MACHINE LEARNING APPROACH FOR ESTIMATING REFERENCE EVAPOTRANSPIRATION USING METEOROLOGICAL DATA

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**ABSTRACT**

The Indian economy's most significant sector is agriculture. Over 70% of rural livelihoods rely on agriculture. Wheat is the most important Rabi cereal crop in northwest India. Wheat crop production is favourable to semi-arid and subtropical areas with a definite rainy season and a dry winter season. In India, wheat is often sown in the month of November. Wheat production is reliant very much on climatic conditions, thus improving the ability to predict crop productivity, different climatic parameters like temperature, rainfall ,humidity, cloud cover, vapour pressure, potential evapotranspiration etc. The key component in irrigation scheduling is evapotranspiration measurement. Evapotranspiration is the term used to describe water loss from soil and plant surfaces. The evaporation potential of the atmosphere at a specific time and place of year is expressed by reference evapotranspiration (ET0). Penman-Monteith FAO-56 equation was first recommended for computing ET0. This chapter focuses on the application of machine learning techniques, incorporating weather parameters as input variables,for accurate evapotranspiration prediction. Machine learning methods are also named data-driven methods. It is categorized as an artificial intelligence technique and falls under the general category of computer science. Various machine learning techniques, such as artificial neural networks, support vector machines, and random forest, are discussed to demonstrate how AI technology contributes to accurate estimation of ET0. Institutions in the hydrological and environmental sciences, including the fields of water treatment ,the field of hydrology ,water quality optimization, and remote sensing applications, are currently giving the growth of artificial intelligence a lot of attention.

**Keywords**—Evapotranspiration; Penman-Monteith FAO-56; machine learning; weather parameters

1. **INTRODUCTION**

Wheat (Triticum aestivum) is one of the most important staple food crop. India is the world's second largest producer of wheat. Major wheat growing states in India are Punjab, Uttar Pradesh, Haryana, Madhya Pradesh, Rajasthan, Bihar and Gujarat. The northern states of Punjab and Haryana plains in India have been prolific wheat producers and occupy large production area of the country. Different weather parameter, agronomical management, improved crop variety, optimum fertiliser dosage, tillage operations, judicious irrigation application, climatic change, temperature, sun radiation, precipitation, and extreme weather all influence crop growth, development, and yield [1-3]. It is essential to use available irrigation water in a way that corresponds to the crop's water requirements. Due to differences in the crop canopy and the surrounding environment, this crop's water needs change significantly as it grows. The combined water loss from a vegetative surface due to evaporation and transpiration is known as evapotranspiration (ET). This process is in charge of storing the water in the atmosphere and is reliant on a number of climatologic parameters [4].The most crucial element in irrigation scheduling is evapotranspiration measurement. Due to the water savings through an adequate irrigation schedule, crop output and income are increased. Therefore, conservation of water resources would positively affect soil and ground water quality. Temperature, solar radiation, relative humidity, and wind speed are the primary weather variables that influence evapotranspiration. One may better understand the evapotranspiration rate and implement more effective approaches in irrigation management and subsequent reclamation designs through monitoring and modeling these processes. The appropriate estimation of water budgeting, water planning, and water allocation depends on an accurate estimate of ET. A farmer needs to be aware of the environmental demand for surface water in order to correctly schedule irrigation. Evapotranspiration can be directly measured using a wide range of techniques. By regularly tracking the change in soil moisture of a known amount of soil that is covered with vegetation, for instance, a lysimeter can be used to estimate ET. [5]. Lysimetry can be expensive, both economically and in terms of the amount of time it takes to install, check, and maintain the machinery. The Penman-Monteith FAO-56 equation was  approved as the FAO's standard model with the publication of FAO-56 in 1998 [6]. Penman-Monteith was chosen as the ET0 estimation equation, hence it was required to choose the physical, physiological, and aerodynamic parameters for the reference grass. The FAO approved a set of guidelines for a hypothetical grass with a crop height of 0.12 meters, an albedo of 0.23, and a fixed surface resistance value of 70 s m-1. The Penman-Monteith FAO-56 methodologies were chosen as the standard for ET0, and the established potential parameters for the grass reference crop were utilized to standardize the estimation of reference evapotranspiration. The Penman-Monteith FAO-56 method was calibrated by Penman-Monteith FAO-56 and found to be inadequate for regional ETo estimation. The scientific community has accepted this method as the most accurate due to its good results when compared to other models in various regions of the world [7-8]. Reference[10] stated that the Penman-Monteith FAO ETo can be overestimated by the Hargreaves technique by 118–167%. Many researchers have examined the ETo forecast during the past few decades[11–13] due to the significant effect of ET0 on climate change, Earth temperature, crops and plants, water management, and runoff quantity. The most widely used model, Penman-Monteith FAO-56, is recognized as a physical ETo model since it approximates a linearized solution that controls energy balance, thermodynamic state, vertical heat, and water vapor diffusion.Penman-Monteith FAO-56, however, necessitates the use of numerous meteorological data, which is a disadvantage for this equation [14–15].

**II MACHINE LEARNING**

Data-driven approaches are another name for machine learning methods. It is a subset of computer science and an artificial intelligence method. It is concerned with the development of approaches that allow the computer to acquire.Basically, the evolution of algorithms that allow the computer to learn, complete tasks, and perform actions. Many approaches for machine learning problems have been developed over time. It can be used in a wide range of situations, and the model can address challenges that are difficult to define analytically. AI models discover relationships between information sources and output. Machine learning is concerned with the development and study of frameworks that can learn from diverse data sets, allowing systems to learn without being explicitly programmed. The framework in predictive learning issues consists of an erratic "output" or "response" variable y and a number of arbitrary "input" or "logical" elements. They construct a model based on proof obtained from a set of input and output data. The preparation stage, which is essentially the training stage, results in a capacity that can be applied to new input data to observe the corresponding outputs. The calculations can recognize complex patterns in the input linked to evapotranspiration or in the output by combining basic components. Across the world, many models have been developed to estimate the ETo. Because of the importance of ETo observations and the variety of weather data available around the world, the number of empirical equations for predicting evaporation has exceeded 100. Recently, groups in the hydrological and environmental sciences have paid close attention to the development of artificial intelligence, including water treatment [16-17], hydrology [18-21], water reservoir optimization [22-24], remote sensing applications [25-26], and so on. As a result of the extremely nonlinear properties of ETo data, AI technology offers an appropriate modeling solution to tackle numerous concerns with the empirical equations that had previously been used [27]. Reference[28] used an artificial neural network (ANN) to predict ET0, with various ANN topologies used for evaporation simulation. The neural network produced the best results for evaporation simulation, and it estimates the number of layers and neurons by trial and error.However, it is generally known that ANN models are prone to become stuck in a local minimum, hence recent studies have used new models based on different AI techniques for ETo modeling. Many techniques, including support vector machine SVM [29-31], have been used for this purpose.The SVM has a well-known basic form, but one of its limitations is the unknown parameter [32]. Others use the random forest (RF) algorithm to improve AI techniques. The RF technique is becoming increasingly popular in recent years [33-35] due to its performance across a variety of datasets, high accuracy estimation, a short range of user-defined parameters, the ability to estimate relative value of variables, and its ability to prevent overfitting.

**A.Computer software for machine learning**

 Machine learning methods can be performed in MATLAB, PYTHON, R software but R is one of the most preferred. It makes statistical computing very easy also graphs are easy to plot and depict in R. Advance statistical and machine learning packages are provided in R software along with various other packages and in built functions which makes statistical analysis very easy. It provides plots, effective data handling in huge amount and storage facility depending on or interest and use. R is very much helpful in predictive analysis, data pre-proccessing , statistical modelling, data visualization and deployment[36].

**B. Model developed for evapotranspiration estimation using support vector machine**

The support vector machine (SVM) was invented in 1992 by Boser, Guyon, and Vapnik. SVMs are regression and classification methods that use supervised learning. They are a sort of classification of generalized linear classifiers, or in new terminology, a regression prediction and classification method that employs machine learning theory to utilize analytical precision while naturally avoiding over-fitting to the data. The SVM can be applied to both grouping and regression problems[37]. The support vector machine (SVM), a unique learning machine based on statistical learning theory and the notion of structural risk reduction, can be employed for nonlinear system modeling [38]. SVM outperforms ANN in terms of accuracy as well as efficiency under the identical training conditions [39]. SVM models have been applied to a wide range of hydrological challenges throughout the previous decade.Some scientists have recently begun to employ SVM for ET0 modeling. The potential of SVM in modeling ET0 was investigated in reference[40] in central California, USA.Reference [40] investigated the modeling of ET0 using the least square support vector machine (LSSVM). SVM technique was used to estimate ET0 using Rs, T, RH, and wind speed, and the performance of SVM models was compared to Penman, Hargreaves, and Priestley-Tailor empirical equations. Reference[29] used Tmax, Tmin, RH, wind speed, and solar radiation as weather inputs to estimate ET0 using machine learning techniques SVM, adaptive neuro-fuzzy inference systems (ANFIS), multiple linear regression (MLR), and multiple non-linear regression (MNLR) for a semi-arid region of Iran, and tested these models against Penman- Monteith FAO- 56 methods. They discovered that SVM and ANFIS models with four input variables (Tmean, RH, Rs, and wind speed) performed the best. Refernce[41] used Least Square Support Vector Machines to estimate daily reference evapotranspiration using environmental factors such as temperature, radiation, humidity, and wind velocity for the semi-arid region of Xinjiang in China and found high accuracy for ET0 estimates. Reference[42] investigated the accuracy of SVM models for estimating daily ET0 in the arid region of the Ejina basin, China, using meteorological data Tmax, Tmin, U2, Rs, and discovered that SVM performed better than ANN and Empirical models.

**C. Model developed for evapotranspiration estimation using artificial neural network**

Many researchers have been using artificial intelligence technologies in hydrology and water resource studies in recent years [43-47]. Artificial neural networks (ANN) are frequently employed nowadays because they can quickly resolve complicated and difficult interactions. ANN is used in a variety of scientific domains. This approach is also utilized to get good results in hydraulics and hydrology, as well as other sectors of study. Researchers have calculated the use of artificial intelligence technologies in anticipating hydrological phenomena such as evaporation or ET0 in recent years [48-50]. An ANN is made up of three layers: input, hidden, and output, and each layer contains an array of artificial neurons. A completely connected neural network is one in which every neuron in any given layer is connected to every neuron in the next or previous layer. An artificial neuron is a mathematical model with components that are similar to those of a real neuron.In the last decade, there has been a lot of interest in using artificial neural networks (ANNs) to estimate evapotranspiration. Several techniques for achieving ANN modeling of the evapotranspiration process have been documented in the literature. The current review examines these techniques, which include ANN architecture construction, training algorithm selection, and performance criteria. ANN applications in hydrological studies began in the early 1990s with rainfall-runoff simulation. Stream flow prediction, ground water modeling, water quality, precipitation forecasting, reservoir operation, and time series analysis of hydrological processes were all added later. The use of artificial neural networks in evapotranspiration modeling began after the year 2000, when [51] developed artificial neural network models to estimate daily pan evaporation using weather data from Rome, Plains, and Watkinsville, Georgia. An artificial neural network model is a mathematical model with highly interconnected processing units stacked in layers that is substantially equivalent to the learning potential of the human brain. Training the network using system instances is the main technique for constructing an artificial neural network-based model of system behavior. If the examples provide enough relevant information about system behavior to qualify as a system model, then the trained neural network will have enough information about system behavior to qualify as a system model. A taught neural network can not only recreate the outcomes of the cases on which it was trained, but it can also approximate the results of additional examples due to its generalization capabilities. Reference[28] created ANN models with six basic parameters, all of which are necessary for the Penman-Monteith FAO-56 approach. They trained ANNs using ET0 estimated by the Penman-Monteith FAO-56 and daily ET0 measured by the Davis lysimeter. He showed that ANN models outperformed the Penman-Monteith FAO-56 technique in estimating ET0.

**D. Model developed for evapotranspiration estimation using Random forest regression**

Random Forest is a novel Machine Learning Algorithm and a new Algorithm Combination. Random Forest is a collection of tree structure classifiers. There are many interesting characters in Random Forest. Random Forest has seen widespread usage in categorization, prediction, and regression. Random forest has numerous advantages over standard algorithms. As a result, Random Forest has a wide range of applications. Random forest involves building decision trees from the given training data and matching them with the test data. It is one of the useful predictive analytic algorithms. The RF approach in estimating the ultimate output is that rather than relying on individual decision trees, the combined decision of numerous trees is used. In the output generation process, RF is utilized for classification by majority regression and voting by an average of the single-tree approach [53].Nonetheless, the model has been found to perform particularly well in handling large datasets and to prevent overfitting as a predictor. Random forests, also known as random decision forests, are a classification and regression learning method that works by constructing a multiple of decision trees during training and then outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random decision forests correct decision trees' tendency to overfit to their training set. The Extra Trees Forest's Decision Trees are built from the initial training sample. Then, at each test node, each tree is given a random sample of k features from the feature-set, from which each decision tree must choose the best feature to partition the data using some mathematical criteria (usually the Gini Index). This random selection of features results in the construction of numerous de-correlated decision trees. The reference[54] investigated machine learning (ML) strategies for estimating ET0 with little weather data. The Penman-Monteith FAO-56 model was used as a baseline, and several models such as RF, SVM, LSTM, and GBR were created to estimate ET0 using climatic data as input parameters. He stated that RF outperforms other models in terms of ET0 estimation. According to reference[55], ET0 prediction by RF model was promising for two stations in northwest China. As a result, it was chosen as the bestfit model for predicting the PMF-56 ET0. Reference[56] constructed an ET0 prediction model combining GEP, SVM,LR, and RF approaches using Tmax, Tmin,Ws,RH,Rs weather input combinations and discovered that random forest estimates ET0 better than other models.

**III CONCEPT OF ACCURATE EVAPOTRANSPIRATION ESTIMATION USING EMPIRICAL METHODS**

ET is the combination of two independent processes in which water is lost from the soil surface by evaporation and from the crop through transpiration. Both the processes of evaporation and transpiration occur at the same time and cannot be distinguished easily. Normally, evapotranspiration is measured in millimetres (mm) per unit time. The rate is the amount of water lost from a cropped surface expressed in depth of water units. The evapotranspiration from the reference surface is referred to as reference evapotranspiration (ET0). A hypothetical grass, reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 s m-1, and an albedo of 0.23 is used as the reference surface. The reference surface resembles a large expanse of green, well-watered grass that is actively growing and totally shading the ground. The Penman-Monteith FAO-56 method can be used to calculate ET0 from meteorological data. This method is accepted as an standard for defining and computing reference evapotranspiration. It requires information on radiation, air temperature, humidity, and wind speed.

**A.Penman– Monteith FAO-56 equation:**

 

Where ETo denotes reference evapotranspiration (mm day-1) and Rn denotes net radiation at the crop surface (MJ m-2 day-1). G =soil heat flux density [MJ m-2 day-1], T =mean daily air temperature at 2 m height [°C], u2 =wind speed at 2 m height [m s-1], es = saturation vapour pressure [kPa], ea = actual vapour pressure [kPa], es-ea =saturation vapour pressure deficit [kPa], es-ea =saturation vapour pressure deficit [kPa]

**B.Hargreaves-Samani equation:**

The Hargreaves-Samani technique is a semiempirical approximation since it uses extraterrestrial radiation as an indicator of global radiation, as well as temperature as an indicator of humidity and cloudiness [57-58]. Cloudiness is inversely connected to temperature range, and the influence of relative humidity is similarly related to temperature range, as both variables have a linear relationship [59]. The inclusion of the temperature range in the equation, according to Hargreaves, compensates for the influence of advection because it is dependent on the interaction of temperature, relative humidity, vapour pressure, and wind speed, all of which are related to the temperature range [60]. The calibration of this method with data from high quality lysimeters under a variety of climatological settings indicated that the method's accuracy was comparable to Penman-Monteith FAO-56 for ET0 estimations at weekly and even longer time increments [61-62]. The Hargreaves-Samani equation [65]can be written as:

ET0=0.0023\*Ra\*√(Tmax-Tmin)\*(Tmean+17.8)

Samani and Hargreaves method is generally described as

 

The Samani and Hargreaves approach is commonly defined as follows: where ET0 is the estimated reference evapotranspiration (mm/d) and Ra is the water equivalent of extraterrestrial radiation (mm/d)[64]. Tmax, Tmin, are the maximum, minimum temperature, and Tmean ,mean daily air temperatures derived as the average of Tmax and Tmin. The initial empirical coefficient proposed by[65] is 0.0023.

**C.Ritchie equation:**

Solar radiation and air temperature are required parameters for Ritchie equation computations, and the equation is presented below [65].

 **ET=α1[3.87\*10-3 \*Rs(0.6Tmax+0.4Tmin+29)]**

In this equation, "Rs" represents solar radiation, whereas "Tmax" and "Tmin" represent maximum and minimum temperatures, respectively. "α1" denotes a coefficient.

**D. Evapotraspiration using Soil Water Balance Equation**

The various components of the soil water balance equation can also be used to calculate evapotranspiration. The method entails measuring the amount of water that enters and exits the crop root zone over a given time period.Water is added to the root zone through irrigation (I) and rainfall (P). Some I and P may be lost by surface runoff (RO) and deep percolation (DP), which will eventually recharge the water table. Water can also be transported upward by capillary rise (CR) from a shallow water table to the root zone, or horizontally by subsurface flow into (SFin) or out of (SFout) the root zone. However, particularly in conditions with steep slopes, (SFin) and (SFout) are minimal and can be ignored in many cases. Water is depleted from the root zone due to soil evaporation and crop transpiration. If all fluxes except evapotranspiration (ET) can be measured, evapotranspiration can be calculated from the change in soil water content (S) over time:

 ETc = I + P+ CR − R − D - ΔS

**IV Estimation of reference evapotranspiration (ET0) using machine learning techniques**

Machine learning (ML) is a subset of artificial intelligence which allows software applications to improve their accuracy in predicting outcomes. Machine learning algorithms predict new output values using historical data as input. Following machine learning techniques was used for estimating reference evapotranspiration (ET0). 1.Support vector regression model(SVR). 2.Random forest regression model(RF Reg). 3.Artificial neural network regression model(ANN Reg). A flowchart of reference evapotranspiration (ET0) estimation by different techniques is presented in Fig 1.



**A. Support Vector Machine(SVM)**

Support vector machines (SVMs) have been recently proposed as an outstanding technique for historical data forecasting, prediction, and estimation. A separating hyperplane defines it as a discriminative classifier. In other words, given labeled training data, the algorithm generates an ideal hyperplane that classifies a new collection of samples. In two dimensions, a hyperplane is a line that divides a plane into two sections, with each class lying on each side. It determines a line/hyperplane (in multidimensional space that divides classes). Support vectors are data points near the decision surface or hyperplane. The schematically representation of SVM for reference evapotranspiration (ET0) estimation has been shown in Fig 2.

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**B. Artificial Neural Network (ANN)**

Numerous synthetic neurons are joined to one another according to a certain network architecture to form an artificial neural network. Different neural network topologies, such as feed-forward networks, feedback networks, lateral networks, etc., can be used to approximate any linear function. The input layer, hidden layer, and output layer are the three layers that make up an ANN. One of the more popular neural network types among the several neural network types is the multilayer perceptron (MLP) approach. Information will flow unidirectionally from the input layer to the output layer through the hidden layer as a result of the sequential arrangement of the neurons. This network is viewed as an input-output model, with weights and thresholds (biases) as model free parameters. Artificial neural networks operate by optimizing the weighted values of variables; the process by which the optimized values are obtained is known as learning. It attempts to teach the output based on the appropriate input provided throughout the learning process. When the trained neural network can update the proper weights and provide the output with the appropriate accuracy according to the input pattern, learning is accomplished. The primary objective of the neural network is to produce its own output with fewer inconsistencies with the intended output value, which will aid in the transformation of the input into meaningful output. The key issue in ANN implementation is determining the parameters needed for cross validation, such as the number of units in the hidden layer and nodes. The schematically representation of ANN for reference evapotranspiration (ET0) estimation has been shown in Fig 3



**Figure 3: figure showing input, hidden and output layer of ANN**

**C.Random forest regression (RF)**

Random Forest is an ensemble method known as bagging that can perform regression as well as classification. One of the useful techniques for predictive analysis is the one that follows. The RF principle requires that different decision trees are combined to determine the final result rather than depending on individual decision trees. In the output generation process, RF is utilized for classification by majority regression and voting by an average of the single-tree technique. Supervised machine learning techniques, which are common in ML and extensively employed in water management, are used in RF models [66]. The model can be expressed as follows: f(x) = f0(x) + f1(x) + f2(x) + f 3(x) + where the combined decision tree bases fi contribute to the final model f. Where the simple decision tree functions as each base regressor. Instead of relying only on one decision tree to determine the outcome, the main idea behind this is to mix several decision trees. The schematically representation of RF for reference evapotranspiration (ET0) estimation has been shown in Fig 4



**Figure 4: Schematic representation of RF**

Approach for random forest is as below: 1. Select K data points at random from the test set; 2. Create the decision tree linked to those K data points; 3. Decide how many N trees you want to construct; and then repeat steps 1 and 2; 4. Predict the value of Y for a new data point using each of your N tree trees, and then give the new data point the average of all the projected Y values. While learning to categorize or forecast data, random forests or random decision forests construct a number of decision trees during training and output the class that is the mean of the classes (classification) or mean prediction (regression) of the individual trees. Decision trees' tendency to overfit their training set is corrected by random decision forests. The initially trained sample is used to build each decision tree in the additional trees Forest. The optimal feature to divide the data according to some mathematical criteria (usually the Gini Index) then has to be chosen by each decision tree from a random sample of k features given to it at each test node. There are multiple de-correlated decision trees produced as a result of this random sample of features.

**V CONCLUSION**

For the effective management of water resources and the timely scheduling of irrigation to crops, reference evapotranspiration (ET0) estimation is essential. The studies we conducted used three empirical approaches for estimating reference evapotranspiration, and the results showed that Penman-Monteith FAO-56 produced superior results to Ritchie and Hargreaves-Samani empirical approaches.The Penman-Monteith equation (PM-FAO 56) is a standard recommended by the Food and Agriculture Organization of the United Nations (FAO). In our study performance of the model developed by machine learning techniques (RF,SVM,ANN) using different weather input combination for estimation of ET0 for different station of semi arid region of India was excellent for more number of weather input combination for all three machine learning techniques and for all the five station. The performance of ANN model is excellent only with more number of weather input combinations. RF and SVM model performed excellent with less number of weather data (Tmax,Rs), (Tmin,Rs) for all five stations. Performance of the model developed for ET0 estimation by all three machine learning techniques using (RHM, RHE) and (Tmin,RHM) weather input combination was poorest as compared to other combination for all the five station. The ET0 estimated by machine learning techniques using two weather input combination (Rs,Tmax) and (Rs, Tmin) performing excellent by RF and SVM and (Tmax,Tmin) by ANN for all the five station. Hence these input combinations can be used in estimation of ET0, when availability of data is limited. ET0 estimated by Penman-Monteith FAO 56 was lowest followed by Ritchie and Hargreaves-Samani equation for all the five stations. The ET0 estimated using soil water balance equation wheat crop growing period was less deviating from ET0 estimated by Penman-Monteith FAO 56 followed by Ritchie and Hargreaves-Samani equation. From this study it can be concluded that instead of large amount of input data which required for ET0 estimation by empirical method, ET0 estimation can be done with less number of input data by machine learning techniques and RF performed best followed by SVM and ANN for ET0 estimation during wheat crop growing period for the study area.

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