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Deep Learning Based Wheat Yield Prophecy and Irrigation Schedule Management to Reduce Water Waste

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ABSTRACT

Water is an incredibly valuable resource on our earth; however, it could have threatened if not managed. The agriculture has the highest necessity for strategies to minimize water usage. Agriculture industry is implementing contemporary farming methods, and farmers are using cutting-edge digital innovations that are modernize decision-making and profitability in agriculture. Numerous sectors have experienced the effective use of deep learning (DL) in the decision-making. There is impetus to use it in other significant fields like agriculture. Estimating yields is essential for managing crops, water planning, ensuring food safety, and determining how much work will be needed for the cultivation and storing of crops like wheat. Predicting wheat crop yield has the potential to diminish energy use like drop in water consumption. In this study, a deep reinforcement learning (DRL) model is implemented to forecast wheat crop yield by monitoring the environment via a DRL agent. Two bidirectional long short-term memory (BiLSTM) models are applied as the DRL agent for exploring the environment. One forecasts the water content in the land and other one was active to calculate the yield considering climate data, growth stage, growing degree days (GD), canopy cover (CC), standard evapotranspiration (ETo), irrigation level and water content in soil. The agent was trained to plan watering for a wheat crop, considering a place in Maharashtra, India. DRL agent provides a schedule identifying irrigation levels. The irrigation level is incorporated into the time required to water the area, facilitating the farmer to manage it more easily. The performance of the proposed model was compared to a fixed base irrigation system. Water use decreased by 35% and wheat crop output increased by 5% when the trained model was compared to the fixed technique.

Article information:

Keywords: Deep Reinforcement Learning, Irrigation Scheduling, LSTM, Time, Water, Wheat Crop Yield, Prediction

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1. INTRODUCTION

The economies of many nations are significantly influenced by agricultural industries. Because of this, technical developments in the agriculture sector are seen as having a significant positive impact on the environment and economic growth. Smart technology in farming fields has enabled farmers to properly monitor their land and take the required actions to maintain yield. In order to promote agricultural practices and improve world food safety, Sowmiya *et al.* [1] developed trustworthy automated disease identification systems. The number of innovative techniques and innovations [2], [3] have been investigated and put into practice to encourage ongoing development in the agricultural industry. Agriculture is the primary consumer of freshwater, making it both a source and a victim of water shortage. Therefore, increasing agricultural water productivity is crucial to addressing global water scarcity and tackling the issues of insufficient food supply. The environment variation has garnered significant interest from research scholars and governments across the globe. Water supplies are becoming increasingly challenged around the world as a result of population growth, socioeconomic

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ture. Around 90 percent of the water worldwide is used for agricultural irrigation [4]. The prediction of future irrigation water demands while taking global warming into consideration is critical for managing local water resources and ensuring safe access to water. Considering these hurdles, water conservation irrigation and effective management of water resources are essential for farming.

India continues to closely follow China, maintaining its position as the world's second-largest source of wheat [5]. Currently, a large number of authors have evaluated the cultivation process to predict the wheat crop yield in conjunction with advanced technology. Many researchers have recently focused on using artificial intelligence to identify and locate the spikes and spikelets in wheat plants. Colour component selection and image analysis approaches, together with deep learning (DL), were presented to identify and quantify wheat spikelets in colour photographs. Convolution neural network (CNN) successfully estimates the quantity of wheat spikelets, which adds to understanding of wheat spike development features [6]. Alkhudaydi and De La lglesia [7] developed a system by using a fully convolutional network that uses a density estimation technique to count spikelets for predicting wheat yield. Misra *et al.* [8] implemented a method for measuring the number of wheat plant spikes in digital photographs by segmenting the image for spike section recognition. To estimate wheat yield in the Guanzhong Plain, China, Tian *et al.* [9] built a long short- term memory (LSTM) model that integrated remotely observed indices, vegetation temperature condition index, and leaf area index as the most critical growth phases with meteorological data. Di *et al.* [10] suggested BO-LSTM based on Bayesian optimization (BO) that combines crop phenology, climatic, and remotely sensed information to estimate country-level winter wheat yields. Compared to linear regression, the BO-LSTM model exhibited the best yield prediction performance with root mean squared error (RMSE) = 177.84 kg/ha, R^2 = 0.82. By taking into account weather datasets containing humidity, temperature, rainfall, wind direction, and evaporation characteristics, a DL based Recurrent neural networks (RNN) and RNN-LSTM model is used to estimate wheat crop output in northern Punjab of India. It was found that the RNN-LSTM model performed well [11]. To predict wheat crop production, Kaur *et al.* [12] constructed the LSTM model by taking into account a number of variables linked to weather and soil data. In order to anticipate the production of soft wheat in Germany, Paudel *et al.* [13] executed LSTM approaches, taking into account the soil's ability to retain water, biomass features, moisture levels, and temperature. They discovered that DL is capable of learning attributes and generating accurate crop yield predictions. Bari *et al.* [14] used LSTM approaches to forecast tomato prices with varying sequence lengths, demonstrating that LSTM works well in time-specific data. Sulistianingsih and Martono [15] revealed that hybrid LSTM with CNN outperforms in predicting stock from several banks, displaying diversity in obtaining complicated trends and offering reliable forecasts.

India's winter wheat crop yield depends on the availability of water, thus it is critical to maintain surveillance on the irrigation of the crop constantly. Researchers have developed systems to address the irrigation system problem with cutting-edge technologies like DL. Kelly et al. [16] tested deep reinforcement learning for irrigation scheduling and calculated maize crop productivity using weather data and soil parameters. Dang *et al.* [17] presented a water requirement model that estimates water demands by combining temperature-based growing degree days with other meteorological factors and LSTM-DL technology. According to Du *et al.* [18], estimating soil moisture condition using hyperspectral data derived from uncrewed arieal vehicles was successful. They have made use of 46 distinct near-infrared narrowbands. They have employed transfer learning approaches for the assessment of soil moisture. Jin *et al.* [19] applied several DL models, including MobilenetV3, VGG16, DenseNet201, and Residual Net-18, to identify the water stress for cotton crops under drip irrigation using images. Compared to other models, they discovered that MobilenetV3 accurately detects water stress. Using simulated data from the AquaCrop model and Landsat7 data, Oulaid *et al.* [20] investigated the Fourier amplitude sensitivity test and the Morris sensitivity analysis test for crop canopy cover and yield analysis. However, it was highlighted that AquaCrop is not suitable for dealing with nutrients or future soil characteristics. A smartphone application for detecting water stress was created by Chandel *et al.* [21]. They fixed together a Raspberry Pi chip and a digital camera to take actual images of wheat and maize crops. Using a DL neural network, the photos are analyzed and categorized as having water stress or not with an accuracy of more than 93%. By considering soil and environmental data, Padmavathi *et al.* [22] created a CNN and LSTM based system to estimate irrigation and applied optimization algorithm. Compared to the current techniques and classification systems, they made innovative farming model, demonstrated higher real-time performance and achieved better accuracy outcomes. A transformer neural network model was created by Perea *et al.* [23] to forecast irrigation demand by districts for water-on-demand management ahead of time. To optimize the consumption of water and energy, this model was integrated with a genetic algorithm.

Ghiat *et al.* used hyperspectral vegetation indices, meteorological data, and physiological indicators as inputs to machine learning (ML) algorithms for transpiration estimation in precision irrigation distribution [24]. Huang *et al.* [25] employed BiLSTM, gated recurrent unit, and LSTM to forecast the walnut crop's evapotranspiration while taking weather conditions and the crop's growth coefficient into account for micro irrigation techniques. They used ablation of parameters and tested different scenarios to predict the crop evapotranspiration. They reported that for every model, the R-squared value is higher than 0.95. To forecast the moisture content range using photographs before irrigation and subsequently calculate irrigation duration based on the projected soil moisture class, a DL integrated mobile application was created. It was demonstrated that research helped save 27.59% on water use and 27.42% on power use [26]. Mpakairi *et al.* [27] classified the Sentinel-2 data for three years between 2019 and 2021 using a DL model and a random forest method. Using random forests, they could identify the type of land cover with 77% accuracy. Also, at the national level, the DL model identified croplands that are rainfed and irrigated with 71% accuracy. Alibabaei *et al.* [28] used a deep Q-network to train a model that helped to plan the irrigation for tomato crop. The model estimated the water content of the soil and computed the amount of water needed. The LSTM-DL model was used by Sami et al. [29] to forecast temperature, humidity, and soil moisture. Using sensors, they recorded temperature, humidity, and soil moisture. The information they gathered was utilized to train the model. They showed how closely the predicted values of LSTM models match actual data. Using deep neural networks to anticipate soil moisture, Cordeiro *et al.* [30] demonstrated management and optimization of the amount of water utilized in the irrigation process. K-nearest neighbour was used to address missing values in datasets. Furthermore, they tested the model on two original datasets of cashew and coconut trees, and their results showed potential for enhancing irrigation water conservation. To evaluate soil moisture contents, Cheng *et al.* [31] considered the multispectral, Red-Green-Blue, and thermal infrared remote-sensing image datasets as sources for different ML methods. The results of their ML model for the maize crop indicate that the most accurate soil moisture contents are produced by the random forest regression method. Sharma *et al.* [32] estimated evapotranspiration with the DRL algorithm by utilizing minimum temperature, maximum temperature, and solar radiation weather parameters. Saravi *et al.* [33] built a deep neural network (DNN) to predict plant growth and the quantity of irrigation required to produce a particular amount of maize harvest. They simulated weather and crop data on Decision Support System for Agrotechnology Transfer (DSSAT) from the experimental investigation. In order to expand the training of the DNN model watering applications, ten irrigation treatments were chosen to produce random scenarios during the growing period. Alibabaei *et al.* [34] used LSTM and BiLSTM models and were able to accurately estimate the yield of tomato and potato crops by utilizing soil and weather data. They could also anticipate the quantity of irrigation needed during the growing season.

The notion of modern precision agriculture has evolved and the agricultural sector has advanced. Still Indian farmers remain unable to participate in current technical developments in the agriculture sector and are dependent on antiquated farming methods. It is, however, difficult for small farms since landowners lack the expertise to deal with the water content of the soil or evapotranspiration, and they require an expert to assess the data. In the investigation study based on wheat crop yield prediction, the authors [35] stated that the majority of the research articles used vegetation indices and weather measurements, which have a direct impact on wheat crop yield prediction, while fewer articles explored water-related characteristics. Existing research on wheat crop yield prediction focuses on identifying water stress and predicting soil moisture; however, a lack of research has examined water scheduling management and wheat yield prediction. In the current study, a DRL model leverages this understanding and provides farmers with simple irrigation guidance on how much and when to water a wheat crop farm to maximize yield while minimizing water waste.

This work presents the aesthetic implementation, and deployment of an irrigation system for a wheat crop field in Maharashtra with the aim of identification of irrigation level and finally predicting crop yield. The system takes humidity, precipitation, and temperature data from a field as inputs. It utilizes the data to determine other features and how much water is needed in a field and then relays it directly to the farmer. The irrigation system then instructs the landowner on how to irrigate the crops with the time required for irrigating. By doing this, the farmer can increase agricultural productivity and conserve water sources. Fig. 1 demonstrates the combination of BiLSTM and water scheduling DRL (WASDRL) model to identify the time required to irrigate winter wheat before one day and predict wheat crop yield. First, the system provides a dataset containing meteorological characteristics and other information as input, and the raw data is pre-processed accordingly. Preprocessed data is fed into one BiLSTM network to predict gross water content (WCTot), while another BiLSTM network uses the data to predict crop yield at season's end. The anticipated WCTot with other characteristics are fed into WASDRL as the current state to determine irrigation level as action, and yield is used to reward the DRL agent for exploring the DRL environment and selecting the correct action. The DRL agent's exploration of the environment will continue until it finds an optimal value for the amount of irrigation to be applied the next day and also predicts wheat crop yield. This irrigation level is converted to time required for irrigating wheat crop. In the following section, each part of the process is explained in detail.

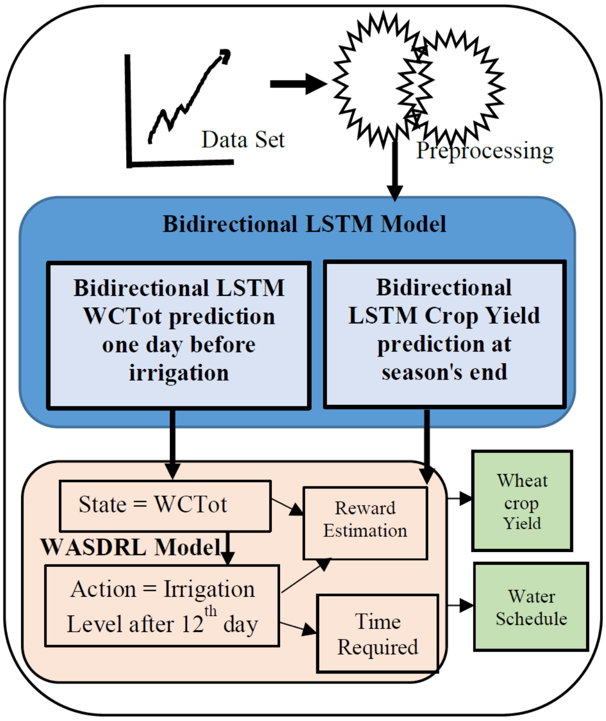


Fig.1: *Process to Determine Irrigation Level with Time and Estimates Wheat Crop Yield.*

2. MATERIALS AND METHODS

2.1 Study Area

The ensemble DL model for wheat crop yield prediction in this article was tested using real data from a farm located in Dhotarkheda hamlet, taluka Achalpur, district Amravati, shown in Fig. 2. The model was trained and validated using 2530 data samples from the year 2000 to 2022 winter harvesting seasons, which were simulated using AquaCrop software. The dataset was divided into two parts: 70% was designated for training, and the remaining 30% was reserved for validation. Testing was conducted using data from the 2023–2024 season. Within the Vidarbha region, which is part of Maharashtra State, India, there are eleven districts, including Amravati district, ideally located in the northern region of the state. It is located between north latitudes 20°32' and 21°46' and east longitudes 76°27' and 78°37'. 12208.77 square kilometers make up the district's whole geographical area. The district experiences extremely hot summers and extremely frigid winters due to its tropical dry and wet environment. In winter, the average lower temperature is 15.1°C, while in summer; the average high temperature is 42.2°C. The temperature ranges from 20°C to 37°C during the southwest monsoon, which lasts from July to October. The district typically receives 843.05 mm of rain.

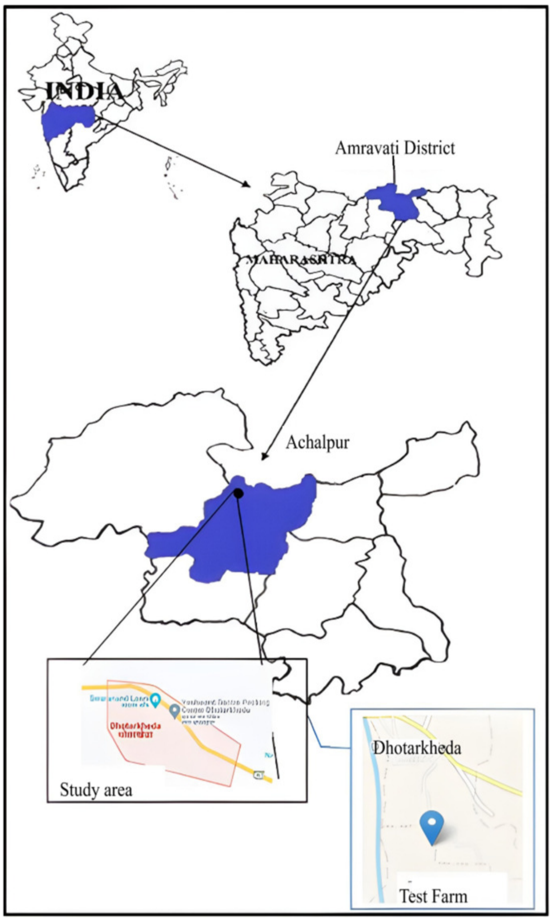


Fig.2: *Place of Study, Winter Wheat Test Zone.*

2.2 Data Collection and Pre-processing

The National Aeronautics and Space Administration (NASA), power agency provided the climatic dataset for Dhotarkheda, India, which was analyzed in this article [36]. In order to better foresee change and comprehend its implications for existence on the globe, the agency's earth science mission is to study, cognize, and simulate the earth system. The recorded weather data for the geography of Dhotarkheda, as provided by NASA was utilized. Location details with longitude and latitude are presented in Table 1. Additional parameters required for predicting wheat crop yield and planning irrigation schedules were simulated using the AquaCrop software. AquaCrop, designed to model crop yield under varying water availability, is particularly valuable for research in water-related environments.

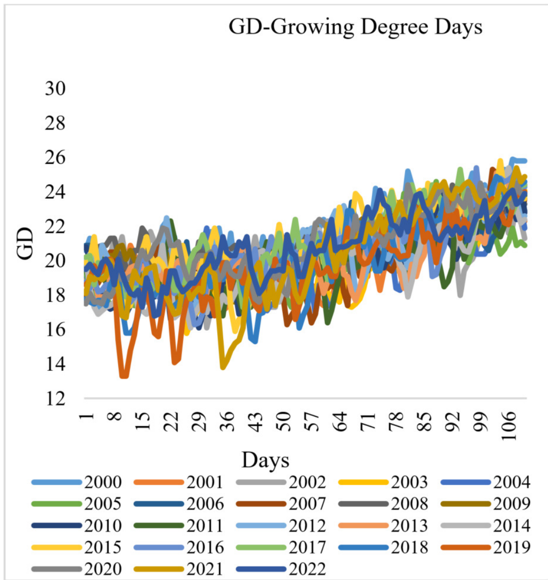
Production of crops and WCTot depending on irrigation were required, along with weather information to establish an environment where a DRL agent operates during the training period. In practice, it

Table 1: *Location Details.*

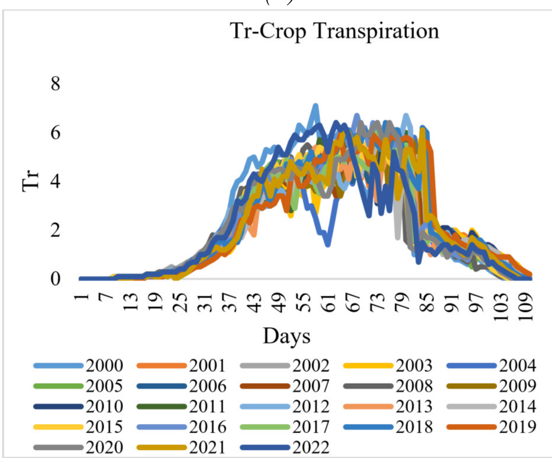
Location	Longitude	Latitude
Dhotarkheda	77.491018	21.306985

can be very laborious and often unfeasible to measure crop productivity and WCTot with different irrigation. Consequently, these factors were simulated using AquaCrop. AquaCrop is an agricultural development framework invented by the Food and Agriculture Organization (FAO). FAO highlights the vital elements of the atmosphere, soil and plant as well as the variables that drive morphology, CC, standard ETo, and final yield of crop (Y(dry)). Climate data (rainfall (mm) and temperature (°C) (minimum (Tmin), average (Tavg), and maximum (Tmax)) were collected from NASA [36] for Dhotarkheda region during year 2000 to 2022 and given to AquaCrop. Winter wheat has been nominated for model setting. Each year, a single sowing date is chosen between Dec. 1 and Dec. 31, and the model generates an expected maturity date based on 110 days period of maturity length. The selected area's soil type is silt clay, which has a minimal to moderate amount of biological material, a little reaction from acidic to a neutral value, is abundant with phosphorus and potassium, and is salinity-free.

The watering approach used was surface irrigation (furrow), which is customizable in the AquaCrop. The irrigation schedules were determined using a predetermined duration of twelve days and a constant depth range of 0 to 70 mm. Various watering regimens were employed in each trial year, including no watering and an assigned irrigation level (Irri) of 20, 30, 40, 50, 60, or 70 mm every twelve days or whenever the permitted deficiency exceeded 80%. Considering the collection of weather knowledge, every day's ETo over each period of growth was simulated with AquaCrop model using the FAO Penman-Monteith technique. This study additionally incorporates into account GD, CC, stage of crop growth, and crop transpiration (Tr), which are valuable parameters for determining yield response [37]. The GD and Tr are simulated using AquaCrop model considers weather condition over each period of growth which is shown in Fig. 3(a) and Fig. 3(b) respectively. The impact of temperatures in the air on canopy growth are simulated using the AquaCrop in terms of GD. GD estimate requires an initial temperature (under which growth of crops is unable to proceed) and a higher temperature (beyond which growth of crops no longer proceeds). In this study, the initial temperature varies from 0°C to 8°C, and the maximum temperature is computed based on the dataset provided. In order to simulate Tr, the crop coefficient and the power of ETo are multiplied while taking temperature and water stressors into account. AquaCrop expresses vegetation growth via CC, rather than leaf area index (LAI). CC, represents the percentage of the soil area occupied by green crops. 25% of the relative weed cover considered with wheat crop. CC is simulated using parameters like GD, Tr, ETo, water contents, and fixed crop coefficient. The different characteristics remained the same. A soil state containing 70% water availability was chosen as the basis for the study. AquaCrop simplified the modeling process of simulating final crop yield in easy-to-understand steps. The phases include simulating Tr, the development of the green crop CC, and the final yield of the crop. One or more, processes as mentioned above are directly impacted by temperature and water stress. Furthermore, AquaCrop generates WCTot utilizing the water balance approach, simplifying irrigation control decisions [38] . Existing articles discuss the details of the AquaCrop model's essential principles, fundamentals, and theoretical and mathematical framework [37], [39]–[42]. The Fig. 4 shows the sample dataset for year 2020.



(a)



(b)

Fig.3: *(a) GD over Period of Growth for Each Year (b) Tr over Period of Growth for Each Year.*

The quality of the provided dataset affects the quality of output that a DL model obtains from the data. Preprocessing involves a set of operations done on the data with the goal of preparing it in better way for detecting features. The technique of moving averages was used in this study to fill in the missing data [43]. The min-max normalization procedure, which is the other pre-processing in this work, aims to harmonize the numerical contents of the dataset without affecting the corresponding ranges of values. Normalization for ML becomes necessary when variables have disparate value ranges.

date	Stage	Rain	ETo	Tmin	Tavg	Tmax	GD	CC	Tr	Irri	WCTot	Y(dry)
20-12-2020	1	0	3.6	9	18.2	27.4	17.5	0	0	40	636.8	0
21-12-2020	1	0	3.4	10.2	18.9	27.5	18.1	0	0	0	621.6	0
22-12-2020	1	0	3.4	9.2	18.3	27.3	17.6	0	0	0	608.3	0
23-12-2020	1	0	3.4	9.3	18.4	27.4	17.6	0	0	0	599.7	0
24-12-2020	1	0	3.1	9	18.4	27.7	17.5	0	0	0	594.4	0
25-12-2020	1	0	3.6	10.1	18.9	27.7	18.1	0	0	0	590.6	0
26-12-2020	1	0	3.3	9.7	19.3	28.9	17.9	0	0	0	588.1	0
27-12-2020	1	0	3.5	10.6	19.8	29	18.3	0	0	0	586.1	0
28-12-2020	1	0	3.2	12.4	20.4	28.5	19.2	0	0	0	584.6	0
29-12-2020	1	0	3.1	11.8	19.8	27.8	18.9	0.7	0	0	583.4	0
30-12-2020	2	0	3.2	11.9	19.5	27.1	18.9	0.9	0.1	0	582.3	0
31-12-2020	2	0	3.2	12.1	19.9	27.6	19.1	1	0	40	619.4	0
01-01-2021	2	0	3.4	12.1	19.7	27.3	19.1	1.2	0.1	0	613.9	0
02-01-2021	2	0	3.1	14	20.1	26.1	20	1.3	0.1	0	606.2	0
03-01-2021	2	0	3	15.2	20.7	26.2	20.6	1.6	0.1	0	599.1	0
04-01-2021	2	0.1	3.4	14.2	20.8	27.4	20.1	1.8	0.1	0	593.6	0
05-01-2021	2	1.2	2.9	14.5	20.7	26.9	20.3	2.1	0.1	0	590	0
06-01-2021	2	0.2	2.9	15.7	22.9	30.2	20.9	2.5	0.1	0	586.3	0
07-01-2021	2	0	2.9	16.4	23.1	29.9	21.2	2.9	0.2	0	583.5	0
08-01-2021	2	0	2.9	17.9	23.5	29.1	21.9	3.4	0.2	0	581.3	0
09-01-2021	2	0	3.2	17.6	23.6	29.6	21.8	4	0.2	0	579.4	0
10-01-2021	2	0	3.4	15.8	23.6	31.5	20.9	4.7	0.3	0	577.7	0
11-01-2021	2	0	3.4	15.8	23.9	31.9	20.9	5.5	0.3	0	576.1	0
12-01-2021	2	0	3.7	16.3	24.1	31.8	21.1	6.5	0.3	40	612.9	0
13-01-2021	2	0	3.7	13.6	22.5	31.4	19.8	7.6	0.4	0	608.7	0
14-01-2021	2	0	3.7	12.1	21.2	30.3	19.1	8.7	0.5	0	603	0
15-01-2021	2	0	3.9	11.4	21.1	30.9	18.7	10	0.7	0	596.8	0

Fig.4: *Sample Dataset for the year 2020.*

2.3 Deep Learning Techniques

DL, a further cutting-edge subset of ML, processes data with multiple layers of algorithms to create perceptions or to mimic the cogitation process. It is regularly attuned to understand spoken language and discriminate objects visually. Every layer conveys data to the one below it, with one layer's output providing another layer's input. The basic structure of each layer is a straightforward, homogeneous algorithm with an activation function. In contrast to classic ML models, DL techniques are more effective and quicker, and they are capable of obtaining traits automatically from the given input data. This is why DL algorithms have gained popularity in the last decade. In multiple areas of agriculture, including crop yield prediction and assessing the effects of various meteorological conditions and agricultural practices on total yields of crops, many ML and DL models have already been examined. In this work BiLSTM-DL algorithm is applied to predict soil water content and wheat crop yield, also DRL is employed to determine irrigation level and finally wheat crop yield.

2.3.1 Bidirectional LSTM

RNN are enhanced version of neural networks that incorporate the idea of recurrent connections. The model's understanding of time is derived from these connections, which pass through subsequent time steps. At subsequent steps, recurring links can build loops that include links returning to the source neurons. Usually RNN face problems regarding the vanishing gradient problem. This problem arises when gradients grow too big or too little, making it challenging to simulate long-range links in the input dataset's structure. The LSTM representation of RNN is an especially efficient method to overcome this problem.

LSTM network is made up of a sequence of LSTM block, each one of having a sequence of input, output, and forget gates to regulate all data that enters and leaves the block. The LSTM can preserve long-term relationships in the input data by using the gates to forget or keep the data from earlier time steps deliberately. Additionally, the LSTM block consists of a memory section that leverages data from earlier time steps to affect the outputs at the present time step. The network passes the result from every LSTM unit to the subsequent, enabling the LSTM to deal with and comprehend consecutive data across several time steps. LSTM-DL network employs supervised learning to modify their weights. It trains on one input at a time and gradually in a series of inputs. Inputs have real values and are transformed into a series of input node activations. Each non-input element calculates the present activation at every particular time step. This activation quantity is calculated as a nonlinear entity of the cumulative sum of the activations of all elements connected to it. For every input, the error is the total of all intended output discrepancies from associated activations that the network has calculated [44]. BiLSTM is a modified form of the LSTM approach that improves performance. The way it works is composed of two distinct transitional LSTM layers that use context-specific data from the two sides of the sequence to transmit an instruction both forward and reversed to the same result layer [34].

In this research, two BiLSTM models are trained for irrigation scheduling: one for predicting wheat yield after maturity days (110 days) and the other for predicting WCTot one day before the day of irrigation (12 days). After discussing with the farmers from the region considered for this study, it was discovered that it takes 3 - 4 months to mature a wheat crop from planting to harvesting. Additionally, the website [45] states that the wheat crop duration from seed until maturity usually is somewhere between 90 and 100 days. Moreover, farmers said that they plan to irrigate their wheat fields between 11 to 15 days. In light of this, the research uses a sequence length of 12 days for the WCTot and 110 days for the yield prediction model, which are displayed as input to the BiLSTM model shown in Fig. 5 (a) and Fig. 5 (b), respectively. The architecture of BiLSTM models for WCTot and yield prediction with the number of trainable parameters are shown in Fig. 5. The

512 nodes make up every single layer of a two-layer BiLSTM network that was created to estimate wheat yield making use of crop development stage, weather data, ETo, GD, Tr, CC, and WCTot. In order to forecast yield, the algorithm gets information regarding these characteristics throughout a season. Every year, a late sowing window spanning from Dec. 1 to Dec. 31 is chosen to produce a maturity period of 110 days for wheat. AquaCrop software was used to simulate and create the dataset.

An additional, BiLSTM model was trained to evaluate the agent, environment and predict everyday WCTot one day before schedule. The following environment's state was forecasted using this model. Using the crop development stage, meteorological data, ETo, GD, and Tr, a two-layer BiLSTM model with 512 nodes was employed to forecast the WCTot level. This effort trains the model to predict WCTot one day in advance. As was previously noted, BiLSTM can examine backward several time steps and utilize this knowledge to anticipate future events. Every twelve days, irrigation takes place in this implementation. As a result, the BiLSTM examines past data spanning 11 days that reflects the current environment's state.

Hyperparameters for both BiLSTM networks are presented below:

Number of nodes and hidden layers: 512 nodes with two hidden layers are selected to predict WCTot and yield in order to prevent overfitting caused by the large number of parameters that can be trained and to speed up and improve the efficiency of the training process. 64, 128, 256, and 512 nodes with 2 and 3 hidden layers have all been used for testing the model. For each potential pairing of layers and nodes, the mean absolute error (MAE) score is computed. The model with 2 layers and 512 nodes was identified to have a lesser MAE compared to other pairings. The outcomes were enhanced by following the BiLSTM layers with a separate dense layer. The nonlinear interaction between input and final result was captured using the tanh function as an activation function following each BiLSTM layer.

Learning rate: For model training, the 10^{-3} learning rate is considered. The model learnt relatively slow for a learning rate of 10^{-5}, as well as for after 500 iterations, the validation loss remains exceptionally large. Additionally, training fluctuates due to the learning rate of 10^{-2}. As a result, learning rate is maintained above 10^{-2} and below 10^{-5}.

Epochs: 500 epochs were allotted for training each model; early stopping was employed to avoid overfitting. The BiLSTM model for WCTot prediction terminated after 162 training epochs, whereas the other model for yield prediction terminated after 455 training epochs. The number of epoch where validation loss stops improving is determined by the early stopping technique's patience hyperparameter. The appropriate point of patience differs depending on the problem and model. Plots of model performance metrics can be examined to assess patience. Plot analysis in this study revealed that the WCTot and yield models' respective patience values were 10 and 50.

Dropout: Since the validation loss was not improved by the dropout value of 0.4, it was decided to be less than or equal to 0.4 and taken from the set {0.1, 0.2, 0.3, 0.4}. For the wheat yield and WCTot estimate models, adding dropout on the repetitive results with dropout size 0.1 enhanced the validation loss and was thus chosen for each model.

```
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 12, 11)]          0

bidirectional (Bidirectiona  (None, 12, 1024)          2146304
l)

dropout (Dropout)            (None, 12, 1024)          0

bidirectional_1 (Bidirectio  (None, 1024)              6295552
nal)

dropout_1 (Dropout)          (None, 1024)              0

dense (Dense)                (None, 512)               524800

dense_1 (Dense)              (None, 1)                 513

=================================================================
Total params: 8,967,169
Trainable params: 8,967,169
Non-trainable params: 0
```

(a) WCTot Prediction

```
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 110, 11)]         0

bidirectional (Bidirectiona  (None, 110, 1024)         2146304
l)

dropout (Dropout)            (None, 110, 1024)         0

bidirectional_1 (Bidirectio  (None, 1024)              6295552
nal)

dropout_1 (Dropout)          (None, 1024)              0

dense (Dense)                (None, 512)               524800

dense_1 (Dense)              (None, 1)                 513

=================================================================
Total params: 8,967,169
Trainable params: 8,967,169
Non-trainable params: 0
```

(b) Wheat Crop Yield Prediction

Fig.5: *Architecture of BiLSTM.*

2.3.2 Deep Reinforcement Learning

In dynamic environments, DRL performs effectively in decision-making processes. In order to accomplish the objective, an agent trains through multiple experiences over the environment. These experiences produce data about the results of the agent's actions and contribute in performance enhancement.

The proposed combinatorial approach interacts with the environment and incorporates the unpredictable input features to acquire model for predicting with a deep reinforcement methodology [46].

Water Scheduling Environment for DRL Agent

In this study, application of DRL is implemented to determine how an agent experiences with the environment, it applies irrigation plan while considering states. An agent attempts to influence its surroundings through interaction. Irrigation levels 0, 20, 30, 40, 50, 60 or 70 mm considered as environment actions, and the reinforcement learning (RL) agent's decisions have an apparent effect on the environment. The agent in this research regulates irrigation by analyzing the development of the crop stage, weather information, ETo, GD, Tr, CC, and WCTot; the state has been determined by combining these factors. Every twelve days, the agent chooses an action based on its current state. In every state, the environment provides judgment to decide if the agent's activities are acceptable. It is critical in the context of RL, because the machine learns entirely on its own and the only feedback that will support it in learning is the reward agent obtains. The reward of agent for watering experiment is designed based on the total wheat crop yield received at the end of the season. The future return is the total outcome of crop productivity and water cost. The consumption of water take place repeatedly during a crop season, therefore the agent receives the reward at the end of the season. In this context, the reward is defined as the net return on crop yield minus the cost of water. During the season, the reward is set to zero.

Water Scheduling DRL (WASDRL) model

The current environmental condition is fed into the WASDRL model, which inputs the result for every action. In RL, the concept of exploration versus exploitation is crucial. The optimal answer needs to be found by the RL agent as soon as feasible. But if it jumps too rapidly to a conclusion without doing acceptable exploration, it can end up at a local minimum or unsuccessful [46]. The Epsilon-Greedy approach [46] was utilized to explore the environment. This approach involves the agent selecting an arbitrary action with chance ϵ and deciding with probability $1 - \epsilon$. After setting the ϵ to 1, the value was dropped by an amount of 0.9997 for every episode and stopping once it got value of 0.001. During training, the model chooses an arbitrary batch of events, and training is done on the selected batch. One hyperparameter that needs to be specified during training is the batch size. In order to expedite training and prevent the model from being either over fit or under fit, the batch size of 64 was selected. The agent was evaluated during the year 2023–2024 after being trained on a dataset of 2000 to 2022, with 1,000 episodes. Eq. (1) was used to determine the rewards that the DRL agent obtained. The net return was very high. The net return was normalized by decimal scaling approach with power of three to avoid excessive computation. The agent's reward was calculated using logarithms to achieve convergence in the process. Wheat prices have been assigned to be ₹25200/- per ton [47], while the cost of irrigation per hectare was fixed at ₹297/- per hectare [48]. These are variables that can be modified. Once the average reward was enhanced, the DRL network's weights were stored. This process was repeated every five episodes. The model predicts the wheat crop yield after each season. The agent's reward for irrigating a field is calculated using Eq. (1) by deducting water expenses from the total wheat yield value.

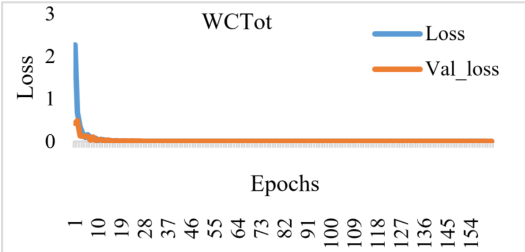
$$Reward = Yield * Price\ of\ Yield - Water\ amount * Price\ of\ water \tag{1}$$

Where, *Yield* – predicted value by an agent after exploring the environment, *Price of Yield* – price in ₹/ton, Water amount – total action taken by the agent in a season during environment exploration, *Price of water* – price in ₹/ hectare.

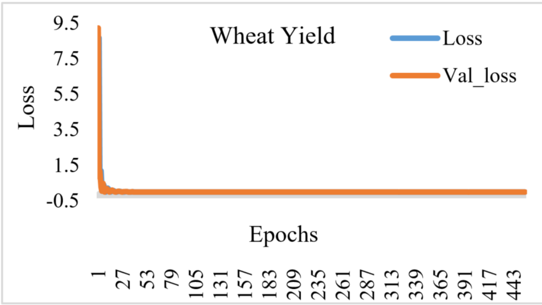
3. RESULTS AND DISCUSSIONS

3.1 Evaluation of the BiLSTM models

The BiLSTM model training took place over a maximum of 500 epochs for wheat yield estimation. In addition, the WCTot BiLSTM prediction model was trained for a maximum of 500 epochs. Training is terminated after a particular number of iterations if the validation loss remains unchanged. The number of iterations during which the loss of validation substantially grows is controlled by the hyperparameter patience in the early stopping approach. The specific range of patience depends on the problem and model. The model performance metrics can be examined with graphs to assess patience [49]. The graph analysis of WCTot and wheat crop yield model's loss shown in Fig. 6 (a) and Fig. 6 (b) respectively, the present study revealed the values of 50 and 10 for patience of the wheat yield and WCTot prediction models respectively. The WCTot and Yield prediction models were fully trained after 162 and 455 epochs, as shown in Fig. 6 (a) and Fig. 6 (b), respectively.
RMSE and MAE are used to assess the WCTot and wheat yield prediction BiLSTM model. MAE analysis of WCTot and wheat yield BiLSTM models are shown in Fig, 7(a) and Fig 7(b) respectively. From Fig. 7, it is noticed that the error in the model for training and validation data is very small. Using the wheat yield experimental data, the yield model obtained an RMSE of 67.93 (kg/ha) and an MAE of 48.55 (kg/ha). The WCTot model produced an RMSE of 19.01 mm and MAE of 13.48 mm per



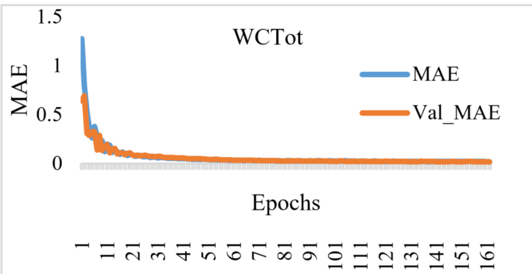
(a) Loss Analysis- WCTot BiLSTM Model



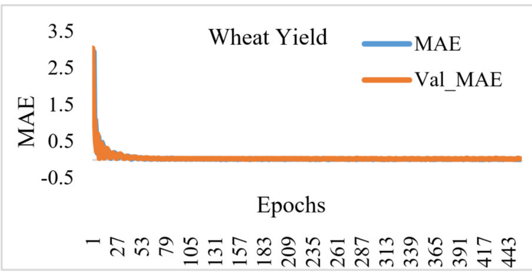
(b) Loss Analysis- Yield BiLSTM Model

Fig.6: *Loss Analysis of BiLSTM Models.*

hectare.



(a) MAE Analysis: WCTot BiLSTM Models

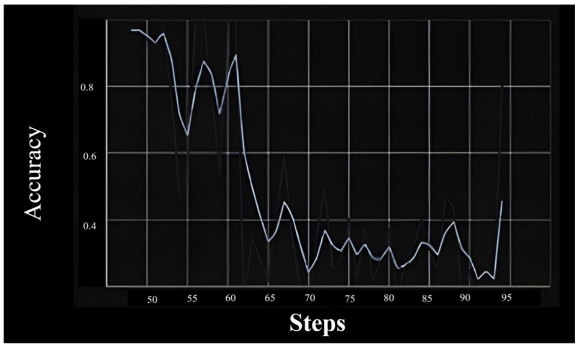


(b) MAE Analysis: Yield BiLSTM Models

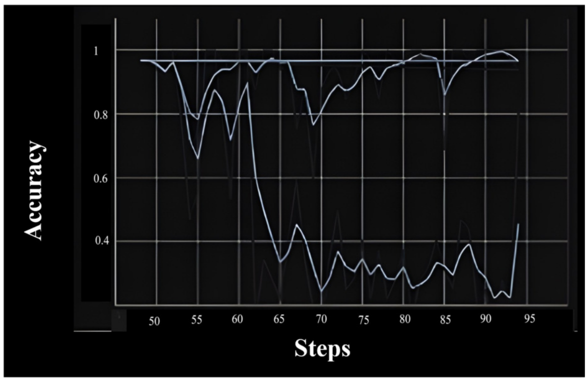
Fig.7: *MAE Analysis of BiLSTM Models.*

3.2 Evaluation of the WASDRL network

The weights of the DRL network are updated during training after every five epochs. The DRL model is evaluated with an accuracy metric. The accuracy of the DRL network is displayed in Fig. 8(a), where the accuracy is lowest after 100 epochs of operation. The accuracy of the DRL network improves when saved weights are used for subsequent runs. Fig. 8(b) shows that accuracy ranges from 90% to 98% for several recent epochs. The DRL model's loss in terms of mean squared error as a training function is also seen to decrease once the network has trained for the successive 100 epochs, as illustrated in Fig. 9(a) and Fig. 9(b). This occurs when the model first explores the environment during training and eventually converge to an ideal course of action. The LSTM performs better as it can improve time-series data predictions by using data from previous data inputs and cycles throughout the LSTM layers. [50]. The average rewards received by an agent over the DRL network's training are displayed in Fig. 10. Epsilon during DRL network training is depicted in Fig. 11. As illustrated in Fig. 10 and Fig. 11, the model investigates the surroundings at the same time, epsilon is high and then begins to exploit when epsilon falls.

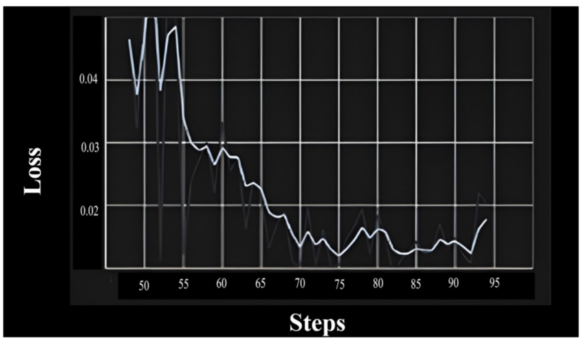


(a)

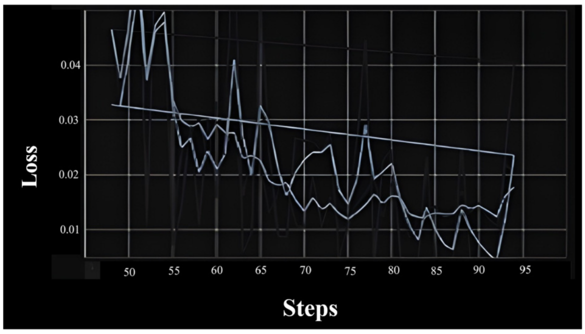


(b)

Fig.8: *(a) Accuracy of WASDRL Model (b) Accuracy of WASDRL for Next Iterations.*



(a)



(b)

Fig.9: *(a) Loss of DRL (b) Loss of WASDRL for Next Iterations.*

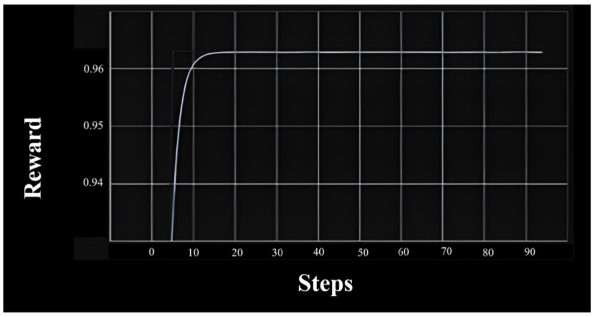


Fig.10: *Reward Obtained by DRL Agent.*

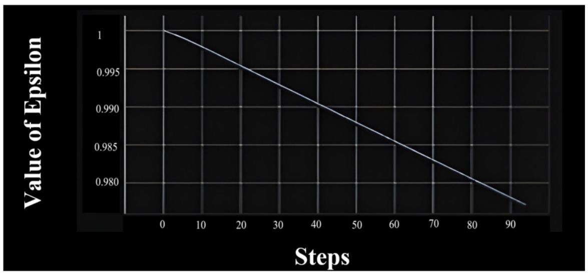
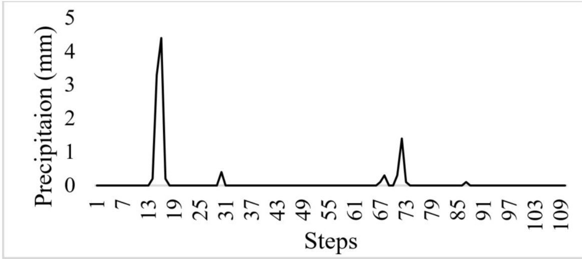


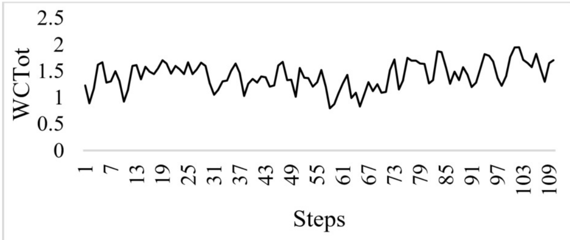
Fig.11: *Epsilon during DRL Network Training.*

Fig. 12(a) depicts the precipitation from Dec. 2023 to Apr. 2024. It is observed that there is 4.5 mm of rainfall on the 12th step, and Fig. 12(b) shows that the water content is sufficient. As a result, the DRL agent selected irrigation of 0 mm on the 12th day, as indicated in Fig. 12(c). The DRL model by itself acquired to adapt irrigation levels depending on precipitation, adjusting the amount of water or none, as demonstrated in Fig. 12. The DRL model recommended the following water schedule for 2023–2024: [40 mm, 0 mm, 30 mm, 60 mm, 60 mm, 50 mm, 40 mm, 20 mm, 50 mm] every twelfth day until the 96th day after seed sowing.

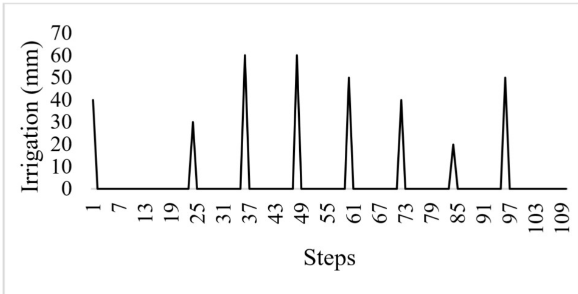
Two separate 25 m^2 patches on a same field were treated identically in the current analysis to compare the water usage of the proposed approach with the conventional one. One patch was watered conventionally with fixed irrigation level while the other patch was watered using the proposed approach. A summary of the gross profit with various irrigation levels is displayed in Table 2. The proposed approach produced more profit when assessed against other fixed irrigation levels, as the table demonstrates. Table 2 also shows the actual and expected yields for 2022-23 and 2023-24. It is observed that the actual and expected yield fluctuate significantly; yet, resultant water schedule assists to reduce water waste in agriculture without hampering the crop yield when compared with fixed irrigation. The model that had been trained performed better than the conventional fixed irrigation system on the data collected in year 2023-2024. The irrigation schedule provided by the WASDRL model is shown in Table 2, and utilized to irrigate the farm. The wheat yield is calculated in two patches by quantifying the amount of grain. In experimental land of 25-m^2, the actual yield obtained is 9 kg per 25-m^2 area, whereas with a fixed irrigation level of 60 mm, the actual yield obtained is 8.6 kg per 25-m^2 area. Thus, compared to fixed irrigation, the proposed approach increases actual output by 5% while using 30% to 35% less water. The drop in water volume is noticeable.



(a) Precipitation in Season of Wheat (Year 2023-2024)



(b)Predicted WCTot with BiLSTM Model



(c)Irrigation Action Obtained by DRL Agent during Season

Fig.12: *DRL Efficiently Determines Irrigation Level.*

Table 2: *Summary of Gross Profit.*

Year	Irrigation after every 12th day (in mm)	Total Irrigation during Season (in mm)	Predicted Yield (kg) per acre	Actual Yield
2022-2023	60 (Fixed)	540	1,573	1500 kg/acre
2023-2024	60 (Fixed)	540	1,075	8.6 kg in 25m^2 area (1,390/acre)
2023-2024	[40, 0, 30, 60, 60, 50, 40, 20, 50]	350	1,570	9 kg in 25m^2 area (1,460/acre)

3.3 Time Needed for Irrigation:

The amount of time taken to provide the desired watering depth in mm is known as irrigation duration in minutes or hours. The area of the land that needs to be watered in hectare (ha), the required irrigation level in millimeter (mm), and the rate of flow in liter per second all affect how long irrigation occurs. The research calculated the rate of water flow in the farm, which turned out to be 10 liter per second. After determining the level of irrigation, the proposed work presents the time required for irrigating the land area in hours. Eq. (2) [51] is applied for determining irrigated duration.

$$Irrigation\ Time(hours) = \frac{2.78 * Irrigation\ area\ (ha) * Level\ of\ irrigation(mm)}{Flow\ of\ irrigation\ (liter/second)} \quad (2)$$

where, *Irrigation area* - measurement of a farm in a hectare, *Level of irrigation* - the amount of water in mm, *Flow of irrigation* - a rate of flow in liters per second (10 liters/second).

The duration needed for the 25-m^2 land patch that was examined under a particular irrigation level for the study assignment is shown in Table 3. The translation of irrigation level to irrigation time makes it easier for farmers to irrigate their land. Thus, this study assists farmers in planning water management and predicting wheat crop yield. The proposed method will be able to predict wheat crop yield and obtain irrigation schedules by varying the meteorological data for various regions.

Table 3: *Time Required to Irrigate 25-m^2 Land.*

Level (mm)	Time required to irrigate (seconds)
70	180
60	150
50	128
40	102
30	80
20	60
10	30

4. CONCLUSIONS

In this article, a DRL approach is applied to predict wheat yield by generating a water schedule for winter wheat. This schedule is converted into irrigation time to make things easier for the farmer. The DRL model was trained with 22 years of data and tested using one year of data. The DRL network adapted to forecast the irrigation level ahead of time and prevent water waste during season. Additionally, the model could modify the watering schedule in response to seasonal variations in precipitation and weather. The WASDRL model's findings were compared to those obtained with fixed irrigation. It is found that wheat yield (Year 2023-2024) is enhanced by 5% in test fields compared to fixed irrigation, notwithstanding a disparity between anticipated and actual yields. As a result, RL can be utilized in this study to schedule watering to reduce water waste in agriculture while maintaining the yield of crops.

A limitation of the proposed study is that it was trained on simulated data. The alternative is to train the model with both field and simulated data to make it more accurate for real-world applications. Another challenge is that the proposed model does not account for soil fertility and nutrient deficiencies on crops, which the researchers can consider in the future.

AUTHOR CONTRIBUTIONS

Conceptualization, Methodology, Software, Investigation, Validation, Writing-original draft, and Editing, Poonam Bari; Conceptualization, Review and Supervision, Lata Ragha. All authors have read and agreed to the published version of the manuscript.

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