Estimation of reference evapotranspiration from climatic data

Abstract

This study investigated the capability of M5 Model Tree (M5MT) to predict reference evapotranspiration ($ET_0$). M5MT was trained and tested with climatic data from eight weather stations located in coastal areas of Iran for the years 2000-2008. It was validated with climatic data from seven California Irrigation Management Information System (CIMIS) weather stations for the year 2015. Four different data combinations were utilized to train, test, and validate the M5MT model. These were: daily mean air temperature, wind speed, relative humidity, and solar radiation (configuration 1); daily mean air temperature and solar radiation (configuration 2); daily mean air temperature and relative humidity (configuration 3); and daily maximum, minimum, and mean air temperature, and extraterrestrial radiation (configuration 4). The Pennan-Monteith (PM) equation was used as a standard method to provide target $ET_0$ values. Mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination ($R^2$) were utilized to evaluate the performance of the M5MT models developed with different input configurations. Results indicated that M5MT was able to successfully estimate $ET_0$. Configuration 1 provided the most accurate results. Configuration 2 showed to have the variables that have a greater influence on $ET_0$ than configuration 3. Configuration 4 performed the worst. MAE of $ET_0$ estimates from M5MT was respectively 29%, 55%, and 91% lower than that of M5MT, M5MT, and M5MT, when the model is validated in California. Also, RMSE from M5MT was 29%, 59%, and 125% smaller than that of M5MT, M5MT, and M5MT, respectively.

Introduction

Evapotranspiration ($ET$) is an important component of the hydrologic cycle, which significantly influences crop water requirement and water resource management. Accurate $ET$ estimates enable the proper determination of water budgeting and allocation, and thus improves water use efficiency of irrigation systems. In situ methods are often used to measure $ET$ in a controlled crop area, but they are costly, labor intensive, and only provide localized estimates. To avoid the high costs, empirical, artificial intelligence, and physical models have been developed to estimate reference $ET$ ($ET_0$). $ET_0$ is the combined process of evaporation and transpiration from a theoretical grass surface with an assumed height of 0.12 meter, a surface resistance of 70 s/m, and a surface albedo of 0.23. The Penman-Monteith (PM) equation has been accepted as a standard approach to estimate $ET_0$. However, this method requires many climatic variables that are typically unavailable. Due to the drawbacks of in situ methods and the PM equation, Artificial Intelligence (AI)-based approaches have been used to estimate $ET_0$, utilized Artificial Neural Network (ANN) to approximate $ET_0$ in the arid, semi-arid, and sub-humid regions of Inner Mongolia. In comparison with Multiple Linear Regressions (MLR), ANN showed more accurate estimates. Estimated daily $ET_0$ in Northern Spain using Gene Expression Programming (GEP) and compared its performance with those of the Adaptive Neuro-Fuzzy Inference System (ANFIS), Hargreaves-Semani, and Priestley-Taylor models. Results indicated that GEP provided the most accurate estimates followed by ANFIS used ANN to predict $ET_0$ in arid and semi-arid areas of northwest China. ANN was found to estimate $ET_0$ more accurately than MLRs, Priestley-Taylor, Hargreaves-Semani, and Penman-Monteith (PM) equations predicted $ET_0$ in northern, mid, and southern part of Iraq using Extreme Learning Machines (ELM). Compared to the PM equation and Feed Forward Back Propagation (FFBP) models, ELM estimated $ET_0$ better. Recently, M5 Model Tree (M5MT) has been used in many engineering problems, and showed promising results. M5MT is an extension of a regression tree and provides the user with multiple linear functions. This approach is capable of handling high dimensional datasets and the resulting model tree is significantly smaller and more precise than regression trees. However, the M5MT is a black-box and provides a relationship between the independent and dependent variables. Several studies have shown M5MT to be an effective technique to provide accurate results shown M5MT is advantageous over ANN because it generated more accurate root mean square error estimates found that the performance of M5MT was comparable to ANN, but indicated that the training process of M5MT was faster than that of ANN performed a comparison of M5MT and Support Vector Machines (SVM) in forecasting daily river flow. Results showed M5MT performed similar to SVM, but it is computationally less expensive concluded M5MT to be better than ANN as it provided a more straightforward structure consisting of linear regression equations. The objective of this study is to estimate $ET_0$ from climatic data using M5MT. Four different combinations of climatic data were used in M5MT. These combinations were daily mean air temperature, wind speed, relative humidity, and solar radiation (configuration 1); daily mean air temperature and solar radiation (configuration 2); daily mean air temperature and relative humidity (configuration 3); and daily maximum, minimum, and mean air temperature, and extraterrestrial radiation (configuration 4). An assessment of which data combination has the most amount of information about $ET_0$ was made.
Data, methods and models

**Studied sites and data:** Daily climatic data as well as $\text{ET}_o$ estimates from the PM equation were used to train, test, and validate the M5MT model. The training dataset consisted of data from eight coastal weather stations in Iran, collected from 2000 to 2007. The testing dataset contained data from the same eight stations, but for 2008. Performance of the M5MT models was evaluated with seven California Irrigation Management Information System (CIMIS) weather stations in 2015. CIMIS dataset was used for models validation to evaluate their feasibility in other regions, and examine whether they are applicable in areas that they were not trained in.

Figure 1 & Figure 2 show the spatial distribution of the utilized weather stations in Iran and California, respectively. The recorded data consisted of daily average relative humidity ($\text{RH}_{\text{mean}}$), wind speed (Ws), daily maximum, minimum and mean air temperature ($T_{\text{max}}, T_{\text{min}}, \text{and } T_{\text{mean}}$), and incoming solar radiation (Rs). Table 1 lists the geographical coordinates of each weather station and the corresponding annual averages of the collected data. $\text{ET}_o$ is the reference evapotranspiration (mm/d), $\Delta$ is the slope of saturation vapor pressure function (kPa/°C), $R_s$ is the net radiation (MJ/m2day), $R_a$ is extraterrestrial radiation (MJ/m2day), $\gamma$ is the psychrometric constant (kPa/°C), $T_{\text{mean}}$ is the daily mean air temperature (°C), $T_{\text{max}}$ is the daily maximum air temperature (°C), $T_{\text{min}}$ is the daily minimum air temperature (°C), Ws is the daily mean wind speed at a height of 2 m (m/s), RH is relative humidity (%), $e_s$ is the actual vapor pressure (kPa), and $e_a$ is the saturation vapor pressure (kPa). The commonly used equations for the estimation of $\text{ET}_o$ are presented in Table 2. Based on the proposed equations in Table 2 and the study conducted by, four input combinations were used to predict $\text{ET}_o$.

The following data configurations were used to train, test, and validate M5MT:

- **Configuration 1:** Ws, RH$_{\text{mean}}$, T$_{\text{mean}}$, and Rs [M5MT$_1$]
- **Configuration 2:** T$_{\text{mean}}$ and Rs [M5MT$_2$]
- **Configuration 3:** T$_{\text{mean}}$ and RH$_{\text{mean}}$ [M5MT$_3$]
- **Configuration 4:** T$_{\text{mean}}$, T$_{\text{max}}$, T$_{\text{min}}$ and Rs [M5MT$_4$]

Three statistical metrics (mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination ($R^2$)) were used to compare performance of the four M5MT models (i.e., M5MT$_1$, M5MT$_2$, M5MT$_3$, and M5MT$_4$). These statistical metrics are given below:

\[
\text{MAE} = \frac{\sum_{i=1}^{n}|O_i - P_i|}{n}
\]

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}}
\]

\[
R^2 = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})^2}{\left[\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2} \sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}\right]^2}
\]

Where $n$ is the number of data points, $O_i$ and $P_i$ are the $i$th estimated $\text{ET}_o$ values respectively from the PM and M5MT models, and $\bar{O}$ and $\bar{P}$ are the mean predicted $\text{ET}_o$ values from the respective models. The $R^2$ signifies the percentage of data that conforms to the regression line at a 45-degree angle. If all points coincide with the regression line, the variation between the variables can be explained by a linear relationship and $R^2$ would result in an optimal value of one. MAE describes the average of a set of absolute errors with an optimal value of zero. Since only the magnitude of the error is considered, non-negative values are obtained with no upper bound. RMSE is a measure of difference between the observed and simulated values. The greater concentration of data around the 1:1 line, the lower the value of RMSE becomes. RMSE does not have an upper bound and its optimal value is zero.

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Table 1 Geographical location of stations and annual averages of climatic data

| Country   | Station      | Location | Climatic Parameters |
|-----------|--------------|----------|---------------------|
| Iran      | Abadan       | 6.6      | 30.2                |
|           |              | 48.2     | 34                  |
|           |              | 18.9     | 26.3                |
|           |              | 19.4     | 26.6                |
|           |              | 18.5     | 2.4                 |
|           |              | 64.7     | 2.4                 |
|           | Ahwaz        | 22.5     | 31.2                |
|           |              | 48.4     | 34                  |
|           |              | 19.4     | 26.6                |
|           |              | 18.5     | 2.4                 |
|           |              | 65.6     | 2.4                 |
|           | Bandar-e-Abbas| 9.8       | 27.1               |
|           |              | 56.2     | 32                  |
|           |              | 23.4     | 27.5                |
|           |              | 17.4     | 3.7                 |
|           |              | 78.6     | 3.7                 |
|           | Bandar-e-Lenge| 22.7     | 26.3               |
|           |              | 54.2     | 33                  |
|           |              | 21.9     | 27.2                |
|           |              | 19.4     | 3.7                 |
|           | Bushehr      | 9        | 28.6                |
|           |              | 50.5     | 30                  |
|           |              | 20.6     | 25.3                |
|           |              | 18.3     | 3.5                 |
|           |              | 75.8     | 3.5                 |
|           | Gorgan       | 13.3     | 36.5                |
|           |              | 54.1     | 23                  |
|           |              | 12.9     | 18.2                |
|           |              | 15.8     | 2.6                 |
|           | Rasht        | -8.6     | 37.1                |
|           |              | 49.4     | 21                  |
|           |              | 12.3     | 16.6                |
|           |              | 15.8     | 1.6                 |
|           | Sari         | 23       | 36.3                |
|           |              | 53       | 23                  |
|           |              | 13.5     | 18                  |
|           |              | 16.3     | 2.2                 |
|           |              | 75.6     | 2.2                 |
| California, USA | Atascadero | 269.8     | 35.5            |
|           |              | -121     | 24                 |
|           |              | 5.8      | 14.1                |
|           |              | 16.5     | 1.2                 |
|           |              | 64.2     | 1.2                 |
|           | Delano       | 91.4     | 35.8                |
|           |              | -119     | 27                 |
|           |              | 9.8      | 17.6                |
|           |              | 18.6     | 1.4                 |
|           | Gilroy       | 56.4     | 37                  |
|           |              | -122     | 24                 |
|           |              | 7.5      | 14.8                |
|           |              | 17.4     | 2.2                 |
|           | Arleta       | 298.7    | 34.3                |
|           |              | -118     | 26                 |
|           |              | 11.6     | 18.3                |
|           |              | 18.6     | 1.6                 |
|           |              | 49.7     | 1.6                 |
|           | Gerber South | 75        | 40                |
|           |              | -122     | 25                 |
|           |              | 9.9      | 17.2                |
|           |              | 18.3     | 2.3                 |
|           | Woodland     | 25       | 38.7                |
|           |              | -122     | 25                 |
|           |              | 9.8      | 17.1                |
|           |              | 17.5     | 2.2                 |
|           |              | 54.8     | 2.2                 |
|           | Diamond Springs | 624.8  | 38.6           |
|           |              | -121     | 22                 |
|           |              | 10.5     | 16.1                |
|           |              | 17.7     | 1.7                 |
|           |              | 49.9     | 1.7                 |

Table 2 Different ET\textsubscript{0} equations

| Study                                   | ET\textsubscript{0} Equation                                      |
|-----------------------------------------|------------------------------------------------------------------|
| Penman-Monteith et al. [2]              | \( ET_0 = \frac{0.408\Delta \left( R_e - G \right) + \gamma \left( \frac{900}{T_{mean} + 273} \right) W_s e - e_a}{\Delta + \gamma \left( 1 + 0.34W_s \right)} \) |
| Makkink [20]                            | \( ET_0 = \frac{0.61 \Delta R_s}{\left( \Delta + \gamma \right) \lambda} - 0.12 \) |
| Romanenko [21]                          | \( ET_0 = 0.0018 \left( T_{mean} + 25 \right)^2 \left( 100 - RH \right) \) |
| Hargreaves & Samani [22]                | \( ET_0 = \frac{R_e}{\lambda} \left( T_{mean} + 17.8 \right)^2 \sqrt{T_{max} - T_{min}} \) |

\[
SDR = sd(T) - \sum_{i=1}^{A} \frac{\left| T_i \right| - sd(T_i)}{\sum_{i=1}^{A} \left| T_i \right|} \left( T_i \right)
\]

(4)

Where \( T \) is the set of values that reach a node, \( T_i \) is the subset of values that have the \( i \)th outcome of a potential set, \( A \) is the final amount of values in set \( T \), and \( sd \) is the standard deviation. This dividing process results in the algorithm to perform iterations, which generates subsequent nodes that will exhibit a reduction in standard deviation from the previous nodes. The algorithm will continue to iterate, considering all possible splits, and ends when the least expected error is attained.\(^\text{17}\) The conclusion of the first stage leaves the model tree to have large structure, which initiates pruning of the overgrown model tree (i.e., the second stage of M5MT).\(^\text{12}\) Pruning will occur if the estimated error of nodes branched below a specific node is greater.\(^\text{17}\)\(^\text{18}\) Linear regression equations will replace the pruned nodes, resulting in a more simplified and accurate model tree.\(^\text{15}\)\(^\text{19}\)

Results and Discussion

Building M5 Model Tree: This study used WEKA (Waikato Environment for Knowledge Analysis), which is a data mining tool.
software to estimate ET₀. It consists of a wide variety of machine learning algorithms including MSMT. The WEKA interface provided different testing options (i.e., percentage split, train-test, and cross validation) to assist in the modeling process. Among the three aforementioned options, the Train-Test method was selected because of its better performance (Table 3).

Table 3 Performance of MSMT for different testing options

| Methods            | MAE (mm/d) | RMSE (mm/d) | R²       |
|--------------------|------------|-------------|----------|
| Percentage Split   | 0.255      | 0.3422      | 0.9904   |
| Train-Test         | 0.2328     | 0.3189      | 0.9914   |
| Cross Validation   | 0.2396     | 0.3337      | 0.9906   |

Performance of MSMT models in Iran (training and testing stages): Table 4 shows MAE, RMSE, and R² of ET₀ estimates from the four MSMT models for training and testing stages. The training process resulted in MAE, RMSE, and R² values ranging between 0.33–0.76mm/d, 0.47–1.03mm/d, and 0.81–0.96, respectively. The testing stage showed similar values that ranged between 0.38–0.77mm/d (MAE), 0.55–1.06mm/d (RMSE), and 0.80–0.95 (R²). It was observed that the presence or absence of certain input parameters influenced the performance of the models. Comparing the models with two input variables, MSMT₁ (whose inputs were Tmean and RHmean) had higher MAE (0.76mm/d) and RMSE (1.0mm/d) than MSMT₄ (whose inputs were Tmean and Rₚ) in the training stage.

Table 4 Statistical metrics of MSMT models for training and testing stages

| Training: Iran (2000-2007) | Testing: Iran (2008) |
|-----------------------------|----------------------|
|                             | MSMT₁    | MSMT₂    | MSMT₃    | MSMT₄    | MSMT₁    | MSMT₂    | MSMT₃    | MSMT₄    |
| MAE (mm/d)                  | 0.33     | 0.62     | 0.76     | 0.53     | 0.38     | 0.64     | 0.77     | 0.56     |
| RMSE (mm/d)                 | 0.47     | 0.85     | 1.03     | 0.73     | 0.55     | 0.92     | 1.06     | 0.82     |
| R²                          | 0.96     | 0.87     | 0.81     | 0.91     | 0.95     | 0.85     | 0.8      | 0.88     |

Solar radiation tends to have a greater effect on ET₀, as replacing mean relative humidity by solar radiation increased accuracy in the training phase and decreased MAE and RMSE by 23% and 21%, respectively. This is in agreement with the results from the testing stage, in which a respective 20% and 15% decrease in MAE and RMSE was observed when solar radiation was used in lieu of mean relative humidity. Assessing the performance of the MSMT models with four input variables during the training stage, MSMT₄ (whose inputs were Tₘₜₐₜ, Tₐₜₔ, Tₘₜₐₜ, and Rₚ) had larger MAE (0.53mm/d), RMSE (0.73mm/d), lower R² (0.91) values than MSMT₁ (whose inputs were Wₛ, RHₘₜₐₜ, Tₘₜₐₜ, and Rₚ). This is consistent with the testing phase because MAE and RMSE are decreased by 47% and 49% by using MSMT₁ instead of MSMT₄. Figure 3A & Figure 3B show estimated ET₀ values from the four MSMT models versus PM ET₀ estimates for training and testing stages, respectively. The concentration of data around the 1:1 line in Figure 3A & Figure 3B reflects the low RMSE values obtained in both training and testing stages. In general, the small MAE and RMSE and high R² suggest that MSMT can accurately estimate ET₀. Overall, the results in Figure 3A & Figure 3B and Table 4 indicate that the combination MSMT₁ provided the most accurate ET₀ estimates during the training and testing stages. In the training stage, MAE (RMSE) of ET₀ estimates from MSMT₁ were respectively 88% (81%), 130% (119%) and 61% (55%) lower than those of MSMT₂, MSMT₃, and MSMT₄. A similar tendency was seen in the testing stage with MAE (RMSE) values of MSMT₁ were 68% (67%), 103% (93%), and 47% (49%) lower than those of MSMT₂, MSMT₃, and MSMT₄, respectively.

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Performance of M5MT models in California (validation stage): To validate the robustness of the M5MT models, they were applied to seven CIMIS weather stations in California. It should be noted that the CIMIS data was not used to train the M5MT models. The statistical metrics of the M5MT models were given in Table 5. MAE, RMSE, and $R^2$ values ranged between 0.65-1.24mm/d, 0.80-1.80mm/d, and 0.68-0.90, respectively Table 5. Figure 4 illustrates plots of ET$_0$ estimates from the four M5MT models versus PM ET$_0$ estimates at the seven CIMIS stations. Performance of the models can be ranked as follows: M5MT$_1$, M5MT$_2$, M5MT$_3$, and M5MT$_4$. Similar to the training and testing phases, M5MT$_1$ outperformed the other models when tested at the California stations. Although no CIMIS data was used to train the M5MT$_1$ model, it performed well when applied to the stations in California. This implies that the M5MT$_1$ can provide accurate results in other regions. Figure 4 & Figure 5 showed that the M5MT$_1$ model with MAE, RMSE, and $R^2$ values of 0.65mm/d, 0.80mm/d, and 0.90, respectively, can be selected as the best M5MT model for ET$_0$ estimation. With only two input parameters (i.e., $R_s$ and $T_{mean}$), M5MT$_1$ showed to provide better results than M5MT$_3$. This implies that a combination of $R_s$ and $T_{mean}$ contributes more significantly towards the estimation of ET$_0$ than a combination of $R_{h}$ and $T_{mean}$. Figure 5 indicates time series of ET$_0$ estimates from M5MT$_1$, M5MT$_2$, M5MT$_3$, and PM models at four CIMIS stations (i.e., Delano, Gerber South, Woodward, and Diamond Springs). As shown, the estimated ET$_0$ values from M5MT$_1$ agree well with those of the PM equation. Remarkably, ET$_0$ estimates from M5MT$_1$ captured the fluctuations of the PM ET$_0$ values. Compared to M5MT$_3$, MAE values of M5MT$_1$, M5MT$_2$, and M5MT$_4$ were respectively 29%, 55%, and 91% larger. Also, RMSE values from M5MT$_1$, M5MT$_2$, and M5MT$_4$ were respectively 29%, 59%, and 125% greater than that of M5MT$_3$.

Table 5 Statistical metrics of M5MT models for validation stage

| Validation: california (2015) | M5MT1 | M5MT2 | M5MT3 | M5MT4 |
|-----------------------------|-------|-------|-------|-------|
| MAE (mm/d)                  | 0.65  | 0.84  | 1.01  | 1.24  |
| RMSE (mm/d)                 | 0.8   | 1.03  | 1.27  | 1.8   |
| $R^2$                       | 0.9   | 0.93  | 0.74  | 0.68  |

Figure 4 The same as Figure 3a, but for validation stage.

Conclusion

This study examined the ability of M5 Model Tree (M5MT) to estimate reference evapotranspiration (ET$_0$) from climatic data. Four combinations of data were used in the M5MT model. These combinations were daily mean air temperature, wind speed, relative humidity, and solar radiation (configuration 1); daily mean air temperature and solar radiation (configuration 2); daily mean air temperature and relative humidity (configuration 3); and daily maximum, minimum, and mean air temperature, and extraterrestrial radiation (configuration 4). The objective was to determine which data combination had the most significant amount of information on ET$_0$. The results indicated that M5MT can estimate ET$_0$ accurately. Data combination 1 generated the most accurate ET$_0$ estimates and thus consisted of variables that have the most amount of information on ET$_0$ compared to data combinations 2, 3, and 4. Comparing M5MT models with two input variables, configuration 2 resulted in more accurate ET$_0$ estimates than configuration 3. This suggests the greater importance of solar radiation and air temperature in comparison to relative humidity and air temperature to estimate ET$_0$.

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Conflict of interest

None.

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