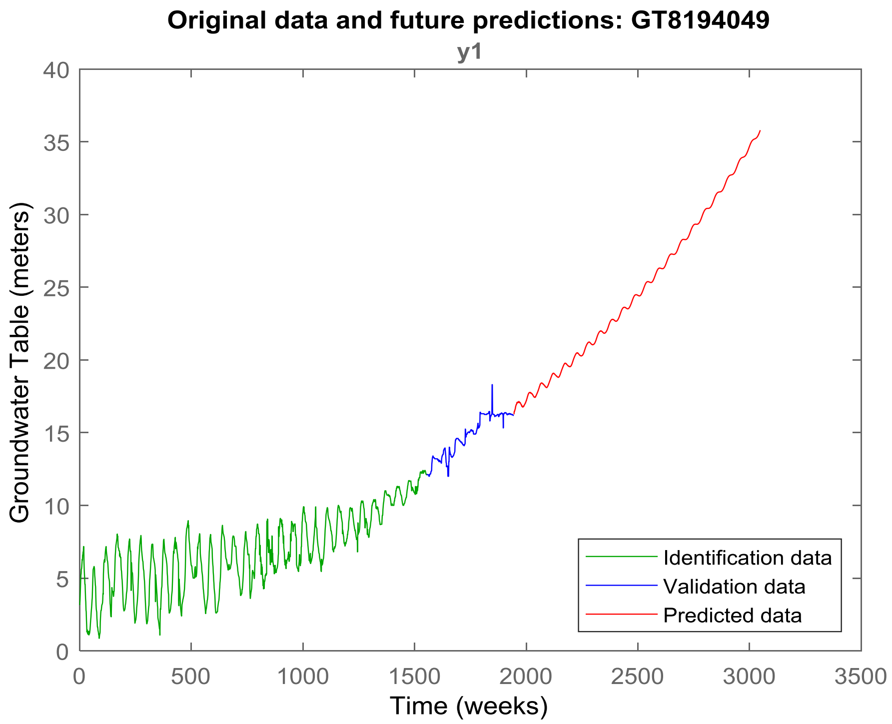


Figure 20. Original and future predicted data at observation well GT8194046.

Figure 21 illustrates groundwater level at the selected three observation wells on 24/09/2018 and the projected (model predictions) groundwater table on 24/09/2040. It is perceived from Figure 15 that groundwater level declination almost doubled at all the three observation wells for the next 22 years if the present rate of abstraction continues. It is concluded that the proposed modeling framework can serve as an alternative approach to simulating groundwater level change and water availability, especially in regions where subsurface properties are unknown.

Of note, the forecasting results are entirely based on the historical groundwater level data based on the previous abstraction and recharge rates. As the increasing demand of water is triggering more and more groundwater abstraction from the aquifer and the recharge rate is decreasing due to scanty rainfall in that area, the groundwater level declination might be even more dangerous than the projected ones if corrective measures are not taken. Moreover, the sticky clay subsurface of the study area slows down the natural recharge to the aquifer. Therefore, groundwater abstraction should be judiciously optimized in the study area to protect the already vulnerable groundwater resources.

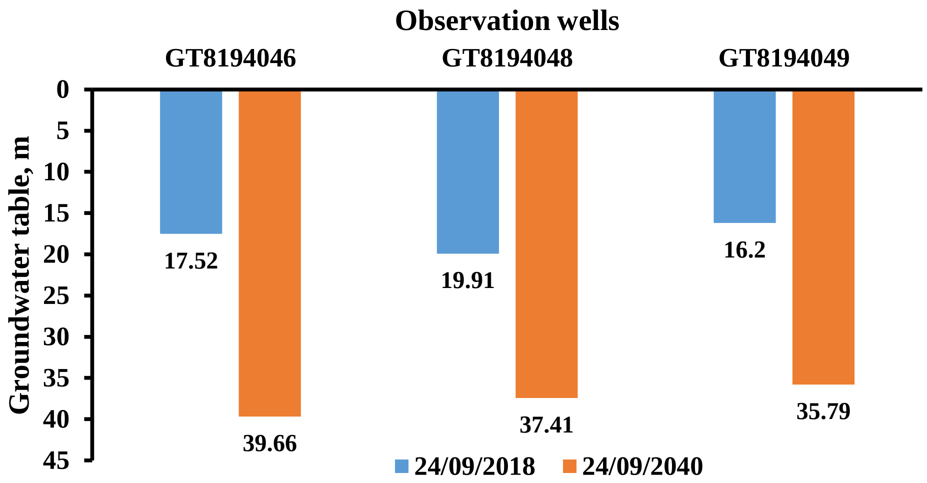


Figure 21. Present and future scenarios of groundwater table at three observation wells.

Trend in GWL fluctuation (MAKESENS Model)

Table 9. Rate of change of maximum water table depth (myear^{-1}) and prediction of maximum water table depth (m) at Tanore of Rajshahi

Observation well	Rate of change of maximum water table (myear^{-1})	Maximum WT change from 1980 to 2018	Maximum WT in 2018	Prediction of maximum water table (WT) depth in different year			
				2025	2030	2035	2040
GT8194046	0.300 ***	11.400	17.250	19.350	20.850	22.350	23.85
GT8194048	0.390 ***	14.820	20.830	22.930	24.880	26.830	28.78
GT8194049	0.298 ***	11.324	16.544	18.644	20.134	21.624	23.114

- 0.3*38 = 11.4, 17.25 + (7*0.3) = 19.35, 17.25 + (12*0.3) = 20.85 and so on…

- Linear interpolation based on the rate of change of maximum water table
- Real systems are not that much straightforward
- Cannot act as an alternative to Numerical simulation in data scarce situations

7.4 Optimization of groundwater abstraction

A numerical simulation model, MODFLOW was employed to determine the groundwater heads as well as to optimize groundwater abstraction at three observation wells under three groundwater recharge scenarios. The model was calibrated using the available hydrogeological data of the study area. The modelling works of Tanore upazilla are presented in this section of the report. The modelling works of the other three upazillas are continuing and will be presented in the next report. The study area of Tanore has an aerial extent of 297.2463 km^2. The aerial map of the study area is presented in Fig 22. In order to optimize groundwater abstraction, the following three scenarios were considered:

Scenario 1: abstraction < recharge; i.e. < 90% (more sustainable)

Scenario 2: abstraction = recharge; i.e. = 100% (less sustainable)

Scenario 3: abstraction > recharge; i.e. > 110% (business-as-usual)

The aquifer processes of Tanore upazilla were simulated using a calibrated 3D finite difference based numerical simulation code MODFLOW. The modelling and the scenario development were performed based on the very limited quantity of available hydrogeological data.

Actual and simulated groundwater levels at three observation wells during the calibration process are presented in Table 10.

Table 10. Actual and simulated groundwater levels at three observation wells the during calibration process

Observation wells	Actual, m	Simulated, m	Residual, m
GT8194046	17.52	16.388	1.13155
GT8194048	19.191	18.133	1.07832
GT8194049	20.20	22.215	-2.01514

The calibration targets at three observation wells are presented in Fig. 22. The components of a calibration target are illustrated in Fig. 5. The center of the target corresponds to the observed value. The top of the target corresponds to the observed value plus the interval and the bottom corresponds to the observed value minus the interval. The colored bar represents the error. If the bar lies entirely within the target, the color bar is drawn in green. If the bar is outside the target but the error is less than 20%, the bar is drawn in yellow. If the error is greater than 20%, the bar is drawn in red.

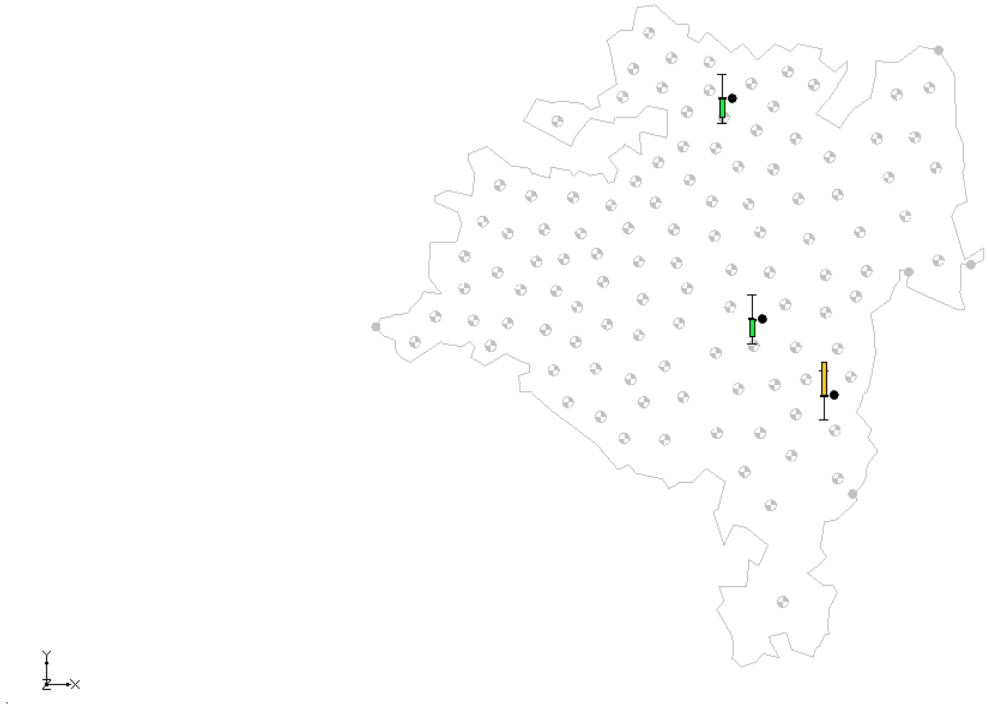


Fig. 22 Calibration target error bars at three observation wells.

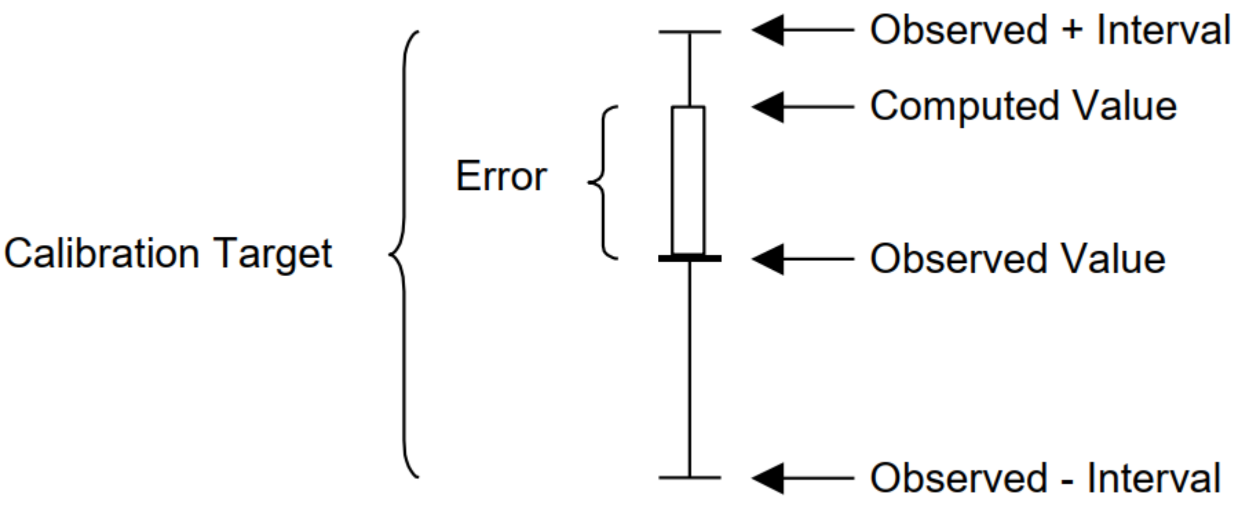


Fig. 23 Components of the calibration target.

Contour plot of the simulated groundwater heads for the calibrated model is presented in Fig. 24.

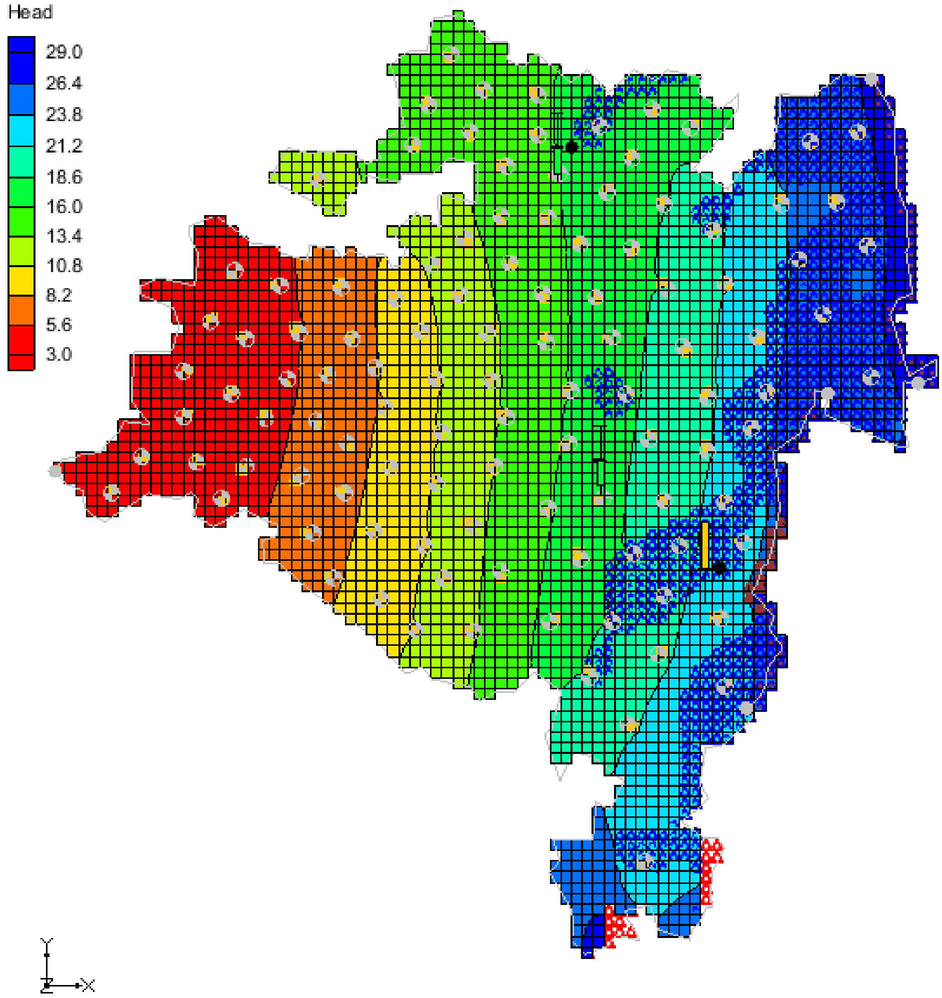


Fig. 24 Contour plot of the groundwater heads in the calibrated model.

Computed groundwater levels for the two scenarios at the observation wells are presented in Table 11. The corresponding contour plots of the computed groundwater heads are presented in Fig. 25 and Fig. 26, respectively.

Table 11. Computed groundwater levels for 90% and 110% of the actual abstraction

Observation wells	Actual, m (business as usual)	Computed, m	
		90% of actual abstraction	110% of actual abstraction
GT8194046	17.52	7.970	20.707
GT8194048	19.191	11.150	21.745
GT8194049	20.20	18.106	24.413

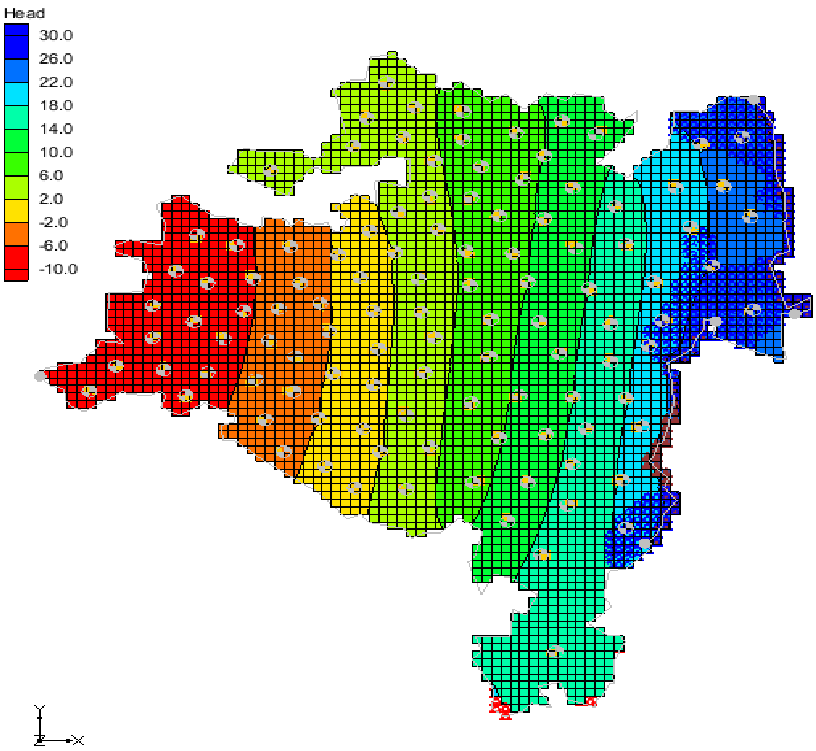


Fig. 25. Contour plot of the groundwater heads with respect to the decreased recharge (90% of the actual).

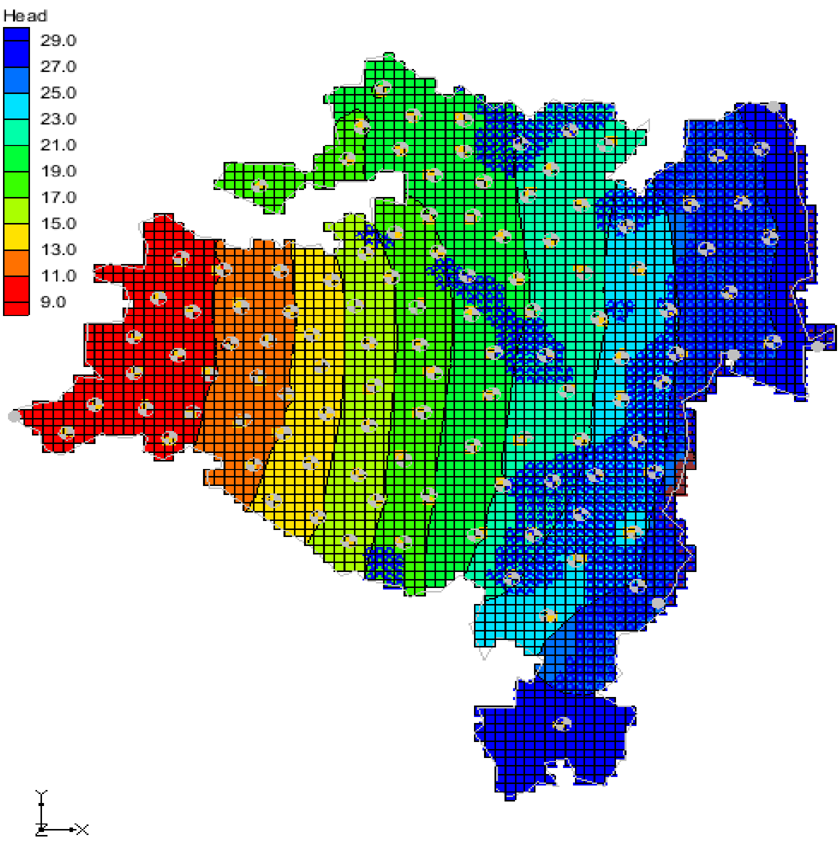


Fig. 26. Contour plot of the groundwater heads with respect to the increased recharge (110% of the actual).

The results revealed that the computed groundwater heads at the three observation wells varied noticeably as a result of the changes in the recharge scenarios. In the business-as-usual case, the MODFLOW computed heads at the three observation wells GT 8194046, GT8194048, and GT8194049 on 24 September 2018 (based on the available groundwater head data obtained from the BWDB) were 16.388m, 18.133m, and 22.215m, respectively. When the abstraction was reduced to 90%, the computed heads rose significantly, and the values were 7.970m, 11.150m, and 18.106m, respectively at the three observation wells. On the other hand, if the abstraction would be increased to 110%, the MODFLOW computed heads at the observations were found as 20.707m, 21.745m, and 24.413m, respectively which indicates a substantial increase (drop) in the quantity of head development. The increased and decreased recharge/abstraction scenarios were computed using the existing groundwater pumping values in the year 2018. Therefore, it is concluded that groundwater abstraction has a significant effect on the head development in the groundwater aquifers of the Tanore upazilla, Rajshahi.

Conclusions

The optimal groundwater abstraction strategy has been considered an effective measure of maintaining groundwater levels in aquifers for the safe and beneficial abstraction. In this research, a finite difference based 3-D flow based numerical code, MODFLOW, was utilized to simulate the groundwater heads with respect to different recharge scenarios in the Tanore upazilla of Rajshahi district in the northern Bangladesh. Input data for the selected study area of about 297.2463 km^2 were collected from different sources. Scarcity and reliability of available data is a challenging issue in implementing regional scale hydrologic models in this location. Therefore, the best possible subjective judgement was used in choosing the data for simulating the aquifer processes. The limited assessment results demonstrate that, groundwater recharge has an influential effect on the groundwater level fluctuations, and using a carefully planned groundwater abstraction strategy, it is possible to modify the groundwater storage that will help in preserving the precious groundwater storage in the study area.

7.5 Suitability of groundwater for irrigation

The chemical compositions of the collected groundwater samples in pre-irrigation and post-irrigation season are presented in Table 12a and 12b, respectively. The pH value was found slightly higher in post-irrigation season than pre-irrigation season. The pH values of groundwater samples in the study area ranged from 7.11 to 7.36, and 7.22–7.54 for pre- and post-season irrigation periods respectively. The high pH value indicated the slight alkalinity of water, possibly due to the presence of appreciable amounts of sodium, calcium, magnesium, and carbonate ions (Rao *et al.*, 1982). All the samples conform to FAO standard of 6.5 – 8.4 for irrigation use. The range of electrical conductivity (EC) was 0.36 – 0.58 dS/m in pre-irrigation season and 0.48 – 0.66 dS/m in post-irrigation season. Over the seasons, EC value of groundwater of the study area ranged from 0.36 to 0.66 dS/m with an average value range 0.47 – 0.57 dS/m, which according to Wilcox (1955) falls within the irrigation water quality classification stand ‘excellent to good’. In terms of the ‘degree of restriction on use’, EC value of < 700 μS/cm refers the water to ‘none’; 700-3000 μS/cm ‘slight to moderate’ and 3000 μS/cm ‘severe’ (UCCC, 1974). It is easily presumable from the EC values in Table 2a and 2b, all water samples of the study area are suitable for irrigation purpose as it falls under category ‘none’ (UCCC, 1974).

The concentrations of Na^+, Ca^{++}, Mg^{++}, and K^+ in water samples varied in the ranges of 10.42-17.81, 18.34-21.27, 2.10-3.20 and 2.02-2.62 mg/L in pre-irrigation season and in the ranges of 11.02-18.86, 18.34-21.27, 3.46-5.52 and 2.22-2.74 mg/L respectively in post-irrigation season. Recommended maximum concentrations of Na^+, Ca^{++}, Mg^+ and K^+ for long-term irrigation use on all soils are 200, 200, 100 and 10 mg/L, respectively (Ayers and Westcot, 1985). Therefore, all the samples in the study area can be used safely for long-term irrigation.

Table 12a. Mean quality parameters of groundwater at different study sites during November - December 2018

Location	Parameters, mg/L except pH											
	Source	pH	EC (dS/m)	PO_4-	K	NO_3-	Cl-	Na	Ca	Mg	HCO_3-	SO_4-
Godagari	DTW (n=6)	7.24	0.42	0.72	2.20	0.64	1.57	14.14	31.27	2.12	191.23	7.48
	STW (n=4)	7.33	0.46	0.80	2.34	0.68	1.38	16.12	34.78	3.20	202.54	8.12
Tanore	DTW (n=5)	7.11	0.36	0.63	2.14	0.76	1.47	15.06	36.42	2.66	205.39	7.66
	STW (n=3)	7.22	0.48	0.82	2.16	0.72	1.49	17.67	19.36	2.72	229.56	7.92
Kalai	DTW n=8)	7.15	0.54	0.54	2.54	0.68	1.63	11.32	37.07	2.54	200.56	8.07
	STW (n=2)	7.23	0.58	0.62	2.70	0.66	1.67	13.46	28.68	2.58	205.39	8.84
Joypurhat Sadar	DTW (n=6)	7.17	0.49	0.65	2.12	0.74	1.42	9.44	39.34	2.10	198.66	9.28
	STW (n=2)	7.36	0.48	0.74	2.32	0.82	1.32	10.36	32.64	2.88	222.38	9.74
Range		7.11-7.36	0.36-0.58	0.54-0.82	2.12-2.54	0.64-0.82	1.32-1.67	9.44-17.67	18.34-21.27	2.10-3.20	191.23-229.56	7.66-9.74
Average		7.23	0.48	0.69	2.32	0.71	1.49	13.45	32.45	2.60	206.96	8.39

One of the toxic major ions in irrigation water is chloride (Bouderbala 2015). Chlorides are not absorbed or held back by soils, therefore, it moves readily with the soil-water, and is taken up by the crops, moves in the transpiration stream and accumulates in the leaves. If the chloride concentration in the leaves exceeds the tolerance of the crop, injury symptoms develop, such as leaf burn or drying of the leaf tissue, yellowing of leaf and spotting on the leaf. High content of Cl- in water also limits its use in sprinkler irrigation. In the present study, chloride concentration varied from 1.32-1.67 in pre-irrigation season and 1.58-1.81 mg/L in post-irrigation irrigation, respectively which fall under excellent category according Ayre and Westcot (1985). The upper limit of NO_3^- , SO_4^{--} and HCO_3^- was 0.84, 9.94 and 222.06 mg/L respectively which is far below their corresponding recommended levels of 50, 250 and 400 mg/L. So, these parameters might not be problematic for irrigation use.

The suitability of groundwater for irrigation is dependent on the effects of the mineral constituents of the water on both the plant and the soil. In this study, SAR, SSP, RSC and KR were used to carry out the assessment of the suitability of water for irrigation purposes (Table 13). Irrigation water that has high sodium (Na^+) content can bring about a displacement of exchangeable cations Ca^{2+} and Mg^{2+} from the clay minerals of the soil, followed by the replacement of the cations by sodium. SAR (Sodium Adsorption Ratio) is a measure of suitability of water for irrigation with respect to the sodium hazard. As higher deposition of sodium may cause damage to soil, soil irrigation with high sodium depositing waters are not suitable. SAR is directly related to adsorption of sodium by soil, therefore it is a better measure of sodium (alkali) hazard in irrigation water. High SAR in any irrigation water implies hazard of sodium (Alkali) replacing Ca and Mg of the soil through cation exchange process, a situation eventually damaging to soil structure, namely permeability which ultimately affects the fertility status of the soil and reduce crop yield (Gupta, 2005). SAR gives the clear idea about the adsorption of sodium by soil. Based on the grading criteria of water for irrigation, SAR is classified into excellent (<10), good (10-18), permissible (18-26), unsuitable (>26) (Khodapanah et al. 2009). The assessment results with these methods are listed in Table 53b. As per SAR value all samples collected either from STW or from DTW in both seasons fall into excellent category. During pre-irrigation season the values of SAR of the collected water samples ranged from 0.40 to 0.99 with an average value of 0.62 and it ranged from 0.69 to 0.95 during post-irrigation season with an average value of 0.79.

Table 12b. Mean quality parameters of groundwater at different study sites during March – April 2019

Location	Parameters, mg/L except pH											
	Source	pH	EC (dS/m)	PO_4-	K	NO_3-	Cl-	Na	Ca	Mg	HCO_3-	SO_4- -
Godagari	DTW (n=6)	7.32	0.54	0.80	2.28	0.72	1.76	14.68	21.27	3.46	208.62	6.98
	STW (n=4)	7.43	0.66	0.82	2.40	0.78	1.60	17.22	20.78	4.12	222.06	7.58
Tanore	DTW (n=5)	7.22	0.48	0.72	2.46	0.82	1.62	15.86	19.42	4.62	203.86	8.04
	STW (n=3)	7.42	0.57	0.88	2.54	0.76	1.72	18.12	19.36	4.84	216.66	8.18
Kalai	DTW (n=8)	7.28	0.62	0.62	2.62	0.70	1.81	13.81	21.07	5.52	196.86	8.36
	STW (n=2)	7.36	0.64	0.68	2.74	0.74	1.85	15.52	20.68	4.58	211.94	8.56
Joypurhat sadar	DTW (n=6)	7.25	0.52	0.74	2.22	0.78	1.66	11.02	18.34	3.54	178.16	9.52
	STW (n=2)	7.44	0.58	0.76	2.40	0.86	1.58	13.32	18.44	3.82	202.08	9.94
Range		7.22-7.54	0.48-0.66	0.62-0.88	2.22-2.62	0.70-0.84	1.58-1.81	11.02-18.86	18.34-21.27	3.46-5.52	178.16-222.06	7.58-9.94
Average		7.35	0.58	0.75	2.46	0.77	1.49	14.94	19.92	4.31	205.03	8.40

The residual sodium carbonate (RSC) is a measure of the hazard involved in the use of high carbonate waters. Water quality for irrigation is influenced when concentration of carbonates and bicarbonates is higher than calcium and Magnesium. Waters containing high concentrations of these ions, calcium and possibly magnesium (Mg^{+2}) may precipitate as carbonates when water is concentrated by transpiration and evaporation. With the removal of calcium and magnesium from soil solution, the relative proportion of sodium is increased with attendant increase in alkali hazard. A high range of RSC in irrigation water means an increase in the adsorption of sodium on the soil. Water having RSC >5 has not been recommended for irrigation because of damaging effects on plant growth. According to USDA (United State Department of Agriculture) any source of water in which RSC is higher than 2.5 is not considered suitable for agriculture purpose, and water <1.25 is recommended as safe for irrigation purpose. A negative value of RSC reveals that concentration of Ca^{2+} and Mg^{2+} is in excess. A positive RSC denotes that Na^+ existences in the soil are possible. RSC calculation is also important in context to calculate the required amount of gypsum or sulfuric acid per acre-foot in irrigation water to neutralize residual carbonates effect. RSC values for pre-irrigation season varied from 1.11 to 2.54 with an average value of 1.55 while for post-irrigation season SRC values varied from 1.71 to 2.18 with an average value of 2.01. In both the seasons, KR values were found less than 1, indicating that all groundwater samples are suitable for irrigation use.

Soluble Sodium Percent (SSP) is also used to evaluate sodium hazard. Water with a SSP greater than 60% may result in sodium accumulations that will cause a breakdown in the soil's physical properties (Khodapanah et al. 2009). The values for the soluble sodium percent (SSP) in the study areas were found to vary from 15.74 to 38.06% with an average value of 23.94 % in pre-irrigation season and from 27.41 to 35.42 with an average value of 31.30 in post-irrigation season (Table 12b). This result corroborates the findinds of Khan *et al*. (1989) who found SSP ranging from 14.50 to 37.55 in the North-West region of Bangladesh. Based on the classification after Wilcox (1955) for SSP, all samples fall under excellent and good class, so can be used safely for irrigation.

Table 13. Water quality indices for suitability assessment of different water sources for irrigation

Location	Source	Pre-irrigation season				Post-irrigation season			
		SAR	RSC	SSP (%)	KR	SAR	RSC	SSP (%)	KR
Godagari	DTW	0.66	1.39	25.50	0.353	0.78	2.07	31.16	0.472
	STW	0.70	1.31	25.33	0.349	0.90	2.26	34.15	0.542
Tanore	DTW	0.65	1.32	23.79	0.321	0.84	1.99	32.70	0.509
	STW	0.99	2.57	38.06	0.643	0.95	2.18	35.42	0.574
Kalai	DTW	0.48	1.22	18.77	0.238	0.69	1.71	27.53	0.397
	STW	0.64	1.72	25.41	0.355	0.80	2.06	31.23	0.477
Joypurhat sadar	DTW	0.40	1.11	15.74	0.192	0.62	1.71	27.41	0.395
	STW	0.47	1.77	18.91	0.241	0.74	2.07	30.79	0.467
Average		0.62	1.55	23.94	0.34	0.79	2.01	31.30	0.48
Range	*DTW*	0.40-0.66	1.11-1.39	15.74-25.50	0.192-0.353	0.62-0.84	1.71-2.07	27.41-32.70	0.39-0.509
	STW	0.47-0.99	1.31-1.77	18.77-38.06	0.241-0.643	0.74-0.95	2.07-2.26	30.79-35.42	0.467-0.574

In the study area, the assessment of groundwater quality for irrigation was also carried out through the estimation of Water Quality Index (WQI) to identify its suitability for irrigation purpose (Fig. 27). This index is an important parameter for assessing groundwater quality and its suitability (Avvannavar and Shrihari, 2008). The advantage of water quality index is based on the relative importance of essential parameters with respect to standards of irrigation purposes.

The WQI ranged from 50.45 to 60.1 for DTW and from 55.15 to 90.24 for STW in pre-irrigation season while it ranged from 53.26 to 67.21 and 60.04 to 101.12 for STW and DTW water, respectively, in post-irrigation season. According to the WQI values, all the samples were found to be "good" in pre-irrigation season whereas in post-irrigation season, all samples were found also "good" except STW's water of Tanore was found poor with WQI value of 101.12. Dissolved ions such as Na, K, Mg, HCO_3, Cl, NO_3, and SO_4, during post-monsoon period affected WQI values. High iron concentration in groundwater caused high WQI values; high chloride concentrations also contributed to high WQI values typically during the post-monsoon period.

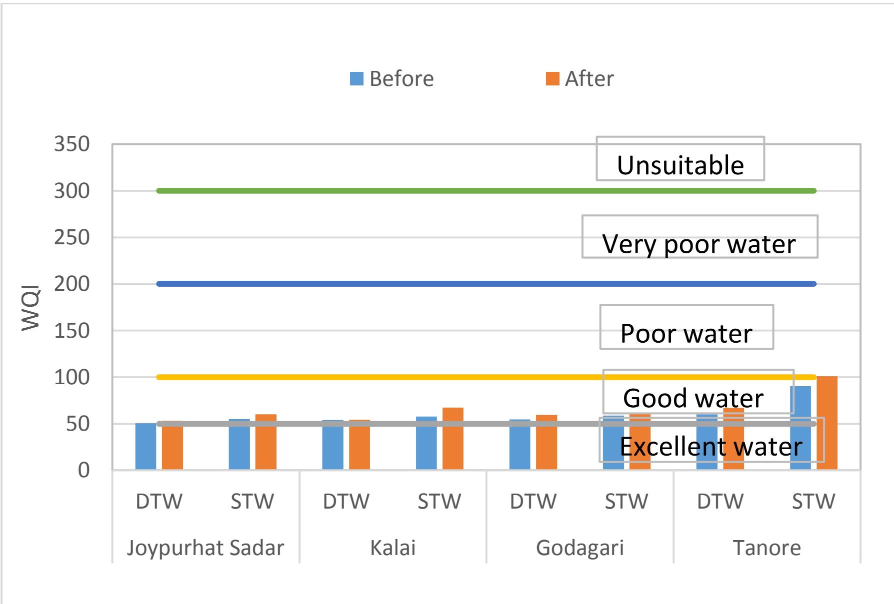


Fig. 27. Water quality index (WQI) of groundwater at different location of the study area (solid line represents the range of different categories of water quality)

Groundwater of the study areas were classified into different categories by using different quality indices such as SAR, RSC, SSP, KR and WQI (Table 3). As per SAR values, all samples collected from DTW and STW were fall in excellent category both in pre-irrigation and post-irrigation seasons as SAR values determined as <10. As per RSC values of all samples except one STW fall into excellent category in pre-irrigation season. One sample from STW of Tanore was found unsuitable for irrigation as RSC value was greater than 2.5. But all samples of DTW and STW in post-irrigation season were found permissible for irrigation purpose. The sodium-hazard on the basis of SSP indicate two-DTW water each from Kalai and Joypurhat and one STW water sample from Joypurhat fall under excellent category. Others groundwater samples were good for irrigation. Irrespective of STW or DTW, KR values of all groundwater samples were less than 1.0 indicate low Na+ ion in water; hence it was suitable for irrigation (Ehya and Saeedi, 2018). The estimation of water quality index (WQI) of all samples collected in pre- and post-irrigation seasons showed that almost all STW and DTW water was good, except one DTW water of Joypurhat was found excellent and one STW water of Tanore was found poor for irrigation.

Table 3: Classification of groundwater quality in the study area

Quality index	Categories	Ranges	Sources of water	
			Pre-irrigation	Post-irrigation
SAR	Excellent Good Permissible Unsuitable	<10 10 – 18 18 – 26 >26	STW, DTW	STW, DTW
RSC	Excellent Permissible Unsuitable	<1.25 1.25-2.5 >2.5	STW, DTW - STW (Tanore)	- STW, DTW -
SSP	Excellent Good Permissible Doubtful Unsuitable	0 – 20 20 – 40 40 – 60 60 – 80 >80	DTW(Kalai), STW/DTW(Joypurhat) STW, DTW - - -	- STW, DTW - - -
KR	Suitable Unsuitable	<1 ≥ 1	STW, DTW -	STW, DTW -
WQI	Excellent Good Poor Very poor Unsuitable	<50 50 – 100 100 – 200 200 – 300 >300	DTW (Joypur) STW, DTW - - -	- STW, DTW STW (Tanore) - -

Conclusions

The groundwater quality in two districts (Rajshahi and Joypurhat) of north-west region has been evaluated for agricultural use. The water quality indices such as SAR, SSP, RSC and KR were calculated to find out its suitability for irrigation. The results based on these indices indicate that quality of groundwater samples fall into excellent and good categories for irrigation use. The water quality index (WQI) has been determined to better assess suitability of groundwater for irrigation and it is observed that all the samples were "good" except few were found "poor" in post-irrigation season. Therefore, in respect of all evaluating criteria, groundwater of the study area was found suitable and can safely be used for irrigation purpose.

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DISSEMINATION OF WATER SAVING TECHNOLOGIES FOR NON-RICE CROPS IN SALINE PRONE AREAS OF BANGLADESH

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Abstract

The experiment was conducted at three upazila under three districts of the southern saline prone areas of Bangladesh. Twelve demonstrations were conducted at the selected areas. Two water saving irrigation technologies (AFI and drip irrigation) were compared with the traditional farmer practice. Alternet furrow irrigation (AFI) was used for maize and sunflower cultivation and drip irrigation system was used for tomato and watermelon cultivation. Solar power was also used for mitigating the pumping cost in drip irrigation system. The plant population, plant height, cob length, number of seeds per cob, 100 seed weight and yield of maize were found highest (7.50, 255.45 cm, 19.95 cm, 474.30, 25.63 gm and 9.01 t/ha) at treatment T_1 compared with farmer practice (T_2). Also, the plant population, plant height, head diameter, number of seeds per head, 1000 seed weight and yield of sunflower were found comparatively high (7.00, 143.57 cm, 59.47 cm, 464.67, 88 gm and 1.99 t/ha) at treatment T_1. Statistically significant yield difference was observed among the treatments (T_1 and T_2) for watermelon and tomato cultivation under solar powered drip irrigation system. Alternet furrow irrigation and drip irrigation treatments gave highest BCR for all crops. The farmers were benefited and interested to use these water saving technologies.

Introduction

Bangladesh is an agro-based country where agriculture has enormous contribution to the national economy and to livelihood of the people (Murshed-E-Jahan and Pemsl, 2011). Agricultural growth of Bangladesh has accelerated after independence, where irrigation expansion happened during mid 80's (Hoque, 2001). But the agricultural growth has been impeded due to natural disasters and fluctuations in food prices. This natural disaster mainly occurs due to unfavorable weather which is now severe (Harun-ur-Rashid and Islam, 2007). Salinity and drought are the main stress environments in Bangladesh (Athar and Ashraf, 2009; Harun-ur-Rashid and Islam, 2007). The nature and extent of these environments vary with season, topography and location (Athar and Ashraf, 2009).

Soil salinity is a major problem in the coastal region during the dry period. Soil salinity starts increasing from last week of December and reaches to its peak level in the month of March and April (≈25 dS/m), and minimum salinity (<2 dS/m) occurs in the months of July and August after the onset of the monsoon rains (Haque, 2006). Coastal soils vary widely in nature of salinity, depth and fluctuation of groundwater along with the seasonal variation in the salinity of surface water (Yan et al., 2015). Farmers mostly grow T.Aman during July-December and the lands remain fallow due to salinity development and scarcity of irrigation water during rest periods of the year.

To minimize water application losses and increase water use efficiencies (WUE) in the saline, drought prone and hilly regions of Bangladesh, modern irrigation technologies developed by Bangladesh Agricultural Research Institute (BARI) that are suitable for non-rice crops should be disseminated in the farmers' field. The promising water management technologies are: (i) drip fertigation that are recommended for high value vegetable and fruit crops, (ii) alternate furrow irrigation method suitable for both field crops and vegetables planted in rows, and (iii) deficit irrigation, mostly suitable for field crops like wheat, maize, mustard, sunflower, etc. Fertigation

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(Drip irrigation with fertilizer) can be used for growing high value vegetable and fruit crops like tomato, brinjal, cauliflower, strawberry, guava, etc. for higher yield, water productivity and economic return. Drip irrigation can increase yield of these crops and water use efficiency (WUE) by 10-19% and 16-23%, respectively as compared to furrow irrigation with a considerable amount of fertilizer (40%) and water saving (48%). This method can be demonstrated intensively in saline prone areas where fresh water availability is very scarce for irrigation. Besides, alternate furrow irrigation (AFI) technology, also suitable for the row field crops, can save irrigation water by about 35% with no loss of yield. In the areas under draught and saline stress to bring more area under cultivation. Dissemination of these technologies to the farmers will help them to harvest the benefits of water irrigation while minimizing the risk of its use for crop production and to increase the crop-water productivity and reduce irrigation water use in saline areas of Bangladesh.

Materials and Method

The experiments were conducted at different locations of Southern districts named Patuakhali, Borguna and khulna. In Patuakhali distric there were 6 AFI experiments and 3 drip irrigation experiments. At Borguna district there were one drip irrigation experiments and in khulna district there were drip irrigation experiments. The location wise experiments and crops details were given in table 1.

Table 1. Location wise Experiemnts and Crop/Variety details

District	Upazila	Village	Crop	Variety	Technology used
Patuakhali	Kalapara	Noyapara	Maize	BHM-9	AFI
	Kalapara	Noyapara, Nobinpur, Diaramkhola, Maithvanga	Sunflower	BARI Surzomukhi-2	AFI
	Kalapara	Azimpur	Watermelon	Jaguar Jumbo	Drip
Borguna	Amtali	Ghotkhali	Brinjal	Hybrid	Drip
Khulna	Koyra	3 no koyra	Tomato	BARI tomato-21 BARI hybrid tomato-5	Drip
	Koyra	3 no koyra	Watermelon	Jaguar Jamboo	Drip

Location wise crop, sowing/planting and harvesting dates along with the treatments are shown in Table 2. The Brinjal experiment of Amtali site was damaged due to Amphan. The fertilizers were applied as per BARI recommended dose. The following data were collected from the selected plant samples from each plot.

- Plant population
- Plant height/ Vine length (cm)
- Cob per plant/ Number of fruit per plant
- Individual fruit weight (gm)
- Cob length/fruit length (cm)
- Fruit diameter (cm)
- Number of seeds per cob/ Number of seeds per head
- 1000 seed weight/100 seed weight (gm)
- Plot yield (t/ha)
- Salinity data (ds/m)

Table 2. Location wise sowing, harvesting dates and the treatments of different crops

Upazila	Crop	Date of Sowing/ Planting	Date of Harvesting	Treattments
Kalapara	Maize	30.12.2019	25.05.2020	T_1= Alternet Farrow Irrigaion (AFI) T_2= Farmer Practice (FP)
Kalapara	Sunflower	24.12.2019	08.04.2020	T_1= AFI T_2= FP
Kalapara	Watermelon	10.01.2020	05.04.2020	T_1= Solar Powered Drip Irrigation T_2= FP
Amtali	Brinjal	10.12.2020	19.05.2020	T_1= Solar Powered Drip Irrigation T_2= FP
Koyra	Tomato	27.11.2019	27.03.2020	T_1= Solar Powered Drip Irrigation T_2= FP
Koyra	Watermelon	12.01.2020	03.04.2020	T_1= Solar Powered Drip Irrigation T_2= FP

Solar Irrigation System

In this project IWM division used solar powered drip irrigation system. Solar power is free of cost. The installation cost was little higher but it was less than a LLP installation cost. Farmers can use this portable solar panel for charging their home system. At the coastal region solar powered home system is available at every house. So farmers can use this portable solar panel for multiple purposes. The specification and cost of solar irrigation system was given below.

Item	Specification	Amount	Unit Price (tk)	Total Cost (tk)
Solar Panel	300 watt	1	32	9600
Pump	180 watt	1	4500	4500
Accessories	-	-	-	500
			Total-	14600

Results and Discussion

The results obtained in the experiment have been presented in this section under relevant headings and sub-headings with necessary tables. The effects of different irrigation practices on different crops have been elaborated.

Table 1 showed the yield and yield components of maize at Kalapara upzilla under Patuakhali district. The plant population, plant height, cob length, number of seeds per cob, 100 seed weight and yield were found highest (7.50, 255.45 cm, 19.95 cm, 474.30, 25.63 g and 9.01 t/ha) at treatment T_1. AFI gave the highest result in all farmer fields. The yield of maize was statistically significant among the treatments.

Table 1. Yield and yield components of maize at Kalapara upazila under Patuakhali district

Treatment	Plant Population/m2	Plant Height (cm)	Number of Cob/Plant	Cob Length (cm)	Number of Seed/ Cob	100 Seed Weight (gm)	Yield (t/ha)
T_1	7.50a	255.45a	1.00	19.95a	474.30a	25.63a	9.01a
T_2	7.25a	246.98a	1.00	18.40a	461.80a	25.18a	8.42b
CV(%)	4.79	6.36	-	6.63	4.92	2.23	1.71
LSD	-	-	-	-	-	-	0.34

Table 2 showed the yield and yield components of sunflower at Kalapara upzilla under Patuakhali district. The plant population, plant height, head diameter, number of seeds per head, 1000 seed weight and yield were found comparatively high (7.00, 143.57 cm , 59.47 cm, 464.67, 88 g and 1.99 t/ha) at treatment T_1. AFI performed better than conventional irrigation in all farmer fields. The head diameter, number of seed per head, 1000 seed weight and yield were statistically significant.

Table 2. Yield and yield components of sunflower at Kalapara upazila under Patuakhali district

Treatment	Plant Population/m2	Plant Height (cm)	Head Diameter (cm)	Number of Seed/ Head	1000 Seed Weight (gm)	Yield (t/ha)
T_1	7.00	143.57a	59.47a	464.67a	88.00a	1.99a
T_2	6.67	139.90a	50.35b	420.00b	77.67b	1.73b
CV(%)	-	4.62	5.11	0.74	5.81	2.09
LSD	-	-	9.85	11.47	16.91	0.14

Table 3 showed the yield and yield components of watermelon at Kalapara upzilla under Patuakhali district. The vine length, number of fruits per plant, individual fruit weight and yield were found comparatively high (292.47 cm, 1.83, 6.18 kg and 35.51 t/ha) at treatment T_1. Drip irrigation performed better than conventional irrigation in all farmer fields. The vine length, and yield of watermelon were found statistically significant among the treatments.

Table 3. Yield and yield components of watermelon at kalapara upazila under patuakhali district

Treatment	Vine Length (cm)	Number of Fruits/ Plant	Individual Fruit Weight (kg)	Yield (t/ha)
T_1	292.47a	1.83a	6.18a	35.51a
T_2	280.17b	1.40a	5.41a	29.91b
CV(%)	0.57	12.62	7.14	2.78
LSD	5.73	-	-	3.20

Table 4 showed the yield and yield components of BARI hybrid tomato-5 at Koyra upzilla under Khulna district. The number of fruits per plant, individual fruit weight, fruit length, fruit diameter and yield were found comparatively high (31.67, 92.33 g, 4.23 cm, 3.90 cm and 94.27 t/ha) at treatment T_1. Drip irrigation performed better than conventional irrigation in all farmer fields. The number of fruits per plant, fruit length, fruit diameter and yield were observed statistically significant among the treatments.

Table 4. Yield and yield components of BARI Hybrid tomato-5 at Koyra upazila under Khulna district

Treatment	Number of plant per plot	Number of fruits per plant	Individual Fruit Weight (gm)	Fruit Length (cm)	Fruit Diameter (cm)	Yield (t/ha)
T_1	6	31.67a	92.33a	4.23a	3.90a	94.27a
T_2	6	18.00b	86.00a	4.18b	3.76b	64.19b
CV(%)	-	8.69	4.84	0.26	0.38	6.43
LSD	-	7.58	-	0.04	0.05	17.89

Table 5 showed the yield and yield components of BARI tomato-21 at koyra upzilla under khulna district.

Table 5. Yield and yield components of BARI tomato-21 at koyra upazila under khulna district

Treatment	Number of plant per plot	Number of fruits per plant	Individual Fruit Weight (gm)	Fruit Length (cm)	Fruit Diameter (cm)	Yield (t/ha)
T_1	6	48.33a	58.33a	4.26a	2.51a	66.72a
T_2	6	35.67b	53.67b	4.18a	2.49a	52.37b
CV(%)	-	1.94	1.92	0.61	0.28	1.12
LSD	-	2.87	3.79	-	-	2.34

The number of fruits per plant, individual fruit weight, fruit length, fruit diameter and yield were found comparatively high (48.33, 58.33 gm, 4.26 cm, 2.51 cm and 66.72 t/ha) at treatment T_1. Drip irrigation performed better than conventional irrigation in all farmer fields. The number of fruits per plant, individual fruit weight and yield were statistically significant among the treatments.

Table 6 showed the yield and yield components of watermelon at Koyra upzilla under Khulna district. The vine length, weight of fruit per plant, individual fruit weight and yield were found comparatively high (243.80, 10.02 kg, 5.01 kg and 44.48 t/ha) at treatment T_1. Drip irrigation performed better than conventional irrigation in all farmer fields. The vine length, weight of fruit per plant, individual fruit weight and yield were statistically significant among the treatments.

Table 6. Yield and yield components of watermelon at Koyra upazila under Khulna district

Treatment	Vine Length (cm)	Number of Fruit per Plant	Weight of Fruit per Plant (kg)	Individual Fruit Weight (kg)	Yield (t/ha)
T_1	242.80a	2	10.02a	5.01a	44.48a
T_2	214.78b	2	7.12b	3.56b	32.35b
CV(%)	0.32	-	0.83	0.83	0.43
LSD	2.58	-	0.25	0.13	0.58

Water requirement and water productivity

Table- 7 represents the total water use during the whole season and the water productivity that represents the productivity of water in producing crop yields. The water productivity for maize production was higher (1.05 kg/m^3) in AFI treatment than farmer practice (0.73 kg/m^3). The water productivity for sunflower production was higher (1.02 kg/m^3) in AFI treatment than farmer practice (0.51 kg/m^3). The water productivity for watermelon production was higher (10.30 kg/m^3) in drip irrigation treatment than farmer practice (7.67 kg/m^3). The water productivity for BARI Hybrid tomato-5 production was higher (9.58 kg/m^3) in drip irrigation treatment than farmer practice (5.89 kg/m^3). The water productivity for BARI tomato-21 production was higher (6.788 kg/m^3) in drip irrigation treatment than farmer practice (4.81 kg/m^3). Water productivity decreases with increasing quantity of water applied.

Table 7. Total water use and water productivity of different crops

Crop	Treatment	Total water use (cm)	Yield (t/ha)	Water productivity (kg/m^3)
Maize	T_1	86.01	9.01	1.05
	T_2	115.4	8.42	0.73
Sunflower	T_1	19.56	1.99	1.02
	T_2	34.20	1.73	0.51
Watermelon	T_1	58.82	40.00	6.79
	T_2	70.62	31.13	4.41
BARI Hybrid tomato-5	T_1	98.38	94.27	9.58
	T_2	128.84	64.19	4.98
BARI tomato-21	T_1	98.38	66.72	6.78
	T_2	128.84	52.37	4.06

Economic Analysis

Table 8 showed the cost components and total cost of different crops and treatments of the project sites. It was observed from the cost analysis that the total cost was high at farmer practice for all crops. In case of watermelon, BARI hybrid tomato-5 and BARI tomato-21 solar irrigation system were used for drip irrigation. So, the cost shown at the irrigation component for watermelon, BARI hybrid tomato-5 and BARI tomato-21 was actually the installation cost of solar irrigation system. For maize and sunflower diesel engine operated LLP was used for irrigation.

Table 8. Cost analysis of different crops and treatments of the project sites

Crop / Treatment	Land preparation (tk/ha)	Seed (tk/ha)	Fertilizer (tk/ha)	Pesticide (tk/ha)	Irrigation (tk/ha)	Labor (tk/ha)	Total Cost (tk/ha)
Maize							
T_1	9375	8000	28800	0	16000	38800	100975
T_2	9375	8000	28800	0	32000	55000	133175
Sunflower							
T_1	9375	3000	23400	0	24000	18800	78575
T_2	9375	3000	23400	0	28000	20000	83775
Watermelon							
T_1	11250	16875	32400	30000	14600	75000	180125
T_2	11250	16875	32400	30000	28000	95000	213525
BARI Hybrid tomato-5							
T_1	12870	4000	14790	5000	14600	51400	102660
T_2	12870	4000	14790	5000	14600	66800	118060
BARI tomato-21							
T_1	12870	1200	14790	5000	14600	51400	99860
T_2	12870	1200	14790	5000	14600	66800	115260

Table 9 demonstrated the BCR of different crops of the project sites. It was observed from table 9 that the BCR of AFI and drip irrigation system was high for all crops and the BCR for farmer practice treatment was comparatively less than the water saving technologies.

Table 9. Benefit Cost Ratio of different crops and treatments of the project sites

Crop / Treatment	Total Cost (tk/ha)	Total Return (tk/ha)	BCR
Maize			
T_1	100975	180200	1.78
T_2	133175	168400	1.26
Sunflower			
T_1	78575	99500	1.27
T_2	83775	86500	1.03
Watermelon			
T_1	180125	400000	2.22
T_2	213525	311300	1.46
BARI Hybrid tomato-5			
T_1	102660	282810	2.75
T_2	118060	192570	1.63
BARI tomato-21			
T_1	99860	200160	2.00
T_2	115260	157110	1.36

Conclusion

The experiments were conducted through Small Holder Agricultural Competitiveness Project (SACP) jointly funded by IFAD and GoB. The project sites were at the coastal region of Bangladesh. There were three upazila (Koyra, Amtali and Kalapara) under three districts (Khulna, Borguna and Patuakhali). Two water saving irrigation technologies (Alternet Farrow Irrigation and Solar Powered Drip Irrigation) were demonstrated at the farmers' field. The farmers were benefited and interested to use these types of water saving technologies. Farrow Irrigation and Solar Powered Drip Irrigation has given better result than farmer practice and the BCR of those water saving technologies were remain high than the existing farmer practice. As we know that the southern districts of Bangladesh is suffering shortage of water and also fresh irrigation water at the Rabi season to grow winter crops. So, we need to disseminate these water saving irrigation technologies as much as possible.

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Appendix: Production Program (Demo.)

Sl. No.	Name of Production Program (Demo.)	Farmers' name	Address (Vill., Union, Dist.)	Mobile No.	Area covered under production program	Seeding/ Transplanting date	Brief findings / present status
০১	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	মোঃ লিটন সিকদার	ঘটখালী, আমতলী, বরগুনা	০১৭৬৭-৪০২৫৫১	২০	২৭ ডিসেম্বর, ২০১৯	(বিটি বেগুন-২)
০২	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	মোঃ জলিল গাজী	নয়াপাড়া, কুয়াকাটা, পটুয়াখালী	০১৭৬৩২৯৫৭৫৪	৬৬	৩০ ডিসেম্বর, ২০১৯	(বারি হাইব্রিড ভূট্টা-৯)
০৩	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	মোঃ ইউসুফ	নয়াপাড়া, কুয়াকাটা, পটুয়াখালী	০১৭৬১৯০০৬৪২	৩৩	০৮ জানুয়ারী, ২০২০	(বারি হাইব্রিড ভূট্টা-৯)
০৪	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	মোঃ রুহুল আমিন	নয়াপাড়া, কুয়াকাটা, পটুয়াখালী	০১৮৫৮৬৬২০৬৭	৩৩	০৯ জানুয়ারী, ২০২০	(বারি হাইব্রিড ভূট্টা-৯)
০৫	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	সিদ্দিক মুসল্লি	নবিনপুর, কুয়াকাটা, পটুয়াখালী	০১৭১৮৩৬৫৪৪৩	৬৬	০৫ জানুয়ারী, ২০২০	(বারি হাইব্রিড ভূট্টা-৯)
০৬	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	মোঃ আব্দুর রশিদ	নয়াপাড়া, কুয়াকাটা, পটুয়াখালী	০১৭০৩৪০৯১৯৭	৩৩	২৪ ডিসেম্বর, ২০১৯	(বারি সূর্যমুখী-২)

০৭	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	আবুল কালাম	দিয়ারামখোলা, কুয়াকাটা, পটুয়াখালী	০১৭৫৯০৬৮২৯০	৩৩	০১ জানুয়ারী, ২০২০	(বারি সূর্যমুখী-২)
০৮	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	মোঃ আল আমিন	মাঈটভাঙ্গা, কুয়াকাটা, পটুয়াখালী	০১৬১০২৩০৬৬৪	৩৩	০৩ জানুয়ারী, ২০২০	(বারি সূর্যমুখী-২)
০৯	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	মোসাহর গাজী	আজিমপুর, কুয়াকাটা, পটুয়াখালী	০১৭১৩৯৫৯০২৩	৩৩	১০, জানুয়ারী, ২০২০	(তরমুজ)
১০	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	দেলোয়ার মৃধা	আজিমপুর, কুয়াকাটা, পটুয়াখালী	০১৮১৩৯৯১৩৭৫	৩৩	১১, জানুয়ারী, ২০২০	(তরমুজ)
১১	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	মোঃ আজিজুল ইসলাম	৩ নং, কয়রা, কয়রা, খুলনা	০১৯১১-৭৫২৭১৩	২০	২৭ নভেম্বর, ২০১৯	(বারি হাইব্রিড টমেটো-৫ ও বারি টমেটো-২১)
১২	Dissemination of Water Saving Technologies for Non-Rice Crops in Saline Area	মোঃ আজিজুল ইসলাম	৩ নং, কয়রা, কয়রা, খুলনা	০১৯১১-৭৫২৭১৩	২০	১২ জানুয়ারী, ২০২০	(তরমুজ)

Suggestions and Comments in the Internal Research Review Workshop, 2020 of IWM Division, BARI, Gazipur

Rapporteur's Report

Date: 16 September, 2020 Venue: Kazi Bodruddoza auditorium

Session Chairman	:	Dr. Md. Shirazul Islam, Ex. Director (Res.), BARI, Gazipur
Expert Members	:	Dr. Md. Abdur Rashid, Ex. Chief Scientific officer & Head, Irrigation and Water management Division, BRRI, Gazipur
		Dr. Abeda Khatun, Director, HRC, BARI, Gazipur
Rapporteurs	:	Dr. Dilip Kumar Roy, SSO, IWM Division, BARI, Gazipur
		Md. Shamshul Alam Kamer, SO, IWM Division, BARI, Gazipur

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- Experiments on groundwater quality and declination of groundwater level should be conducted in the tea growing Panchagar region
- The effects of using industrial wastewater for crop irrigation by the farmers of Gazipur area need to be monitored especially for heavy metal contents in food grains
- The nutrient contents of the used industrial effluent (by the farmers of Gazipur area for crop irrigation) should be determined
- Experiment on rainwater harvesting in the southern coastal belt should be undertaken
- Effective rooting depth and irrigated area of mango tree should be determined for prescribing proper irrigation scheduling
- Program may be taken on sub-surface drip irrigation for irrigating permanent orchards
- Irrigation interval should be checked and re-adjusted for Lysimeter study. An irrigation interval of 22 days should be discarded. 4, 8, 12, and 16 days' interval may be used instead.
- Irrigation interval may be increased (3 to 4 days) for the roof top gardening experiment
- Emphasis may be given on developing irrigation scheduling of citrus crops
- Program may be taken in the Sylhet region
- It is advisable to use Fertilizer Recommendation Guide 2018 instead of using Fertilizer Recommendation Guide 2012
- For water quality experiment, standard values of water quality parameters may be provided in a separate row or column
- The duration of Aus rice needs to be checked. In addition, variety of Aus rice should be mentioned.

List of the Scientists and Scientific Staffs Involved in IWM Research Program during 2020-2021

SL. No.	Name	Designation
1	Dr. Md. Anower Hossain	Chief Scientific Officer (in-charge) & Head
2	Dr. Sujit Kumar Biswas	Senior Scientific Officer
3	Dr. Dilip Kumar Roy	Senior Scientific Officer
4	Farzana Akter	Scientific Officer
5	Khandakar Faisal Ibn Murad	Scientific Officer
6	SK. Shamshul Alam Kamar	Scientific Officer
7	Md. Kamal Hossain	Scientific Assistant
8	Md. Enayet Sharif	Scientific Assistant
9	Mostafa Kamal	Scientific Assistant
10	Mohammad Samim Miah	Office Assistant Cum-computer Operator
11	Md. Abul Kalam	Office Assistant Cum-computer Operator
12	Md. Jahirul Islam	Surveyor
13	Md. Monayem Kabir	Laboratory Attendant