Desalination and Water Treatment
www.deswater.com
doi: 10.5004/dwt.2022.28290

251 (2022) 123–133
March

Water management for irrigation scheduling by computing evapotranspiration using ANFIS modelling

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Received 15 September 2021; Accepted 4 February 2022

ABSTRACT

Agriculture is one of the most important areas that is wedged by a variety of factors such as climate change, water level, soil characteristics, seasonal variations, and so on. Forecasting water level plays a major role in water management because it seriously affects the crop production. The prediction of water level is based on numerous sorts of data collected and derived from various sources that are relevant for growth using data mining techniques. These techniques used to estimate the evapotranspiration (ET) in the water level needed for crop and yield amount ahead of time, before the harvest takes place. The model is designed with six inputs parameters as minimum temperature and maximum temperature (°C), average humidity (%), wind speed (km/d), duration of sunshine (h), and radiation (MJ/m^2 d) and evapotranspiration (mm) as output parameter. The model used in this work for computing evapotranspiration is adaptive network based fuzzy inference system (ANFIS) with grid partitioning (GP) method. The membership functions (MFs) have smoothness and components for mathematical calculation, and each piece of input data can be used to get the optimal result in the ANFIS models by utilizing a triangular membership function (trimf). The goal of this system is to forecast water management to schedule irrigation based on change in climatological parameters and other considerations. The results show that the ANFIS is a reliable tool for calculating evapotranspiration and crop production prediction can be immensely beneficial to farmers. The model is confirmed using the coefficient of correlation, which shows that the observed and evaluated yields have a coefficient of correlation of more than 0.9. The Nash–Sutcliffe efficiency (NSE), performance index and Willmott's refined index of agreement have been used for performance evaluation and their values are 0.99, 0.998 and 0.040 respectively, suggesting satisfactory model performance. The ANFIS method demonstrated in this work holds promise in modelling evapotranspiration.

Keywords: Evapotranspiration; Water management; Fuzzy logic; Adaptive network based fuzzy inference system; Irrigation

1. Introduction

Due to the diverse climatic conditions in countries like India, a wide range of plants are grown. In drought or flood-prone areas crop failure has major consequences on the local and global economy as well as food security. The evapotranspiration can be calculated using different factors such as climatic variables, biometrical traits and agricultural inputs and these are used separately or in tandem to generate a composite model. Several studies have been undertaken to forecast the harvest and to predict the yield

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Presented at the Virtual International Conference on New Strategies in Water Treatment and Desalination (WTD-2021), 21–23 March 2021, by SRM Institute of Science and Technology, Kattankulathur, India

using statistical models such as extreme learning machine and generalized regression neural network [1]. The consequences of changing environmental conditions and weather fluctuations in various locations require continuous monitoring to assist policymakers in making effective decisions to combat bad situations in process of food production.

In dry and semi dry environments where there is a water constraint, evapotranspiration is critical for optimizing irrigation water usage. Estimating evapotranspiration is not only critical for agricultural purpose but also for hydrological and climatic research since water usage is involved in these areas. Artificial intelligence techniques have garnered increasing interest in recent years for modelling and predicting evapotranspiration. The hybrid of random forest, support vector regression and whale optimization algorithm have been investigated to evaluate the performance of evapotranspiration process [2,3].

Models that describe how evapotranspiration estimation respond to diverse weather conditions are essential to examine the impact of climate change on crop productivity. Weather and its influence are frequently contradicted by predictions from various models. A common technique is to use statistical models based on historical yields and certain basic climate parameters, such as average growing season temperature and precipitation [4]. Climate change is a serious issue that affects everyone. It is critical to comprehend its direct impact on crop growth and output. The evapotranspiration estimation model can be constructed by an adaptive network based fuzzy inference system that takes into account several climatic variables such as duration of sunshine, radiation, temperature, humidity, wind and evaporation parameters [5].

Evapotranspiration is a process that combines two separate processes: evaporation and transpiration. The passage of water from a soil or water surface into the atmosphere is referred to as evaporation. The transfer of water from the earth into a plant, up the plant body, and from the leaves of the plant into the atmosphere is referred to as transpiration. Fig. 1 depicts the simultaneous occurrence of evaporation and transpiration. Lakes, rivers, pavements, soils, and moist plants all experience evaporation by vaporization. The energy required to change the state of water molecules from liquid to vapour is provided by direct sunshine and the ambient temperature. Water vapour is evacuated from the evaporating surface due to the difference in water vapour pressure between the evaporating surface and the surrounding atmosphere. While evaporation proceeds, the surrounding air becomes gradually saturated, and if the wet air is not evacuated to the atmosphere, the process would slow down and possibly cease. The pace at which saturated air is replaced by dry air is influenced by wind speed. As a result, climatological factors such as temperature, humidity, sun radiation, and wind speed must be considered while analysing evaporation. The evaporating process in the soil surface is affected by the water level available at the evaporating surface. Irrigation, rainfall, and upward water movement makes the soil surface wet frequently. Evaporation in the soil is based on the weather conditions when the soil can deliver water quickly enough to meet the evaporation demand. When the gap between rainfall and irrigation becomes substantial and the ability of soil to carry humidity to the surface is weakened, the water level in the ground lowers and the soil surface dries up. The limited availability of water in these conditions has an effect on soil evaporation. The availability of water in the soil surface reduces and consequently the evaporation process diminishes and stops completely within a few days [6].

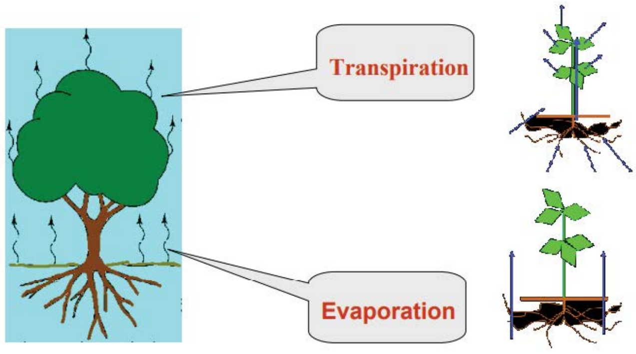

Fig. 1. Combination of evaporation and transpiration processes results evapotranspiration process.

Stomata are the pores through which most of the water content of plant is lost. Fig. 1 depicts the little holes on the plant leaf for the passage of gases and water vapour. The plant roots collect water and certain nutrients, which are then carried throughout the plant. The vaporisation takes place within the leaf and the stomatal aperture regulates the vapour exchange with the atmosphere. Transpiration loses nearly all of the water taken in, with only a small amount being utilised by the plant. Transpiration, like direct evaporation, is influenced by the amount of energy available, the vapour pressure gradient, and the wind. During evaluation of transpiration, the effects of radiation, temperature, humidity, and wind should be considered. Water content in the soil and the ability of soils to transfer water to the roots, as well as waterlogging and soil water salinity, all influence transpiration rate. Crop features, ambient circumstances, and production practises also impact transpiration rate. Depending on the type of plant, the rate of transpiration differs. When determining transpiration, it is critical to consider not just the type of crop but also its growth, atmosphere, and supervision.

The neural network has an advantage of being able to learn and adapt to its surroundings. Similarly, fuzzy logic has ability to account for the inherent uncertainty and imprecision of real world systems using fuzzy if-then rules [7] and that constitutes its prominent feature. An integrated forecasting approach incorporating both the fuzzy logic and the neural network offers unique advantage of the self-adaptability and learning capability of neural network, as well as the fuzzy system's capacity to use fuzzy if-then rules to account for the uncertainty and imprecision of real-world systems. Because of its expert knowledge, the fuzzy system works as a frontend pre-processor for the neural network input and output layers. The parameters of the expert knowledge based fuzzy system are determined using neural network learning techniques based on historical data. The use of adaptive network based fuzzy inference system, a hybrid system, aids in compensating for the limitations of the individual approaches [8]. The parameters related with the input membership functions are estimated using back propagation, whereas the parameters associated with the output membership functions are estimated using least squares estimation. Sugeno fuzzy inference uses trimf for input values and linear function output values in the suggested method. Sugeno defuzzification outperforms Mamdani defuzzification in terms of computational efficiency [9].

2. Background

Evaporation pans are useful in hydrology because they combine significant physical elements such as radiation, temperature, humidity, sunshine length, and wind speed into a single evaporative demand assessment. However, evaporation cannot be built at every location where a reservoir and irrigation are proposed or currently in place. It is also unusual to see it in remote places without accurate instrumentation. When no pans are accessible, hydrologists, meteorologists, and agriculturalists require a practical approach to anticipate evaporation.

Goyal et al. [10] investigated pan evaporation in sub-tropical climates along with two models Hargreaves and Samani method and Stephens–Stewart using various machine learning methods such as least squares-support vector regression, artificial neural network, fuzzy logic, and adaptive neuro-fuzzy inference system modelling. Among those, least squares-support vector regression and fuzzy logic methodologies provided the best estimates for evaporation in the studied watershed.

Kisi [9] explained the evapotranspiration prediction models based on meteorological data have been constructed using soft computing technologies for successful estimation. The test results were compared using the daily meteorological data as inputs for fuzzy genetic models that were used to estimate ET using Penman–Monteith equation. According to the comparison results the Sugeno fuzzy approach was faster and more accurate in modelling daily ET than the Mamdani fuzzy genetic technique.

Feng et al. [11] developed an evapotranspiration estimation model that included a number of climate change factors and used random forest and generalized regression neural networks. Temperature, humidity, rainfall, and wind speed are all factors in evapotranspiration estimation in the crop yield model. The model was based on data on agricultural yields from 2009 to 2015, as well as climate data from the same period. The *k*-fold test was used to assess model performance in terms of temporal and geographical criteria, as well as scanning strategies for data sets. However, the model did not focus on forecasted temperature data, a critical aspect for water resource management.

Mousa et al. [12] discussed the combination of fuzzy rule-based system learning and distant microwave sensing. The reported studies illustrate the ability of technique to solve a number of agricultural problems. Fuzzy logic is a simple method for obtaining a clear conclusion from evidence that is imprecise, ambiguous, perplexing, noisy, or absent.

Roderick et al. [13] used the PenPan model, which used the radiation, temperature, wind speed, and humidity as input data, is used to observe evaporation. Temperature and humidity changes were infrequent enough to have little effect on pan evaporation rates. The attribution approach provided here can be utilized to decipher the aerodynamic and radiative drivers of the hydrologic cycle using the pan evaporation data.

Pandey et al. [14] used subtractive fuzzy inference algorithm for evaluating potato crop. At various stages of growth in potato crop, the variables such as plant height, leaf area index, biomass as well as soil moisture were measured. The dispersion coefficient for the horizontal transmit and horizontal receive and vertical transmit and vertical receive polarizations was used as an input during the network training and validation. The crop/soil parameter values calculated using this technology were significantly nearer to the experimental values. The investigation confirmed the good estimation capabilities of fuzzy subtractive grouping in potato cultivation parameters. Other crops grown on a regional or continental scale should benefit from such strategies [15–17].

3. Methodology

Evapotranspiration (ET) is an important aspect of consideration in designing an irrigation system and management, and it is measured indirectly based on climatic factors including temperature, wind and humidity. Evapotranspiration can be computed using a variety of techniques, including experimental relationships and combination approaches based on physical processes like Penman and Monteith. ET prediction is a complex process because the lack of the relevant data can result in erroneous estimation.

The proposed strategy in this work is based on an adaptive network based fuzzy inference system (ANFIS) model with six inputs such as minimum and maximum temperature, humidity, wind, duration of sunshine, radiation and one output as evapotranspiration [18–20]. The output of each production is passed on to the next stage, which entails performing particular activities in accordance with current circumstances. Each input variable is considered to have three levels of values as low, medium, and high in inputmf (input membership function) stage and 729 rules are generated in the rule stage, following which the output evapotranspiration is estimated from the outputmf (output membership function) as shown in Fig. 2.

3.1. Evapotranspiration calculation

The flowchart for computing evapotranspiration in ANFIS using MATLAB is shown in Fig. 3. In this method, the data set is collected and values are loaded for training and testing. Grid partitioning method is selected for framing fuzzy rules and membership function for six input variables and each has three levels of values as low, medium and high. The input parameter value is set as [333333]. The system is trained and tested till the best fuzzy inference system is obtained at epoch 100. The predicted result for evapotranspiration is computed with minimal training RMSE as 7.19888×10^{-7}.

Weather variables, crop factors and environmental circumstances influence evapotranspiration. Climate

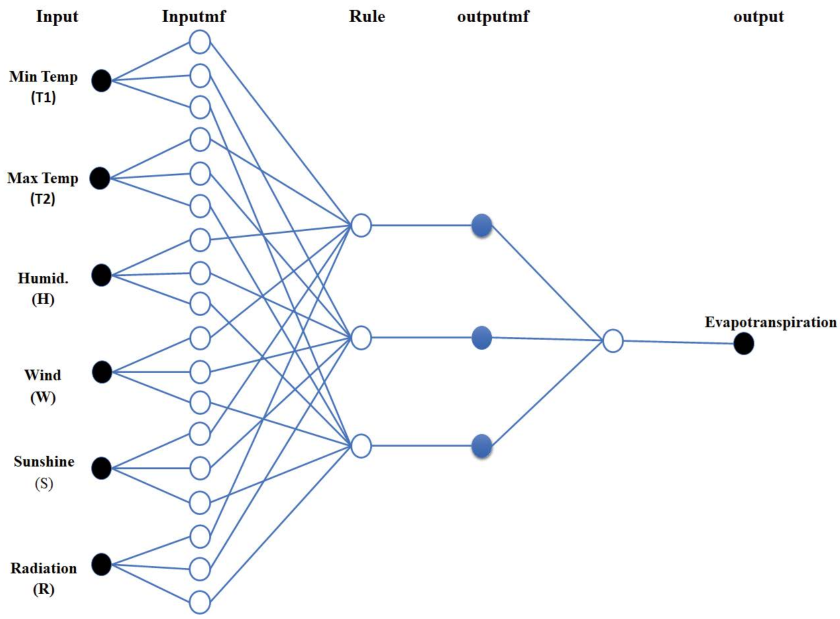

Fig. 2. The ANFIS methodology combines neural networks and fuzzy logic principles, as well as the benefits of both, into a unified framework for calculating evapotranspiration at various stages.

parameters are experimentally measurable factors affecting ET. Thus, ET can be determined with the help of meteorological data. ET is a measurement of the evaporating power of atmosphere at a certain place and time of year that takes crop attributes and soil conditions into account. The Penman–Monteith methodology is the only method suggested for determining ET. The method is chosen to closely depict grass ET in the region studied since it is physically based and clearly incorporates both physical and aerodynamic properties [16].

4. Dataset description of input and output variables

In the proposed methodology, six fuzzy input variables, namely, minimum temperature, maximum temperature, duration of sunshine, wind, humidity, radiation and one output variable, ET, are used. The system built in this work is based on an adaptive network based fuzzy inference system with a triangle membership function. There are a variety of membership functions that can be constructed for the given inputs and the suggested methodology employs the triangle membership function to simplify the system with Sugeno as shown in Fig. 4.

Each of the variables is represented by three terms: low, medium and high, with values for input variables including minimum temperature (T_1) and maximum temperature (T_2), humidity (H), wind (W), duration of sunshine (S) and radiation (R). The membership function plots are shown in Fig. 5a–f. The ranges of values of each input variable with low, medium and high values are given in Table 1.

Here a weighted sum of a few data points is computed rather than calculating the centroid of a two-dimensional area. According to the simulation results, the ANFIS model serves as a promising tool for calculating evapotranspiration. The data is defuzzified using the weighted average method as expressed in Eq. (1). The output y is calculated using the following mathematical relation.

$$y = \frac{\sum_{i=1}^{n} w_i z_i}{\sum_{i=1}^{n} w_i} \tag{1}$$

where the membership of each rule's output is y, the weight associated with each rule is z_i, the number of rules is n, and the defuzzified output is y. A part of these numerous rules is shown in Fig. 6.

5. Results and discussion

It is tough to tell the difference between water lost by evaporation and transpiration because they happen at the same time. Aside from topsoil water availability, the quantity of solar radiation that reaches the surface of soil is the most important factor in determining evaporation from a cropped soil. This percent decreases with time when crop matures and crop canopy covers more of the ground surface. When the crop is tiny, soil evaporation is the primary source of water loss; however, once the crop has matured and fully covers the soil, transpiration becomes the primary source of water loss. During sowing, evaporation accounts for roughly 100% of ET, but under complete crop cover, transpiration accounts for more than 90% of ET [17]. Evaporation is usually measured in millimetres (mm) per unit time. The rate is a water depth measurement that expresses how much water is lost from a chopped surface. The time unit could be an hour, day, decade, month, or even a full growth season or year.

The reported works suggest that the ANFIS models generally outperform the other models [21]. A fundamental

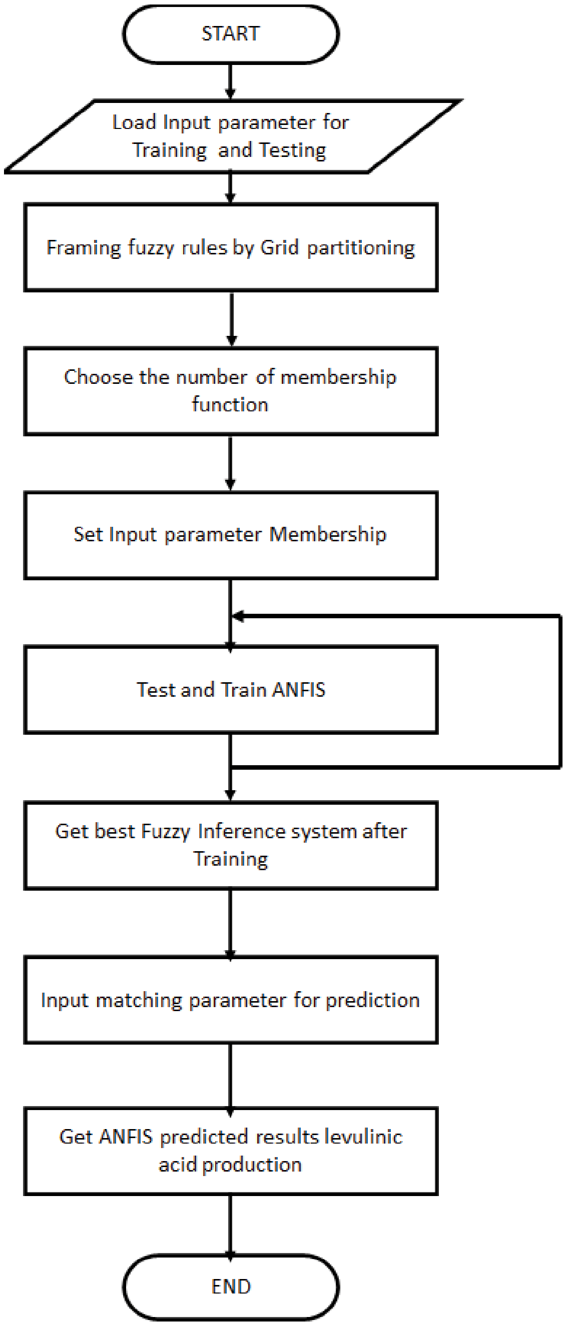

Fig. 3. Methodology developed to carry out evapotranspiration computation.

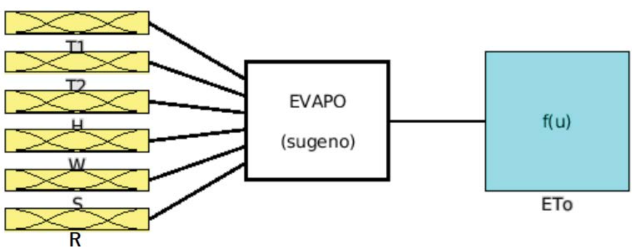

Fig. 4. Fuzzy inference system for evapotranspiration computation using Sugeno method with six inputs and one output.

Table 1
Input values ranges for membership function construction

Input variable	Range	Low	Medium	High
		14.9	17.6	20.3
T_1	17.3–26	17.58	20.28	22.98
		20.28	22.98	25.5
		22.35	25.1	27.85
T_2	25.1–30.6	25.1	27.85	30.6
		27.85	30.6	33.35
		75	78	81
H	78–84	78	81	84
		81	84	87
		38.5	69	99.5
W	69–130	69	99.5	130
		99.5	130	160.5
		0.45	2.3	3.55
S	2–5.1	2.3	3.55	5.1
		3.55	5.1	6.65
		9.6	12.2	14.8
R	12.2–17.4	12.2	14.8	17.4
		14.8	17.4	20

advantage of these models is their ability to train several ANFIS models separately for different ranges. The meteorological data linked with each range is used to optimise the parameters of the ANFIS model. Because each ANFIS was not exposed to the entire range of substantially different values, the ET estimates of the subgroup ANFIS were less likely to diverge significantly from the related data. Because a single ANFIS was used without a range specification, a single model was built for the whole data set, which was subsequently subjected to extraordinarily high and low ET values on a regular basis. As a result, weights inside the ANFIS are restricted, resulting in lower overall estimations [22].

The performance of our proposed model in estimating evapotranspiration using ANFIS and its comparison with Penman–Monteith method is shown in Table 2. The results of estimating evapotranspiration are done by using the input variables such as temperature, wind speed, radiation level, duration of sunshine and air humidity.

The seasonal impact also plays an important role on evapotranspiration and water management and must be captured by the model. In addition to the low ET rate during winter, there is a chance that it may rain during these months, so the soil would remain hydrated for a longer period of time than during the rest of the year. This minimizes the demand for irrigation during the winter months, allowing water resources to be conserved. In the summer, when rainfall is less and evapotranspiration is high, irrigation water is the only resource available to give the soil the appropriate moisture content, and thus irrigation is dosed frequently. As a result, the behaviour of our system mimics the actual scenario well, demonstrating its efficiency, adaptability, and suitability for the management and control of irrigation systems, along with proper

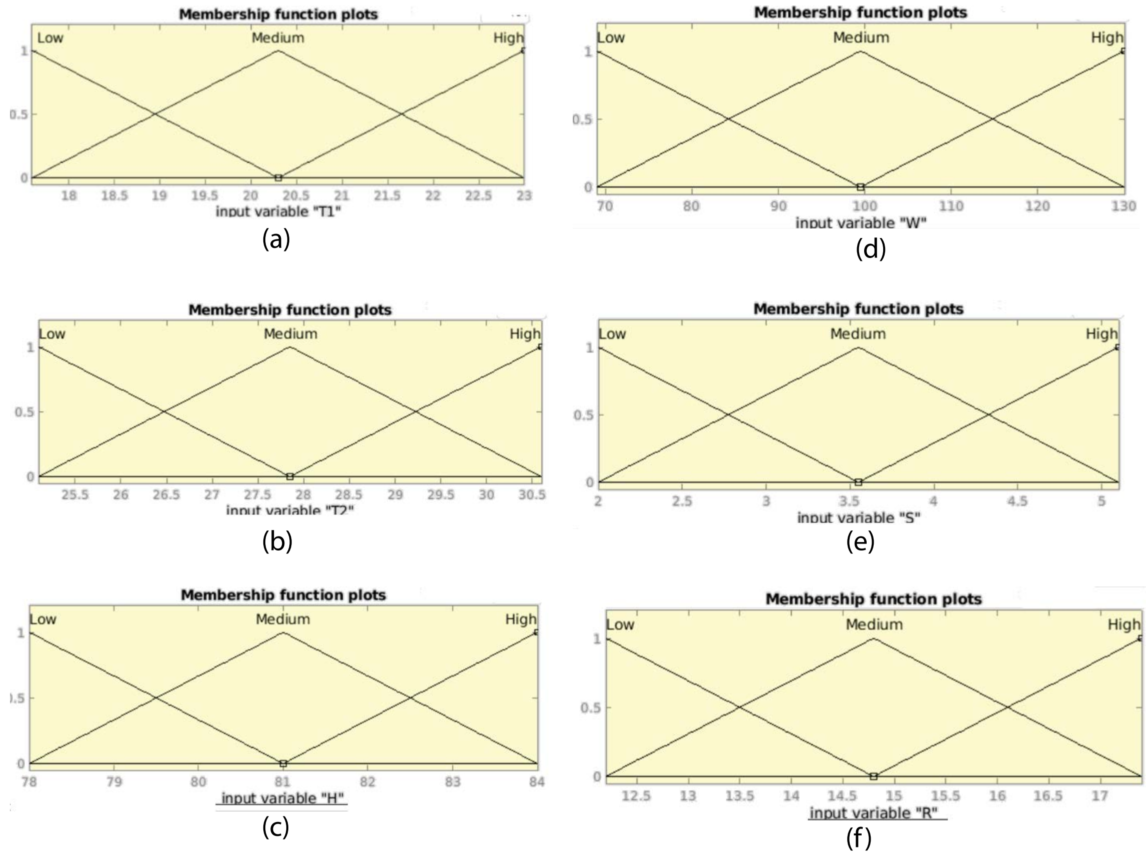

Fig. 5. (a) Membership function plot for minimum temperatures T_1 ranges from 17.3°C to 26°C where low, medium and high plotted in the range of L(14.9,17.58,20.28), M(17.6,20.28,22.98), H(20.3,22.98,25.5). (b) Membership function plot for maximum temperatures T_2 ranges from 25.1°C to 30.6°C where low, medium and high plotted in the range of L(22.35,25.1,27.85), M(25.1,27.85,30.6), H(27.85,30.6,33.35). (c) Membership function plot for humidity (*H*) ranges from 78%–84% where low, medium and high plotted in the range of L(75,78,81), M(78,81,84), H(81,84,87). (d) Membership function plot for wind (*W*) ranges from 69–130 km/d where low, medium and high plotted in the range of L(38.5,69,99.5), M(69,99.5,130), H(99.5,130,160.5). (e) Membership function plot for duration of sunshine (*S*), ranges from 2–5.1 h where low, medium and high plotted in the range of L(0.45,2.3,3.55), M(2.3,3.55,5.1), H(3.55,5.1,6.65). (f) Membership function plot for radiation (*R*) ranges from 12.2–17.4 (MJ/m^2 d) where low, medium and high plotted in the range of L(9.6,12.2,14.8), M(12.2,14.8,17.4), H(14.8,17.4,20).

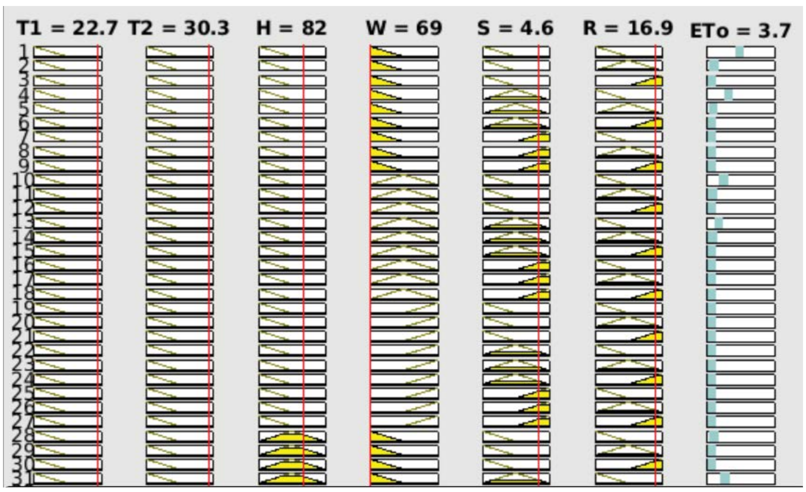

Fig. 6. Classical operators AND = min, OR = max, and NOT = additive complement used in this work to form fuzzy rule set with 729 rules and each rule's output fuzzy sets are then combined into a single output fuzzy set. The resulting set is then defuzzified for evapotranspiration computation using ANFIS in MATLAB.

adaptation to various types of soils, various types of crops, a wide range of locations, and various irrigation strategies and equipment due to soil, crop, and atmospheric conditions. The simulation results revealed that evapotranspiration can be quantitatively estimated using the inputs and its variation as a function of various combination of inputs is presented in Fig. 7a–d. A surface map of ET fuzzy prediction can be constructed using the fuzzy rule table as illustrated in Fig. 7. It can be shown that as temperature, radiation, and wind speed rise, ET increases. Furthermore, it decreases when the relative humidity increases. The evapotranspiration is influenced by the temperature and relative humidity as shown in Fig. 7a and the effect of temperature and windspeed is plotted in Fig. 7b. The effect of humidity and radiation is depicted in Fig. 7c and humidity and wind speed influence on output is shown in Fig. 7d.

Table 2
Evapotranspiration computation using ANFIS model

Run	Min. Temp. (T_1) °C	Max. Temp. (T_2) °C	Humid. (H) %	Wind (W) km/d	Duration of sunshine (S) h	Radiation (R) MJ/m^2 d	ET (Penman method) mm/d	ET (ANFIS method) mm/d
1	22.8	29.6	81	78	4	15.7	3.4	3.4
2	22.7	30.3	82	69	4.6	16.9	3.7	3.7
3	23	30.6	80	78	5.1	17.4	3.8	3.8
4	23	30.2	82	69	5	16.4	3.5	3.5
5	22	28.6	84	69	3.8	13.5	2.9	2.9
6	19.2	26.5	81	69	3.3	12.2	2.6	2.6
7	17.6	25.1	78	78	3.2	12.3	2.6	2.5
8	18.6	25.3	78	78	2.6	12.4	2.6	2.56
9	20.5	26.5	78	104	2	12.4	2.8	2.8
10	22.5	28	79	130	2.2	12.9	3.1	3.1
11	23	28.7	80	104	3.2	14.4	3.3	3.3
12	23	29.1	82	95	3.8	15.2	3.4	3.4
13	21.5	28.2	80	85	3.6	14.3	3.1	3.2

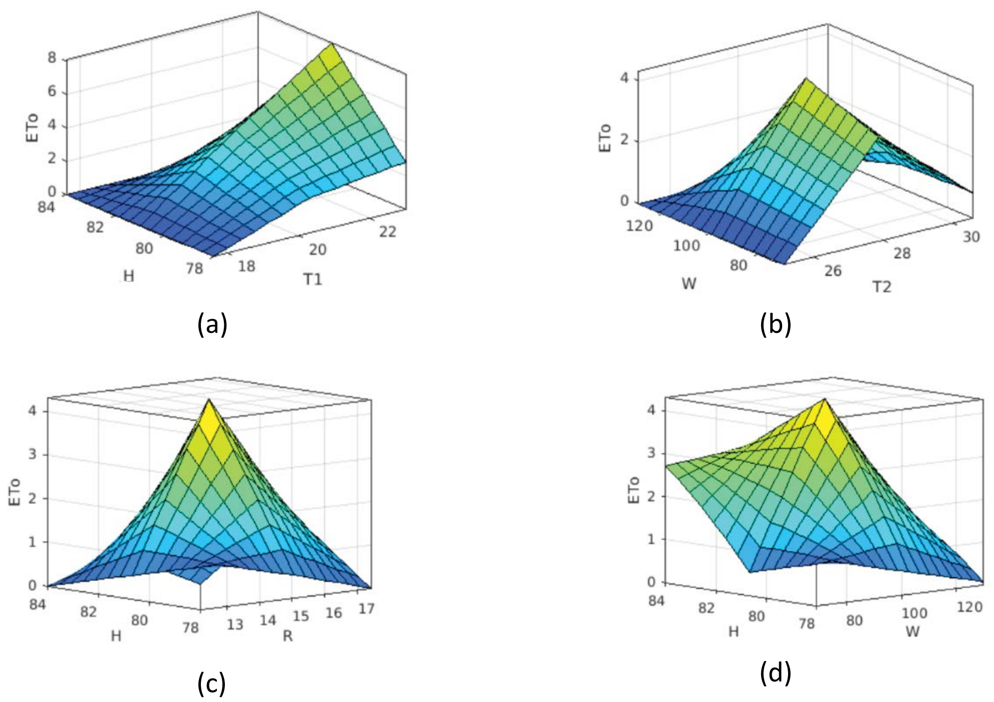

Fig. 7(a). Temperature and humidity are indirectly proportional to one another, therefore as the temperature rises, the relative humidity falls. As a result, temperature has a direct relationship with the amount of moisture that the atmosphere can hoard. (b) Transpiration at plant leaves impacts temperature dependent on wind speed variations, and tends to decrease as wind speed increases due to increased cooling efficiency by heat change. (c) Humidity and radiations are indirectly proportional to each other, therefore as the humidity rises, when radiation is low. (d) Humidity and wind speed influence evaporation rates by allowing more water vapor to escape, and evaporation will continue as the wind blows.

The pressure of vapor is calculated by assuming that the dewpoint temperature (T_{dew}) which is close to the daily minimum temperature (T_{min}) when humidity data is scarce or questionable. When the air is saturated with water vapour and the relative humidity is approaching 100%, it means the air temperature is near the lowest temperature. ANFIS is an accurate and efficient approach for forecasting and managing irrigation volume, according to simulation results. Based on evapotranspiration, it translates the imperfect fluctuation in weather conditions to the required amount of irrigation to be applied. Fig. 8 depicts the likelihood of ET calculation between observed and expected values.

With an objective to get the minimum error and maximum coefficient of regression values between observed and predicted values, optimal model parameters were chosen and calculated using MATLAB tools. The error measured using SSE (sum of the squared errors), R-square, adjusted R-square and RMSE (root mean square error) are 0.01903, 0.9916, 0.9908 and 0.04159 respectively using Eq. (2).

$$f(x) = p_1 \times x^2 + p_2 \times x + p_3 \tag{2}$$

where p_1 = –0.1406, p_2 = 1.919, p_3 = –1.48. The remaining values are given in Table 3 and corresponding error values are calculated accordingly. The comparison between Penman method and ANFIS is shown in Fig. 9 based on error statistics for ET computation. The learning time of ANFIS is much less than that of a neural network. It means that ANFIS is faster than neural networks at reaching the aim. When a more complicated system with a large amount of data is considered, the usage of ANFIS rather than a neural network would be more beneficial in overcoming the complexity of problem sooner. ANFIS provides results with the relatively lesser data required for training.

5.1. Performance evaluation criteria

The performance evaluation criteria assess the system performance by comparing the predicted results from model with the experimentally observed results. The Nash–Sutcliffe efficiency (NSE), performance index (PI) and Willmott's refined index of agreement (WI) were used in the system for performance evaluation to measure the closeness of ANFIS results of evapotranspiration modelling with experimental data [23–25].

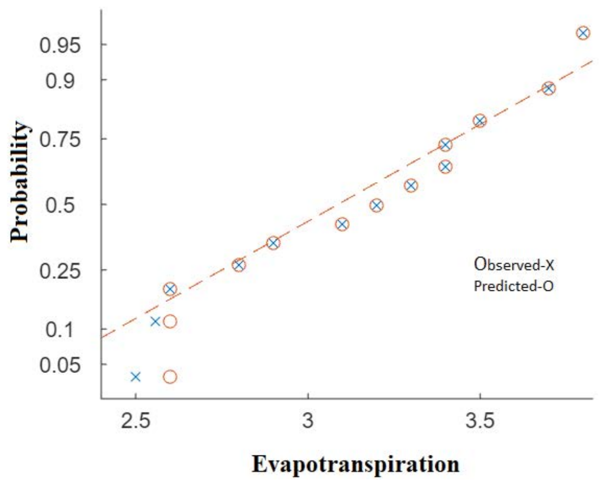

Fig. 8. Probability for ET calculation between the experimental value using Penman method and predicted value using ANFIS model.

5.1.1. Nash–Sutcliffe efficiency

Nash–Sutcliffe efficiency (NSE) is a normalized statistic for determining the goodness of match between the predicted and the observed data. In the proposed system, the NSE is calculated using Eq. (3). The NSE value of 1 indicates that the results of both predicted and observed data from experiments are perfectly matched. The NSE value of 0 indicates that the system predictions are more accurate than the observed data from experiments and the NSE values ranging between –∞ and 0 indicate that the observed values are better than the system predicted results.

The Nash–Sutcliffe efficiency coefficient for the estimation of evapotranspiration using ANFIS is determined as 0.99 using Eq. (3). The results revealed that the predicted and observed values are matched well as shown in Fig. 10.

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}\left(\text{ET}_{\text{oi}} - \text{ET}_{\text{pi}}\right)^2}{\sum_{i=1}^{n}\left(\text{ET}_{\text{oi}} - \overline{\text{ET}_o}\right)^2} \tag{3}$$

where ET_{oi} denotes observed value of evapotranspiration from experiment, ET_{pi} is predicted value evapotranspiration using ANFIS model and $\overline{\text{ET}_o}$ is the average of observed values.

5.1.2. Wilmott's refined index

Willmott's refined index (WI) is a standard measure of assessing agreement between the observed and the system predicted results and ranges from 0 to 1. The value of WI as 1 indicates a perfect match between the observed and the predicted results, and 0 suggests no agreement between the

Table 3
Error statistics for ET computation

Degree	SSE	R-square	Adjusted R-square	RMSE
1	0.01903	0.9916	0.9908	0.04159
2	0.01903	0.9916	0.9908	0.04159
3	0.01203	0.9947	0.9929	0.03655
4	0.0117	0.9948	0.9922	0.03824
5	0.01101	0.9951	0.9916	0.03966
6	0.01099	0.9951	0.9903	0.04279
7	0.01022	0.9955	0.9891	0.0452
8	0.01007	0.9955	0.9866	0.05017
9	0.01007	0.9955	0.9821	0.05793

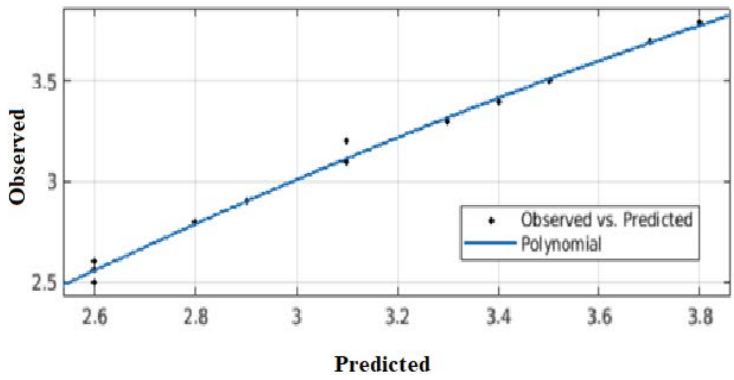

Fig. 9. Error statistics for ET is compared between experimental value using Penman method and predicted value using ANFIS model.

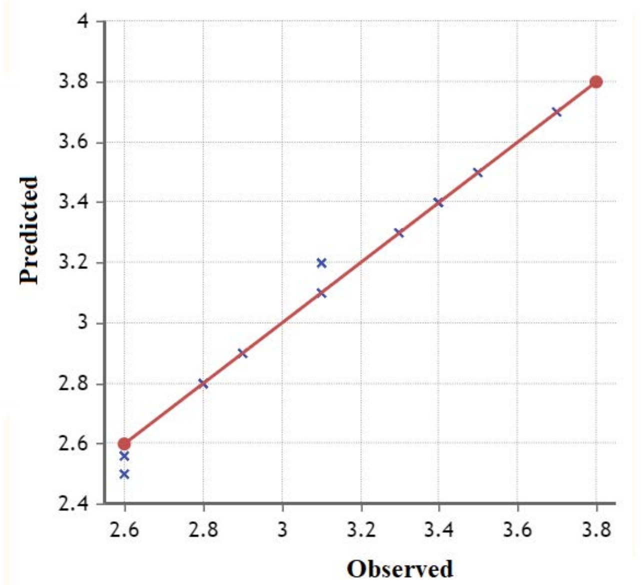

Fig. 10. Nash–Sutcliffe efficiency (NSE) plot against the values between the evapotranspiration computation using ANFIS model (predicted) and experimental values (observed).

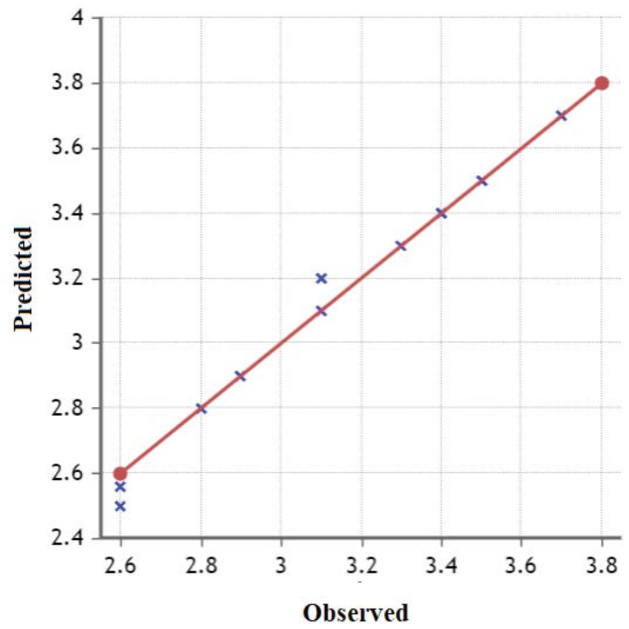

Fig. 11. Wilmott's Refined Index plot against the values between the evapotranspiration computation using ANFIS model (predicted) and experimental value (observed).

observed and the predicted values. The Willmott's refined index (WI) for the estimation of evapotranspiration using ANFIS is calculated as 0.998 using Eq. (4).

$$\text{WI} = 1 - \frac{\sum_{i=1}^{n}\left(\text{ET}_{\text{oi}} - \text{ET}_{\text{pi}}\right)^2}{\sum_{i=1}^{n}\left(\left|\text{ET}_{\text{pi}} - \overline{\text{ET}_p}\right| + \left|\text{ET}_{\text{oi}} - \overline{\text{ET}_o}\right|\right)^2} \quad (4)$$

where ET_{oi} is the observed experimental value and ET_{pi} is the predicted value using ANFIS model and the averages of observed and predicted values are $\overline{\text{ET}_o}$ and $\overline{\text{ET}_p}$ respectively. The corresponding plot is shown in Fig. 11.

5.1.3. Performance index

Performance index (PI) is a statistical parameter for evaluating model performance in comparison to experimental observations and it varies from 0 and ∞. The PI values close to zero represent that the modelling system has highly accurate results. The performance index for estimating evapotranspiration using ANFIS models in comparison to experimental values is calculated using Eq. (5) as 0.040. The value being close to zero proved that the model prediction achieved highly accurate results.

$$\text{PI} = \frac{\text{RMSE} / \overline{\text{ET}_o}}{1 + \frac{\sum_{i=1}^{n}\left[\left(\text{ET}_{\text{oi}} - \overline{\text{ET}_o}\right)\left(\text{ET}_{\text{pi}} - \overline{\text{ET}_p}\right)\right]}{\sqrt{\sum_{i=1}^{n}\left(\text{ET}_{\text{oi}} - \overline{\text{ET}_o}\right)^2\left(\text{ET}_{\text{pi}} - \overline{\text{ET}_p}\right)^2}}} \quad (5)$$

where ET_{oi} and ET_{pi} are evapotranspiration values observed from experiments and predicted from ANFIS modelling, respectively, whereas $\overline{\text{ET}_o}$ and $\overline{\text{ET}_p}$ denote corresponding averages of the observed and the predicted values of evapotranspiration.

5.1.4. Kruskal–Wallis test between the estimation and observation values

The Kruskal–Wallis test is a non-parametric test for independent measurements and is an alternate to ANOVA. It relies on the ranking of data rather than means and variances calculations. It is evaluated using the differences between observed and predicted evapotranspiration values as independent samples as shown in Fig. 12 as boxplot diagram. The Kruskal–Wallis test was performed to estimate the statistical significance to measure the similar distribution among the values obtained from the experimental results and the predicted data computed for evapotranspiration as shown in Fig. 13. The probability value of 0.9179 and H value of 0.01063 showed 95% of significantly satisfied results were between the predicted and the observed

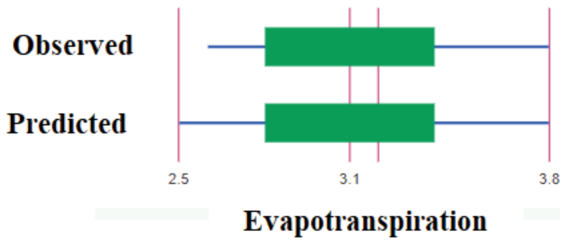

Fig. 12. Boxplot diagrams of the proposed system between mean observed and predicted values.

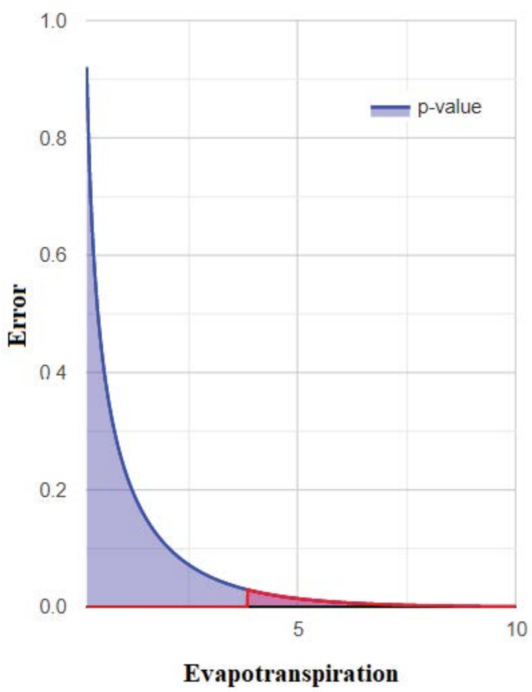

Fig. 13. Error distribution diagram for evapotranspiration using chi-square method.

values for evapotranspiration estimation obtained from Eqs. (6) and (7).

$$H' = \frac{12}{n(n+1)}\sum\left(\frac{R_j^2}{n_j}\right) - 3(n-1) \tag{6}$$

$$H = \frac{H'}{1 - \text{correction}} \tag{7}$$

where R_j is a summation of sample in a set j, n_j is a sample size of set j, n is a total sample size of all sets such as $n = n_1 + n_2 + \ldots n_j$ and H denotes hypothesis.

6. Conclusions and future work

Effective water management in agriculture facilitates farmers in adapting to changing climatic conditions. The suggested system predicts evapotranspiration based on the meteorological data from previous conditions, thereby giving the farmers an early indication of the irrigation needs. The anticipation of water requirements can help farmers in preventing agricultural losses. Before ploughing and sowing, the farmer can acquire an estimate of the irrigation scheduling. Often, farmers perform agricultural operations without holistic consideration of various environmental factors. As a result, they face crop yield losses, which has far-reaching consequences. A new modelling schema based on ANFIS was established in this study for quantitative prediction of evapotranspiration. The modelling approach for the subset ANFIS was built utilizing an active learning loop to produce reliable ET predictions. The estimated ET was found to be accurate when using local meteorological data, air temperature, and sun radiation. The model can be further expanded to consider additional factors involved. The approach demonstrated in this work can aid in the development of automated irrigation systems for optimal use of water resources.

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