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Evaluation of different machine learning methods for estimating daily reference evapotranspiration

Mojtaba Khoshravesh [1✉], Seyed Mohammad Reza Hosseini-Vardanjani [1], Roohollah Fatahi Nafchi [2], Ramin Fazloula [1], and Farahnaz Doustalizadeh [1]

[1]Department of Water Engineering, Faculty of Agricultural Engineering, Sari Agricultural Sciences and Natural Resources University, Sari, Iran
[2]Department of Water Science and Engineering, Faculty of Agriculture, Shahrekord University, Shahrekord, Iran

ARTICLE INFO	ABSTRACT
Paper Type: Research Paper **Received**: 20 December 2024 **Revised:** 11 April 2025 **Accepted**: 15 April 2025 **Published**: 01 June 2025 **Keywords** Irrigation Kuhrang Tree Model Water Demand Wind Speed **Corresponding author:** M. Khoshravesh ✉ m.khoshravesh@sanru.ac.ir	Accurate estimation of reference evapotranspiration (ET_0) is essential for effective water management in agriculture. However, ET_0 is a complex, nonlinear process influenced by many factors, and its prediction accuracy depends on the quality and combination of large, ever-growing meteorological datasets. Therefore, this study investigates the performance of the M5 tree model, the KStar algorithm, Support Vector Machines (SVM), and multiple linear regression in reducing the number of input parameters required for estimating daily reference evapotranspiration. The data used in this research include minimum and maximum temperature, average relative humidity, wind speed at two meters height, and sunshine hours, recorded at the Kuhrang station, Iran, over the period 2016–2020. The FAO Penman-Monteith model was used as the benchmark for evaluating the performance of the models. Based on data availability, various scenarios were developed for estimating ET_0 by excluding certain input variables. Evaluation metrics included Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the correlation coefficient (R^2). The results showed that the M_5 tree model outperformed the other models in scenarios $(T_{max}, T_{min}, RH_{mean}, u_2, n)$ and $(T_{max}, T_{min}, u_2, n)$, with correlation coefficients of $R^2 = 0.96$ and $R^2 = 0.97$, respectively. Further sensitivity analysis revealed that accurate estimation of evapotranspiration in this region requires temperature data, sunshine duration, and wind speed.

| **Highlights** | • M5 tree model achieved highest ET_0 accuracy ($R^2=0.97$) in humid climates with minimal inputs.
• Temperature, sunshine, and wind speed were key ET_0 predictors.
• Tree-based models (M5) outperformed kernel/regression methods (KStar, SVM, MLR).
• Weka & Python proved effective for ET_0 modeling in irrigation planning. |

1. Introduction

According to a United Nations report, the global population, which stood at 7.7 billion in 2019, is projected to increase under a medium scenario to approximately 8.5 billion by 2030, 9.7 billion by 2050, and 10.9 billion by 2100 (Leong et al., 2018). In agriculture, improving crop yields is critical to meet the growing population's demand for agricultural products. Among the water-consuming sectors, agriculture is the main user of water resources worldwide, and water scarcity has become a major global concern. More than 69% of the freshwater available on Earth is used for agricultural purposes (Alves et al., 2023). Approximately 70% of the water used for agricultural activities is wasted due to poor management. The main reason for water wastage in agricultural activities is irrigation without considering reference evapotranspiration, ET_0, (Bellido-Jiménez et al., 2021). Accurate ET_0 calculations are essential for optimizing water resource management and

developing more precise irrigation planning (Bellido-Jiménez et al., 2022).

The direct measurement of evapotranspiration (ET) using a lysimeter is accurate but costly and time-consuming. As a result, estimating ET from climatic data has become more common. The Penman-Monteith model, recommended by the FAO, estimates ET using temperature, humidity, wind speed, and solar radiation. However, these variables are not always available at a single station. Moreover, ET is a complex and nonlinear process influenced by multiple interrelated climatic factors, making accurate modeling difficult, error-prone, or dependent on extensive and hard-to-obtain data (Doogers and Allen, 2002).

In recent years, the application of machine learning models in water engineering sciences has expanded significantly. Numerous studies have been conducted worldwide on modeling ET using machine learning models. Samadianfard and Panahi (2019) estimated daily ET_0 using support vector regression (SVR) and M_5 tree models. In their study, the accuracy of these methods in estimating reference crop was compared with the empirical Hargreaves and Turc-Thornthwaite methods using meteorological data series of the Tabriz synoptic station from 1992 to 2015. Statistical analysis and Taylor diagrams demonstrated that the SVR and M_5 models, when considering all meteorological parameters, yielded root mean square errors of 0.398 and 0.411, respectively, outperforming the empirical Hargreaves and Turc-Thornthwaite methods. Siasar and Tooraj (2019) applied support vector machines (SVM), CHAID, and random forest (RF) models to estimate daily ET_0 in northern Sistan and Baluchestan Province. Their results indicated that among the SVM, CHAID, and RF models, the RF model demonstrated the highest accuracy, achieving a correlation coefficient (R) of 0.983 and the lowest mean absolute error (MAE) of 0.798 when using maximum temperature, mean temperature, mean humidity, wind speed, and pan evaporation as inputs. Piri (2024) examined the effectiveness of SVM, Decision Trees, Random Forests, and Gaussian Process Regression in predicting daily reference evapotranspiration at coastal stations in southern Iran. Twenty years of climatic data were used to calculate reference evapotranspiration using the FAO Penman-Monteith method, and six combined scenarios based on variable correlations were evaluated. The results showed that all four data-driven methods performed well, with Gaussian Process Regression delivering the most accurate estimates.

In the study by Lum et al. (2017), the capability of the M_5 tree model (M_5MT) for predicting ET_0 was examined. The M_5MT model was trained and tested using climatic data from eight meteorological stations in coastal regions of Iran for the period 2000–2008. The model was further validated with meteorological data from seven stations in the California Irrigation Management Information System (CIMIS) for the year 2015. The results indicated that M_5MT performed effectively in estimating ET_0. Malekahmadi et al. (2022) evaluated the modeling of daily ET using regression and intelligent models at the Scottsbluff station in Nebraska. The results indicated that wavelet transformation, support vector machines (SVM), artificial neural networks (ANN), decision trees, and multiple linear regression showed progressively better performance in estimating daily ET at this station.

Bakhtiari et al. (2022) investigated the capability of four data-driven methods, including artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), support vector machines (SVM), and the M_5 tree model, for estimating daily ET_0 in the southern Caspian Sea region. Different combinations of climatic data, such as solar radiation, mean air temperature, mean relative humidity, and wind speed, were used as input variables for the period 1991–2020. The estimates from these models were compared with the FAO-56 Penman-Monteith method as a standard reference. The results showed that ANFIS demonstrated higher accuracy for ET_0 estimation, especially during the validation phase when all climatic variables were used as inputs in synoptic stations. Overall, based on performance evaluations, ANFIS with inputs including solar radiation, mean air temperature, mean relative humidity, and wind speed provided the highest accuracy, while ANN, SVM, and M_5 with only wind speed as an input showed the lowest performance. ANFIS models using temperature and solar radiation are recommended for ET_0 modeling in regions with limited climatic data availability. Makwana et al. (2023) developed and compared artificial intelligence models for estimating daily ET_0 using limited input variables. Meteorological data, including maximum temperature (T_{max}), minimum temperature (T_{min}), relative humidity (RH), wind speed (WS), and sunshine hours, from the Sardarkrushinagar station in northern Gujarat, India, were used in this study. The artificial intelligence models evaluated included ANN, extreme learning machines (ELM), M_5 tree, and multiple linear regression (MLR). The FAO Penman-Monteith model was used for evaluation. The results revealed that ANN models outperformed ELM, M_5 Tree, and MLR in terms of performance metrics.

Mikaeili and Samadianfard (2021) investigated the application of tree-based and kernel-based models for determining daily ET_0 in two contrasting regions of Iran: humid and arid. The study utilized support vector regression (SVR), RF, and the M_5P tree model to predict daily ET_0 at the Astara and Sirjan stations, located in humid and arid regions of Iran, respectively. The input data included meteorological variables such as minimum, average, and maximum temperatures, relative humidity, solar radiation, and wind speed, collected over the period 2000–2020. The accuracy of these methods and various empirical methods for estimating daily ET_0, including Hargreaves-Samani, McGuinness, Turc, and Dalton methods. Validation results demonstrated that the SVR_3 (scenario 3 with support vector regression) and M_5P_3 (scenario 3 with the M_5P tree model) performed better at the Astara station, while SVR_3 outperformed other methods at the Sirjan station, compared to the aforementioned empirical models.

A review of previous studies highlights the strong performance of intelligent, data-driven models in estimating ET_0. Given the critical importance of accurate ET calculation for the design, planning, and management of irrigation and drainage networks, this study evaluated tree-based models (M_5, KStar), SVM, and MLR for reducing the number of input parameters required to model daily ET_0 in the humid climate of Kuhrang.

2. Materials and Methods
2.1 Study area

Kuhrang County is the largest county in the Chaharmahal and Bakhtiari Province of Iran, with its administrative center located in the city of Chelgerd. Kuhrang is one of the coldest regions in Iran, with an average annual temperature of 2.9 °C. Based on the De Martonne index, the area has a very humid climate, while according to the Ambrothermic index, it is classified as highly humid (Anonymous, 2020). According to Dr. Karimi's classification, the region has a very humid climate with mild summers and extremely cold winters. This county serves as the source of the Zayandeh River, Karun River, and Dez River. The Kuhrang synoptic station is located at a latitude of 32.46 degrees and a longitude of 50.13 degrees, at an altitude of 2365 meters above sea level. The geographical and climatic characteristics of the study area are shown in Fig. 1.

Fig. 1 Study Area
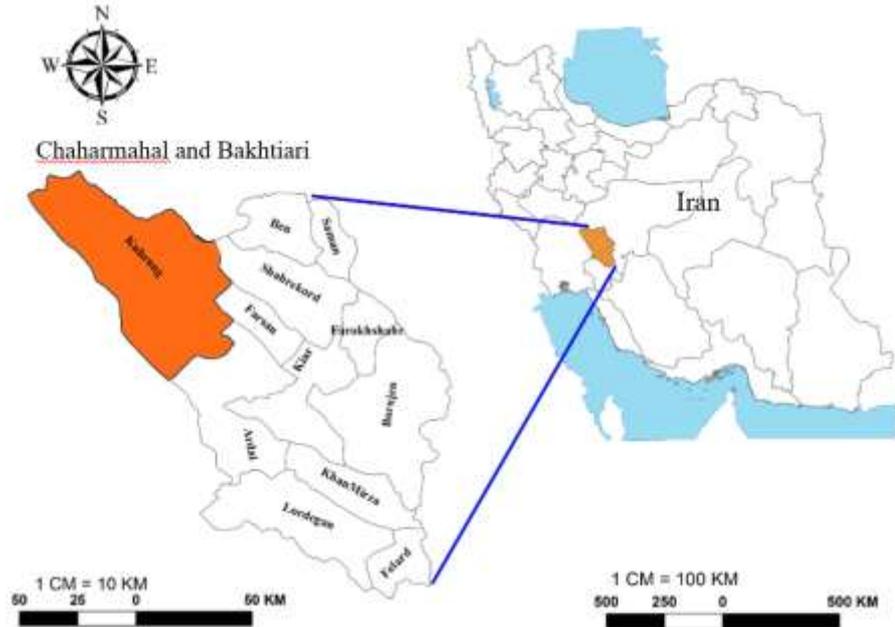
The station is located in Kuhrang at a latitude of 32.46° and a longitude of 50.13°. It is situated in a humid climate region at an elevation of 2,365 meters above sea level. The data used in this study include minimum and maximum temperature, mean relative humidity, wind speed at a height of two meters, and sunshine duration, collected from the Kuhrang station for the period 2016–2020.

2.2 FAO Penman-Monteith Model

The FAO Penman-Monteith model is one of the most reliable methods used by experts for estimating ET_0. In this method, the reference crop is grass with a height of 12 cm and a radiation reflection coefficient (albedo) of 23%. This model is recognized as the standard reference equation for ET, and other methods are calibrated against it. The equation is represented as shown in Eq. 1 (Hosseini-Vardanjani et al., 2022)

$$ET_0 = \frac{0.408 . \Delta (R_n - G) + \gamma \left[\frac{900}{(T+273)}\right] U_2 (e_a - e_d)}{\Delta + \gamma (1 + 0.34\, U_2)} \qquad (1)$$

where ET_0: daily evapotranspiration (mm/day), R_n: the daily solar radiation reaching the plant surface (MJ/m²/day), G: the soil heat flux (MJ/m²/day), γ: the psychrometric constant (kPa/°C), T: the mean daily air temperature (°C), u_z: the wind speed at 2 meters above the ground (m/s), e_a: the saturated vapor pressure (kPa), e_a : the actual vapor pressure (kPa), and Δ: the slope of the saturated vapor pressure curve (kPa/°C). The parameters for this model were calculated based on the guidelines provided in the FAO Irrigation and Drainage Paper No. 56 using the available data.

2.3 M₅ Tree Model

The M_5 tree model is advantageous due to its interpretability, straightforward training process, and lack of reliance on trial-and-error. It performs robustly when dealing with missing data and is well-suited for large datasets with high dimensionality. The M_5 tree model is a binary decision tree, where each terminal node contains linear regression relationships capable of predicting numerical values.

The development of the M_5 tree model occurs in two stages:

1. Determining the optimal input parameter for branching and identifying the splitting criterion to create a decision tree. Selecting an appropriate splitting parameter and establishing split points in the tree are crucial. Various methods are available for identifying the breakpoint. Each node is divided into two sub-nodes based on the similarity among its members.

2. The splitting criterion for the M_5 tree algorithm is based on considering the standard deviation of the values leading to each node as the measure of error at that node. It calculates the expected reduction in this error as a result of testing each attribute at that node.

The reduction in standard deviation is calculated using Eq. 2 (Shojaei et al., 2022):

$$SDR = sd(T) - \sum \frac{|T_i|}{|T|} sd(T_i) \qquad (2)$$

Where T: the set of samples that reach the node, T_i: the subset of samples corresponding to the i-th output from the potential split, and Sd : the standard deviation. The splitting process at

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each node is repeated iteratively until a terminal node is reached, where the squared deviation from the mean of the data approaches zero.

The second stage in the model design involves pruning the overgrown tree. This is achieved by replacing a branch with a single leaf (substituting linear regression relationships for the branches). This tree-building technique divides the input parameter space into subdomains and provides a linear relationship for each of them. The models used minimum and maximum temperatures and wind speed at a height of two meters as input data, while the output was ET_0 calculated using the FAO Penman-Monteith model. The dataset was split into 75% for training and validation and 25% for testing (Hosseini Vardanjani et al., 2024).

2.4 Kstar Model

In the KStar algorithm, the distance between one instance and another can be described as the complexity of transforming one instance into the other (Granata et al., 2019). This algorithm employs an entropy-based distance function. The entropic distance is used to identify the instances within the dataset that share the greatest similarity (Ekmekcioğlu et al., 2020).

To implement the M_5 tree and KStar models, the input and output data were processed using Weka software (version 3.9.2), developed by the University of Waikato in New Zealand. Weka is well-known for its extensive suite of data mining algorithms. In these models, the ET_0 values obtained from the FAO Penman-Monteith method served as the output, while the input variables included minimum and maximum temperatures, mean relative humidity, sunshine duration, and wind speed at two meters.

2.5 Support vector machine model

This technique involves a set of supervised machine learning models associated with kernel functions, used for regression (SVR) and nonlinear classification implementation (SVC). It creates an optimal separating hyperplane by taking a low-dimensional input vector and mapping it into a higher-dimensional feature space using the Vapnik-Chervonenkis dimension theory as the basis for ensuring high generalization capability of the network (Anifowos et al., 2015; Vapnik, 2000).

The optimal hyperplane functions as a maximum-margin separator between two classified vectors using a few training data points to determine the margin for error-free separation. When this occurs, the ratio of expected support vector values to the training data constrains the expected error probability values.

2.6 Multiple linear regression

Multiple Linear Regression, MLR, often referred to simply as multiple regression, is a statistical method used to predict the outcome of a response variable by combining multiple explanatory variables. MLR is applied when simple linear regression alone cannot fulfill the desired objective and helps determine the effectiveness of selected predictor variables in forecasting the dependent variable.

This study evaluated the M_5 tree, KStar, SVM, and MLR models for reducing the input parameters required to model daily ET_0 in the humid climate of Kuhrang. The input data for the models included minimum and maximum temperatures and wind speed at a height of two meters, while the output was ET calculated using the FAO Penman-Monteith model. The dataset was divided into 75% for training and validation and 25% for testing. (Hosseini Vardanjani et al., 2024). To implement the M_5 tree and KStar models, the input and output data were processed using Weka software (Weka 3.9.2), a tool developed by the University of Waikato in New Zealand. Weka is notable for its comprehensive coverage of data mining algorithms. The ET values computed via the FAO Penman-Monteith model were used as the output for the M_5 tree and KStar models, while input variables included minimum and maximum temperatures, mean relative humidity, sunshine duration, and wind speed at two meters. The SVM and MLR models were executed using Python programming.

2.7 Performance assessment criteria

To evaluate the methods, the following statistical indices were calculated based on Eqs. 3 to 5 (Valipour et al., 2017; Karami et al., 2020):

$$RMSE = \sqrt{\frac{\Sigma(O_i - P_i)^2}{n}} \qquad (3)$$

$$MAE = \frac{\sum_{i=1}^{N}(|O_i - P_i|)}{N} \qquad (4)$$

$$R = \frac{\sum_{i=1}^{N} O_i P_i}{\sqrt{\sum_{i=1}^{N} O_i^2 \sum_{i=1}^{N} P_i^2}} \qquad (5)$$

where O_i: *ET* calculated using the FAO Penman-Monteith method, P_i: ET estimated by the models, *MAE*: the mean absolute error, *RMSE*: the root mean square error, and *R*: the correlation coefficient.

3. Results and Discussion

The results for the M_5 tree and KStar models are presented in Table 1. The M_5 tree model demonstrated high accuracy across various input scenarios, with R^2 values consistently exceeding 0.88. Scenario 4, which included the inputs T_{max}, T_{min}, u₂, and n (sunshine duration), achieved the highest accuracy with R^2 = 0.97, MAE = 0.2370, and RMSE = 0.3208. This highlights that incorporating wind speed (u₂) and sunshine duration (n) significantly enhances the model's predictive capability. Conversely, Scenario 5 (T_{max}, T_{min}, RH_{mean}) yielded the lowest accuracy, with R^2 = 0.83, MAE = 0.5890, and RMSE = 0.7478, representing the poorest performance. These results emphasize the critical role of temperature-related variables in modeling ET.

The KStar model performs comparably to the M_5 tree model. Scenario 4 (T_{max}, T_{min}, u₂, n) yields the highest R^2 value of 0.97, with MAE = 0.2665 and RMSE = 0.34, confirming the robustness of this input combination. Similar to the M_5 model, adding sunshine duration (n) and wind speed (u₂) significantly enhances predictive accuracy.

In contrast, Scenario 5 (T_{max}, T_{min}, RH_{mean}) shows the lowest R^2 value (0.83) and the highest errors (MAE = 0.6216, RMSE = 0.7670 mm/day), indicating reduced model capability in the absence of wind speed and sunshine duration. Overall, the

KStar model demonstrates stable performance with slightly higher errors compared to the M_5 tree model.

Table 1 Statistical Analyses of the M_5 Tree and Kstar Model

Number	Scenario	R^2	MAE	RMSE
	M_5 Tree Model			
1	$T_{max}, T_{min}, RH_{mean}, u_2, n$	0.97	0.2507	0.3429
2	$T_{max}, T_{min}, RH_{mean}, u_2$	0.90	0.4644	0.5826
3	$T_{max}, T_{min}, RH_{mean}, n$	0.92	0.3940	0.5147
4	T_{max}, T_{min}, u_2, n	0.97	0.2370	0.3208
5	$T_{max}, T_{min}, RH_{mean}$	0.83	0.5890	0.7478
6	T_{max}, T_{min}, u_2	0.88	0.5126	0.6337
7	T_{max}, T_{min}, n	0.92	0.4071	0.5167
	KStar Model			
1	$T_{max}, T_{min}, RH_{mean}, u_2, n$	0.97	0.2734	0.3597
2	$T_{max}, T_{min}, RH_{mean}, u_2$	0.89	0.50	0.6168
3	$T_{max}, T_{min}, RH_{mean}, n$	0.92	0.4322	0.5523
4	T_{max}, T_{min}, u_2, n	0.97	0.2665	0.34
5	$T_{max}, T_{min}, RH_{mean}$	0.83	0.6216	0.767
6	T_{max}, T_{min}, u_2	0.88	0.5418	0.6578
7	T_{max}, T_{min}, n	0.92	0.4348	0.54

The results of the SVM and MLR models are presented in Table 2. The SVM model demonstrates moderate performance compared to the M_5 and KStar tree models. Scenario 4 (T_{max}, T_{min}, u_2, n) again emerges as the most effective scenario, yielding R = 0.96, MAE = 0.32, and RMSE = 0.4. However, the errors are slightly higher than those of the M_5 and KStar models for the same scenario. The lowest performance is observed in Scenario 5 ($T_{max}, T_{min}, RH_{mean}$) with R^2 = 0.76, MAE = 0.64, and RMSE = 0.78. These findings reiterate the significance of temperature-related variables for accurately estimating ET. While SVM shows notable robustness, the error metrics suggest it may be less reliable than the M_5 and KStar models for precise predictions.

The MLR model generally performs weaker than the other three models. Scenario 4 (T_{max}, T_{min}, u_2, n) achieves the highest R^2 value of 0.90, with MAE = 0.42 and RMSE = 0.49, but the errors are considerably higher than those of the M_5 and KStar models for the same scenario. Scenario 5 ($T_{max}, T_{min}, RH_{mean}$) shows the poorest performance, with R^2 = 0.76, MAE = 0.65, and RMSE = 0.78. This highlights the limitations of the MLR model in capturing the complex interactions between variables without including temperature-related data. Overall, while MLR provides a baseline comparison, it lacks the accuracy and reliability of the other models. Ayaz et al. (2021) focused on estimating ET_0 using machine learning models under limited data conditions. In their study, the FAO56 Penman-Monteith model was used as the standard reference, and several ML models including Long Short-Term Memory (LSTM) neural networks, Gradient Boosting Regression (GBR), RF, and SVR were developed to estimate ET_0 using various climatic variables as input parameters.

Table 2 Results of the Support Vector Machine (SVM) Model

Number	Scenario	R^2	MAE	RMSE
1	$T_{max}, T_{min}, RH_{mean}, u_2, n$	0.90	0.38	0.49
2	$T_{max}, T_{min}, RH_{mean}, u_2$	0.79	0.60	0.73
3	$T_{max}, T_{min}, RH_{mean}, n$	0.86	0.44	0.56
4	T_{max}, T_{min}, u_2, n	0.92	0.32	0.40
5	$T_{max}, T_{min}, RH_{mean}$	0.76	0.64	0.78
6	T_{max}, T_{min}, u_2	0.81	0.57	0.69
7	T_{max}, T_{min}, n	0.88	0.41	0.52
	Multivariate Regression Model			
1	$T_{max}, T_{min}, RH_{mean}, u_2, n$	0.90	0.41	0.50
2	$T_{max}, T_{min}, RH_{mean}, u_2$	0.81	0.58	0.69
3	$T_{max}, T_{min}, RH_{mean}, n$	0.86	0.48	0.59
4	T_{max}, T_{min}, u_2, n	0.90	0.42	0.49
5	$T_{max}, T_{min}, RH_{mean}$	0.76	0.65	0.78
6	T_{max}, T_{min}, u_2	0.79	0.60	0.73
7	T_{max}, T_{min}, n	0.86	0.47	0.58

The results indicated that LSTM and SVR were the most effective ML models for estimating ET_0 with minimal meteorological data. While the highest accuracy was achieved using the full set of input variables, the study also demonstrated that even reduced input combinations such as a three-variable set (temperature, wind speed, and relative humidity) or two-variable sets (temperature and relative humidity, or temperature and wind speed) can still yield promising results for ET_0 estimation. Sharafi et al. (2024) investigated the accuracy of artificial intelligence models (M_5P

and Random Forest) in comparison with the Hargreaves model for estimating daily evapotranspiration at two stations: Urmia and Yazd. The results indicated that incorporating meteorological parameters such as maximum and minimum temperature, relative humidity, wind speed, and sunshine hours as model inputs significantly improved estimation accuracy. At the Yazd station, the hybrid Hs-M_5P model achieved the best performance, while at the Urmia station, the Hs-RF model produced the most accurate estimates of daily evapotranspiration.

In all scenarios, the M_5 tree model consistently demonstrates the best performance in terms of accuracy (higher R values) and lower error metrics (MAE, RMSE). The KStar model ranks second, achieving similar R^2 values but with slightly higher errors. The SVM model shows moderate performance but falls behind the M_5 and KStar models. The MLR model exhibits the least accuracy and the highest errors, revealing its limitations in managing the complex relationships in ET data. Scenarios including temperature variables (T_{max}, T_{min}) alongside wind speed (u_s) and sunshine duration (n) yield the best results across all models, emphasizing the importance of these variables for accurate ET_0 predictions. Future studies

could explore additional variables or advanced hybrid models to further enhance prediction accuracy.

The modeling results using the M_5 tree model revealed that this model offers high accuracy in estimating ET in this region. The M_5 tree model provides simple linear relationships for estimating ET_0, with each relationship tailored to specific conditions of temperature, humidity, sunshine hours, wind speed, and other factors. Among the various models tested, Model 1, which includes the most input parameters, and Model 4, with four input parameters, showed the least error and the highest correlation with the FAO Penman-Monteith model. Reducing the input parameters led to a decline in model accuracy, primarily due to the decreased number of inputs and their combined effects. Among the models with three input parameters, Model 7, which uses maximum temperature, minimum temperature, and sunshine hours, demonstrated the highest correlation and the lowest error with the FAO Penman-Monteith model. Overall, the results indicate the strong performance of the M_5 tree model in estimating ET_0. The distribution of results from the M_5 tree model and the FAO Penman-Monteith model is illustrated in Fig. 2.

Fig. 2 The distribution of ET calculated using the M_5 tree model compared with the FAO Penman-Monteith model (mm/day)
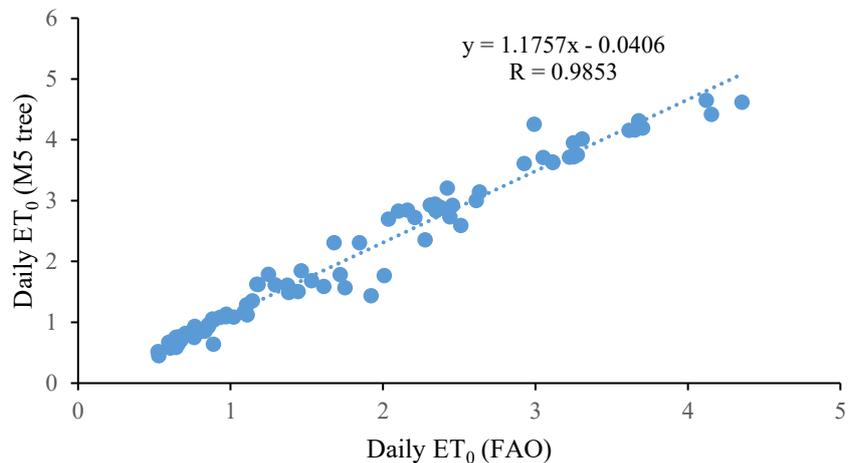
As shown in Fig. 2, there is a strong correlation between ET_0 estimated by the M_5 tree model and the FAO Penman-Monteith model. Mirhashemi et al. (2020) evaluated the M_5P algorithm for estimating potential ET using minimum and maximum temperatures at the Sari station. The results indicated that the tree model performed well in estimating potential ET at this station.

For the KStar model, the results showed that among the various designed models, Model 1 with the highest number of input parameters and Model 4 with four input parameters had the least error and the highest correlation with the FAO Penman-Monteith model. Reducing input parameters decreased model accuracy, mainly due to fewer inputs and their combined effects. Among the models with three inputs, Model 7, which used maximum temperature, minimum temperature, and sunshine hours, had the highest correlation and the lowest error with the FAO Penman-Monteith model. However, the KStar model's performance was weaker compared to the M_5 tree model. Terzi (2007) modeled pan evaporation using meteorological data from Lake Eğirdir in Turkey and found that air temperature, water temperature,

solar radiation, and relative humidity were the most influential factors on pan evaporation. This study used data mining algorithms such as KStar, M_5Rules, M_5, neural networks, and regression methods. The results demonstrated the superior accuracy of the M_5 model compared to other methods.

The results of the SVM and MLR models for reducing the required parameters for daily ET_0 modeling also showed that reducing input parameters decreases the accuracy of these models. For both models, Model 1 with the most input parameters and Model 4 with four input parameters showed the least error and the highest correlation with the FAO Penman-Monteith model. Removing input parameters consistently reduced model accuracy. Kavoosi et al. (2017) evaluated the least-squares support vector machine (LS-SVM) model for estimating evaporation and compared it with empirical models in the Birjand plain. The results showed that the support vector machine performed well in estimating ET in this region. The findings of this study align with another research conducted nationwide. Zorati Pure et al. (2018) simulated and compared potential ET using artificial neural networks, neuro-fuzzy systems, and the M_5 decision tree

model at the Shiraz synoptic station. The results demonstrated the reliable performance of the M_5 tree model in predicting ET_0. Mikaeili et al. ([2024](#)) evaluated strategies for combining empirical and tree-based models to predict ET_0. Three data-driven models (M_5P tree, REP tree, and RF) were used to estimate daily ET_0. Validation results indicated that the standalone M_5P model (with RMSE = 0.083 and NS = 0.998 at the Bam station) and the weighted averaging method combining tree-based models (RMSE = 0.155 and NS = 0.994 at Bam and Sirjan stations) produced the most accurate estimates of ET_0 across all studied stations.

Samadianfard and Panahi ([2019](#)) applied SVR and M_5 tree models to estimate daily ET_0. Based on statistical evaluations and Taylor diagram analysis, the SVR and M_5 models, when incorporating all available meteorological variables, achieved lower root mean square errors of 0.398 and 0.411, respectively, indicating superior accuracy over the traditional empirical models. Ganjei and Nazemi ([2024](#)) investigated the performance of machine learning methods in modeling daily reference evapotranspiration and its spatial distribution across Zanjan Province. They evaluated the effectiveness of several machine learning approaches—namely, multiple linear regression, gene expression programming, and RF—in estimating daily reference evapotranspiration. The results indicated that the RF model generally outperformed the other methods in estimating evapotranspiration, except at the Zanjan station.

Although reducing input parameters and combining them increased the error and decreased the models' accuracy, the tree-based model proved to be a more effective solution when the required data are unavailable compared to other models examined in this study. Moreover, it was identified that, given the exclusion of certain input parameters in this region, the ET equation exhibits a higher dependency on temperature, wind speed, and sunshine duration. Therefore, these variables are essential for accurately estimating ET in this area.

4. Conclusion

1. Machine learning models achieve high accuracy in estimating daily ET_0 in this region and offer a suitable solution for estimating evapotranspiration under limited climatic data conditions.

2. ET modeling using the various models presented in this study showed that the M_5 tree model provides highly accurate estimations of ET in this area.

3. The M_5 model offers simpler, more linear, and more interpretable relationships. Therefore, this study recommends the M_5 tree model for ET estimation in this region.

4. The use of machine learning methods with limited meteorological data can still provide satisfactory estimates of daily reference evapotranspiration.

Future research should investigate the application of hybrid models, such as combining decision trees with neural networks or ensemble learning techniques, which may offer improved accuracy and robustness across diverse climatic regions by capturing more complex patterns and interactions in climatic data. Based on these findings, it is recommended that the methods used in this study be further evaluated alongside other

machine learning algorithms in regions with different climatic conditions. The results should then be compared to identify the most suitable method for each climate type.

Data availability

Data can be sent from the corresponding author by email upon request.

Conflicts of interest

The author of this paper declared no conflict of interest regarding the authorship or publication of this paper.

Author contribution

S. M. R. Hosseini-Vardanjani: Modeling and Results Analysis; Mojtaba Khoshravesh: Writing-review & editing, Supervision; R. Fatahi Nafchi: Research Management; R. Fazloula: Supervision and F. Doustalizadeh: Modeling and Results Analysis

AI Use Declaration

This study did not incorporate artificial intelligence techniques; instead, all analyses and optimizations were conducted using conventional and widely accepted analytical methods.

References

Alves, R. G., Maia, R. F., & Lima, F. (2023). Development of a Digital Twin for smart farming: Irrigation management system for water saving. *Journal of Cleaner Production, 388,* 135920, DOI: https://doi.org/10.1016/j.jclepro.2023.135920

Anifowose, F., Labadin, J., & Abdulraheem, A. (2015). Improving the prediction of petroleum reservoir characterization with a stacked generalization ensemble model of support vector machines. *Applied Soft Computing, 26,* 483–496. DOI: https://doi.org/10.1016/j.asoc.2014.10.017

Anonymous. (2020). Water Productivity Improvement Program for Agriculture in Chaharmahal and Bakhtiari Province. Chaharmahal and Bakhtiari Agricultural and Natural Resources Research and Education Center. 25 pages.

Ayaz, A., Rajesh, M., Singh, S. K., & Rehana, S. (2021). Estimation of reference evapotranspiration using machine learning models with limited data. *AIMS Geosciences, 7,* 268-290. DOI: 10.3934/geosci.2021016

Bakhtiari, B., Mohebbi-Dehaghani, A., & Qaderi, K. (2022). Comparative analysis of data-driven methods for daily reference evapotranspiration estimation of Southern Caspian Sea. *Meteorological Application, 29*(4), 16. DOI: https://doi.org/10.1002/met.2091

Bellido-Jim´enez, J. A., Est´evez, J., & García-Marín, A. P. (2022). A regional machine learning method to outperform

temperature-based reference evapotranspiration estimations in Southern Spain. *Agricultural Water Management, 274*. DOI: https://doi.org/10.1016/j.agwat.2022.107955

Bellido-Jiménez, J. A., Estévez, J., & García-Marín, A. P. (2021). New machine learning approaches to improve reference evapotranspiration estimates using intra-daily temperature-based variables in a semi-arid region of Spain. *Agricultural Water Management, 245*, 106558. DOI: https://doi.org/10.1016/j.agwat.2020.106558

Droogers, P., & Allen, R. G. (2002). Estimating reference evapotranspiration under inaccurate data conditions. *Irrigation and Drainage. Systems, 16*, 33-45. DOI: 10.1023/A:1015508322413

Ekmekcioğlu, Ö., Başakın, E. E., & Özger, M. (2020). Tree-based nonlinear ensemble technique to predict energy dissipation in stepped spillways. *European Journal of Environmental and Civil Engineering,* 1-19. DOI: 10.1080/19648189.2020.1805024

Ganjei, S., & Nazemi, A. H. (2024). Comparing the performance of machine learning methods in modeling daily reference ET and its spatial distribution (case study: Zanjan province). *Irrigation Science and Engineering, 48*(1), 77-92 [In Persian].

Granata, F., Di Nunno, F., Gargano, R., & de Marinis, G. (2019). Equivalent discharge coefficient of side weirs in circular channel- a lazy machine learning approach, *Water, 11*(11), 2406 DOI: 10.3390/w11112406

Hosseini Vardanjani, S. M., Ganjikhorramdel, N., Khaltabadi Farahani, A., Khoshravesh, M., & Nouri Khajebelagh, R. (2024). A generalization of the M5 Tree model and artificial neural network model for estimating daily reference evapotranspiration under minimal climatic data conditions. *Journal of Water and Climate Change, 15*(12), 5882-5892. DOI: 10.2166/wcc.2024.500

Hosseini Vardanjani, S. M., Khoshravesh, M., Hosseini-Kakolaki, S. E., & Pourgholam-Amiji, M. (2022). Evaluation of hybrid model ANN-PSO and different data mining methods in estimating monthly evapotranspiration in two different climates. *Iranian Journal of Irrigation and Drainage, 16*(5), 924-936 [In Persian].

Kavoosi, M., Khasheisiuki, A., Pourrezabilondi, M., & Najafi, M. H. (2017). Evaluation of LSSVM model to estimation of evaporation and its comparison with empirical models. *Environment and Water Engineering, 3*(3), 235-246 [In Persian].

Karami Moghadam, M., Amini, A., & Keshavarzi, A. (2020). Intake design attributes and submerged vanes effects on sedimentation and shear stress. *Water and Environment Journal*. https://doi.org/10.1111/wej.12471

Leong, D. P., Teo, K. K., Rangarajan, S., Lopez-Jaramillo, P., Avezum Jr, A., & Orlandini, A. (2018). World Population Prospects 2019. Department of Economic and Social Affairs Population Dynamics. New York (NY).

Lum, M., Bateni, S. M., Shiri, J., & Keshavarzi, A. (2017). Estimation of reference evapotranspiration from climatic data. *International Journal of Hydrology, 1*(1), 25-30. DOI: https://doi.org/10.15406/ijh.2017.01.00005

Makwana, J. J., Tiwari, M. K., & Deora, B. S. (2023). Development and comparison of artificial intelligence models for estimating daily reference evapotranspiration from limited input variables. *Smart Agricultural Technology, 3*, 100115. DOI: https://doi.org/10.1016/j.atech.2022.100115

Malekahmadi, H., Mirzania, E., Khosravi, S., & Ebrahim Zadeh, A. (2022). Daily evapotranspiration modeling using regression and intelligent models (Case Study). *Iranian Water Research Journal, 16*(1), 49-62 [In Persian]. DOI: 10.22034/iwrj.2022.10026.2338

Mikaeili, F., Samadianfard, S., and Delirhasannia, R. (2023). Evaluating the strategy of ensemble empirical and tree-based methods in estimating reference evapotranspiration. *Environment and Water Engineering, 9*(2), 256-270 (In Persian). DOI: https://doi.org/10.22034/ewe.2022.345198.1789

Mirhashemi, S., Panahi, M., & Zareei, L. (2020). Evaluation of M5P algorithm for estimation of potential evapotranspiration, minimum and maximum temperature (Case study: Sari weather station). *Journal of Meteorology and Atmospheric Sciences, 2*(4), 287-295 [In Persian].

Piri, H. (2024). Investigating the effectiveness of data mining methods in predicting daily reference evapotranspiration (Case study: coastal strip stations in southern Iran). *Ecohydrology, 11*(2), 271-286. DOI: 10.22059/ije.2024.375755.1816

Sadeghian Agkandy, M., Rezaie, H., Khalili, K., & Ahmadie, F. (2024). Investigating the performance of Kstar and GPR algorithms in modeling RDI meteorological drought index (Case study: east of Urmia Lake basin). *Journal of Civil and Environmental Engineering, 54.1*(114), 142-151. DOI: 10.22034/ceej.2023.55292.2225. [In Persian]

Samadianfard, S., & Panahi, S. (2019). Estimating daily reference evapotranspiration using data mining methods of support vector regression and M5 model tree. *Journal of Watershed Management Research, 9*(18), 157-167. DOI: 10.29252/jwmr.9.18.157 [In Persian].

Sharafi, M., Abdi, E., Mohebbiyan, M., & Samadianfard, S. (2024). Prediction of daily evapotranspiration using the strategy of combining tree models with empirical Hargreaves method. *Water and Soil Science, 34*(2), 107-119. DOI: 10.22034/ws.2023.55840.2519

Shojaei, M. O., Mikaeili, F., & Samadianfard, S. (2022). Evaluating capabilities of gradient boosted tree and optimized random forest models in estimating daily dew point temperature. *Environment and Water Engineering, 8*(3), 654-668. DOI: https://doi.org/10.22034/jewe.2022.313219.1662

Siasar, H., & honar, T. (2019). Application of support vector machine, CHAID and random forest models, in estimated daily Reference evapotranspiration in northern Sistan and Baluchestan province. *Iranian Journal of Irrigation and Drainage, 13*(2), 378-388 [In Persian].

Temesgen, B., Eching, S., Davidoff, B., & Frame, K. (2005). Comparison of some reference evapotranspiration equations for California. *Journal of Irrigation and Drainage Engineering, 131*(1), 73–84. DOI: https://doi.org/10.1061/(ASCE)0733-9437(2005)131:1(73)

Terzi, Ö. (2007). Data mining approach for estimation evaporation from free water surface. *Journal of Applied Science, 7*(4), 593-596. DOI: 10.3923/jas.2007.593.596

Valipour, M., Gholami Sefidkouhi, M. A., & Khoshravesh, M. (2017). Estimation and trend evaluation of reference evapotranspiration in a humid region. *Italian Journal of Agrometeorology, 1*, 19-36. DOI:10.19199/2017.1.2038-5625.019

Vapnik, V., & Lerner, A. (1963). Pattern recognition using generalized portrait method. *Automation and Remote Control, 24*, 774–780.

Vapnik, V. N. (2000). The Nature of statistical learning theory, the nature of statistical learning theory. Springer New York, New York, NY.

Zorati Pur, E., Neisi, L., Golabi, M., Bazaz, A., & Zoratipur, A. (2019). Simulation and comparison of potential evapotranspiration by artificial neural networks, ANFIS (Fuzzy Neural Network) and decision making M5 (Case study; synaptic station of Shiraz). *Iran-Water Resources Research, 15*(1), 365-371 [In Persian].