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Feed-Forward Neural Network for Prediction of Reference Evapotranspiration and Irrigation Scheduling

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Abstract: Water scarcity is a global concern and impacts several facets of human life. India is facing a severe decline in water levels due to overuse in agriculture. Punjab is an agricultural state of India witnessed huge overconsumption of groundwater that needs precise irrigation scheduling. Evapotranspiration is an essential process in hydrology that estimates crop water requirements from evaporation and transpiration losses. The use of weather parameters to predict evapotranspiration is a cost-effective approach for scheduling irrigation in areas without access to specialised evapotranspiration measuring equipment. This study presents and assesses a multilayer Feedforward Neural Network (FNN) for predicting reference evapotranspiration (ETo) in the Fatehgarh Sahib districts of Punjab. The model utilizes an input layer with a number of neurons equivalent to the input parameters. It also incorporates two hidden layers that are activated by the Rectified Linear Unit (ReLU) activation function and an output layer that corresponds to the output. The dataset utilised for testing and training purposes is obtained from a weather forecast website. The dataset employed the Hargreaves-Samani approach to calculate the ETo. The model underwent testing of combinations of input parameters, including Tmean, Tmin, Tmax, Humidity, Wind Speed, Pressure and Cloudiness. The efficacy of the models was evaluated with R2, MSE, and MAE metrics. The optimal outcomes were achieved by considering the parameters Tmean, Tmin, Tmax, Humidity, Wind speed, and Cloudiness, resulting in a R2 of 0.972, MSE of 0.090, and MAE of 0.221. The paper emphasises the utilisation of ETo in the scheduling of irrigation and proposes that in future studies, the model be validated using a larger dataset including many sites in order to further expand its practicality.

Keywords*: Evapotranspiration, FNN (Feed-forward Neural Network), Hargreaves-Samani, Irrigation Scheduling*

1. Introduction

Water shortage is a global concern that has implications for various aspects of life such as the economy, climate, soil composition, food shortage and life. Excessive water consumption is observed across all sectors whereas the agriculture sector is a major consumer of water. It is observed that regions in the northwestern and western states of India such as Haryana, Punjab, and Rajasthan, exhibit greater depths of water, often exceeding 40 meters [1]. Punjab is a food basket of India where agriculture is the main source of livelihood. The state exhibits a substantial demand for water to facilitate irrigation in its agricultural activities. Various techniques are proposed to conserve agricultural water such as precision irrigation, crop diversification, laser leveling, and irrigation scheduling. According to Gu et al. (2020), the primary methods utilized for irrigation scheduling are evapotranspiration and water balance (ET-WB), soil moisture-based approaches, plant water status assessment, and computerized models. Hence estimation of evapotranspiration is a prominent area of research for irrigation scheduling.

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Evapotranspiration (ET) is an estimate of water consumption in plants due to evaporation and transpiration. This is the amount of water essentially required by crops for their optimal growth. The agricultural water requirement is crucial for planning, budgeting, and managing water resources. The calculation of ET is useful in estimation of water consumption and management, irrigation scheduling and drought forecasting [7]. ETo is the water losses from a hypothetical reference surface that is completely irrigated and has 0.12 m tall grass crop. Crop Evapotranspiration (ETc) is calculated from the ETo by multiplying it with standardized crop coefficients [5][9].

The direct and indirect approaches are used to determine ETo. Direct approaches have high degree of precision use equipment such as lysimeters and pan evaporators. However, the primary drawback of these methods is the expenses related to installation, use and maintenance. The indirect approaches use empirical equations and data obtained from weather stations [20]. The Penman-Monteith, Blaney Criddle, and Hargreaves-Samani methods are widely used indirect approaches for estimating ETo. The Penman-Monteith technique is utilised to estimate the ETo is as follows in equation (1).

$$ETo = \frac{0.408\,D(Rn - G) + k\,\frac{900}{T+273}\,U2\,(es - ea)}{D\ + k\,(1 + 0.34U2)} \qquad (1)$$

Here, Rn is the net radiation, U2 is mean wind speed at a height of 2 m, T is the average daily air temperature, G is the soil heat flux at the surface of the soil, ea is the saturation vapour pressure, es is the actual vapour pressure, D is the slope of the saturation vapour pressure curve, and k is the psychrometric constant [5]. This approach needs meteorological and altitude-related factors specific to the respective locations. The Hargreaves-Samani approach uses air temperature as a means to determine the daily reference ETo [25].

1.1 Literature View

The ETo is used in irrigation scheduling can be estimated with several ways like empirical methods, machine learning techniques, and historical data analysis. Zanetti et al. (2007) used a multilayer perceptron to predict ETo. The estimation was based on characteristics, including daylight hours, extraterrestrial radiation, and maximum and minimum air temperatures. The research findings indicate that the utilisation of the proposed model for estimating ETo only requires the inclusion of maximum and minimum temperatures. Jain elal.(2008) developed models for estimating evapotranspiration with limited input parameters using ANN. Kia et al. (2009) proposed the development of an evapotranspiration based fuzzy logic controller that demonstrates effectiveness in estimating the quantity of water uptake by plants at various depths. Migliaccio et al. (2010) conducted an experimental study to evaluate the effects of different irrigation techniques on the development and productivity of papaya plants in the southern area of Florida. The ET and soil water-based treatments conserved irrigation water to around 31-36%.

Manikumari et al. (2017) proposed using Bagged Neural Network (Bagged-NN) and Boosted Neural Network (Boosted-NN) ensembles for ETo forecasting. Adamala (2017) introduced a Wavelet Neural Network (WNN) to estimate ETo utilising the Hargreaves Samani empirical technique. The primary input parameters for this estimation were identified as the lowest and maximum air temperature. Antonopoulos and Antonopoulos (2017) employed Artificial Neural Networks (ANN) as well as empirical methods such as Priestley-Taylor, Makkink, and Hargreaves to estimate ETo. Unes et al. (2018) proposed a study comparing ETo by Hargreaves-Samani, Turc equations, and Artificial Neural Networks (ANN). Daily air temperature (highest, lowest, and average), wind speed, solar radiation, and relative humidity were the primary input parameters. Abdullahi and Elkiran (2018) employed artificial neural networks as a predictive tool for ETo. The ETo of a dataset was calculated using the Penman-Monteith of the CROPWAT 8.0 software. Saggi and Jain (2019) introduced a Deep Neural Network (DNN) model with H2O framework to assess the daily ETo for the districts of Patiala and Hoshiarpur in Punjab. The system utilises four supervised learning algorithms, namely the Generalised Linear Model, Random Forest, and Gradient-Boosting Machine.Khedkar et al. (2019) suggested the use of ANN models for estimation of ETo for Padegaon, Satara region, Maharashtra, India. The five different models based on input parameters such as ANN1 (Pan evaporation), ANN2 (Tmax and Tmin), ANN3 (Tmax, Tmin and SSH), ANN4 (Tmax, Tmin, RHmax, RHmin, and SSH) and ANN5 (Tmax, Tmin, RHmax, RHmin, WS and SSH) tested and evaluated.

Ogunrinde et al. (2020) utilised one-year Standardised Precipitation Evapotranspiration Index (SPEI) to estimate ETo. The model employed a Levenberg-Marquardt training approach and utilized Tansig activation functions. Lucas et al. (2020) put up a methodology for estimating ETo utilising a Convolutional Neural Network (CNN) architecture consisting of three distinct layers: fully connected, pooling, and convolutional. The estimation of ETo was conducted by employing three distinct CNNs characterized by unique architectural design. Walls et al. (2020) introduced seven ANN models to forecast real-time evapotranspiration during the day. The primary components of the model are sigmoid and ReLU activation functions as well as the stochastic gradient descent (SGD) and RMSprop learning methods. Chandrappa et al. (2020) provided smart irrigation systems utilize localised meteorological data to determine Evapotranspiration (ET), which is then employed to modify the irrigation schedule and duration. The primary focus of research in estimating ETo involves the application of several machine learning techniques and neural networks. Sattari et al. (2021)comparednon parametric kernel-based methods with ANN and deep learning methods

1.2 Motivation

The domains of artificial intelligence (AI) machine learning (ML) has huge potential in the agricultural sector. There is a lack of research regarding the use of Neural Network and ML models in predicting ETo specifically for regions of Punjab. The previous research explored different combinations of weather parameters in ETo prediction in regions like tropical, arid and semi-arid regions [9]. The variation of region decides the applicability of specific parameters. The paucity in previous research makes multi featured nonlinear process ETo is suitable candidate for

ANN modeling due to its correlation to weather and altitude based factors. The cultivated crops in Punjab are water intensive. Water resources such as surface water and groundwater are required to be preserved. The ETo prediction and irrigation scheduling are prominent research areas.

1.3 Objectives

The literature review showsthat ANN and DNN are widely used models for the prediction of ETo. The various factors impact ETo like average daily air temperature, maximum and lowest air temperatures, wind speed, solar radiation, and relative humidity. The recent increase in academic publications can be attributed to the capacity of ANNs to build correlations between input and output variables without understanding the underlying physical mechanisms [22][26]. The research on machine learning models for the prediction of reference evapotranspiration, particularly within the Indian region, is limited. The FNN is a straightforward computational model capable of effectively handling several input variables and interrelationships among these variables. Hence, the utilisation of FNN is appropriate for the purpose of ETo prediction in this study.

The primary focus of this study is to develop and evaluate the effectiveness of an FNN model to predict the ETo by including input parameters derived from a weather forecast. Subsequently, the forecasted ETo can be utilised to plan the irrigation schedule for the forthcoming days.

2. Methodology

This section presents various phases of the FNN model such as data collection, pre-processing, the proposed model, irrigation scheduling and performance evaluation.

2.1 Data Collections

The FNN model for ETo prediction was implemented for Fatehgarh Sahib district of Punjab located at 30.6435° N latitude and 76.3970° E longitude. Fig. 1 depicts the geological position of the study area. The data was obtained from the openweathermap weather forecast website. The website employs services to obtain raw data from airport weather stations, as well as data from NOAA and satellite sources [6]. The data was extracted in JSON format and converted into an Excel file for further analysis. The dataset underwent a process to identify and remove duplicate columns, as well as convert the units of measurement for various columns.

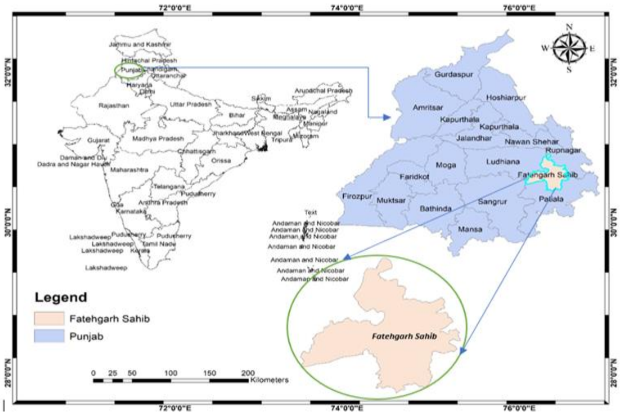

Fig 1 Geographical Location of Study Area

The dataset encompasses a time frame of fifteen years from 2005 to 2020. Table I presents the statistical characteristics of the weather data. The minimum and maximum temperatures are 0.8°C and 47°C, respectively. The average cloudiness is 20% suggesting the arid climate of the region. Sunlight is the primary factor responsible for water evaporation.

The calculation of ETo relies on air temperatures. Therefore, Hargreaves-Samani approach is employed for calculating ETo in the dataset. The following equation (2) presents the methodology:

$$ETo = \alpha * (Tmean + 17.8) * (Tmax - Tmin)^{0.5} Ra \qquad (2)$$

The mean daily temperature, denoted as Tmean, is calculated by taking the average of the maximum temperature (Tmax) and the minimum temperature (Tmin). Ra refers to extraterrestrial solar radiation originating from outside the atmosphere of earth. An empirical constant denoted as α, with a specific value of 0.0023 is associated with Ra [5].

Table I Statistical properties of Weather data

Parameter	Description	Type	Max	Min	Mean
Tmin	Minimum Temperature	Independent	31.7	0.8	18.1
Tmax	Maximum Temperature	Independent	47	11.4	31.1
Tmean	Mean Temperature	Independent	39.0	6.0	24.1
P	Pressure	Independent	1024	990	1008
RH	Relative Humidity	Independent	100	10	70
WS	Wind Speed	Independent	7.0	0.8	1.8
Cl(%)	Cloudiness	Independent	96.0	0.0	20.7
Ra	Extra-terrestrial Radiation	Independent	16.89	7.9	12.95
ETo	Reference Evapotranspiration	Dependent	9.3	1.4	4.5

2.2 Input parameters for FNN Model

The relation between input parameters and ETo has observed with heatmap of correlations represented in Fig. 2. This heatmap helps to identify the suitable combinations of input parameters for the optimal model. The heatmap reveals a positive association between ETo and temperature parameters (Tmean, Tmax, and Tmin), while a negative correlation is detected with humidity and pressure. The heatmap clearly indicates that the maximum temperature (Tmax) exhibits a strong positive association (0.95), while wind speed has the weakest positive correlation (0.11). Tmax is a prominent factor in estimating ETo but wind speed, humidity and pressure are other factors influence ETo.

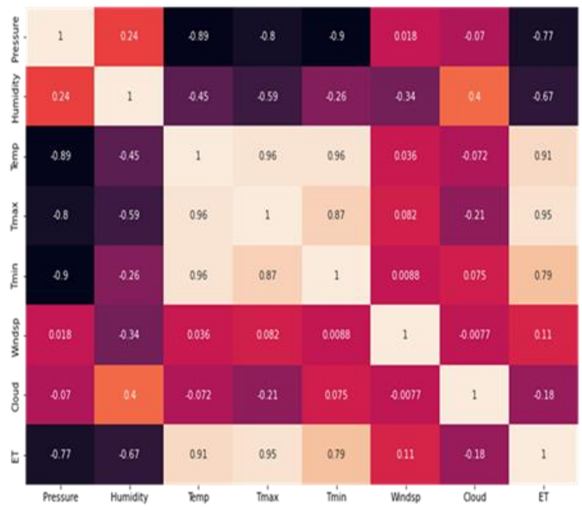

Fig 2 Correlation Heatmap of Attributes from Dataset

The six distinct combinations of parameters were proposed to ETo prediction. Each parameter combination corresponds to one model for ETo [15][22]. Table II presents various combination of parameters used by FNN model for predicting ETo. In the initial model, denoted as M1, all parameters (Tmean, Tmin, Tmax, Humidity, Wind Speed, Cloudiness, and Pressure) are included as input variables [17]. Pressure is omitted in model M2. In

Model 3, the mean daily temperature variable is not included, whereas in Model 4, the variables for pressure, minimum temperature (Tmin), and maximum temperature (Tmax) are excluded to determine Tmean in estimating ETo. The M5 and M6 exclusively consist of models based on temperature only.

Table II Different Models for FNN based on Input Parameters

Model No	Attributes
M1	Tmean, Tmin, Tmax, Humidity, Wind Speed, Cloudiness, Pressure
M2	Tmean, Tmin, Tmax, Humidity, Wind Speed, Cloudiness
M3	Tmin ,Tmax, Humidity, Wind Speed, Cloudiness
M4	Tmean, Humidity, Wind Speed
M5	Tmin, Tmax
M6	Tmin, Tmax, Tmean

2.3 Model Architecture and Design

ETo is predicted using a multilayer FNN with one input layer based on meteorological input parameters, two ReLu-activated hidden layers, and one output layer containing a neuron corresponding to ETo. It is a machine learning model composed of neurons interconnected as a network in a manner resembling the human brain, including input, hidden, and output layers. Neurons in the input layer represent independent variables, while neurons in the output layer represent dependent variables. This section explains the primary components of a neural network.

Normalization: The data is then normalized using a Min-Max scaling approach that rescales the values of every column between 0 and 1, so that every parameter contributes equally [11]. It is also known as scaling with equation (3).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (3)$$

The maximum and minimum values of features are x_{max} and x_{min}, respectively. The value of x is between the minimum and the maximum value, indicating that the value of x' is between 0 and 1. Using a process of division, the dataset was split into a training set and a testing set with an 80:20 split.

Activation Function: The activation function activates neurons by transforming the summed and weighted input of a node into the activation of that node. Saggi and Jain (2019) were able to activate a model by utilising the ReLU function. This investigation made use of the ReLU activation function because it is a linear function and a faster learning procedure than other options. The activation function of RELU is shown by equation (4).

$$f(x) = ma(0, x) \qquad (4)$$

If the input variable x is positive then it will contribute to output, otherwise it will become zero with negative value of x [11].

Learning functions: Learning functions, also known as optimizers, are algorithms that reduce losses by fine-tuning the neural network's weights and learning rate. Some ways to enhance the neural network include backpropagation, gradient descent, gradient boosting, and RMSProp (Root Mean Square Propagation). The RMSProp uses the following equation (5):

$$Wnew = Wold - \frac{n * gt}{\sqrt{vt + \epsilon}} \qquad (5)$$

Where Wnew = the updated weight; Wold = the previous value of the weight; n = the learning rate = 0.1; and gt = output error computed by the objective function.

2.4 Irrigation scheduling using ETo

Farooque et al. (2021) used weather forecast based ETo irrigation scheduling for crops in Canada. The daily irrigation can be scheduled using inputs like Crop Evapotranspiration (ETc), rainfall and root depth of plant [12]. The following equation (6) uses ETo as an input to determine ETc.

$$ETc = Kc * ETo \qquad (6)$$

Where Kc is crop coefficient and ETc is crop evapotranspiration. The crop coefficients are obtained from FAO dataset. The crop coefficients are according to crop stage. Three different crop stages Kcini, Kcmid and Kclast are included to determine irrigation schedule. The following equation (7) gives soil moisture for each day.

$$\theta_i = \theta(i - 1) - 100((ETc - P)/D) \qquad (7)$$

Where θ_i is soil moisture of current day, θ(i-1)soil moisture of previous day, ETc crop evapotranspiration at that day, P is rainfall and D is root depth. The root depth and crop coefficients are crop specific and average values of various crops of study area are taken [12].

Then, the calculated soil moisture of each day compared with field capacity. If it is less than field capacity then the day is candidate for irrigation.

2.5 Performance Metrics:

The performance of the model was evaluated using Mean

Square Error (MSE) and Coefficient of determination(R2) and Mean Absolute Error (MAE). The MSE is average squared difference between original and predicted values, MAE is absolute difference between actual and predicted values.

3. Data Analysis and Results

This section presents the results of various FNN models to predict ETo and irrigation scheduling. It has three subsections that are organized as:1) Results of various ETo models, comparison between various models and 2) Irrigation scheduling module.

3.1 Results of Various ETo modela:

The various models, based on different combinations ofinput parameters from the weather dataset, produce different values of ETo. Their performance is examinedwith performance indicators like MSE, R2, and MAE.Model efficiency is considered based on the highest R2values, while the MSE and MAE are expected to be thelowest. The various models have different FNN architectures based on the number of input neurons, epochs and hidden layers.

The architecture of Model M1, with seven input parameters (Tmean, Tmin, Tmax, Humidity, Wind Speed,Cloudiness, and Pressure), results in R2 = 0.956,MSE=0.147, and MAE=0.302 with architecture (7-49-98-1). Model M2 takes the input parameters (Tmean,Tmin, Tmax, Humidity, Wind Speed, and Cloudiness)and examines them on different architectures. The architecture with neurons (6-24-48-1) yields R2 = 0.972,MSE=0.090, and MAE=0.221, showing the best performance. Model M6 (3-32-64-1) with input parameters (Tmean, Tmax, and Tmin) has R2 = 0.967,MSE=0.105, and MAE=0.243.Model M3 takes the input parameters (Tmin, Tmax,Humidity, Wind Speed, and Cloudiness) and evaluatesthem on several architectures. The architecture 5-20-40-1 with R2 = 0.955, MSE=0.152, and MAE=0.296shows the best performance. Model M4 takes the input parameters (Tmin, Tmax, Humidity, Wind Speed)and tests them on multiple architectures; the

architecture 4-28-56-1 has R2 = 0.932, MSE=0.252, and MAE=0.330, demonstrating the best performance.Model M5 takes the input parameters (Tmin, Tmax)and tests them on several architectures; the 2-18-36-1 architecture exhibits the greatest performance withR2 = 0.884, MSE=0.397, and MAE=0.510. ModelM2 outperforms the various other models, as shown in TableIII. It exhibits higher accuracy with various architectures.

Table III Results of various FNN ETo prediction models

Model	Architecture	R^2	MSE	MAE
M1	7-35-42-1	0.937	0.215	0.376
M1	7-28-56-1	0.922	0.263	0.388
M1	7-49-98-1	0.956	0.147	0.307
M2	6-42-84-1	0.949	0.17	0.320
M2	6-24-48-1	0.972	0.090	0.221
M2	6-64-128-1	0.951	0.168	0.317
M3	5-35-70-1	0.948	0.175	0.320
M3	5-20-40-1	0.955	0.152	0.296
M3	5-64-128-1	0.954	0.156	0.305
M4	4-28-56-1	0.932	0.252	0.387
M4	4-16-32-1	0.913	0.296	0.427
M4	4-32-64-1	0.911	0.305	0.441
M5	2-24-48-1	0.853	0.503	0.583
M5	2-18-36-1	0.884	0.397	0.514
M5	2-64-128-1	0.873	0.432	0.534
M6	3-32-64-1	0.967	0.105	0.243
M6	3-15-30-1	0.912	0.299	0.447
M6	3-9-27-1	0.900	0.339	0.455

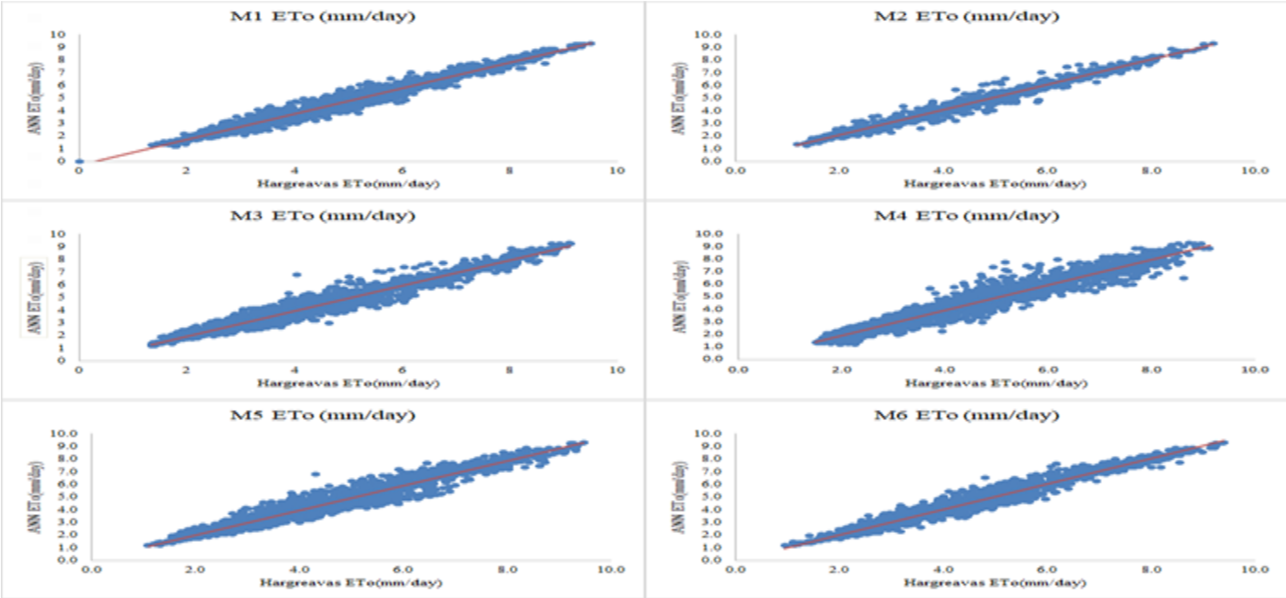

Fig 3 comparison ANN model architecture with Hargeaves Model

The various models are implemented with the Tensor Flow library, where the number of neurons in the input layer depends on the parameters in a model. They have one output, ReLU activation function, and 100 epochs in training for each model. The predicted ETo is compared with ETo in a test dataset calculated with the Hargreaves-Samani method, with the help of a scatter plot, as shown in Fig.3. It is observed from the scatter plot that models M1, M2, and M6 are less scattered, indicating better results compared to other models. Model M4 is the most scattered and gives the least accuracy.

3.1.1 Irrigation Scheduling

The daily ETc is calculated using ETo and crop coefficients specific to different crop growth stages, which are categorized as initial, mid, and late stages. These coefficients are denoted as Kcmid, Kcini, and Kclast. For wheat specific crop coefficients are considered. For wheat, Kcmid = 0.25, Kcini = 1.15, and Kclast = 0.5 [12].

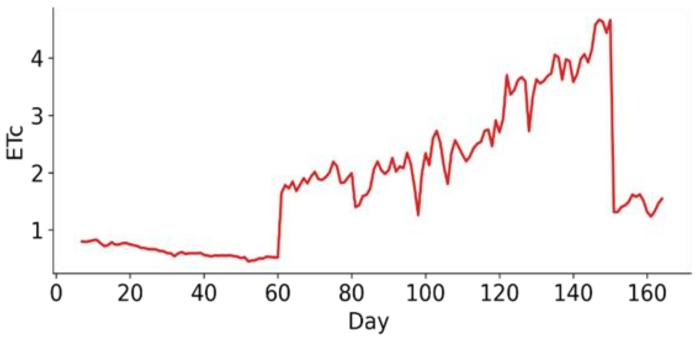

Fig 3 Wheat Crop Evapotranspiration variation in crop cycle

The variations in crop coefficients are related to the crop's growth stages. In the initial stage, crops require less water, while the mid-stage is a developmental phase that consumes the most water and takes up a significant portion of the crop cycle. In the last stage of crops, the water requirement is reduced. The variation in crop coefficients during the entire crop cycle for wheat is presented in Fig.4. The Kc values serve as estimates of the cropwater requirements, allowing for the scheduling of irrigation based on ETc.

3.2 Limitations of Study

The availability of a dataset related to climate data of the locations in Punjab presents a challenge to AI and ML-based research, which primarily relies on datasets for training and testing. Therefore, a climate dataset needs to be developed for various locations in Punjab to enhance the research.

This model considers only climate parameters such as temperature, humidity, wind speed, and pressure. However, several other parameters have hidden relationships with ETo, suchas altitude, soil texture, and distance from water sources which have not been considered.

4. Conclusion:

Water conservation is a significant challenge, especiallyin Indian Punjab. To prevent the excessive use of waterin irrigation, various techniques have been employed,such as sensor and ET o-based irrigation scheduling. In this paper, various ET o prediction models for Fatehgarh Sahib utilizing historical weather data are presented. Various machine learning ET o models basedon the Penman-Monteith equation are found in the literature. However, this study used the Hargreaves-Samaniempirical method to prepare the dataset. The model's performance has been analyzed according to R2, MSE,and MAE. The results from the test datasets revealed the ability of FNN model M2 to predict the daily values using daily climate parameters as input, outperforming withR2(0.972) among various models. It has the combination of input parameters, i.e., Tmean, Tmin, Tmax,Humidity, Wind speed, and cloudiness for obtaining accurate results. The ET o is used for irrigation scheduling according to crop stage and average root depth. Inthe future, the model could be included in IoT-basedirrigation for irrigation automation. This model simplifies the task of estimating ETo through an empirical equation and can become an important tool for irrigation scheduling and planning.

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