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. Reference evapotranspiration (ETo) expresses the evaporation potential of the atmosphere at a certain location and time of year. Penman-Monteith FAO-56 equation was first recommended for computing ETo. 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 a subtype of computer science and is classified as an artificial intelligence method. 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.Recently, the development of artificial intelligence has received significant attention from communities in the hydrological and environmental sciences, including water treatment, hydrology, water treatment optimization and remote sensing applications etc.

**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]. Accessible irrigation water needs to be utilized in a manner that matches the water needs of this crop. Water requirements of this crop vary substantially during growth period due to variation in crop canopy and climatic conditions. Evapotranspiration (ET) is the combined water loss from a vegetative surface through evaporation and transpiration. This process is dependent upon numerous climatologic variables and is responsible for the water stored in the atmosphere [4].The measurement of evapotranspiration is the most important factor for irrigation scheduling. Appropriate irrigation scheduling enhances crop yield and income, resulting from water saving. Therefore, conservation of water resources would positively affect soil and ground water quality. The principal weather parameters affecting evapotranspiration are temperature, solar radiation, relative humidity, wind speed. By monitoring and modeling these processes, one can understand the evapotranspiration rate better and adopt more effective strategies in irrigation management and future reclamation designs. An accurate estimation of ET enables proper computation of water budgeting, water planning and water allocation. To schedule irrigation properly, a grower must know the environmental demand for surface water. Several methods are available to measure evapotranspiration directly. For instance, a lysimeter is used to measure ET by routinely measuring the change in soil moisture of known volume of soil that is covered with vegetation [5]. Lysimetry can be expensive both economically and in time investments to install, check, and maintain the equipment. With the publication of FAO-56 in 1998, the Penman-Monteith FAO-56 equation was finally accepted as the FAO's standard model [6]. It was necessary to select the physical, physiological, and aerodynamic parameters for the reference grass because Penman-Monteith was chosen as the ETo equation. With a crop height of 0.12 metres, an albedo of 0.23, and a fixed surface resistance value of 70 s m-1 , the FAO adopted a range of standards for a hypothetical grass .The estimation of reference evapotranspiration has been standardised according to the choice of the Penman-Monteith FAO-56 methods as the norm for ETo and the defined hypothetical parameters for the grass reference crop. e. Scientific community has accepted the Penman-Monteith FAO-56 method as the most precise one for its good results when compared with other models in various regions of the entire world [7-8] calibrated Hargreaves method by Penman- Monteith FAO-56 and found that this method is poor for regional ETo estimation. Reference[10] reported that Hargreaves method can overestimate Penman- Monteith FAO ETo by 118–167%. Due to the significant effect of ETo on climate change, Earth temperature, crops and plants, water management, and runoff quantity, many researchers have studied the ETo prediction over the last decades[11-13]. Penman–Monteith FAO-56 is the most widely used model, and it is considered as a physical ETo model as it is an approximate linearized solution governing energy balance, thermodynamic state, vertical heat, and watervapor diffusion .However, Penman–Monteith FAO-56 requires many meteorological data to be applied, which can be considered as a drawback for this equation [14-15].

**II MACHINE LEARNING**

Machine learning methods are also named data-driven methods. It is a subtype of computer science and is classified as an artificial intelligence method. It bothers with the perfection of techniques which empower the computer to acquire .In simple terms evolution of algorithms which permit the machine to learn, accomplish tasks and actions. Over the period of time many methodologies were developed for tasks of machine learning. It may be utilized in a large areas and in this technique model can tackle issues which are difficult to express by calculations. The AI models discover relation among information sources and output. Machine learning is concerned about the development and investigation of frameworks that can gain from international data sets, enabling system to learn without being explicitly programmed. In the predictive learning issues, the framework comprises of an irregular “output” or “response” variable y and a lot of arbitrary “input” or “logical” factors. They build a model from proof acquired from a set of information which is input and output. The preparation stage that is basically the training phase brings about a capacity that can be applied to new input data to see the relating outputs. The calculations can recognize the complicated patterns in the input with connection to evapotranspiration or the output by combining simple components. There are many models used to estimate the ETo around the world. Number of empirical equations for modeling the evaporation has exceeded 100 due to the importance of ETo measurements and the variety of meteorological data around the world. Recently, the development of artificial intelligence has received significant attention from communities in the hydrological and environmental sciences, including water treatment [16-17], hydrology [18-21] ,water reservoir optimization [22-24], remote sensing applications[25-26], etc. Consequently, due to the highly nonlinear characteristics associated with the ETo data, AI technology presented a suitable modeling approach to solve many issues with the empirical equations that has been used before [27].Reference[28] utilized the artificial neural network (ANN) for predicting ETo, where different ANN architectures were implemented for evaporation simulation. Neural network yielded the best results for evaporation simulation, and it calculates the number of layers and neurons based on a trial and error process .However, it is well established that ANN models easily get stuck in a local minimum, and, therefore, recent studies have employed new models adopting other AI techniques for ETo modeling. Many approaches have been utilized for this purpose, including support vector machine SVM [29-31].The SVM is well known to have a basic form, but one of the drawbacks of SVM is the unknown parameter [32]. Others utilize random forest (RF) algorithm to enhance the AI techniques. Due to its success over a variety of datasets, high precision estimation, a small range of user-defined parameters, the ability to estimate relative value of the variables, and its ability to preclude overfitting, the RF approach has become extremely popular in recent years [33-35].

1. **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**

Support vector machine (SVM) first perceived in 1992 and was familiarized by Boser, Guyon, and Vapnik. SVMs are supervised learning methods applied for regression and classification. They are the type of classification of generalized linear classifiers, or in new terms it is a regression prediction and classification means that practices machine learning theory to exploit analytical accuracy while spontaneously escaping over-fitting to the data. The SVM can be used equally for grouping and regression problems [37]. Support vector machine (SVM), which is a novel learning machine based on statistical learning theory and a structural risk minimization principle, can be used for nonlinear system modeling [38].Compared with ANN, SVM provides more reliable and better performance under the same training conditions [39]. In last decade, SVM models have been extended to a wide range of hydrological problems .Recently, some scientists began to use SVM for ET0 modeling. Reference [40] studied the potential of SVM in modeling ET0 in central California, USA. Reference [40] examined the performances of least square support vector machine (LSSVM) the modeling of ET0. Modelling for ET0 estimation by SVM technique using Rs, T, RH and wind speed and compared performance of SVM models with Penman, Hargreaves , Priestley- Tailor empirical equations. Reference[29] used Tmax , Tmin , RH, wind speed and solar radiation as a weather inputs for estimating 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 found that SVM and ANFIS models with four input variables (Tmean, RH , Rs ,wind speed) had the better accuracy. Refernce[41] estimated daily reference evapotranspiration by Least Square Support Vector Machines using weather parameters such as temperature , radiation, humidity and wind velocity for semi arid region Xinjiang in China and found good accuracy for ET0 estimation. Reference[42] checked the accuracy of SVM models for estimating daily ET0 using meteorological data Tmax, Tmin, U2, Rs in arid region of Ejina basin, China and he found that SVM performed better than ANN and Empirical models.

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

In recent years, many researchers have used artificial intelligence methods in hydrology and water resources studies [43-47]. Nowadays, artificial neural networks (ANN) are being used widely because they can easily resolve complex and difficult relationships. ANN is applied to many fields of science. This approach is also used in hydraulics and hydrology as other fields of science to achieve good results. In the past years, researchers have estimated the use of artificial intelligence methods in predicting hydrological events such as evaporation or ET0 [48-50]. An ANN consists of input, hidden, and output layers, and each layer includes an array of artificial neurons. A fully connected neural network, in which there is a connection between each of the neurons in any given layer with each of the neurons in the next layer or previous layer. An artificial neuron is a mathematical model whose components are analogous to the components of actual neuron.The use of artificial neural networks (ANNs) in estimation of evapotranspiration has received enormous interest in the present decade. Several methodologies have been reported in the literature to realize the ANN modeling of evapotranspiration process. The present review discusses these methodologies including ANN architecture development, selection of training algorithm, and performance criteria. The ANN applications in hydrological studies were started from rainfall-runoff modeling during the early 1990s. Later, the application further proliferated into stream flow prediction, ground water modeling, water quality, precipitation forecasting, reservoir operation and time series analysis of hydrological processes. The evapotranspiration modeling using ANN initiated after 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 whose architecture is essentially analogous to the learning capability of the human brain in which highly interconnected processing elements arranged in layers. The basic strategy for developing an artificial neural network-based model of system behavior is to train the network on examples of the system. If the examples contain the relevant information about the system behavior, then the trained neural network would contain sufficient information about the system behavior to qualify as a system model. Such a trained neural network not only able to reproduce the results of examples it was trained on, but through its generalization capability, is able to approximate the results of other examples. Reference [28]developed ANN models using six basic parameters, which are also required for Penman–Monteith FAO-56 method. They trained ANNs against ETo estimated by Penman–Monteith FAO-56 and daily ETo measured by lysimeter for Davis. He reported that ET0 was better estimated by ANN models than the Penman–Monteith FAO-56 method.

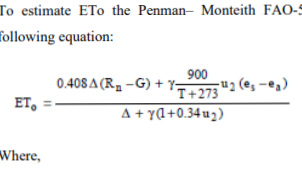
**D. Model developed for evapotranspiration estimation using Random forest regression**

Random Forest is a new Machine Learning Algorithm and a new combination Algorithm. Random Forest is a combination of a series of tree structure classifiers. Random Forest has many good characters. Random Forest has been wildly used in classification and prediction, and used in regression. Compared with the traditional algorithms random forest has many good virtues. Therefore the scope of application of Random Forest is very extensive. Random forest includes construction of decision trees of the given training data and matching the test data with these. It is one of the practical algorithms for predictive analysis. In determining the final output, the principle of RF is rather than depending on individual decision trees, combined decision of various trees. RF is used for classification by majority regression and vote by an average of the single-tree method in the output generation process [53].Nonetheless, the model has been found to perform especially very fast and efficiently handled big datasets and to avoid overfitting as a predictor. Random forests or random decision forests are an learning method for classification, regression that operate by constructing a multiple of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random decision forests correct for decision trees habit of over fitting to their training set. Each Decision Tree in the Extra Trees Forest is constructed from the original training sample. Then, at each test node, each tree is provided with a random sample of k features from the feature-set from which each decision tree must select the best feature to split the data based on some mathematical criteria (typically the Gini Index). This random sample of features leads to the creation of multiple de-correlated decision trees. Reference [54] evaluated machine learning (ML) techniques to estimate ET0 with minimal weather inputs. In these Penman - Monteith FAO-56 model considered as standard and different models RF, SVM, LSTM, GBR were developed to estimate ET0 with climatic variables as input parameters. He reported that RF is performing better for ET0 estimation compared to other model. Reference [55] reported that ET0 prediction by RF model were encouraging for two station of northwest China. Thus, it was selected as the best fit model for estimating the PMF-56 ET0. Reference[56] developed ET0 prediction model by GEP, SVM ,LR, and RF techniques using Tmax, Tmin, Ws, RH, Rs weather input combinations and found that ET0 estimation by random forest is better than other model.

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

Evapotranspiration (ET) is the combination of two separate processes in which water is lost from the soil surface called evaporation and from the crop by transpiration. Both the processes Evaporation and transpiration occur simultaneously and there is no easy way of distinguishing between them. Evapotranspiration is normally expressed in millimetres (mm) per unit time. The rate expresses the amount of water lost from a cropped surface in the unit of depth of water. Reference evapotranspiration (ETo) is the evapotranspiration from the reference surface. Reference surface is 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. The reference surface closely resembles an extensive surface of green, well-watered grass, actively growing and completely shading the ground. ETo can be calculated from meteorological data using Penman– Monteith FAO-56 method. This method is recommended as the standard method for the definition and computation of the reference evapotranspiration. It requires radiation, air temperature, air humidity and wind speed data

1. **Penman– Monteith FAO-56 Method To estimate ETo was derived from the following equation:**



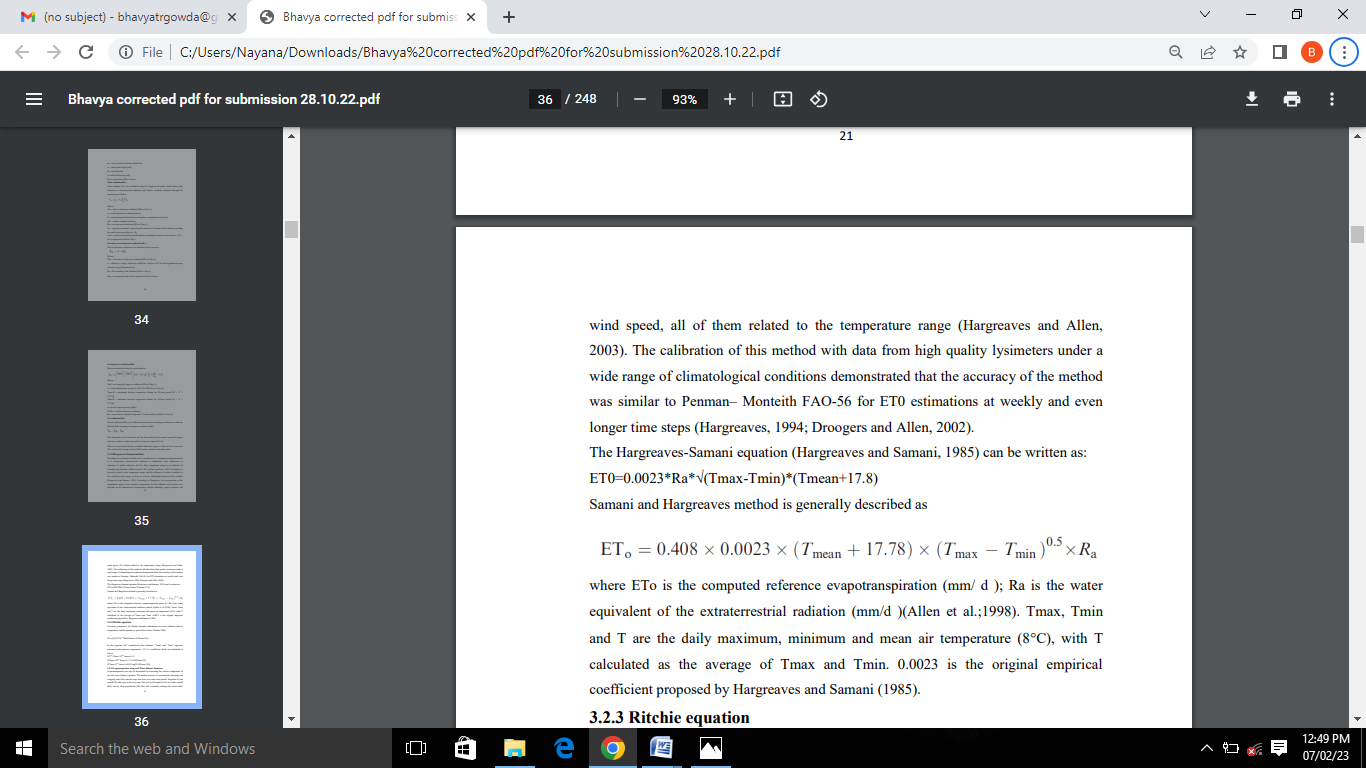
Where, ETo = reference evapotranspiration [mm day-1 ], Rn =net radiation at the crop surface [MJ m-2 day-1 ] G =soil heat flux density [MJ m-2 day-1 ], T =mean daily air temperature at 2 m height [°C], u2 =wind speed at 2 m height [m s-1 ], es = saturation vapour pressure [kPa], ea = actual vapour pressure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

1. **Hargreaves-Samani method to estimate ETo was derived from the following equation:**

The Hargreaves-Samani method can be considered as a semiempirical approximation as it incorporates extraterrestrial radiation in combination with temperature as indicators of global radiation, and the daily temperature range as an indicator of humidity and cloudiness [57-58]. Cloudiness is inversely related to the temperature range, and the influence of relative humidity is also related to that range, as there is a linear relationship between both variables [59].According to Hargreaves, the incorporation of the temperature range in the equation compensates for the influence of advection as it depends on the interaction of temperature, relative humidity, vapour pressure and wind speed, all of them related to the temperature range [60]. The calibration of this method with data from high quality lysimeters under a wide range of climatological conditions demonstrated that the accuracy of the method was similar to Penman– Monteith FAO-56 for ET0 estimations at weekly and even longer time steps [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



Samani and Hargreaves method is generally described as where ETo is the computed reference evapotranspiration (mm/ d); Ra is the water equivalent of the extraterrestrial radiation (mm/d) [64]. Tmax, Tmin are the daily maximum, minimum temperature and mean air temperature calculated as the average of Tmax and Tmin. 0.0023 is the original empirical coefficient proposed by [65].

1. **Ritchie equation to estimate ETo was derived from the following equation:**

Necessary parameters for Ritchie formula calculations are solar radiation and air temperature, and the equation is given below [65];

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

In this equation “Rs” symbolized solar radiation, “Tmax” and “Tmin” represent maximum and minimum temperatures. “α1” is a coefficient

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

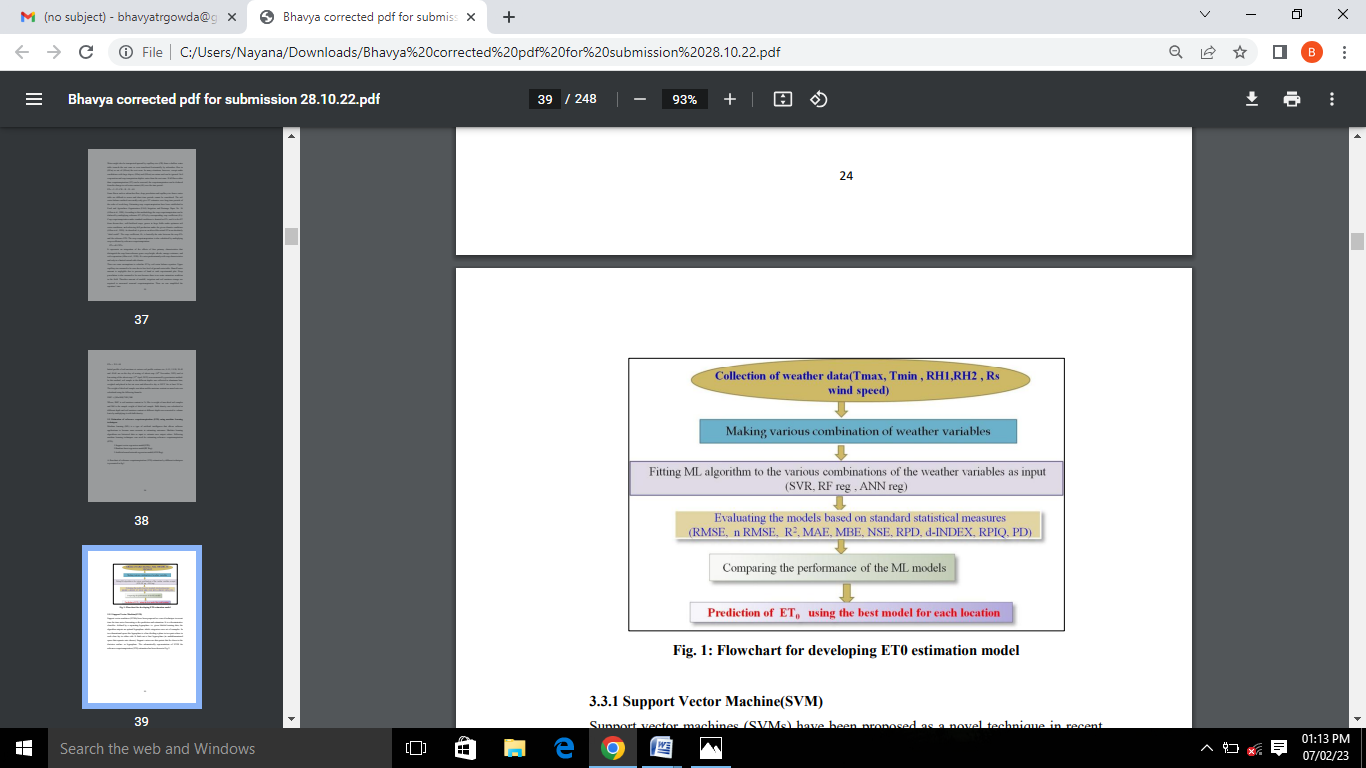
Evapotranspiration can also be determined by measuring the various components of the soil water balance equation. The method consists of assessing the incoming and outgoing water flux into the crop root zone over some time period .Irrigation (I) and rainfall (P) add water to the root zone. Part of I and P might be lost by surface runoff (RO) and by deep percolation (DP) that will eventually recharge the water table. Water might also be transported upward by capillary rise (CR) from a shallow water table towards the root zone or even transferred horizontally by subsurface flow in (SFin) or out of (SFout) the root zone. In many situations, however, except under condititions with large slopes, (SFin) and (SFout) are minor and can be ignored. Soil evaporation and crop transpiration deplete water from the root zone. If all fluxes other than evapotranspiration (ET) can be assessed, the evapotranspiration can be deduced from the change in soil water content (ΔS) over the time period:

ETc = I + P+ CR − R − D - ΔS

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

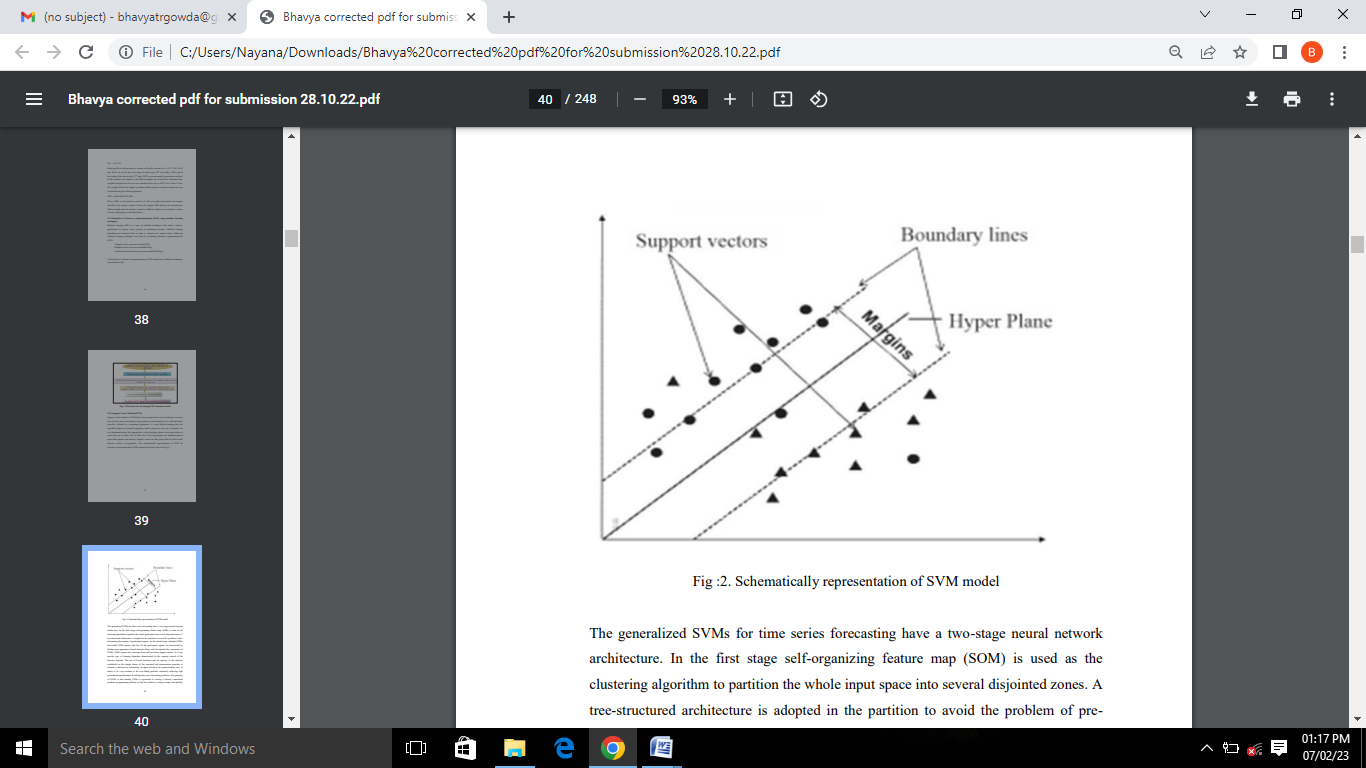
Machine learning (ML) is a type of artificial intelligence that allows software applications to become more accurate at estimating outcomes. Machine learning algorithms use historical data as input to estimate new output values. Following machine learning techniques was used for estimating reference 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



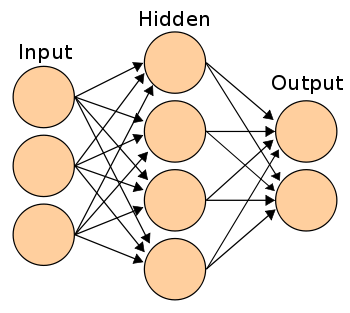
**A. Support Vector Machine(SVM)**

Support vector machines (SVMs) have been proposed as a novel technique in recent time for time series forecasting or the prediction and estimation. It is a discriminative classifier defined by a separating hyperplane. i.e. given labeled training data, the algorithm outputs an optimal hyperplane which categorizes new set of examples. In two dimentional space this hyperplane is a line dividing a plane in two parts where in each class lay in either side. It finds out a line/ hyper-plane (in multidimensional space that separate outs classes). Support vectors are data points that lie closes to 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)**

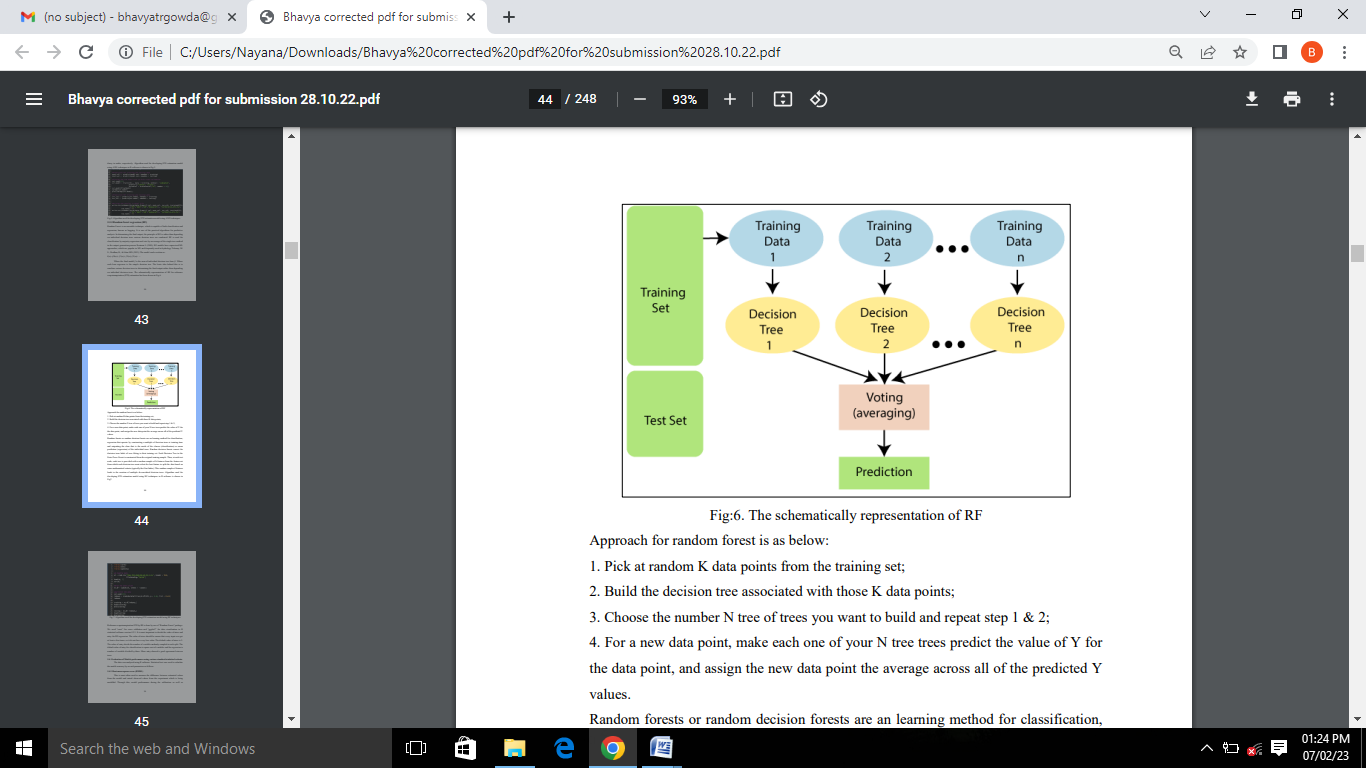
Artificial neural network consists of many artificial neurons that are connected together to network architecture specifically. Neural network has various architectures to approximate any linear function such as feed forward network, feedback network, lateral network etc. ANN composed of three layers namely, input layer, hidden layer and output layer. Multilayer perceptron (MLP) technique is one of the popular neural network types than other different neural network types. The neurons are arranged in a successive pattern, through which information will flow unidirectionally from the input layer to the output layer through the hidden layer. This network interpreted as input-output model, with weights and threshold (biases) as free parameters of the model. Artificial neural network work through the optimised weighted value of variables, the method by which the optimised values are attained is called learning. In the learning process it tries to teach to produce the output based on the corresponding input provided. Learning will complete when the trained neural network can able to update the optimal weights and produce the output within the desired accuracy corresponding to the input pattern. The main objective of the neural network is to produce its own output having reduced discrepancies with target output value, which will help to transform the input into meaningful output. The main problem in the implementation ANN is to find the parameters which are used for cross validation such as number of units in 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 technique, which is capable of both classification and regression, known as bagging. It is one of the practical algorithms for predictive analysis. In determining the final output, the principle of RF is rather than depending on individual decision trees various decision trees are combined. RF is used for classification by majority regression and vote by an average of the single-tree method in the output generation process. RF models have supervised ML approaches, which are popular in ML and frequently used in hydrology [66]. The model can be written as: f(x) =𝑓0(𝑥)+ 𝑓1(𝑥)+ 𝑓2(𝑥)+f 3(𝑥)+ ⋯ Where the final model f is the sum of individual decision tree base fi. Where each base regressor is the simple decision tree. The basic idea behind this is to combine various decision trees in determining the final output rather than depending on individual 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. Pick at random K data points from the training set; 2. Build the decision tree associated with those K data points; 3. Choose the number N tree of trees you want to build and repeat step 1 & 2; 4. For a new data point, make each one of your N tree trees predict the value of Y for the data point, and assign the new data point the average across all of the predicted Y values. Random forests or random decision forests are an learning method for classification, regression that operate by constructing a multiple of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random decision forests correct for decision trees habit of over fitting to their training set. Each Decision Tree in the Extra Trees Forest is constructed from the original training sample. Then, at each test node, each tree is provided with a random sample of k features from the feature-set from which each decision tree must select the best feature to split the data based on some mathematical criteria (typically the Gini Index). This random sample of features leads to the creation of multiple de-correlated decision trees.

**V CONCLUSION**

The accurate estimation of reference evapotranspiration(ET0) is needed for timely scheduling of irrigation to crops and also management of water resources. In our studies the reference evapotranspiration is calculated using three empirical approach and results showed that Penman-Monteith FAO-56 had better results compared to other Ritchie and Hargreaves-Samani empirical approach.The United Nations Food and Agriculture Organization (FAO) recommends the Penman-Monteith equation (PM-FAO 56) as a standard 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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