Internet of Things 24 (2023) 100962

Contents lists available at ScienceDirect

Internet of Things

journal homepage: www.elsevier.com/locate/iot

Research article

Smart reference evapotranspiration using Internet of Things and hybrid ensemble machine learning approach

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ARTICLE INFO

Keywords:
Internet of Things (IoT)
Hybrid ensemble machine learning model
Reference Evapotranspiration (ET_o)
Smart irrigation
Agriculture

ABSTRACT

Reference Evapotranspiration (ET_o) is the cornerstone of efficient water utilization for sustainability in agriculture. The standard Penman–Montieth (PM) approach of Reference Evapotranspiration (ET_o), is complex due to the involvement of an extensive set of climatic conditions. The existing solutions of simplification of ET_o predictions are not in accordance with the Penman–Montieth approach. A hybrid ensemble machine learning approach for simplification of ET_o prediction is proposed using the Internet of Things(IoT) based crop field sensed climatic data. The proposed hybrid ensemble model is implemented with an Artificial Neural Network (ANN) and regression models. The proposed solution is unique for its utilization of flexible climatic conditions and in accordance with the standard Penman–Montieth (PM) approach. The proposed solution is able to predict daily ET_o from only temperature and also can adjust ET_o according to wind speed, humidity, and sunshine duration. The assessment of the proposed model exhibits a high coefficient of determination (R^2) of 0.94 compared to 0.91 from the basic ANN model. The proposed hybrid ensemble model also exhibits a low RMSE of 0.86, MAE of 0.75 mm day^{-1}, and MAPE of 15.05%, compared to 0.91, 0.75 mm day^{-1}, and 20.40% from the basic ANN model. The ET_o predictions by the proposed hybrid ensemble model also exhibit a higher Pearson correlation coefficient of 0.917 with the ET_o by the Penman–Montieth (PM) approach, compared to 0.778 by the basic ANN model. The statistics reveal the accuracy and goodness of fit of the proposed hybrid ensemble machine learning model.

1. Introduction

Agriculture is the main supplier of human livelihood [1]. The scarcity of natural resources has created serious concerns to feed the world's increasing population [2]. Agriculture productivity needs to be improved, to serve the basic needs of the large human population [3]. Water scarcity has become a major issue across the world [4,5]. More than sixty-nine (69%) percent of available fresh water on earth is used for agricultural purposes [3]. Around seventy percent (70%) of the water used for agricultural activities, is wasted due to poorly managed agricultural activities. The core cause of wastage of scarce water in agricultural activities is the

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https://doi.org/10.1016/j.iot.2023.100962
Received 24 July 2023; Received in revised form 25 September 2023; Accepted 3 October 2023
Available online 12 October 2023

application of irrigation water without ET_o consideration [6]. Efficient water resource management is key to sustainable development in agriculture [2].

Evapotranspiration (ET) is the core element of water management [7–9]. Reference Evapotranspiration (ET_o) is the ET of grass under specific climatic conditions [10]. The ET_o is the basis of effective water management and the scheduling of irrigation in agriculture [8,11]. ET_o has significant importance in determining the efficient irrigation management strategy [12,13]. ET_o is essential to conserve irrigation water to support sustainable development in agriculture [6,14]. The estimation of ET_o for water resource management is critical, and challenging due to the complexity of the standard Penman-Montieth (PM) approach of ET_o calculations [15]. The standard PM approach requires an extensive set of climatic data to calculate ET_o according to these climatic conditions. The inherent complexity of the standard PM approach of ET_o determination makes it difficult to use the standard PM approach for precise irrigation water management [16]. The major reason for the lack of ET_o application in smart irrigation water solutions is the complexity of the standard PM approach for ET_o and the unavailability of the crop field climatic conditions [9,11,17]. Simplification of ET_o prediction with the limited number of climatic conditions is the core of productivity and sustainability in agriculture [18–20]. Temperature, humidity, wind speed, and sunshine are significant elements for calculating ET_o using the standard PM approach, expressed by Eq. (1) [21].

$$ET_o = \frac{0.0408\Delta(R_n - G + \gamma\frac{900}{T+273}WS(e_s - e_a))}{\Delta + \gamma(1 + 0.34WS)} \tag{1}$$

Where ET_o represents the reference evapotranspiration measured in millimeters per day, G is the soil heat flux density measured in mega-joules per square meter per day, R_n is the net radiation at the crop surface measured in mega-joules per square meter per day, WS is the wind speed measured in meter per second (ms^{-1}) at 2-meter height, and T as the air temperature at a 2-meter height measured in degrees Celsius (°C). e_a and e_s denote the actual vapor pressure and saturated vapor pressure respectively, both measured in kilo-pascals (kPa). The difference between e_s and e_a is known as the vapor pressure deficit measured in kPa. γ is the psychometric constant measured in kilo-pascals per degree Celsius, and Δ is the slope of the vapor pressure curve measured in kilo-pascals per degree Celsius (°C).

Internet of Things (IoT) is the major paradigm to cope with major issues of low productivity in agriculture and the conservation of natural resources by leveraging context-aware applications [3,22]. IoT has revolutionized every aspect of life with context-aware applications [23,24]. IoT is emerged as the potential technology for smart irrigation water systems [25]. IoT is the basic pillar of precision agriculture by assisting in monitoring and controlling various farming activities [2,26]. IoT is also very effective for efficient irrigation water management by providing real-time crop field climate context [27,28].

Machine learning is an exciting paradigm with enormous capabilities to deal with real-life complex problems through data-driven decisions [23]. Machine learning has played a substantial influence in all facets of life [29]. Machine learning has also played a substantial role in agriculture from plant disease identification to quality control [30]. Machine learning also has a substantial role in efficient irrigation water management by simplifying the ET_o determination with limited meteorological conditions [31–33].

Modern machine learning capabilities are used to simplify the ET_o determination with limited climatic conditions [34]. To deal with the complexity of standard PM approaches of ET_o many efforts were made to determine ET_o with limited meteorological conditions. The existing approaches for simplifying ET_o determination are not in accordance with the standard PM approach for ET_o calculations. Moreover, these existing methods of ET_o simplification do not take into account the real-time climatic conditions of the crop field. To overcome these issues a hybrid ensembled machine learning model is proposed with the following unique characteristics.

1. The proposed solution is flexible to use the variable number of input climatic conditions.
2. The ET_o predictions are based on real-time crop field climatic conditions sensed using IoT capabilities.
3. The proposed solution is in accordance with the ET_o by the standard PM approach.

2. Literature review

IoT and machine learning are extensively used for addressing various challenges in agriculture. The recent developments in machine learning and IoT-based solutions for agriculture monitoring and simplification of ET_o with limited climatic conditions are reviewed with the following objective:

1. To explore recent emerging smart irrigation water management solutions.
2. To explore major advancements in agriculture monitoring technologies like IoT for precision irrigation water management.
3. To explore the machine learning approaches for ET_o prediction with limited climatic conditions.

Zu Zhengguang et al. [35] proposed a framework for efficient irrigation water management for recovery of drought conditions in the Yangtze River Basin. The recommended solution proved to be very effective in efficient water management in drought-affected areas. Alvis Rafael Gomes et al. [3] proposed a digital twin of irrigation to enable the real-time simulation of the irrigation system's behavior to design a smart irrigation system. Rodrigo Togneri et al. [36] proposed a data-driven model of irrigation water requirement estimation with soil moisture observations. The results reflect that the Light Gradient Boosting Machines (GBM) model performs better in irrigation water requirements estimation using soil moisture conditions. Alexander Kocian et al. [12] presented a crop water usage modeling for soil-less cultivation using IoT to defines a stochastic crop coefficient with temperature.

Ravi Kant Jain [37] proposed an automated drip irrigation water system with IoT and web portal-based field monitoring to overcome the problem of continuous human vigilance for the conservation of irrigation water. Simrat Walia and Jyotsna Sengupta [27] proposed an automated irrigation water system with remote monitoring of climate conditions. The proposed irrigation water system is made up of sensors and climate data for accurate irrigation water forecasting. Rab Nawaz Bashir et al. [23] introduced a machine learning-oriented leaching process to deal with soil salinity using IoT data to observe the soil salinity. The recommended method employs the Gaussian Naive Bayes (GNB) machine learning technique to determine the most effective irrigation water for leaching. Muhammed Enes Bayrakdar et al. [22] proposes a cognitive terrestrial and underground Wireless Regional Area Network (WRAN) for agriculture monitoring in rural areas. The proposed solution for agriculture monitoring is based on Consumer Premise Equipment (CPE) and base station for low interference and spectrum cost.

Muhammed Enes Bayrakdar et al. [24] proposed a relay selection approach for agricultural monitoring over a large area to improve network sustainability. The simulation of the proposed model reveals the use of few sensor nodes to serve the intended purpose. Arfat Ahmad Khan et al. [34] present an IoT and ensembled machine learning model for estimating monthly ET for saline soil reclamation. The ensembled LSTM model shows 92% accuracy from the test dataset.

Xiang Jiao et al. [38] introduced a model to examine the primary climatic influences on ET_o in a sub-alpine wetland valley in China. The findings of the study indicate a robust positive linear correlation between monthly mean ET_o and air temperature, net radiation, and vapor pressure deficit. Genan Wu et al. [39] explored the changes in major factors affecting the ET_o in China over the last thirty-four (34) years. Chen Junxu et al. [37] explored the ET_o variation in different geographical distributions of Red River basin and also explored the sensitivity ET_o to various climatic conditions. Mona Ghafouri-Azar and Sang Lee [40] investigated the influence of climatic conditions on ET_o across diverse geographical regions in Korea. The forty-two (42) years of data reveal that the impact of climatic factors varies across geographical locations. Neha K. Nawandar et al. [13] proposes an ANN-based model for ET_o determination with limited meteorological conditions. ET_o by the proposed solution shows a maximum error of 0.4 mm day^{-1}.

Darbi Homa et al. [7] evaluated different methods of the Thornthwaite equation for ET_o determination. The study compared the six different methods of the Thornthwaite to adjust the Thornthwaite equation for the Sistan region of Iran. Feng Xuyu et al. [41] recommended a model of forecasting of crop specifics evapotranspiration (ET_c) and crop coefficient (K_c). Rongfei Zhang et al. [42] recommended an ET estimation model using Thermal Dissipation Probes (TDP) in southwest China using Landsat −8 images. Branislav Kandra et al. [43] proposed a model to measure and analyze actual ET in the east Slovakian Lowland. Francesco Granata [44] evaluated three models of ET using the Support Vector Machine (SVM), with different combinations of inputs in the central Florida region. The implementation of the solution shows that Model 1, using solar radiation, soil moisture, wind speed, humidity, and temperature provided the best results for ET_o determination.

Sevim Seda Yamaç and Mladen Todorovic [45] evaluated various machine learning models with different climatic conditions to determine the ET_o of the potato crop. The results revealed that the ANN model performs better with all climatic conditions. The k-nearest neighbor (kNN) based model is recommended in case of limited climatic conditions. The results were compared against the soil water balance model and soil water content. Xianming Dou and Yongguo Yang [46] evaluated the SVM and Extreme Learning Machine (ELM) in the forecasting of daily ET_o for four types of ecosystems. The study concluded that ELM and Adaptive Neuro-Fuzzy Inference System (ANFIS) outperformed in the forecasting daily ET_o.

Srdić et al. [47] assessed the performance of different empirical methods for ET_o estimation in Bosnia and Herzegovina. The results show that the calibrated Hargreaves–Samani method (HC) performed best, while the Hargreaves–Samani method (HS) and Copais method (COP) showed an overestimation of ET_o. Esther Lee et al. [48] evaluated the performance of different models for daily ET_o estimation in South Korea. The evaluation of the different models reveals that temperature-radiation-based models outperformed the other models in ET_o. Su Yuexia et al. [49] observed the changes in ET_o over time and discovered the major driving factors affecting the ET_o in cotton production areas in China. The results of the observations showed a declining trend of ET_o. Moreover, the maximum air temperature (Tmax), relative humidity (RH), sunshine duration (SD), wind speed at 2-meter height (WS), and minimum air temperature (Tmin) are the major influential factors affecting the ET_o in China.

Yixiao Zhang et al. [50] proposed a machine learning framework for estimating actual evapotranspiration (ETa) across the Hai River Basin using remote sensing data to forecast ET over a large area. The results reveal that maximum temperature is the major influential factor of ET. Ravi Kant Jain [51] recommended drip irrigation water monitoring and control system using IoT. The proposed solution is intended to be designed for the conservation of irrigation water without constant human vigilance. Zeng Cui et al. [52] observed the variations in ET in Alpine meadows and its driving factors with climatic changes. The increasing ET pattern is observed in Alpine meadows.

From the literature review, it is found that many machine learning approaches have been proposed to simplify the ET_o predictions. Following are the major limitations of existing machine learning approaches for ET_o simplification.

1. The existing solutions use a fixed number of limited climatic conditions. The existing solutions are not flexible enough to take advantage of additional climatic conditions in case they are also available to refine estimated ET_o according to these available conditions.
2. Many existing proposed solutions ignore the standard PM approach of ET_o and are limited in predicting the ET_o according to the standard PM approach.
3. The implementation of the standard PM approach required sensing of crop field climate data at a 2-meter height from the soil surface [7]. The existing solutions are limited in the use of real-time crop field climatic conditions. This limitation of existing solutions results in inconsistencies in ET_o predictions.
4. The existing solutions of ET_o predictions are limited for specific geographical locations.

Keeping in view the above-mentioned limitations of the existing solution there is a need for an ET_o predictions solution that addresses these limitations.

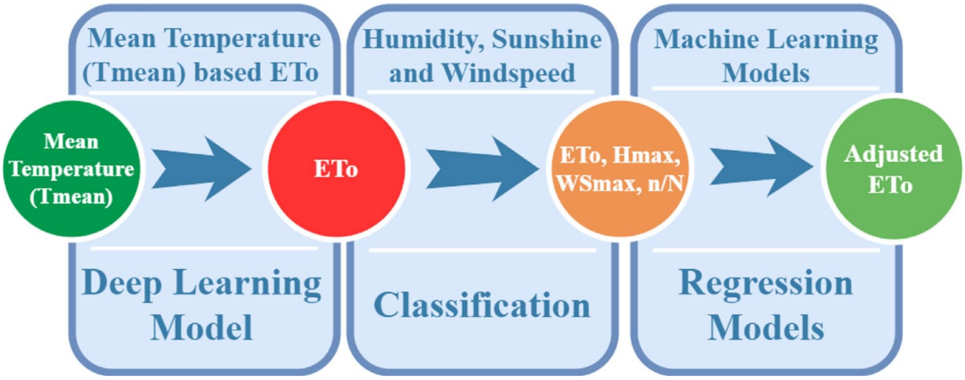

Fig. 1. Model of smart Reference Evapotranspiration (ET_o).

3. Material and method

In this section, the model of the proposed solutions, the configuration of the hybrid ensemble machine learning model, the IoT architecture used to collect crop field data, and the dataset used in the study are presented.

3.1. Proposed model of Reference Evapotranspiration (ET_o)

The proposed model of ET_o prediction is shown in the Fig. 1, where the ET_o determination with daily mean temperature (Tmean) along with adjustments in ET_o according to the daily maximum humidity (RHmax), maximum wind speed (WSmax) and sunshine duration ratio (n/N) are also made. Initially, the ET_o is determined from the Tmean using a deep learning model. The ET_o is adjusted according to the RHmax, WSmax, and n/N in the next phase. The RHmax, WSmax, and n/N are classified according to impact on ET_o. For each class of climatic conditions, a separate regression model is applied to deal with the complexity and non-linear structure of the problem. The ET_o from the previous step with the classification of the RHmax, WSmax, and n/N act as input to one of the appropriate regression models. The output of the regression models is the adjusted ET_o (adj.ET_o). The proposed model can predict ET_o with only Tmean and enable to make an adjustment to ET_o according to additional available climatic conditions. The salient features of the proposed model of the ET_o prediction are listed below.

1. ET_o prediction are in according to the standard PM approach of ET_o.
2. The proposed solution relies on directly sensing climatic conditions from the crop field, at a 2-meter height from the soil surface. It is the basic requirement for the standard PM approach [7]. The crop field sensed data, facilitated by IoT technology, is utilized to make accurate predictions of ET_o.
3. The hybrid ensemble machine learning model is enabled to make predictions with only temperature, as well as flexible enough to adjust ET_o, according to other available climatic conditions, in case they are also available.

The temperature is the most influential climatic condition of ET_o [50,53]. The air temperature, humidity, sunshine duration, and wind speed (WS) at 2-meter height, are the major influential factors affecting the ET_o [49]. Moreover, the correlation between climatic conditions and ET_o is shown in the Fig. 2, reveals the importance of climatic conditions especially the use of temperature as the major factor in the proposed model of ET_o prediction. The Pearson correlation coefficient (r) between ET_o and Tmean, RHmax, WSmax, and n/N is 0.88, −0.74, 0.50, and 0.21 respectively. This correlation analysis between the ET_o and climatic condition reveals the importance of the use of Tmean, RHmax, WSmax, and n/N for ET_o determination.

3.2. Configuration of hybrid ensemble machine learning model

In this section, a detailed explanation of the configurations of machine learning models is given. The configuration of the proposed hybrid machine-learning model is shown in Fig. 3 This particular configuration corresponds to the boosting ensemble machine learning model, where two models, namely Model-C and Model-A, are combined in such a manner that the output of Model-C, serves as input to Model-A. Model-C can predict ET_o with only Tmean. Model-C is implemented with the ANN model. In case other climatic conditions are available then the ET_o determined by Model-C, is adjusted according to additional available climatic conditions by using Model-A. RHmax, WSmax, and n/N are classified according to their impact on ET_o before being used as input to Model-A. For each set of RHmax, WSmax, and n/N a different regression model is defined. Based on the classification of climatic conditions, the appropriate regression algorithm is applied in Model-A. The step-by-step working of the hybrid ensemble machine learning model is as follows.

1. Train the Model-C: The Model-C is implemented by the ANN model. ANN model is configured to take Tmean as input variables and output ET_o prediction using only Tmean.

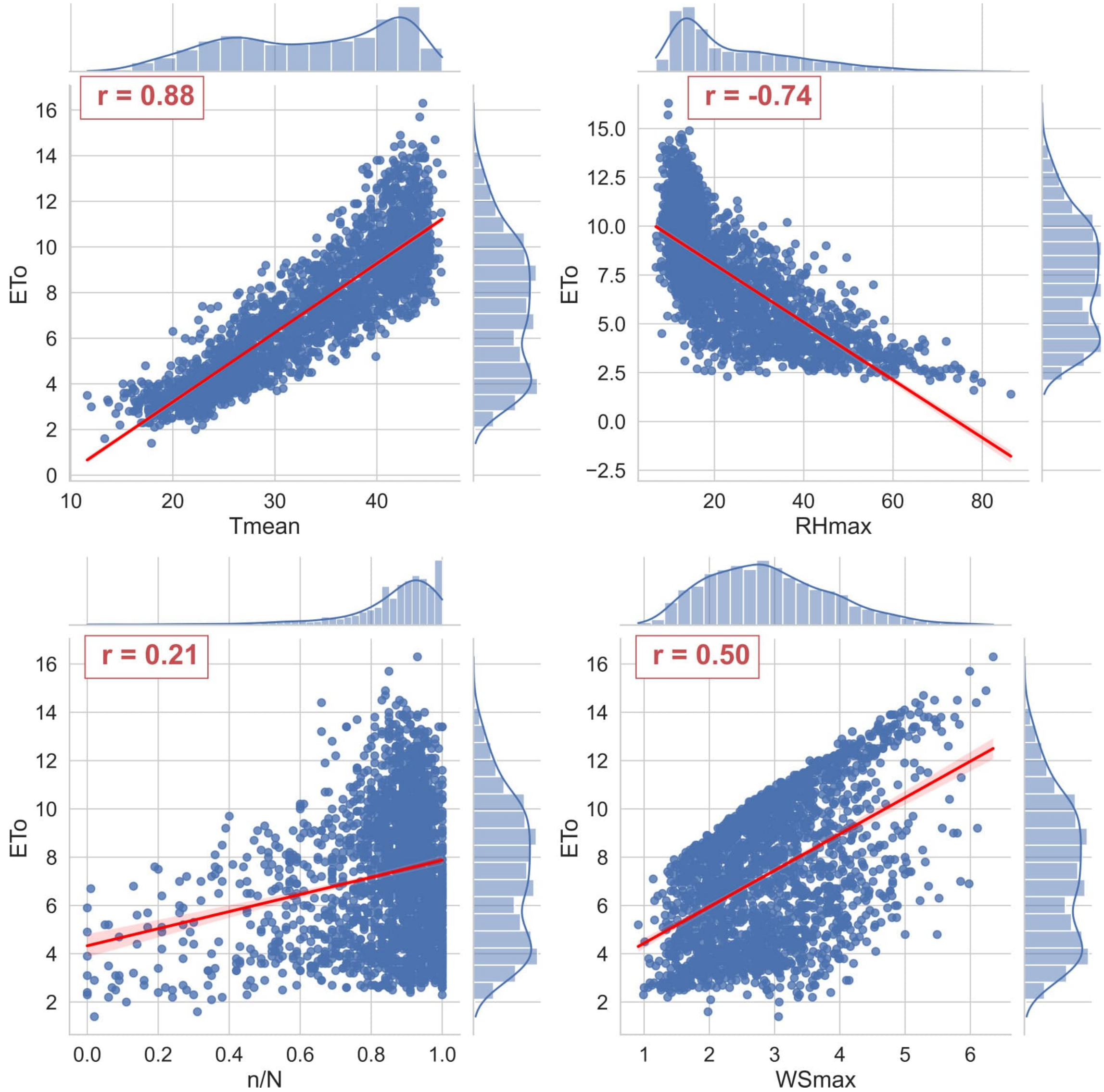

Fig. 2. The correlation analysis between climatic conditions and ET_o.

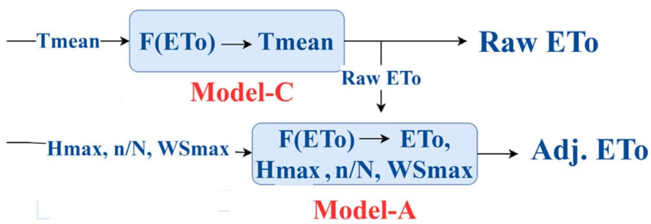

Fig. 3. Configurations of Hybrid ensembled machine learning model.

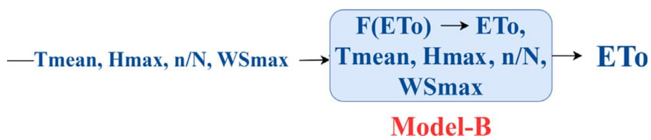

Fig. 4. Configuration of simple Machine learning model with all input.

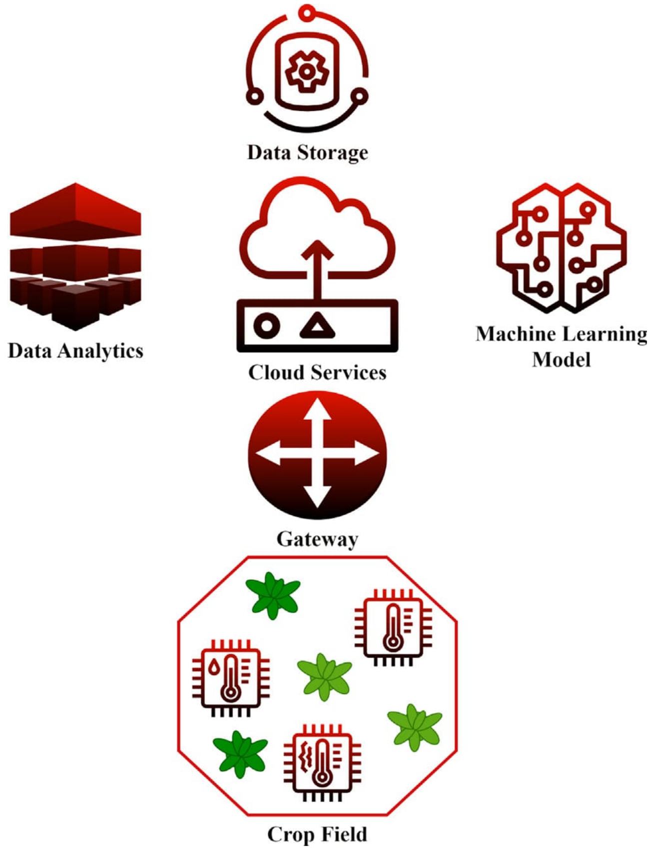

Fig. 5. IoT architecture for collection of crop field climate data.

Table 1
Summery of configurations of machine learning models.

Name	Input	Output
Model-A	ET_o, RHmax, WSmax, n/N	Adj. ET_o
Model-B	Tmean, RHmax, WSmax, n/N	ET_o
Model-C	Tmean	ET_o

2. Generate ET_o predictions from the Model-C: Use the trained ANNs to generate ET_o predictions with only Tmean as input.
3. Classification of climatic conditions: RHmax, WSmax, and n/N are classified according to the range of values with similar impacts on ET_o
4. Train Model-A: Use the classified training data of RHmax, WSmax, n/N, and the initial ET_o prediction from the Model-C, to train regression models selected according to the class identified in the previous section. The regression models output a refined prediction of the ET_o in the form of adj.ET_o.

To evaluate the proposed hybrid ensembled machine learning model, the performance is compared against Model-B, where all the inputs are used to determine the ET_o. The configuration of Model-B is shown in the Fig. 4. The configuration of Model-B is implemented using the ANN model. The summary of reconfiguration of the machine learning models is given in Table 1, where the inputs and output to each configuration of the machine learning model are given.

3.3. Dataset and implementation

The climate data is collected from Pakistan which is an agriculture-intensive country. Pakistan is suffering from the severe threat of a shortage of irrigation water and the implementation of the proposed solution is significant for the economic development of Pakistan. The climate data from Pakistan is collected from the Years 2016 to 2022. The climate of Pakistan is arid. The data from the crop field is sensed using a simple IoT architecture shown in Fig. 5. The sensor nodes are deployed in the field to sense the crop field climate conditions. The sensor nodes sense data from the crop field at a 2-meter height from the soil surface as shown in Fig. 6.

Fig. 6. IoT sensor node deployed in the crop field at 2 meter height.

Table 2
Daily maximum relative humidity (RHmax) classes.

RHmax range %	Class
<20	Low (L)
20–50	Medium (M)
>50	High (H)

Table 3
Daily maximum wind speed (WSmax) classes.

Daily maximum wind speed (WSmax) ms^{-1}	Class
<2	Low (L)
2–5	Medium (M)
>50	High (H)

The IoT-assisted crop field sensed data from the crop field helps the proposed solution to be accurate and in accordance with the standard PM approach. The IoT server receives the sensed climate data from the sensor nodes deployed in the crop field, through the gateway node. The server process, and store the data as well as provide data analysis services. The trained machine learning model deployed at the server makes ET_o predictions from the sensed climate conditions from the crop field. The collected climate data is processed for both training the machine learning models and validating the ET_o predictions. The use of crop field climate data using IoT enables ET_o determination according to the crop field climate. The use of IoT also enables to proposed solution to be universally applicable according to different climates. The Tmean is calculated from the daily maximum temperature (Tmax) and daily minimum temperature (Tmin) by Eq. (2).

$$T_{mean} = \frac{(T_{max} + T_{min})}{2} \tag{2}$$

Fig. 2 illustrates the climate data at the selected location and Pearson correlation coefficient of different climate conditions with ET_o. There exists a positive relationship between Tmean and ET_o with a Pearson correlation coefficient (r) of 0.88, revealing that temperature is the most influential climatic condition for ET_o. Therefore a separate model (Model-C) is configured for ET_o determination when only temperature data is available. The RHmax from the year 2016 to 2022 of the selected location with its relationship to ET_o is also shown in Fig. 2, with Pearson correlation coefficient (r) of −0.74. There exists a negative correlation between the RHmax and ET_o. The Pearson correlation between WSmax and ET_o is 0.50 revealing a positive correlation between the WSmax and ET_o. The correlation between n/N and ET_o is 0.21. The existence of a strong correlation between ET_o and selected climatic conditions justifies the use of these climatic conditions for ET_o predictions in the proposed solution.

The climatic conditions are classified according to their impacts on ET_o. The climate classes are defined on the basis of their ranges with subtle impact on ET_o to define a separate regression model for each set of climate conditions.

The RHmax classes defined according to the RHmax values and their encoding are given in Table 2. The WSmax classes defined according to the WSmax values and their encoding are given in Table 3. The n/N ratio is 0.8 for the bright sunshine day, 0.60–0.8 for forty percent daytime hours with partial cloudiness, and 0.6 for total cloudiness [54]. The n/N classes according to the n/N values and their encoding are given in Table 4.

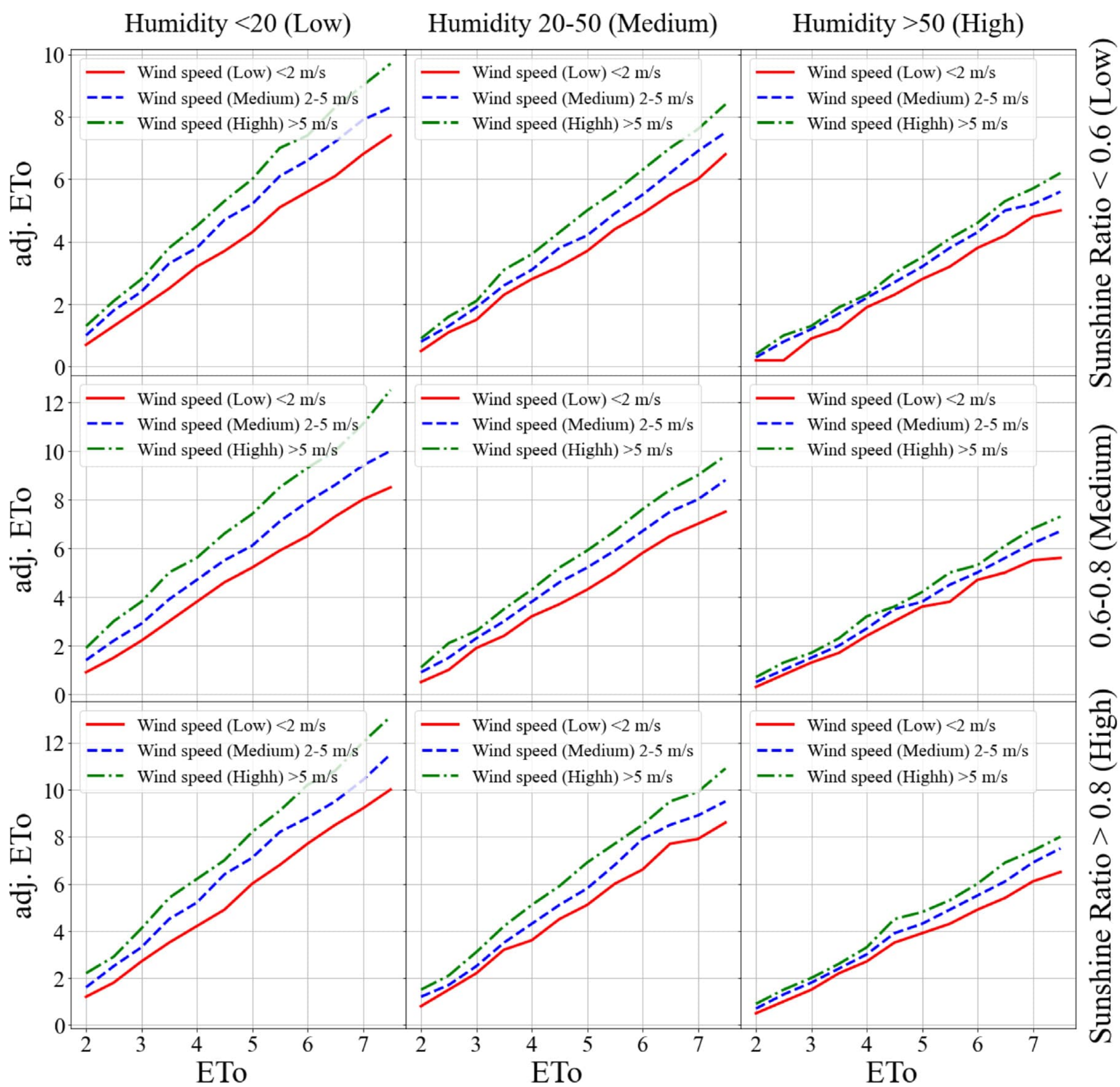

Fig. 7. Dataset for regression models [54].

Table 4
Sunshine duration (n/N) classes.

Sunshine duration ratio (n/N)	Class
<0.6	Low (L)
0.6–0.8	Medium (M)
>0.8	High (H)

Table 5
Encoding of climate conditions.

Class	Code	Class	Code	Class	Code	Class	Code	Class	Code	Class	Code
L, H, L	1	L, H, M	2	L, H, H	3	M, H, L	4	M, H, M	5	M, H, H	6
H, H, L	7	H, H, M	8	H, H, H	9	L, M, L	10	L, M, M	11	L, M, H	12
M, M, L	13	M, M, M	14	M, M, H	15	H, M, L	16	H, M, M	17	H, M, M	18
L, H, L	19	L, H, M	20	L, H, H	21	M, H, L	22	M, H, M	23	M, H, H	24
H, H, L	25	H, H, M	26	H, H, H	27						

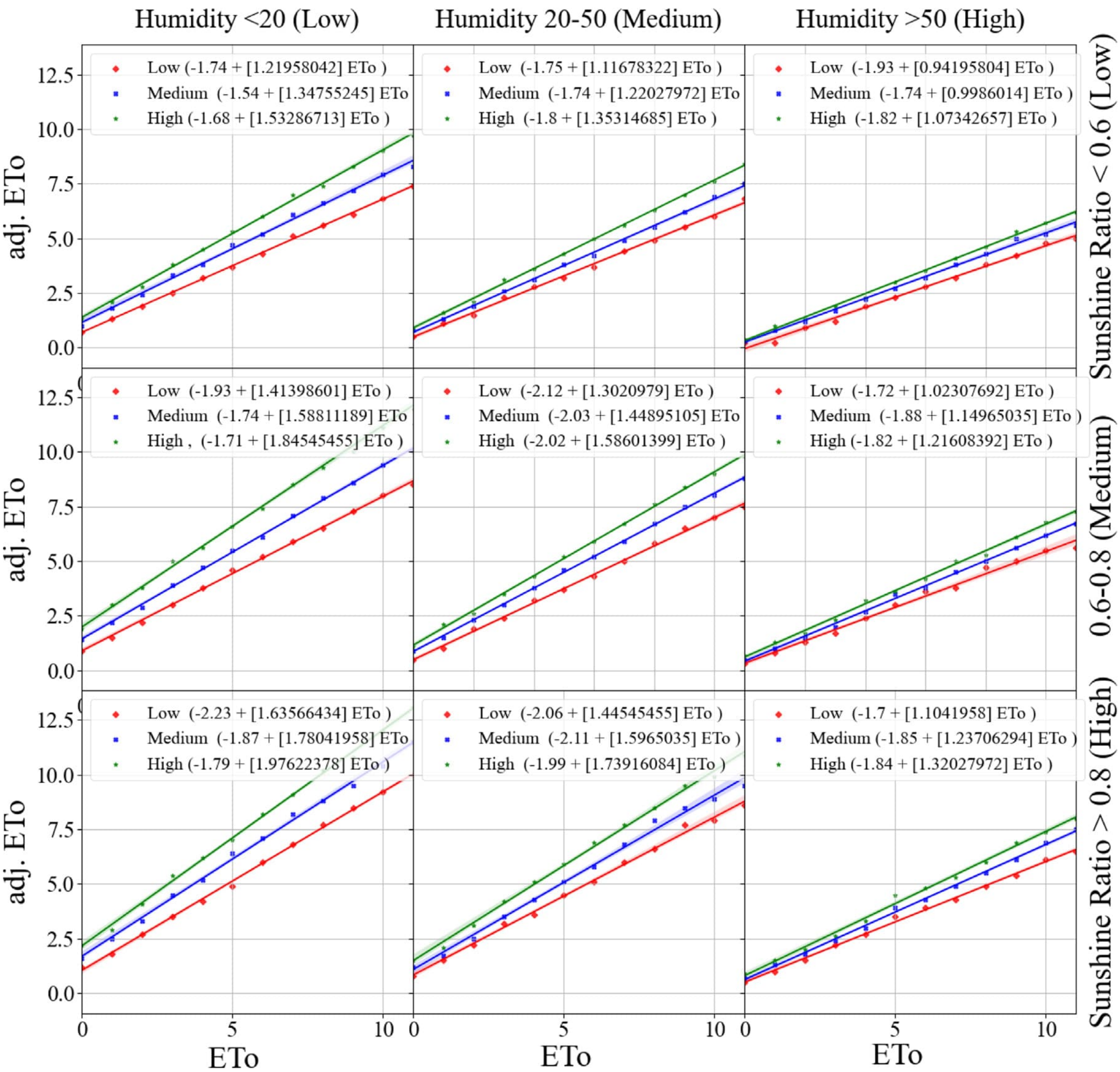

Fig. 8. Regression models.

Twenty-seven (27) unique combinations of climatic conditions are made with each defined range of RHmax, WSmax, and n/N. The encoding of the climate combination is defined in Table 5. For each set of climatic conditions, a different dataset is used as shown in Fig. 7. Each dataset is used to train a different regression model. For each encoded class a different regression model is defined as shown in Fig. 8. The encoding of climatic conditions into different classes is used to select an appropriate regression model defined in Table 5. The ET_o from the Model-C and encoded climatic conditions are made as input to the Model-A, to get a refined ET_o according to additional climatic conditions in the form of adj.ET_o by applying appropriate regression models. The twenty-seven regression models for each of the twenty-seven combinations of RHmax, WSmax, and n/N are given in Fig. 8. The classification of climatic conditions helps to deal with the non-linear nature of the ET_o prediction problem, with the help of linear regression models. The residual plot of each regression model is shown in Fig. 9, from where it is observed that residual values in each plot are randomly scattered around zero point without any trend, revealing the goodness of fit of each regression model.

4. Results

The evaluation of the proposed solution is performed from the following aspects.

1. Assessment of performance of regression model used in the configuration of proposed hybrid ensemble model (Model-A).
2. Assessment of performance of proposed hybrid ensemble model against other configurations of machine learning models. For evaluation purposes, 30% of the dataset is set as the test dataset. The machine learning models are assessed based on

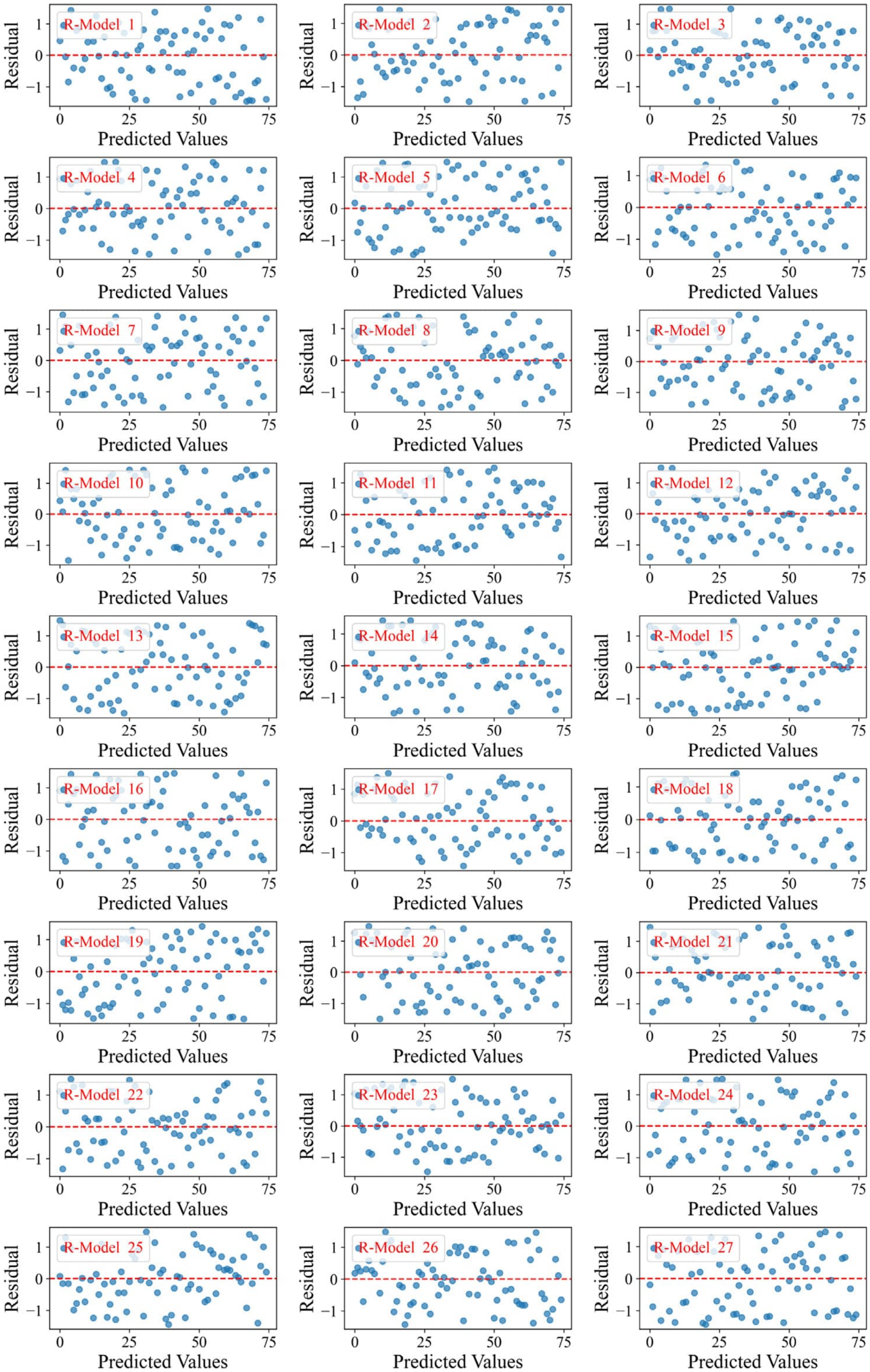

Fig. 9. Residuals plots for regression models.

Table 6
Performance metric of regression models.

Model	R^2	RMSE	MAE mm day^{-1}	MAPE %
1	0.93	0.88	0.77	24.38
2	0.93	0.87	0.75	20.48
3	0.94	0.77	0.65	19.33
4	0.94	0.83	0.69	18.36
5	0.94	0.85	0.73	20.11
6	0.94	0.83	0.72	25.25
7	0.95	0.88	0.76	23.84
8	0.94	0.85	0.72	22.92
9	0.94	0.82	0.70	20.91
10	0.94	0.89	0.75	26.01
11	0.95	0.82	0.70	21.42
12	0.94	0.81	0.69	18.89
13	0.92	0.92	0.81	20.87
14	0.95	0.86	0.74	18.66
15	0.92	0.89	0.73	20.25
16	0.94	0.92	0.80	20.41
17	0.94	0.82	0.71	17.12
18	0.95	0.83	0.71	18.07
19	0.93	0.92	0.82	24.53
20	0.93	0.89	0.78	21.12
21	0.93	0.84	0.72	14.41
22	0.94	0.84	0.71	16.31
23	0.94	0.80	0.67	20.46
24	0.92	0.88	0.77	20.80
25	0.94	0.77	0.63	18.90
26	0.95	0.79	0.67	18.06
27	0.93	0.90	0.80	20.31

the coefficient of determination (R^2), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error(MAPE) from the test dataset. Moreover, the performance of different configurations of the machine learning model is also assessed based on the similarity between the ET_o predicted by these models and ET_o by the standard PM approach, using the Pearson correlation coefficient analysis.

For each combination of climatic conditions, twenty-seven regression models are trained. The performance of

4.1. Assessment of performance of regression models

For each combination of climatic conditions, twenty-seven regression models are trained. The performance of regression models is evaluated using R^2, RMSE, MAE, and MAPE and reported in Table 6 and comparative analysis is shown in Fig. 10. The R^2 of each regression model is high in the range of 0.92 and 0.95. and RMSE assesses the average errors in predicted value by a machine learning model. The RMSE of each regression model is low in the range of 0.77 to 0.92. The MAE assesses the magnitude of errors in predicted values by a machine learning model. The MAE by all the regression models is in the range of 0.63 to 0.82 mm day^{-1}. The MAPE is the measure of goodness of fit of the regression model. The lower values of MAPE of all the regression models are in the range of 14.4% to 26.01% revealing the goodness of fit of all of the regression models. Comparative analysis of each regression model using these performance matrices is also shown in Fig. 10. The lower values of MEA, MSE, and RMSE for each regression model reflect that there is a minimum difference in actual and predicted values of the ET_o from the test dataset.

4.2. Assessment of the performance of the proposed hybrid ensemble model

The performance of the proposed hybrid ensemble model (Model-A) is assessed by evaluation metrics of R^2, RMSE, MAE, and MAPE. Model-A is the hybrid ensemble machine learning model, which takes ET_o from Model-C and incorporates RHmax, WSmax, and n/N with a classification process as input. Model-B uses all the inputs to the machine learning model while Model C uses only Tmean as input to the model. The performance of Model-A is compared against Model-B and Model-C using the evaluation metrics. Moreover, the ET_o prediction by each configuration of the machine learning model is also compared against the standard PM approach using the Person correlation (r), to assess the accuracy of each configuration of the machine learning model. The R^2, RMSE, MAE, MAPE, and r of each of the three configurations of machine learning models is reported in Table 7. The proposed hybrid ensemble model (Model-A) outperformed other configurations with high R^2 of 0.94 and low values of RMSE, MAE, MAPE, and r. The performance of the proposed hybrid ensemble model (Model-A) is also assessed by comparing it against ET_o by the standard PM approach from the test dataset. The ET_o predictions made by three models are numerically correlated with the ET_o values obtained through the standard PM approach. The correlation between ET_o from Model-A and ET_o derived from the standard PM approach is found to be 0.917, as illustrated in Fig. 11. The ET_o by model-B shows a correlation of 0.778 with the ET_o by the

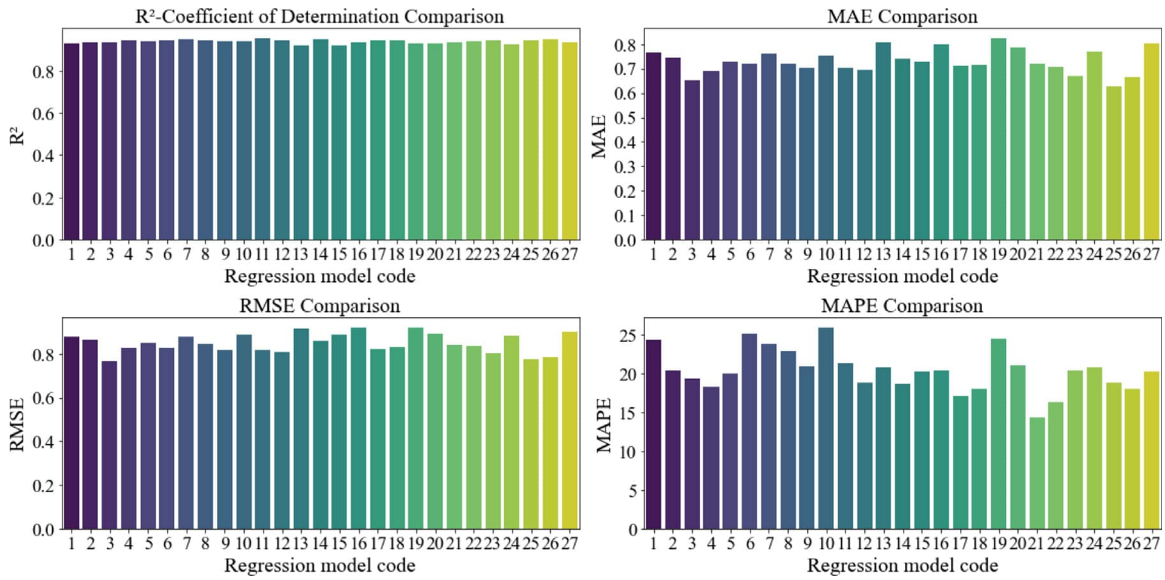

Fig. 10. Performance Analysis of regression models.

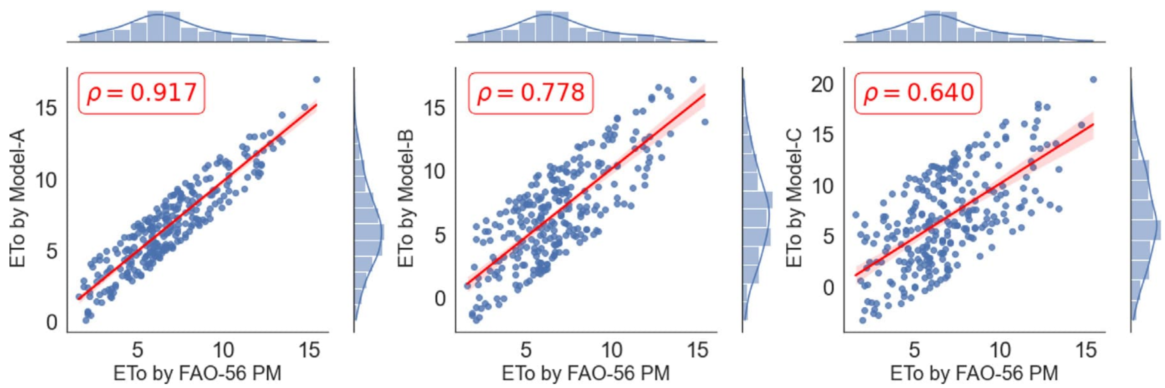

Fig. 11. Relationship between ET_o by different models and the standard PM approach.

Table 7
Performance analysis of different configurations of machine learning models.

Model	R^2	RMSE	MAE (mm day^{-1})	MAPE (%)	Pearson correlation
Model-A	0.94	0.86	0.75	15.05	0.917
Model-B	0.91	0.91	0.95	20.40	0.778
Model-C	0.89	1.16	1.01	23.76	0.640

standard PM approach. Model-C determines the ET_o from the only temperature. Model-C is part of Model-A, but it can also be used as an independent model to predict ET_o with only temperature. The ET_o predicted by model-C with its correlation to ET_o by the standard PM approach is 0.64.

The comparison of the correlation of ET_o predictions by all the models against the standard PM approach is summarized in Table 7. The ET_o by Model-A shows a Pearson correlation of 0.917 with the ET_o by the standard PM approach. The ET_o predictions by Model-A are more similar to the ET_o by the standard PM approach, compared to ET_o predictions by Model-B and Model-C. The ET_o by Model-C exhibits a Pearson correlation of 0.64 with the ET_o by the standard PM approach. The performance of Model-C is less than Model-A and Model-B in the prediction of ET_o.

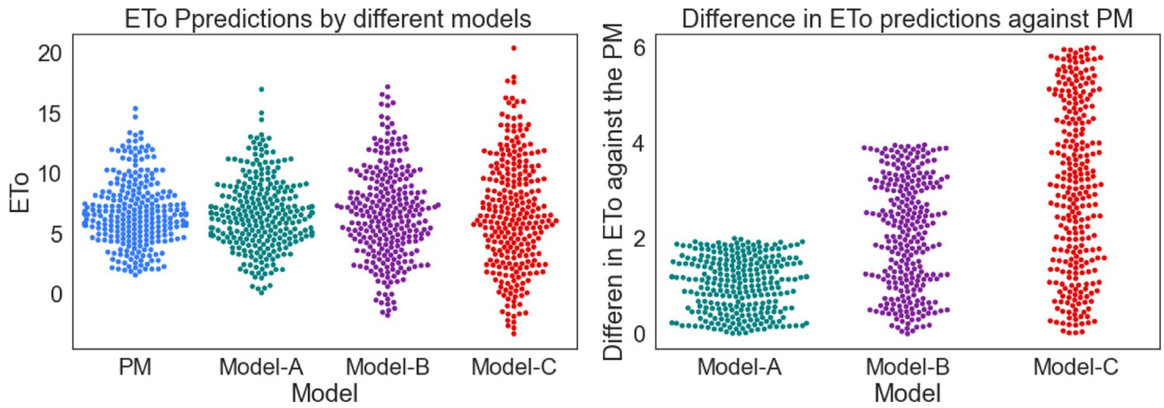

Fig. 12. Comparison of ET_o prediction by all models.

For comparison purposes, the ET_o by all the configurations of machine learning models against the standard PM approach is also shown in Fig. 12, from where it is observed that pattern ET_o predictions by the Model-A is similar to the ET_o determined by the standard PM approach. The difference in ET_o predictions against the standard PM approach by all the models is also shown in Fig. 12. The difference in ET_o prediction against the standard PM approach by Model-A is less compared to Model-B, and Model-C. The performance of Model-C in ET_o prediction is low compared to Model-B.

4.3. Discussion

The study proposed a hybrid ensembled machine learning for ET_o predictions using the IoT-based crop field sensed climatic data. IoT-sensed crop field climatic conditions help to accurately predict the ET_o according to the crop field conditions and to be in accordance with the standard PM approach. The standard PM approach of ET_o implies that climatic data should be taken at a 2-meter height from the soil surface [7]. Therefore the implication of IoT in the proposed solution helps to accurately predict the ET_o in compliance with the standard method of ET_o, and according to the real-time crop field conditions.

The proposed solution simplifies the ET_o determination process with minimum climatic conditions and is flexible in the use of the number of climatic conditions. A hybrid ensemble machine learning model (Model-A) is proposed that can use only temperature to predict ET_o, as well as can take advantage of other climatic conditions in case they are available. The proposed hybrid ensemble machine learning model is comprised of an ANN and multiple regression models. Initially, the ET_o is determined from the ANN model (Model-C) with only temperature as input. The ET_o from Model-C can be used when only temperature data is available. In case other climate data is also available the ET_o from Model-C is used as input to Model-A along with other available climate data. The other available climate data are classified according to their impact on ET_o, to serve as input to model-A. For each set of climatic conditions, a different regression model is defined. The performance of each regression model is analyzed in terms of R^2, RMSE, MAE, and MAPE of each regression model. The assessment results of regression models reveal a wide range of performance. The R^2 of regression models is in the range of 0.92 and 0.95 exhibits high R_2 values of each regression model and lower values of MAPE in the range of 14.4% to 26.01% revealing the goodness of fit of all of the regression models. The RMSE and MAE of each regression model are also low in the range of 0.77 to 0.92 and 0.63 to 0.82 mm day^{-1} respectively. This goodness of fit and accuracy of each regression model used in Model-A reveals the accuracy of Model-A.

The proposed hybrid ensemble model (Model-A) exhibits a higher R^2 value of 0.94 compared to 0.91 from Model-B. Model-A also achieves a lower MAPE value of 15.05%, compared to the MAPE value of 23.76% from Model-B. These statistics reveal that Model-A exhibits better goodness of fit compared to Model-B. Moreover, Model-A also exhibits lower RMSE and MAE values of 0.86 and 0.75 respectively compared to RMSE and MAE values of 0.91 and 0.95 from Model-B. The ET_o predicted by Model-A also exhibits the highest Pearson correlation coefficient of 0.917 with the ET_o by standard PM approach. In contrast, the ET_o predictions by Model-B exhibit the Pearson correlation of 0.778 to the ET_o by the standard PM approach. These statistics reveal that the ET_o predictions by Model-A are more accurate and in accordance with the ET_o by the standard PM approach, compared to Model-B. Model-C which uses only temperature exhibits a lower R^2 value of 0.89 compared to Model-A and Model-B. Model-C also exhibits low RMSE and MAE values of 1.16, and 1.01 mm day^{-1} respectively. The performance of Model-C is reasonable due to the use of only temperature data.

The performance analysis of the different configurations of the machine learning model describes the importance of selecting the appropriate machine learning model for ET_o prediction. Model-A shows superior performance across various metrics compared to Model-B and Model-C. However, the choice of the model should consider the availability of climatic conditions and trade-offs between the accuracy and the cost of acquiring additional climatic data. The Model-C can be used when only temperature data is available with a slight sacrifice of accuracy in ET_o predictions.

The recommended solution helps in the conservation of irrigation water by simplification the ET_o determination process. The proposed solution of ET_o determinations has several implications in precision and smart irrigation water management. The proposed hybrid ensemble machine learning model (Model-A) helps to simplify the complexity associated with the standard ET_o method using the variable number of climatic conditions. The proposed solution is limited in terms of applications and evaluation in other parts of the world with different climatic conditions. The applications and performance evaluations of the proposed solutions in other parts of the world and improving the accuracy of ET_o predictions using only temperature data are recommended for future work.

5. Conclusion

A hybrid ensemble machine learning model for ET_o predictions is proposed by using the Internet of Things (IoT) based crop field climate data to simplify the ET_o determination. The application of crop field sensed data by leveraging IoT helps to predict the ET_o according to crop field climate conditions and to be in accordance with the standard Penman-Montieth approach of ET_o determination. The proposed solution is unique in the use of a flexible number of climate conditions and in accordance with the standard Penman-Montieth approach (PM) of ET_o. The hybrid ensemble machine learning model is implemented with ANN and regression models using the climate data of Pakistan from Year 2016 to 2022. The proposed hybrid ensemble machine learning model exhibits a R^2 of 0.94, RMSE of 0.86, and MAE of 0.75 mm day^{-1} in ET_o prediction from 30% test dataset, revealing the accuracy of the proposed hybrid ensemble machine learning model in ET_o predictions. The ET_o prediction by the proposed model exhibits a Pearson correlation of 0.917 with the ET_o by the standard Penman-Montieth (PM) approach, compared to 0.778 with simple configurations of the machine learning model using ANN. The application and evaluation of the proposed solution in other parts of the world with different climate conditions is recommended for future work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgment

The authors extend their appreciation to the Deputyship for Research and Innovation, Ministry of Education in Saudi Arabia for funding this work through the project number 445-9-495. The work of Muhammad Faheem was supported in part by the University of Vaasa, and in part by the Academy of Finland.

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