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THE MODELLING OF POTENTIAL EVAPOTRANSPIRATION BASED ON CLIMATE DATA USING EMPIRICAL AND HEURISTIC METHODS

Abstract:

The aim of this paper titled “The Modelling of Potential Evapotranspiration Based on Climate Data Using Empirical and Heuristic Methods” is to estimate the potential evapotranspiration in the Ergene Basin, Turkey. Accurately observing the amount of total evapotranspiration in any given region usually is a perilous task given the fact that setups to directly observe evapotranspiration are costly build and highly effort-inducing to operate. Therefore, calculating the potential evapotranspiration of a region by using the FAO-56 Penman-Monteith formula instead of observing directly is preferred. However, FAO-56 PM formula requires a lot of different data sets, which may not be accessible in various regions, to effectively utilize. For this reason, scientists have been researching different methods to calculate potential evapotranspiration without the need for numerous climate data sets. In this paper, in the first step, reference evapotranspiration was calculated using the FAO-56 PM empirical formula. In the second step, potential evapotranspiration was calculated using the Blaney-Criddle empirical formula. In the third step, climate data including Rs, E, Tmax, Tort, Tmin, and Sh were used to calculate potential evapotranspiration using the MARS and GMDH heuristic methods. Among these methods, the GMDH method combining Rs, E, Tmax, Tort, Tmin, and Sh yielded the best performance with performance criteria of R2= 0.9846, MSE=49.07, MAE=5.56, and AARE=7.23 compared to the reference evapotranspiration.

Keywords:

Evapotranspiration, FAO-56, Blaney-Criddle, Heuristic Methods, Ergene Basin

JEL Classification: C51, C52

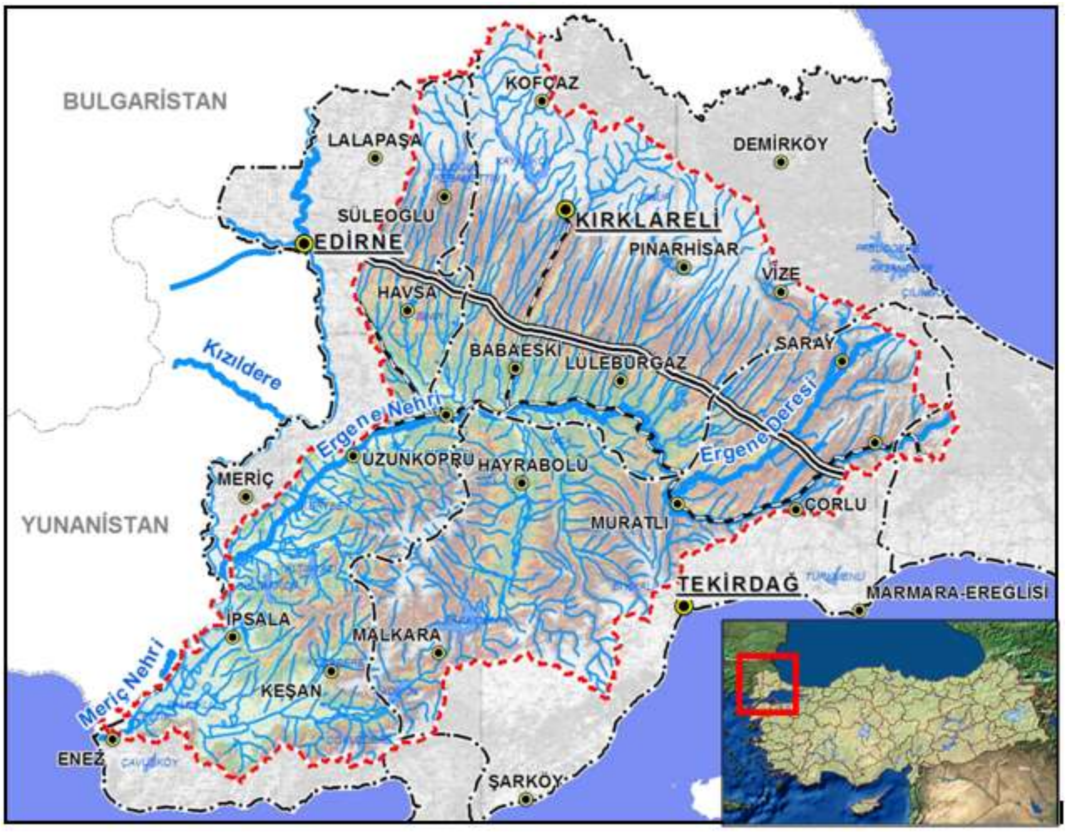
1. Introduction

The field of hydrology harbors a variety of applications and research topics, however it’s almost certain that any of these applications and research topics will require suitable climate data to be worked upon. It is therefore fair to state that meteorological data is vital for hydrology in turn engineering applications of hydrology. Most of this meteorological data are locally and periodically observed by meteorological observations stations all over the world. However, given the fact that there are many different types of climate data and not all observation stations have the perfect means, it is not out of the ordinary for observation stations to not observe and record some data sets for any given region. In the case of evapotranspiration, accurately observing the total amount of evapotranspiration in any given region usually is a perilous task given the fact that setups to directly observe evapotranspiration are costly build and highly effort-inducing to operate (Li, Zhao-Liang, et al. 2009). As this is the case, most observation stations don’t record evapotranspiration data sets of their region. This results in a great loss of scientific data and applications which could stem from said data as evapotranspiration is regarded as an important data set for many studies, first and foremost being agricultural research (Hargreaves, 1982). In order to obtain this data, scientists developed methods which eliminated the need for direct observation of evapotranspiration. Regarded as the most respected method to calculate evapotranspiration, Penman-Monteith formula is utilized by many researchers. However, the formula owes its success to the amount of different accurate data sets it uses to estimate evapotranspiration. As stated above, with many observation stations lacking in data sets, it is crucial to accurately estimate evapotranspiration with as little amount of different data as possible to make the data set obtainable and accessible everywhere. Machine learning models have been used in hydrology research extensively over the years, in this study 2 machine learning methods are used to obtain accurate and accessible evapotranspiration data.

2. Study Area and Data

Ergene Basin in Marmara Region of Turkey is selected as the study area. The climate data for the study area is acquired from various meteorological observation stations. Ergene Basin is situated in Thracia region of Turkey and holds importance for the country for various reasons. The basin has a surface area of 14486 km^2 and encompasses a great percent of Edirne, Tekirdağ and Kırklareli while also encompassing a small portion of İstanbul. The basin’s border coordinates are 40,56 – 47,12 North and 20,03 – 28,17 East. One of the most defining factors for the basin is the fact that it hosts the Ergene River inside its border (Cengiz, 1996). Ergene River enters the basin’s borders from Istranca Mountains Range through North and joins the Meriç River in the South, which then pours into the Aegean Sea at Saroz Bay. The Basin borders Istranca Mountains Range and Bulgaria country border at North, Çerkezköy and Vize counties at East, Tekirdağ city at South and Greece and Bulgaria country borders at West (TCTOB, 2022). The borders of the Ergene Basin are given with dashed lines in Figure 2.1 (Konukcu, 2016).

Figure 2.1. Ergene Basin Border



Ergene Basin hosts many different meteorology observation stations. However, the observation periods and the climate data the stations are tasked to observe vary greatly from one station to another. This situation stems from the fact that some observation stations are smaller in size and scope and may be funded locally, such that their operation range doesn't reach far from their location. The climate data used in this study are acquired from the meteorological observation stations are listed and their information are given in figure 2.2 (TAGEM, 2017).

Figure 2.2. Utilized Meteorological Observation Stations in Ergene Basin

Station Number	Station Name	Host City	Latitude (°)	Longitude (°)	Attitude (m)
17056	Tekirdağ	Tekirdağ	40,9836	27,4904	59
17050	Edirne	Edirne	41,6706	26,5488	38
17052	Kırklareli	Kırklareli	41,7352	27,2173	213

2.1 Data

The climate data used in this study are sourced from Tekirdağ center 17056 station, Edirne center 17050 station and Kırklareli center 17052 station which are located in the study area, Ergene Basin. The shared climate data from these stations are put together by calculating their average for each month, this makes it so that shared climate data from each station is homogenized for the whole basin. The missing data of any given station is compensated by other stations. From the stated 3 observation stations, monthly climate data from the year 1990 to 2020, 31 years in total, are acquired. 6 separate monthly data sets are used in this study, each data set contains 372 data values, which in total makes 2232 individual data values. The monthly climate data sets used in this study are as follows: Average solar radiation (R_s), average evaporation (E), maximum temperature (T_{max}), minimum temperature (T_{min}), average temperature (T_{avg}) and average sunshine duration (S_h) (MGM, 2021). In order to investigate the correlation between the independent variable reference evapotranspiration and dependent variables climate data sets, Pearson's correlation coefficient (r) is calculated. Direct and strong proportion between independent and dependent variables are expected to yield well estimation results. The correlation coefficient can have values between -1 and +1, negative values indicate inverse proportion while positive values indicate direct proportion, proximity to boundary values indicate strong proportion for correlations. In this study, Pearson's correlation coefficients are calculated with the formula given below. Correlation coefficients calculated are given in figure 2.3. As it can be seen from figure 2.3, correlation coefficients between independent and dependent variables are found to have strong direct proportion.

$$r = \frac{\sum_{i=1}^{N}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{N}(X_i - \bar{X})^2 \sum_{i=1}^{N}(Y_i - \bar{Y})^2}} \tag{2.1.1}$$

In the given formula;

X_i: i. Independent variable

$\bar{X}$: Average of independent variables

Yi: i. Dependent variable

$\bar{Y}$: Average of dependent variable

N: Number of data

On the other hand, to deduce if the data sets are in normal distribution, are distributed homogeneously or heterogeneously, some descriptive statistics are designated and calculated. Descriptive statistics utilized are, total data number (N), smallest value (X_{min}), highest value (X_{max}), average value ($\bar{X}$), standard error (S_e), standard deviation (σ), variance (Var), skewness coefficient (S_c) and kurtosis coefficient (K_c). Pearson's correlation coefficients for climate data sets are given in figure 2.3 and descriptive statistics are given in figure 2.4. From the descriptive data sets in figure 2.4, it can be seen that climate data sets are close to normal distribution and have a mostly homogenous data value.

Figure 2.3. Pearson's correlation coefficients

	ET_o (mm)	T_{max} (°C)	T_{min} (°C)	T_{avg} (°C)	E (mm/month)	R_s (cal/cm2)	S_h (hours)
Reference Evapotranspiration ET_o (mm)	1	0,924	0,839	0,868	0,925	0,964	0,766
Max. Temperature T_{max} (°C)	0,924	1	0,924	0,957	0,937	0,863	0,806
Min. Temperature T_{min} (°C)	0,839	0,924	1	0,978	0,927	0,792	0,761
Average Temperature T_{avg} (°C)	0,868	0,957	0,978	1	0,950	0,812	0,785
Evaporation E (mm/month)	0,925	0,939	0,927	0,950	1	0,864	0,832
Global Solar Radiation R_s (cal/cm2)	0,964	0,863	0,792	0,812	0,865	1	0,705
Sunshine Duration S_h (hours)	0,766	0,806	0,761	0,785	0,832	0,705	1

Figure 2.4. Descriptive statistics

	r	X_{min}	X_{maxs}	$\overline{X}$	S_e	σ	Var	S_c	K_c
ET_o	192,2	24,80	217,00	95,34	2,58	49,82	2 482,46	0,39	-1,08
T_{max}	28,10	12,50	40,60	26,42	0,37	7,18	51,69	-0,09	-1,26
T_{min}	30.67	-13,03	17,63	3,55	0,41	7,96	63,24	0,02	-1,15
T_{avg}	27,83	0,00	27,83	14,16	0,39	7,63	58,24	0,01	-1,30
E	243,53	0,00	243,53	80,59	3,90	75,23	5 660,60	0,35	-1,28
R_s	599,70	54,30	654,00	291,51	8,15	157,33	24 753,58	0,33	-1,15
H_s	352,50	4,00	356,50	170,31	4,69	90,61	8 211,57	0,35	-1,1

3. Methodology

In this study, FAO-56 Penman-Monteith (FAO-56 PM) formula which is used extensively in hydrology and Blaney-Criddle empirical formulas, as well as MARS and GMDH machine learning methods are used to calculate evapotranspiration. Below the formulas and methods are explained.

3.1. FAO-56 Penman-Monteith Formula (FAO−56 PM)

Food and Agriculture Organization-56 Penman-Monteith formula is developed by Allen et al. (1998). FAO−56 Penman−Monteith (FAO-56 PM) equation is widely accepted to be one of the best ways to calculate reference evapotranspiration (ET_0) and is extensively utilized (Allen, et al.1998). Daily evapotranspiration values, energy and mass equilibrium-based Penman-Monteith formula requires climate data such as solar radiation (R_s), average temperature (T_{avg}), wind speed above 2 meters ground level (S_w) and relative humidity (RH). FAO−56 PM equation is detailed below (Allen, et al. 1998).

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T_{ort}+273}S_w(e_s - e_a)}{\Delta + \gamma(1 + 0.34*)S_w} \quad (3.1.1)$$

In the formula;

ET_0: Daily reference evapotranspiration (mm)

R_n: Net radiation at crop surface (mJ/m^2-day)

G: Soil heat flux density (mJ/m^2-day)

T_{avg}: Mean daily temperature (°C)

S_w: Wind speed at 2 meters high (m/sc)

e_s: Saturation vapor pressure (kPa)

e_a: Actual vapor pressure (kPa)

e_s-e_a: Saturation vapor pressure deficit (kPa)

Δ: Slope vapor-pressure curve (kPa/°C)

γ: Psychrometric constant (kPa/°C)

3.2. Blaney-Criddle Formula

Blaney-Criddle Formula is an empirical formula developed with the information and experience gained with studies and experiments made out on the field. Blaney-Criddle formula is based on analyzing periods of a given climate and mainly aims to calculate the required irrigation water for crops. The formula is given below (Blaney-Criddle, 1950).

$$U = k * \frac{p * t'}{100} \quad (3.2.1)$$

In the formula;

U: Monthly potential evapotranspiration (inch)

k: Monthly crop irrigation water constant

p: Rate of monthly morning duration to years morning duration (%)

t': Monthly mean temperature (°F)

3.3. MARS Method

Multivariate Adaptive Regression Splines method, shortened to MARS is a respected method in the field of hydrology. With this method, data sets with numerous values can be easily processed and meaningful results are able to be obtained (Friedman, 1991). MARS method can be used with both linear and nonlinear approaches (Sharda, et al. 2008). MARS method uses basic functions regarding different intervals of variables and builds a flexible regression model (Toprak, 2011). The model is detailed below (Nacar, 2020).

$$Y = \beta_0 + \sum_{i=1}^{N} a_i \beta_i(X_i) + \varepsilon_i \tag{3.3.1}$$

In the method;

i: Number of knots

N: Number of basic functions (Number of data values)

X_i: Independent variable

a_i: Basic function coefficient

β_0: Constant

$\beta_i(X_i)$: Basis function for independent variable

ε_i: Error term

In the MARS method, the first step is creating basic functions. Afterwards, independent variables and their interactions with each other in those basic functions are determined and generalized cross validation is used to find the best results, which are the results with the least mean squared error (Ünal, 2009; Uzlu, 2011).

In the most general sense, basic functions are created as;

$$B_m(X) = \prod_{i=1}^{L_m} \left[S_{1,m} \left(X_{v(1,m)} - k_{1,m} \right) \right] \tag{3.3.2}$$

In the method;

L_m: Level of interaction

$S_{1,m}$: ∈[±]

$k_{1,m}$: Knot value

$X_{v(1,m)}$: Independent variable value

3.4. GMDH Method

Group Method of Data Handling method, shortened to GMDH method is widely used in the field of hydrology. The model requires multiple inputs and gives results of a single output, therefore in order for the model to work, at least two separate independent variables are needed as inputs. GMDH model is classified as a deep learning method and is also known as a polynomial neural network method and it is for the first time proposed to solve complicated problems by Ivakhnenko (1968). In this method, a relation is built between multiple inputs and a sole output. The difference between sum of the squared values of the dependent variable estimated by the model and of the observed dependent variable is expected to converge to minimum. Said difference can be controlled with the formula below.

$$\sum_{i=1}^{M}\left[\hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots\ldots x_{in}) - \hat{y_i}\right]^2 \to min \qquad (3.4.1)$$

Here;

$\hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots\ldots x_{in})$: Vectoral value of each input

$\hat{y_i}$: Output vector value

M: Number of inputs and outputs

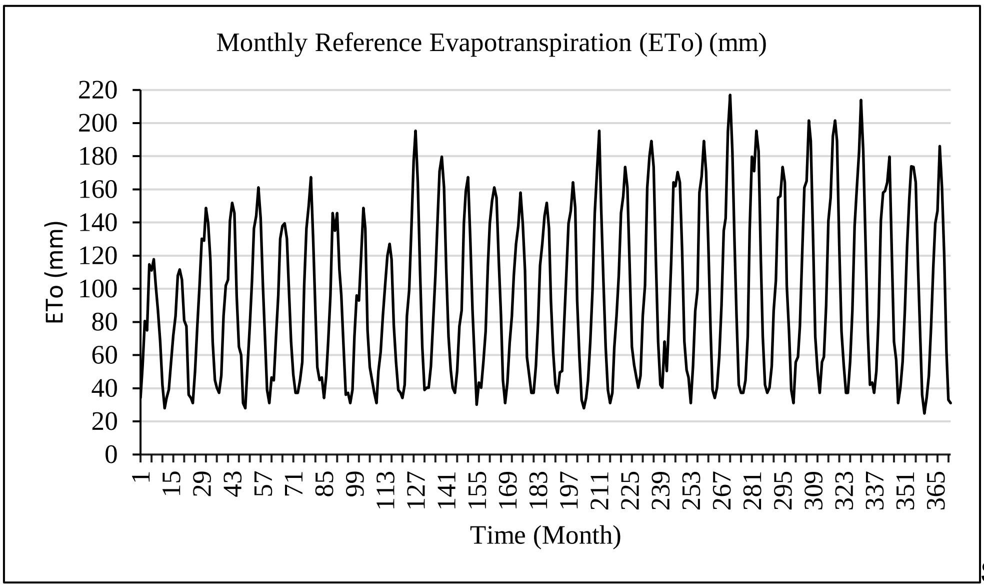
4. Applications

In this section, monthly average evapotranspiration is calculated with, in order, FAO-56 Penman-Monteith, Blaney-Criddle, MARS and GMDH methods. The calculation results are given below respectively.

4.1. FAO-56 Penman-Monteith Formula Evapotranspiration Results

The monthly average evapotranspiration results obtained with FAO-56 Penman-Monteith formula are determined as reference evapotranspiration values. In figure 4.1, 372 data values which are obtained by the formula are given.

Figure 4.1. FAO-56 PM reference evapotranspiration results



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4.2. Blaney-Criddle Formula Evapotranspiration Results

Blaney-Criddle Formula utilizes various climate data, including crop irrigation water constant. In order to calculate potential evapotranspiration with the formula, a suitable crop irrigation water constant needs to be determined. In this study, with study area kept in mind, sunflower crop which are farmed in abundance in Ergene Basin are chosen and data is chosen based on their growing season. For this case, Blaney-Criddle formula is used from April until September of each year between 1990 and 2020. Basing the calculations in this setup yields 155 data values. Results are given in figure 4.2.

Figure 4.2. Blaney-Criddle Crop Season Potential Evapotranspiration

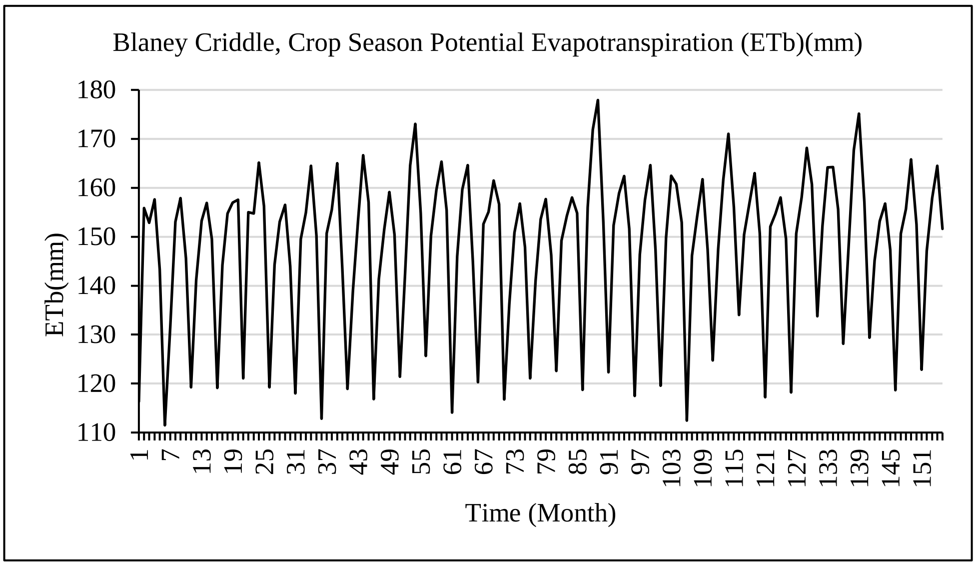
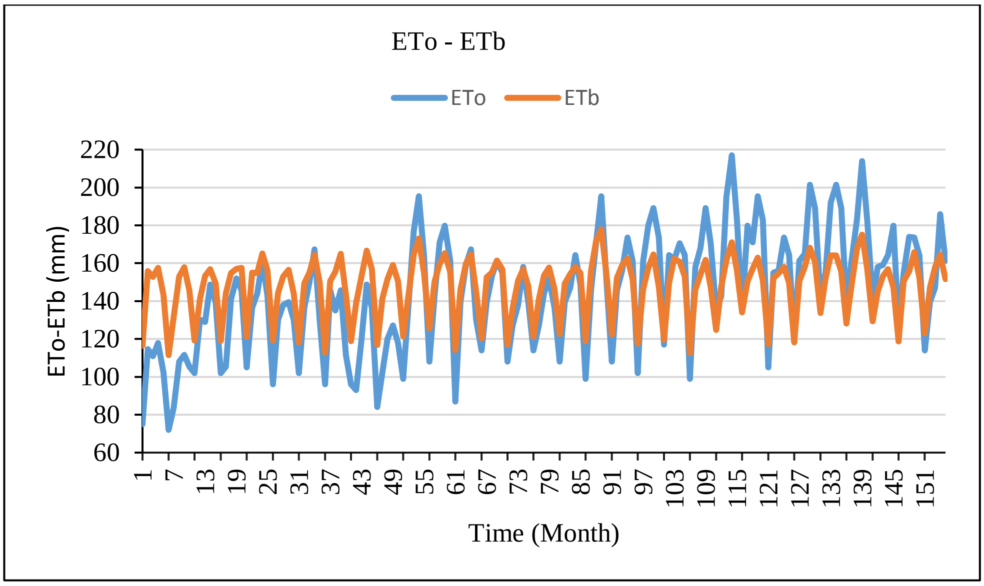


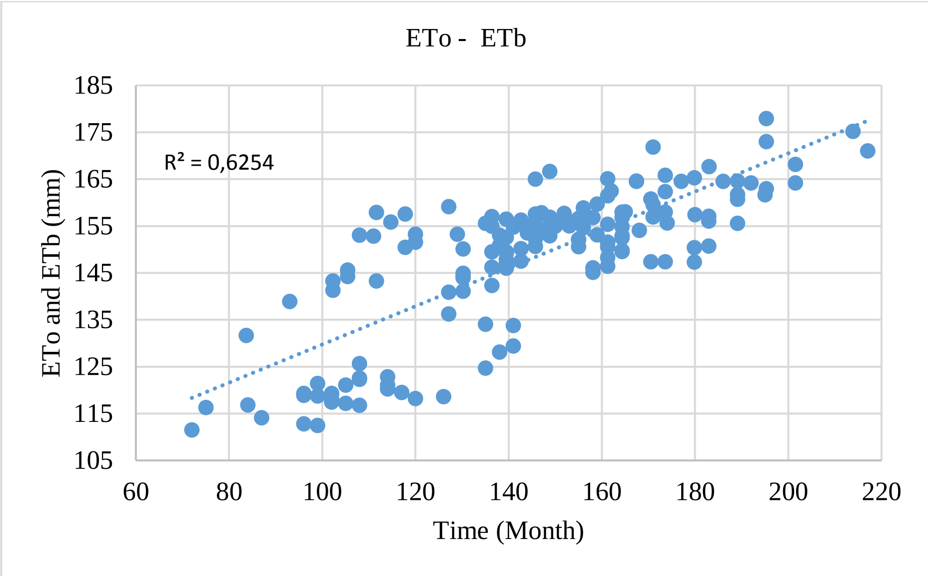
Figure 4.3. Crop Season Reference and Blaney-Criddle Potential Evapotranspiration Values



Crop season for each year is determined to be 5 months starting from and including April to and including August. From 1990 to 2020, 155 data values in total from 31 years of Blaney-Criddle potential evapotranspiration results and reference evapotranspiration values from same time frames are given in figure 4.3. According to figure 4.3, reference evapotranspiration values and Blaney-Criddle potential evapotranspiration results have a significant difference between them.

In order to calculate said difference, a scatter-dot diagram with deformation constant (R^2) of the comparison is given in figure 4.4. The deformation constant is calculated to be 0,6254 which further proves the significance of difference between reference and potential evapotranspiration values.

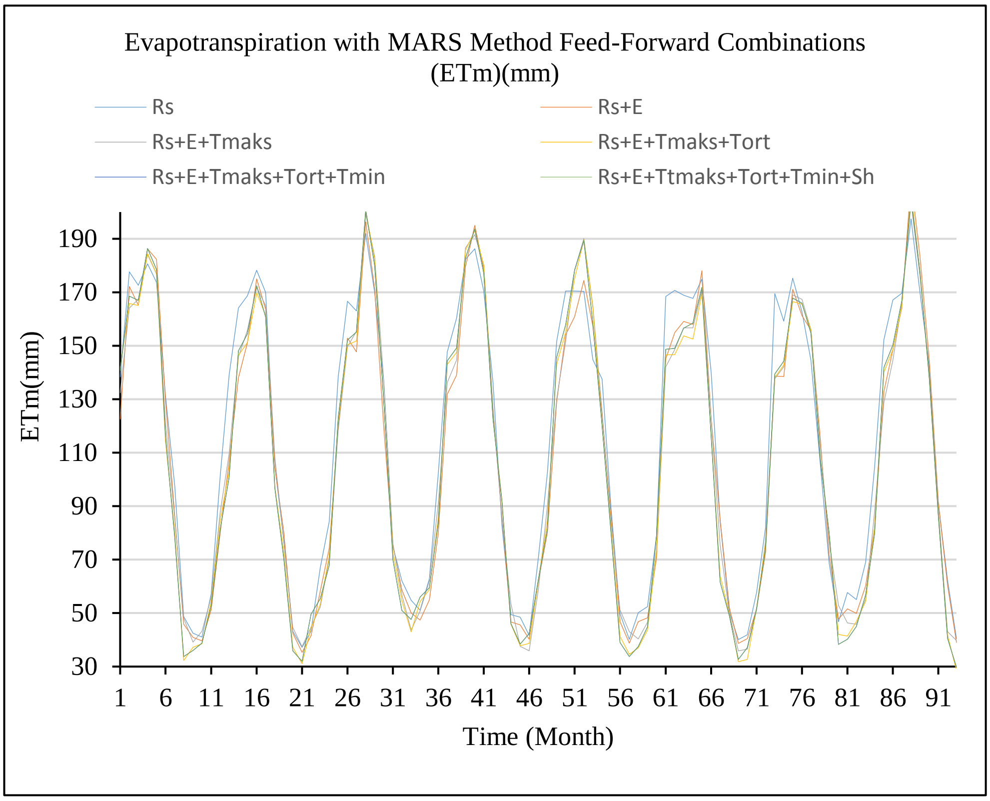
Figure 4.4. Crop reason reference and Blaney-Criddle potential evapotranspiration values comparison



4.3. MARS Method Evapotranspiration Results

While estimating potential evapotranspiration with MARS method, data sets such as solar radiation (R_s), evaporation (E), maximum temperature (T_{maks}), average temperature (T_{ort}), minimum temperature (T_{min}) and sunshine duration (S_h) are put into the model in a feed-forward manner in respective order.

Figure 4.5. MARS method feed-forward combinations evapotranspiration results



As it can be seen from figure 4.5, all combinations yielded similar potential evapotranspiration values.

In figures 4.6, 4.7. 4.8, 4.9, 4.10, and 4.11, all respective combinations results are shown with their R^2 values in order to find the best combination.

Figure 4.6. MARS model performance with input as R_s

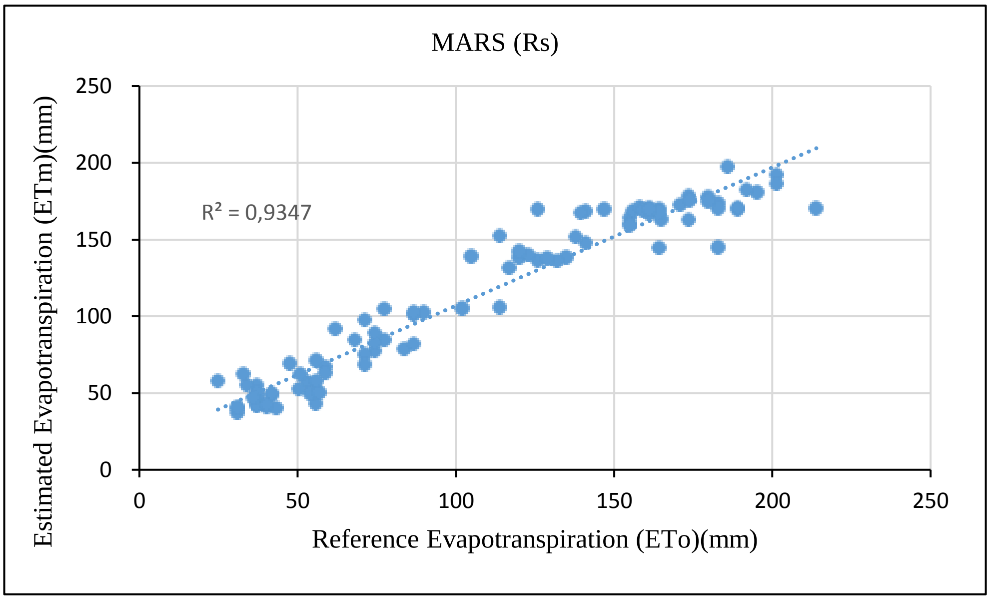


Figure 4.7. MARS model performance with inputs as R_s and E

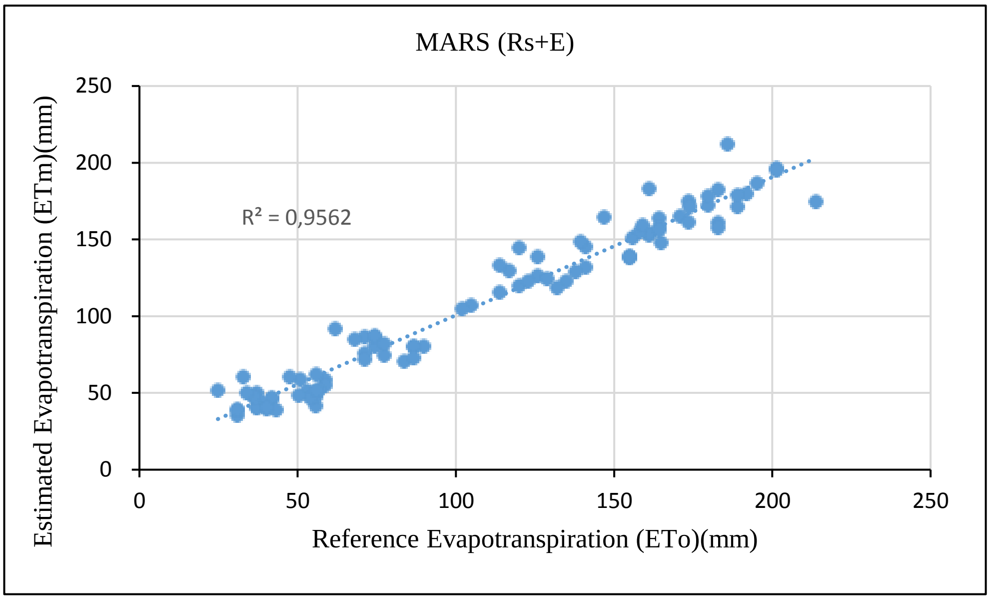


Figure 4.8. MARS model performance with inputs as R_s, E and T_{maks}

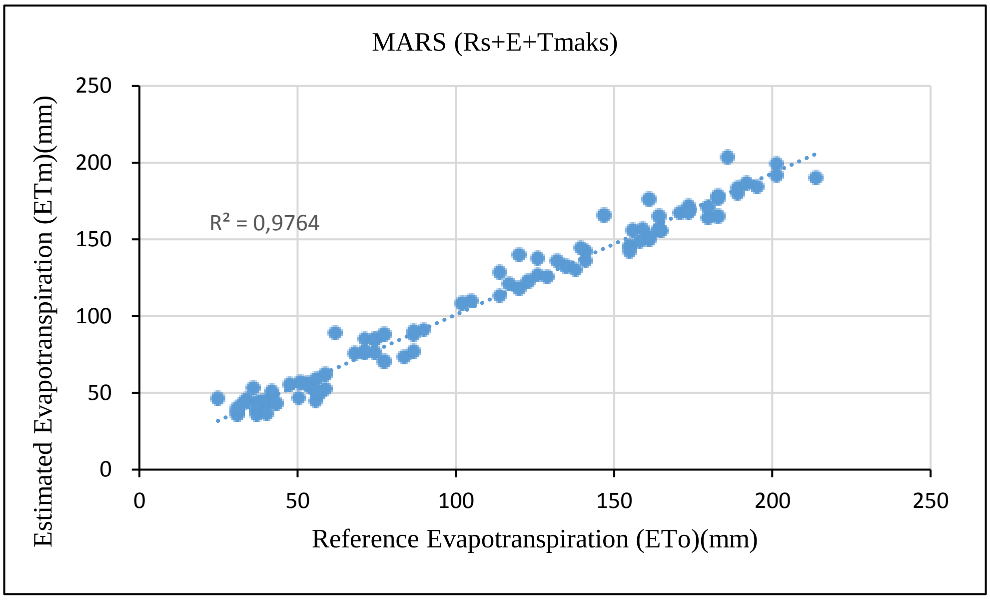


Figure 4.9. MARS model performance with inputs as R_s, E, T_{maks} and T_{ort}

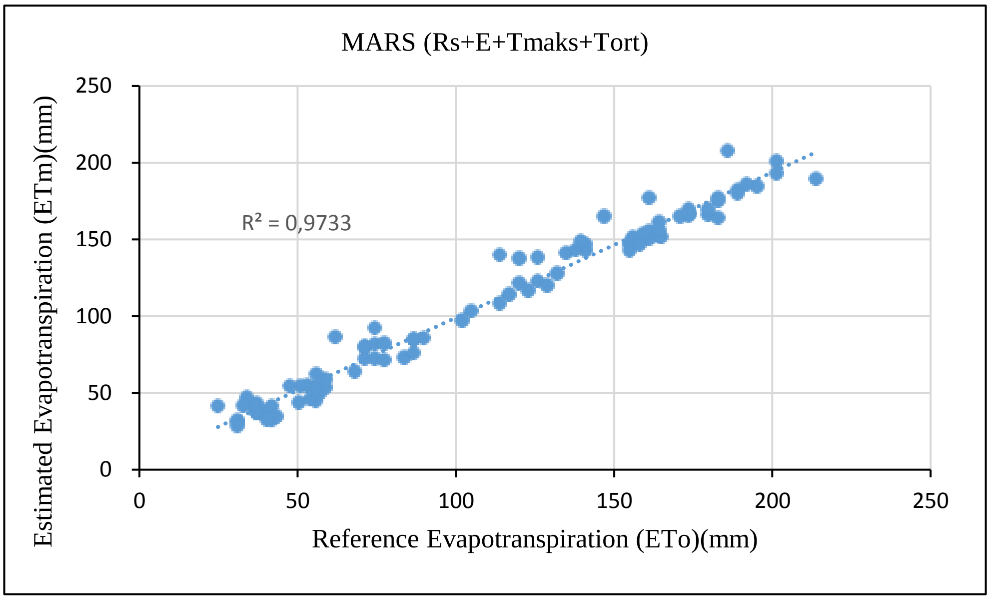


Figure 4.10. MARS model performance with inputs as R_s, E, T_{maks}, T_{ort} and T_{min}

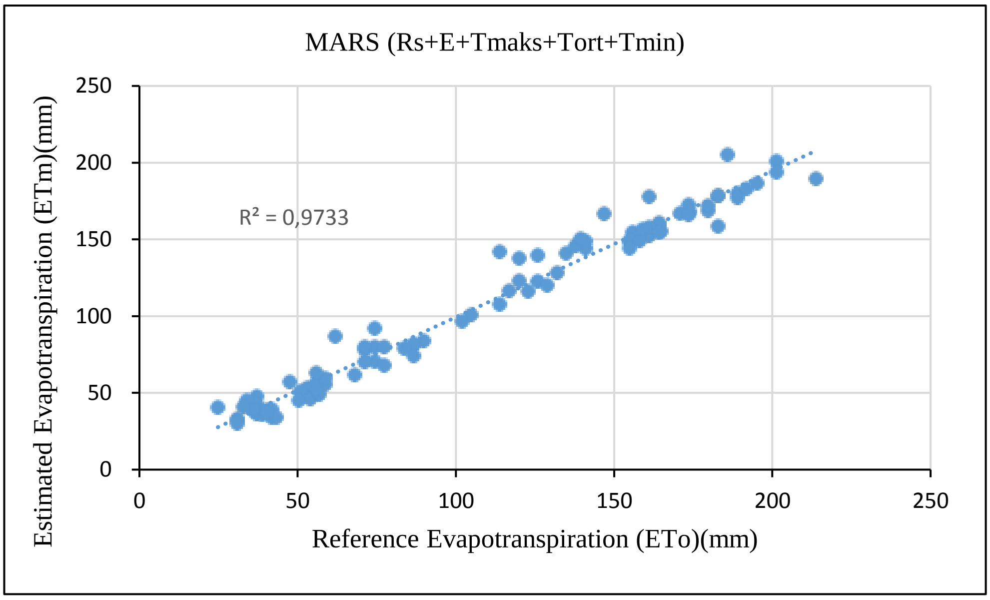
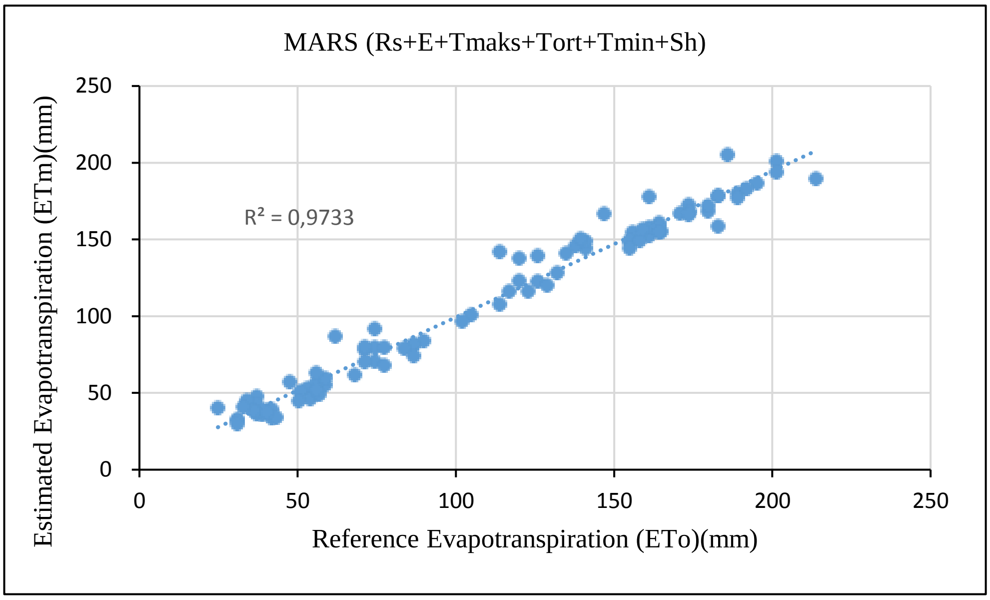


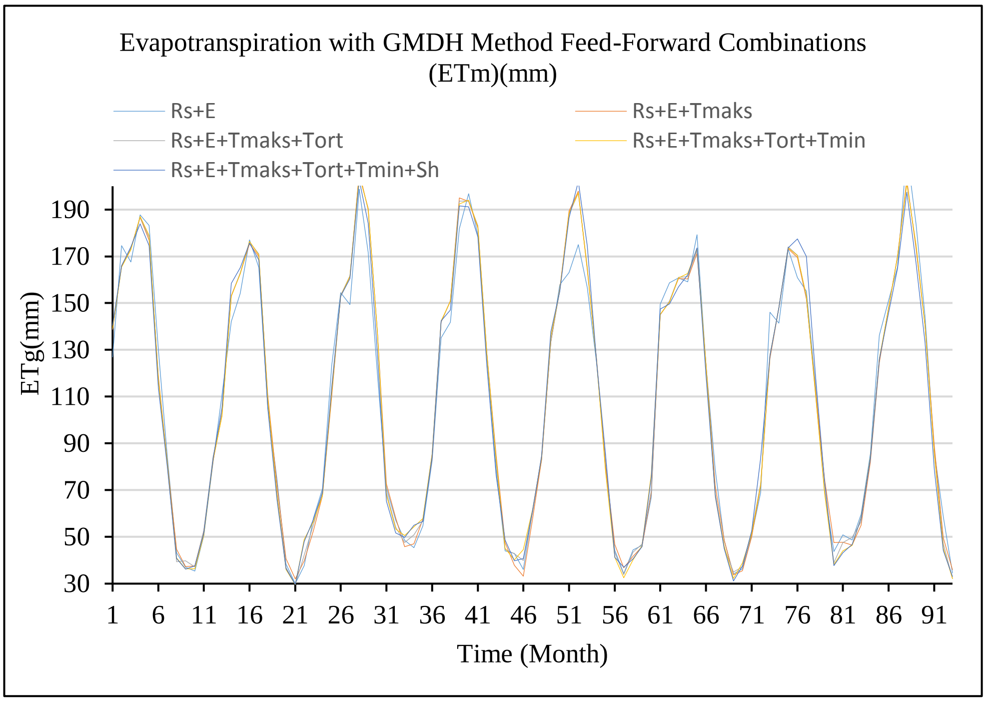
Figure 4.11. MARS model performance with inputs as R_s, E, T_{maks}, T_{ort}, T_{min} and S_h



4.3. GMDH Method Evapotranspiration Results

While estimating potential evapotranspiration with GMDH method, data sets such as solar radiation (R_s), evaporation (E), maximum temperature (T_{maks}), average temperature (T_{ort}), minimum temperature (T_{min}) and sunshine duration (S_h) are put into the model in a feed-forward manner in respective order.

Figure 4.12. GMDH method feed-forward combinations evapotranspiration results



As it can be seen in figure 4.12, all combinations yield very similar results

The results of each combination are given in figures 4.12, 4.13, 4.14, 4.15, 4.16 and 4.17.

Figure 4.13. GMDH model performance with inputs as R_s and E

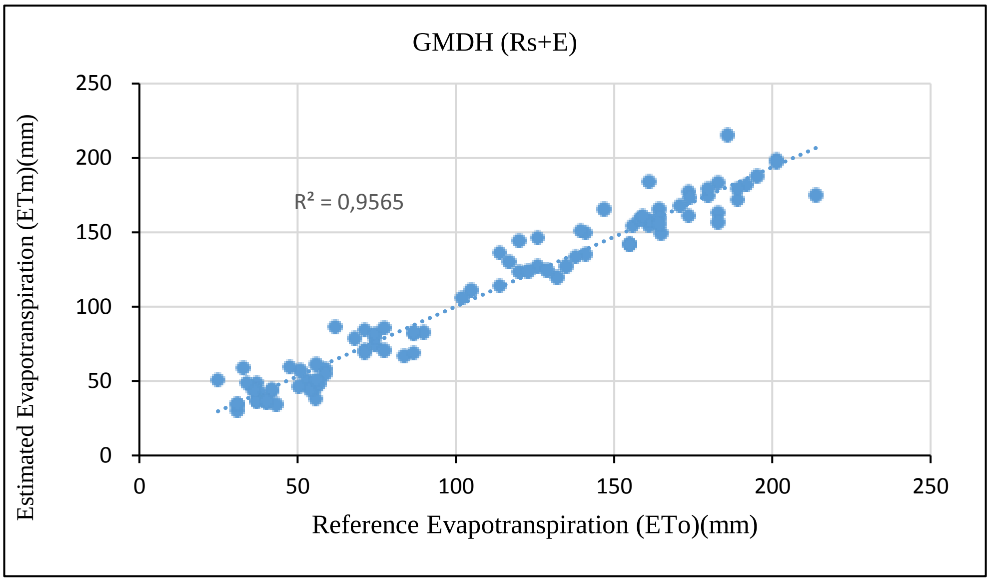


Figure 4.14. GMDH model performance with inputs as R_s, E and T_{maks}

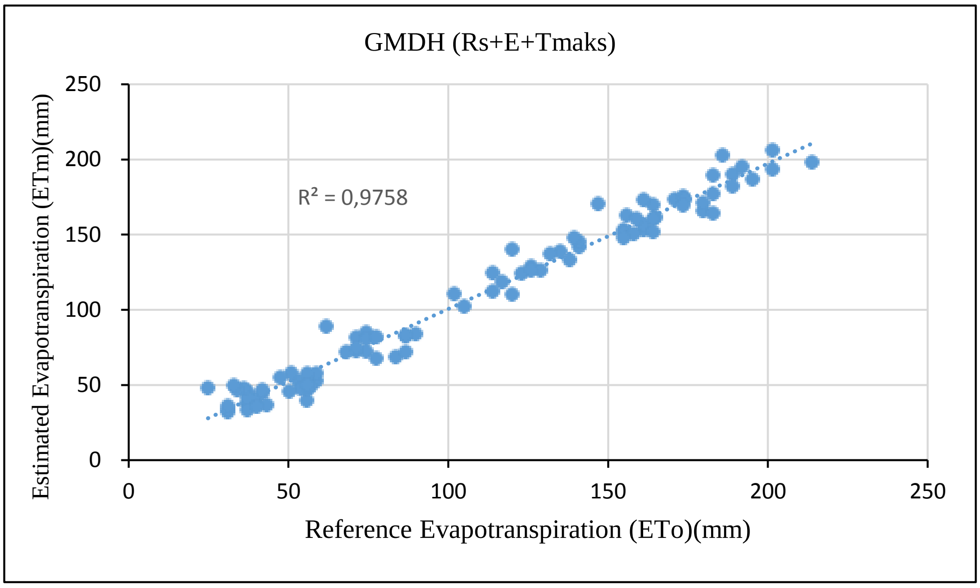


Figure 4.15. GMDH model performance with inputs as R_s, E, T_{maks} and T_{ort}

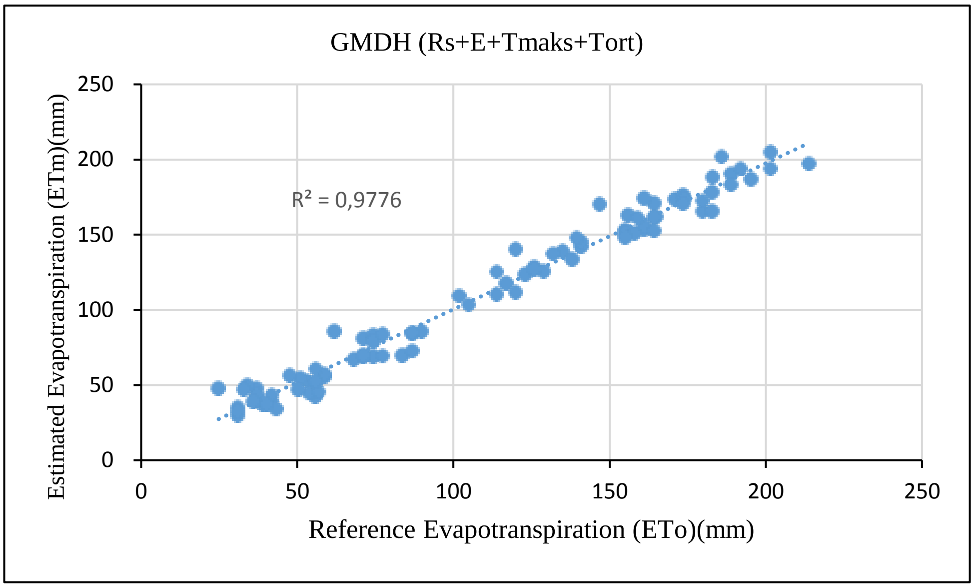


Figure 4.16. GMDH model performance with inputs as R_s, E, T_{maks}, T_{ort} and T_{min}

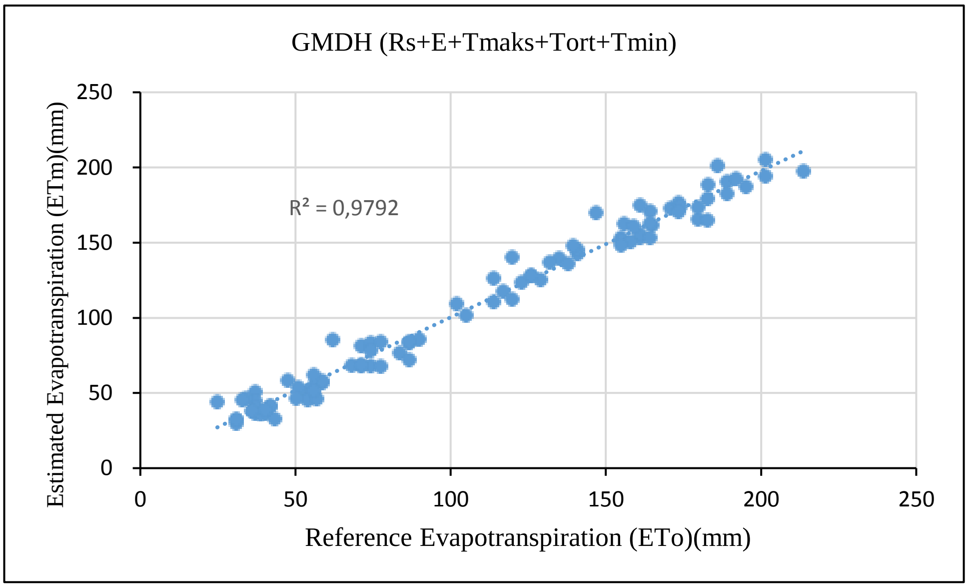
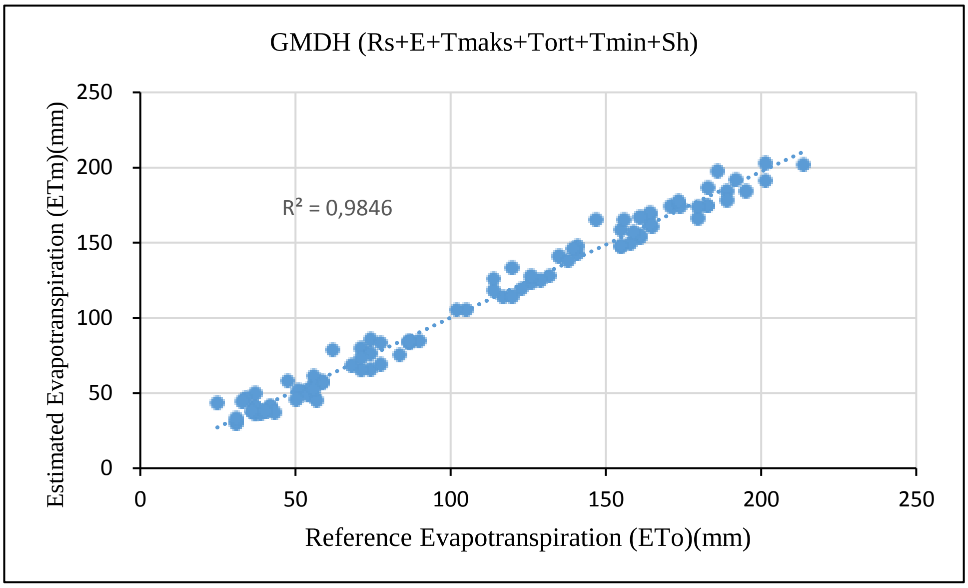


Figure 4.17. GMDH model performance with inputs as R_s, E, T_{maks}, T_{ort}, T_{min} and S_h



4.4. Performance Evaluation Criteria

In order to compare estimated evapotranspiration results with reference evapotranspiration, some performance evaluation criteria are determined. The best model is determined with performance evaluation criteria deformation constant (R^2), mean squared error (*MSE*), mean absolute error (*MAE*), average absolute relative error (*AARE*) respectively. The calculations for performance evaluation criteria are given below.

$$R^2 = \frac{\sum_{i=1}^{N}[(ET_0)_i - \overline{ET_0}]^2 - \sum_{i=1}^{N}\left[(ET_0)_i - (ET_{0,e})_i\right]^2}{\sum_{i=1}^{N}\left[(ET_0)_i - (ET_{0,e})_i\right]^2} \quad (4.4.1)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left[(ET_0)_i - (ET_{0,e})_i\right]^2 \quad (4.4.2)$$

$$MAE = \frac{\sum_{i=1}^{N}\left|(ET_0)_i - (ET_{0,e})_i\right|}{N} \quad (4.4.3)$$

$$AARE = \frac{1}{N}\sum_{i=1}^{N}|RH| \quad (4.4.4)$$

$$RH = \frac{(ET_0)_i - (ET_{0,e})_i}{(ET_0)_i}100 \quad (4.4.5)$$

Here;

$(ET_0)_i$: Reference evapotranspiration (mm)

$(ET_{0,e})_i$: Estimated evapotranspiration (mm)

RH: Relative error (%)

N: Number of data

Figure 4.18. Performance Criteria

Method		R^2	MSE	MAE	AARE
Blaney-Criddle		0,6254	425,90	16,76	12,85
MARS	Combinations				
	R_s	0,9347	247,90	12,25	15,83
	R_s+E	0,9566	148,65	9,40	12,21
MARS	R_s+E+T_{maks}	0,9764	84,56	7,34	9,58
	R_s+E+T_{maks}+T_{ort}	0,9733	88,10	7,46	8,65
	R_s+E+T_{maks}+T_{ort}+T_{min}	0,9734	86,64	7,26	8,45
	R_s+E+T_{maks}+T_{ort}+T_{min}+H_s	0,9732	86,63	7,25	8,46
	Combinations				
	R_s+E	0,9565	138,68	8,76	11,07
	R_s+E+T_{maks}	0,9758	76,73	6,77	9,15
GMDH	R_s+E+T_{maks}+T_{ort}	0,9776	70,63	6,43	8,69
	R_s+E+T_{maks}+T_{ort}+T_{min}	0,9792	65,70	6,17	8,07
	R_s+E+T_{maks}+T_{ort}+T_{min}+H_s	**0,9846**	**49,07**	**5,56**	**7,23**

In figure 4.18, methods used in this study are evaluated with specified performance criteria and the best results is marked with bold text.

5. Results

The reference evapotranspiration values obtained with FAO-56 PM empirical formula are compared with potential evapotranspiration results obtained with various models in this study. Reference evapotranspiration is compared 12 models in total, 5 of them belonging to GMDH method, 6 of them belonging to MARS method and the last one being the Blaney-Criddle empirical method.

In figure 4.4, Blaney-Criddle formula only yielded 62,54% correlation while the rest of the models all yielded correlations above 90%. This was expected within the aim of the study and further proved the success of machine learning methods over standard empirical methods.

Among machine learning methods, the best correlation was found to be 98,46% with GMDH method using R_s, E, T_{max}, T_{avg}, T_{min} and S_h data sets as seen in figure 4.17. This amount of correlation is regarded as very high and proves this model can be safely used to determine the amount of potential evapotranspiration.

However, the initial scope of this study is acquiring a successful model with the least amount of data sets as possible. While increasing the amount of data sets for both MARS and GMDH methods generally further improved the models, it can be seen from figure 4.18 that even with limited data, all models yielded strong correlation levels, with the least successful model yielding a 93,47% correlation and the rest of the models yielding correlation levels above 95%. Therefore, it is fair to say all models presented in this study are suitable for estimating potential evapotranspiration.

6. References

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