

# Reference evapotranspiration evaluation using solar radiation estimated by ANN and empirical models

---

## ABSTRACT

**Aims:** The reference evapotranspiration ( $ET_0$ ) estimation with Penman-Monteith or Priestley-Taylor methods requires measurements of temperature, radiation, humidity, and wind velocity. In this study, we evaluated the estimations of  $ET_0$  by Penman-Monteith ( $ET_0$ -PM) and Priestley-Taylor ( $ET_0$ -PrT) methods using indirect methods of calculating solar radiation ( $R_s$ ).

**Place and Duration of Study:** Daily meteorological measurements from two stations in northern Greece were used for the development of solar radiation models and  $ET_0$  calculation.

**Methodology:** The indirect methods of calculating solar radiation ( $R_s$ ) are based on Artificial Neural networks (ANN) technology and models using the multi-linear regression method (MLR). Three different ANN and MLR models were derived. The Hargreaves method is also used. The evaluation of the indirect  $R_s$  derived models and the  $ET_0$  estimation by the two methods was performed with the use of correlation coefficients ( $r$ ), root mean square error (RMSE), and efficiency (EF) indexes.

**Results:** The statistics of  $ET_0$  estimation at the two stations showed that the  $r$  and EF values, between the estimated  $ET_0$  using the indirect  $R_s$  models and estimated  $ET_0$  using  $R_s$  measured, were greater than 0.963 and 0.918, respectively, while the RMSE values were lower than 0.646 mm d<sup>-1</sup>. The statistics of  $R_s$  models, showed that the  $r$  and EF values were greater than 0.860 and 0.605, respectively, while the RMSE values were lower than 4.47 MJ m<sup>-2</sup>d<sup>-1</sup>.

**Conclusion:** The results of ANN models in comparison to MLR models, when using the same input variables, are consistent between them. These findings indicate that the Penman-Monteith and Priestley-Taylor methods can accurately predict  $ET_0$  using  $R_s$  values estimated indirectly through the examined methods and models.

*Keywords:* Solar radiation; Reference evapotranspiration; Penman–Monteith method; Priestley-Taylor method; Empirical methods; ANNs models; Daily datasets; Regression models

## 1. INTRODUCTION

The irrigation water management, the irrigation networks planning and design, the sustainability of agricultural systems, the hydrologic balance, the watershed hydrology, and

the droughts studies are based on the accurate estimation of the reference evapotranspiration ( $ET_o$ ).

The  $ET_o$  estimation depend mainly upon the availability of meteorological variables. The most accurate are those that are based on energy budget and the combination of radiation and temperature as the Priestley-Taylor method [1], the corrected FAO-24 Penman method [2, 3, 4, 5], and the FAO-56 Penman-Monteith method [5].

The evaluation of various evapotranspiration methods includes comparison of numerous equations describing evaporation or evapotranspiration. Among the articles on comparison between different approaches are, among many others, the works of [6, 7, 8, 9, 10, 11, 12, 13, 14, 15].

The solar radiation is a meteorological variable which is either not measured or is of low accuracy in many cases. Many empirical methods have been developed and evaluated to predict the solar radiation using daily meteorological parameters [16, 17, 18, 19, 20, 21].

During the last decades there has been a widespread interest in the application of Artificial neural networks (ANNs) in the field of water sciences and specially to estimate evaporation from free water surface as well as actual and reference evapotranspiration [18, 20, 21, 22, 23, 24, 25, 26, among others] and climate variables.

In Antonopoulos et al. [18], the suitability of Hargreaves method, Artificial Neural networks (ANN) and multi-linear regression methods (MLR) to estimate solar radiation was evaluated using daily meteorological data from two stations in Northern Greece. Daily data of three successive years were used in this work. The use of extraterrestrial radiation ( $R_a$ ) and the square root of daily difference in temperature,  $(T_{max}-T_{min})^{0.5}$ , in the ANN and MLR models resulted in more accurate estimations.

The main objective of this study is to evaluate the computed  $ET_o$  using the Penman – Monteith and Priestley-Taylor methods, in which the solar radiation variable is estimated using indirect methods, including models based on ANNs and MLR methods. An analytical work on derivation of indirect methods suitability was presented in Antonopoulos et al [18]. The  $R_s$  and  $ET_o$  of Hargreaves method is also evaluated. The indirect  $R_s$  models and the results of  $ET_o$  were derived and evaluated using daily data at two meteorological stations. The daily datasets covered five consecutive years at these two meteorological stations located in northern Greece, areas of high significance in agricultural irrigation and water resources management.

## 2. MATERIAL AND METHODS

### 2.1 Daily reference crop evapotranspiration

The FAO-56 Penman-Monteith (PM) method of daily reference crop evapotranspiration ( $ET_o$ -PM), which consider according to FAO the standard method, is described by the following equation [5]:

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_a - e_d)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

where  $ET_o$  is the daily reference crop evapotranspiration ( $\text{mm d}^{-1}$ ),  $R_n$  is the net radiation ( $\text{MJ m}^{-2}\text{d}^{-1}$ ),  $u_2$  is the mean wind speed at 2 m above soil surface ( $\text{m s}^{-1}$ ),  $T$  is the mean air temperature ( $^{\circ}\text{C}$ ),  $G$  is the soil heat flux density at the soil surface ( $\text{MJ m}^{-2}\text{d}^{-1}$ ),  $e_a$  is the saturation vapour pressure (kPa),  $e_d$  is the actual vapour pressure (kPa),  $\Delta$  is the slope of the saturation vapour pressure-temperature curve ( $\text{kPa}^{\circ}\text{C}^{-1}$ ),  $\gamma$  is the psychrometric constant ( $\text{kPa}^{\circ}\text{C}^{-1}$ ).

The Priestley-Taylor method [1] of daily reference crop evapotranspiration ( $ET_o$ -PrT) is a modification and simplification of the Penman formula. It is described by the following form:

$$ET_o = \alpha \frac{\Delta}{\Delta + \gamma} \frac{(R_n - G)}{\rho_w \lambda} \quad (2)$$

where  $\lambda$  is the latent heat of vaporization ( $\text{MJ kg}^{-1}$ ),  $\rho_w$  is the water density ( $\text{kg m}^{-3}$ ) and  $\alpha$  is an empirically derived parameter with an average value of 1.26 [15]. This method is a radiation based method. The Priestley-Taylor method has been used to estimate the reference crop evapotranspiration in many works [13, 14, 27, 28].

The Hargreaves method [29] estimates daily  $ET_o$ , with the following equation

$$ET_o = (a_h / K_{RS}) (T_{\text{mean}} + b_h) R_s \quad (3)$$

where  $T_{\text{mean}}$  is the mean temperature ( $^{\circ}\text{C}$ ), and  $a_h=0.0023 \text{ }^{\circ}\text{C}^{-1.5}$ , and  $b_h=17.8 \text{ }^{\circ}\text{C}$  empirical constants,  $K_{RS}$  is the adjustment coefficient of the radiation formula ( $^{\circ}\text{C}^{-0.5}$ ), and  $R_s$  is the solar radiation ( $\text{mm d}^{-1}$ ) of Hargreaves equation.

The incoming shortwave solar radiation  $R_s$  ( $\text{MJ m}^{-2} \text{d}^{-1}$ ), according to Hargreaves and Samani [29,30], is computed by the following equation:

$$R_s = K_{RS} \cdot R_a \cdot (TD)^{0.5} \quad (4)$$

where  $R_a$  is the extraterrestrial radiation ( $\text{MJ m}^{-2} \text{d}^{-1}$ ) and  $TD$  (equal to  $T_{\text{max}} - T_{\text{min}}$ ) is the temperature difference between maximum ( $T_{\text{max}}$ ) and minimum ( $T_{\text{min}}$ ) daily temperature ( $^{\circ}\text{C}$ ). Hargreaves [35] recommended using  $K_{RS}= 0.162$  for "interior" locations, and  $K_{RS}= 0.19$  for coastal locations. [13, 14, 31, 32,33, 34].

The Multivariable regression method (MLR) is based on the fact that the meteorological parameters are highly correlated with  $R_s$  and  $ET_o$ . A general form of these equations is as

$$R_s = m_1 + m_2 X_1 + m_3 X_2 + m_4 X_3 + \dots + m_{n+1} X_n \quad (5)$$

where  $m_1, m_2, m_3, m_4$  and  $m_n$  are regression coefficients and  $X_i$  are meteorological parameters or factors. The variables of  $X_i$  can be simple meteorological parameters ( $T_{\text{ave}}, T_{\text{max}}, T_{\text{min}}, RH_{\text{av}}, u_2$ ) or combinations of them ( $(TD=T_{\text{max}}-T_{\text{min}})$  and  $(TD)^{0.5}$ ) [36, 37, 38, 39, 40].

## 2.2. Artificial neural networks

The artificial neural networks are non-linear models that make use of a structure capable to represent arbitrary complex non-linear processes that relate the inputs and outputs of any system [14, 17, 22, 23, 24, 26, 41, 42, 43, 44, 45].

In this article, an algorithm of the multi-layer feed forward artificial neural networks and of the back-propagation for optimization was used [44]. The main task in developing an ANN model is to identify the input variables and the optimal network structure in order to produce the desired output accurately. Before training and testing, the variables (as example  $T_{\max}$ ,  $T_{\min}$ ,  $T_{\text{av}}$ ,  $RH_{\text{av}}$ ,  $u_2$ ) were standardized and were used as input variables. The target output variable (as  $R_s$ ) was also standardized before training and testing.

The trial and error procedure showed that the number of neurons in the hidden layer is between 4 and 6, because they are produced similar results. Details of ANN models selection and the procedure that followed in this study have been presented elsewhere [14, 22, 26, 46].

### 2.3. Modeling Performance Criteria

The model's performance was evaluated using statistical criteria including the correlation coefficient ( $r$ ), the root mean square error (RMSE) and the coefficient of efficiency (EF):

$$r = \left( \frac{\sum_{i=1}^N (O_i - O_m)(C_i - C_m)}{\sqrt{\sum_{i=1}^N (O_i - O_m)^2} \sqrt{\sum_{i=1}^N (C_i - C_m)^2}} \right) \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (C_i - O_i)^2} \quad (7)$$

$$\text{EF} = 1 - \left( \frac{\sum_{i=1}^N (C_i - O_i)^2}{\sum_{i=1}^N (O_i - O_m)^2} \right) \quad (8)$$

where  $O$  are the observed values (the solar radiation or the reference evapotranspiration),  $C$  are the computed values by the other methods and  $O_m$  and  $C_m$  are the mean observed and computed values, respectively. In most cases the coefficient of determination ( $R^2$ ) is the square of  $r$ . The range of EF (which is also known as Nash and Sutcliffe model efficiency) lies between 1 (perfect value) and  $-\infty$ .

### 2.4. Study area and data

The meteorological data, that was used in this study to estimate daily solar radiation and  $ET_o$ , are consisted of daily data of air temperature, solar radiation, wind speed, and humidity for a period of five years (2011 to 2015) measured at two meteorological station in northern Greece [18].

The 1<sup>st</sup> meteorological station of Aristotle University of Thessaloniki Farm (AUTH) is located in Central Macedonia (40° 37'54"N, 22° 57'27"E, 34 m above sea level) of Greece and the

2nd meteorological station of Amyntaio (AMIN) at West Macedonia is located at northern latitude of 40° 46'27"N, 21°39'E, 580 m above sea level.

Table 1 presents the average and standard deviation values of temperature (°C), relative humidity (%), wind velocity (m s<sup>-1</sup>), and solar radiation (MJ m<sup>-2</sup> d<sup>-1</sup>) for each station for the study period of five years. The daily data sets of meteorological station of AUTH present missing data which estimated to 17 % of available data.

**Table 1. Average temperature, relative humidity, wind velocity and solar radiation for each station during study period**

	T, oC		RH, %		u <sub>2</sub> , m sec <sup>-1</sup>		R <sub>s</sub> , MJ m <sup>-2</sup> d <sup>-1</sup>	
	mean	sd	mean	sd	mean	sd	mean	sd
AUTH	16.43	8.23	70.57	15.48	0.56	0.80	15.94	8.58
AMIN	12.59	8.56	66.07	15.16	1.80	1.14	17.19	9.29

### 3. RESULTS

The results of Hargreaves equation, ANNs and MLR models to estimate the R<sub>s</sub> are presented firstly in this part of article. Meteorological data sets of 3 years, from the same station, were used in a former published paper [18] to evaluate the R<sub>s</sub> models. In the present study 5 years of daily data are employed. Therefore, only the more important information are showcased here.

Subsequently, this section examines mainly the impact of employing the indirectly estimated R<sub>s</sub> (via empirical and ANN models) as inputs for ET<sub>o</sub> calculations using the Penman-Monteith, the Priestley-Taylor and Hargreaves equations.

#### 3.1. Results of estimated R<sub>s</sub> at Aristotle University Farm Station

The daily datasets of 5 years at Aristotle University Farm station was used to derive the Hargreaves (HG) equation of R<sub>s</sub> estimation. The daily R<sub>s</sub> values predicted by the Hargreaves (HG) method using the recommended value of K<sub>RS</sub> coefficient (K<sub>RS</sub>=0.162) and the value adjusted to local conditions (K<sub>RS</sub>=0.158), compared with the R<sub>s</sub> measurements. In Table 2 the values of statistical criteria of these comparisons are presented. The correlation coefficient (r), the RMSE and EF of the Hargreaves method for R<sub>s</sub> are 0.893, 3.049 MJ m<sup>-2</sup>d<sup>-1</sup> and 0.732, respectively for K<sub>RS</sub>=0.162, and 0.893, 3.032 MJ m<sup>-2</sup>d<sup>-1</sup> and 0.722, respectively for K<sub>RS</sub>=0.158.

The architecture of the ANN model was identified by the trial and error procedure [14, 18]. Three different ANN models were developed. The difference, among them, are in the number and the combination of input variables. The input and output variables were standardized before training and testing.

In the 1<sup>st</sup> model, the standard meteorological parameters (T<sub>max</sub>, T<sub>min</sub>, T<sub>ave</sub>, RH<sub>av</sub>, u<sub>2</sub>) were used as input variables. The most appropriate architecture of this model (ANN-I), that finally chosen, was the 5-6-1 structure, with 5 neurons in the input layer, 6 neurons in the hidden

layer and 1 neuron in the output layer which corresponds to the solar radiation. All of the available data sets were used for training and testing the model.

Two other cases of input variables were examined. In one of them (ANN-II), four (4) input variables were used [ $R_a$ ,  $(T_{max}-T_{min})$ ,  $(T_{max}-T_{min})^{0.5}$ ,  $RH_{av}$ ], while in the other (ANN-III), two (2) variables, the  $R_a$ , and  $(T_{max}-T_{min})^{0.5}$  were used.

In Table 2 the statistical properties of three different ANNs models to estimate  $R_s$  at Aristotle University Farm station are presented. The correlation coefficient ( $r$ ), the RMSE and EF of the ANNs models for  $R_s$  ranged from 0.861 to 0.925, the RMSE ranged from 3.271 to 4.451  $MJ\ m^{-2}d^{-1}$  and the EF ranged from 0.652 to 0.806.

The derived MLR equations, which are based on the available variables of the daily datasets of 2011-15 and different combinations of independent variables, are given as

$$R_s = 8.6705 + 0.2407T_{max} - 1.2386T_{min} + 1.4692T_{ave} - 0.1299RH_{av} + 0.1466u_2 \quad (8)$$

$$R_s = -4.4342 + 0.4355R_a - 0.2949(T_{max} - T_{min}) + 5.8188(T_{max} - T_{min})^{0.5} - 0.13702RH_{av} \quad (9)$$

$$R_s = -17.6084 + 0.5367R_a + 5.2621(T_{max} - T_{min})^{0.5} \quad (10)$$

The  $R^2$  of these approaches are 0.758, 0.811 and 0.850, respectively.

In Table 2 the statistical properties of three different MLRs models to estimate  $R_s$  at Aristotle University Farm station are presented. The correlation coefficient ( $r$ ) of the MLRs models for  $R_s$  ranged from 0.871 to 0.922, the RMSE ranged from 3.502 to 4.178  $MJ\ m^{-2}d^{-1}$  and the EF ranged from 0.681 to 0.780.

The estimated values of  $R_s$  using MLR-III and ANN-II models correlated very well with the measured values of  $R_s$ , outperforming other MLR and ANN models as well as the Hargreaves method. The ANN-I and MLR-I showed lower accuracy.

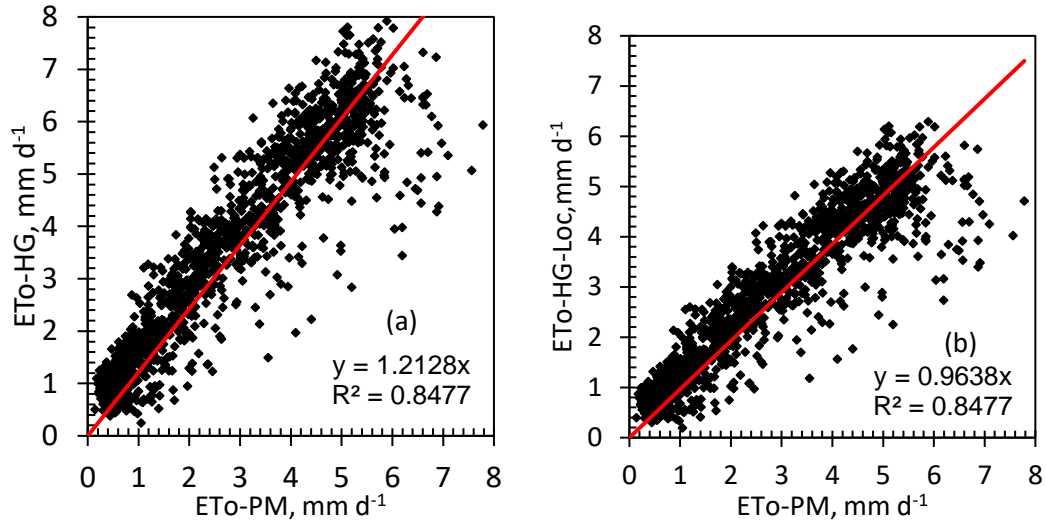
**Table 2. Statistical criteria of ANN model to estimate  $R_s$  at Aristotle University Farm station**

	$R_s$		$r$	index		Ranking		
	Mean MJ $m^{-2}d^{-1}$	sd MJ $m^{-2}d^{-1}$		RMSE MJ $m^{-2}d^{-1}$	EF	$r$	RMSE	EF
Measured	15.940							
HG	16.441	7.506	0.893	3.049	0.732	4	2	5
HG local	16.035	7.320	0.893	3.032	0.722	4	1	6
ANN -I	14.906	7.551	0.861	4.451	0.652	6	8	8
ANN -II	16.300	7.436	0.925	3.271	0.806	1	3	1
ANN -III	15.713	7.669	0.893	3.837	0.750	4	6	4
MLR -I	15.938	7.404	0.871	4.178	0.681	5	7	7
MLR -II	15.936	7.655	0.900	3.697	0.767	3	5	3
MLR -III	14.805	7.472	0.922	3.502	0.780	2	4	2

Note: ANN-I ( $T_{max}$ ,  $T_{min}$ ,  $T_{ave}$ ,  $RH_{av}$ ,  $u_2$ ); ANN-II ( $R_a$ ,  $(T_{max}-T_{min})$ ,  $(T_{max}-T_{min})^{0.5}$ ,  $RH_{av}$ ); ANN-III ( $R_a$ ,  $(T_{max}-T_{min})^{0.5}$ ); MLR-I ( $T_{max}$ ,  $T_{min}$ ,  $T_{ave}$ ,  $RH_{av}$ ,  $u_2$ ); MLR-II ( $R_a$ ,  $(T_{max}-T_{min})$ ,  $(T_{max}-T_{min})^{0.5}$ ,  $RH_{av}$ ); MLR-III ( $R_a$ ,  $(T_{max}-T_{min})^{0.5}$ )

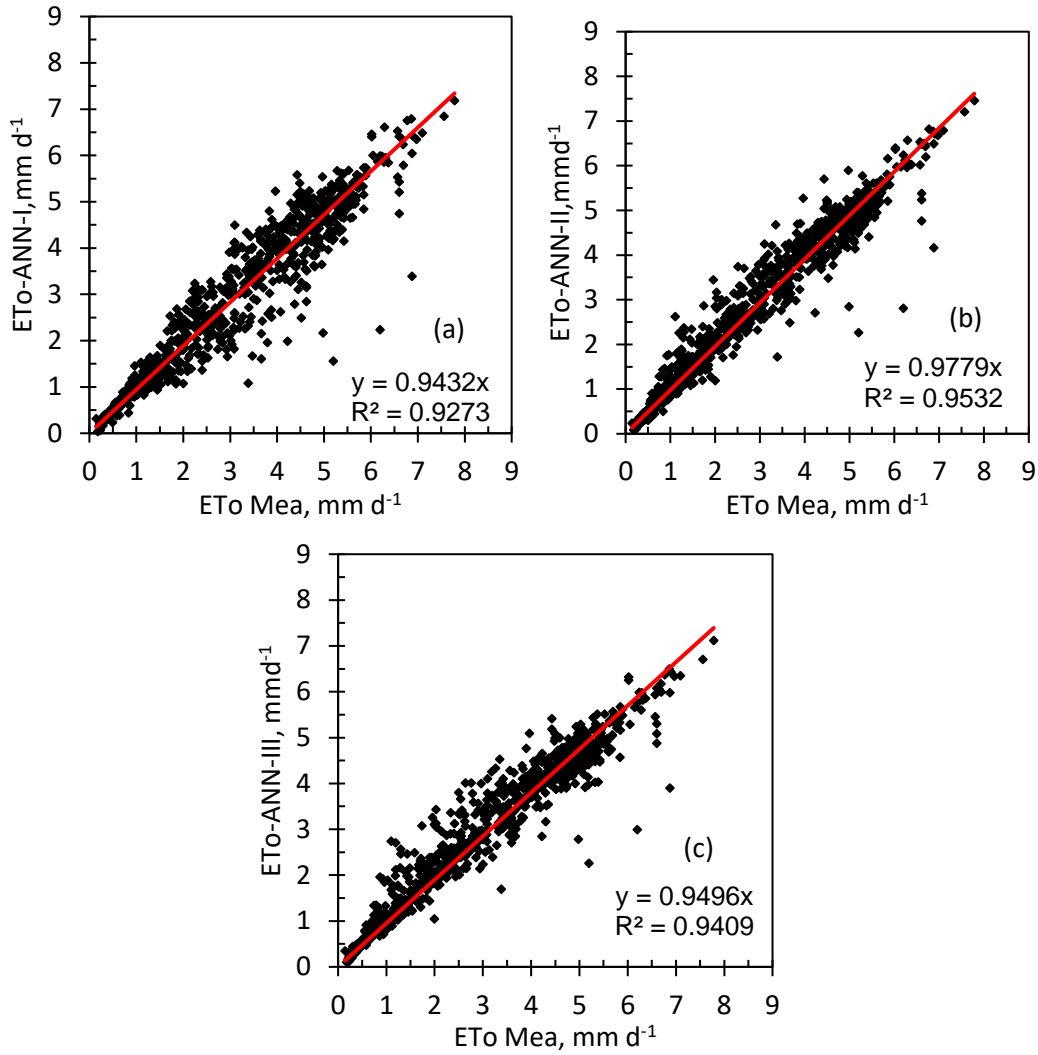
### 3.2 Results of ET<sub>o</sub> at Aristotle University Farm Station

Figure 1 shows the comparison of daily ET<sub>o</sub> values estimated using the R<sub>s</sub> values of Hargreaves equations (original and modified to local conditions) and the ET<sub>o</sub> values estimated by Penman – Monteith method using the measured values of R<sub>s</sub> at Aristotle University Farm station.



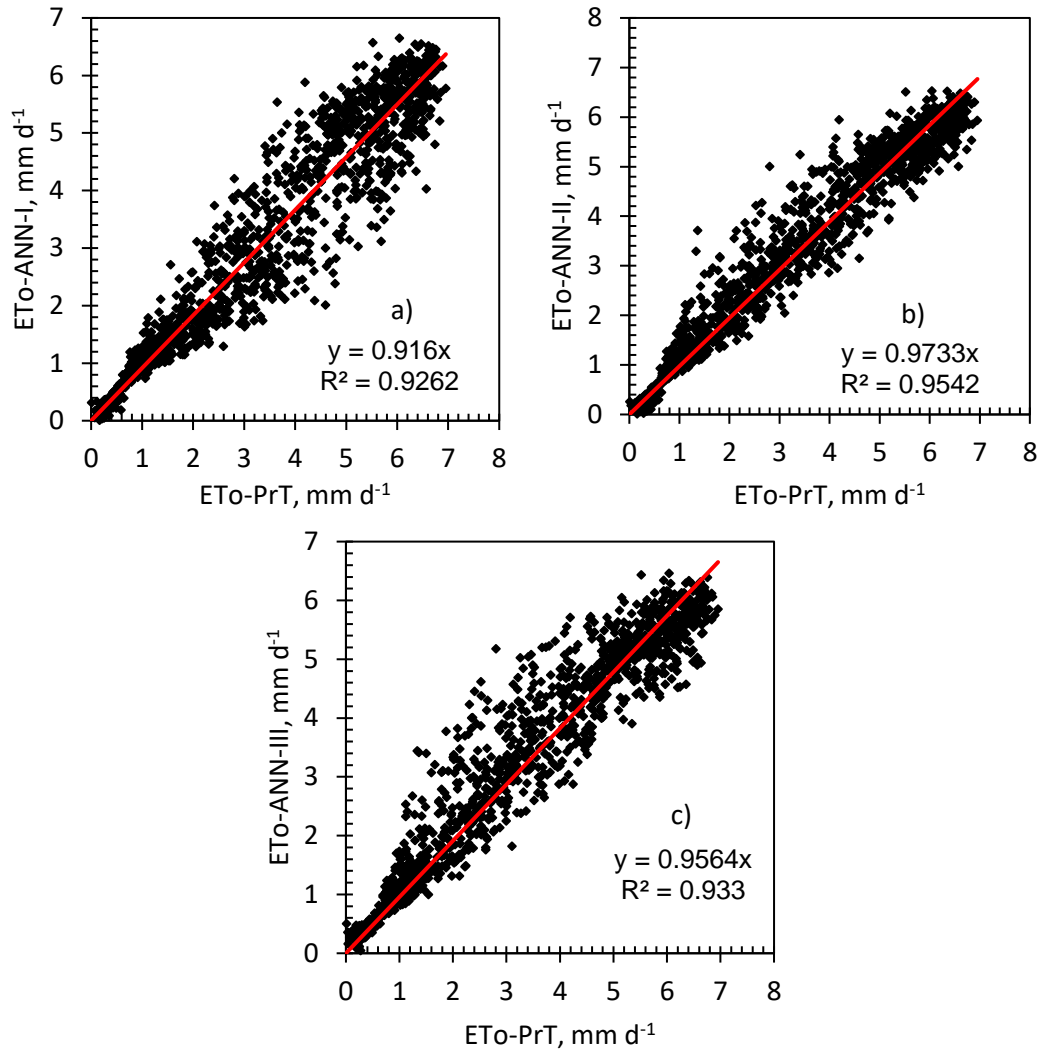
**Fig. 1. Scattering diagrams of daily ET<sub>o</sub> estimated by the Hargreaves (HG) and the ET<sub>o</sub> values estimated by the Penman – Monteith method using measured values of R<sub>s</sub>, a) K<sub>RS</sub>=0.162; b) K<sub>RS</sub>=0.158 local adjusted coefficient.**

Figure 2 presents the scattering diagrams between ET<sub>o</sub> of Penman-Monteith method using R<sub>s</sub> estimated using the ANN models and the measured values of R<sub>s</sub> at Aristotle University Farm, respectively.



**Fig. 2. Scattering diagrams between  $ET_0$  estimated with  $R_s$  measured and  $ET_0$  estimated with  $R_s$  computed with Artificial Neural Networks (a. ANN-I; b. ANN-II and c. ANN-III) models at Aristotle University Farm station.**

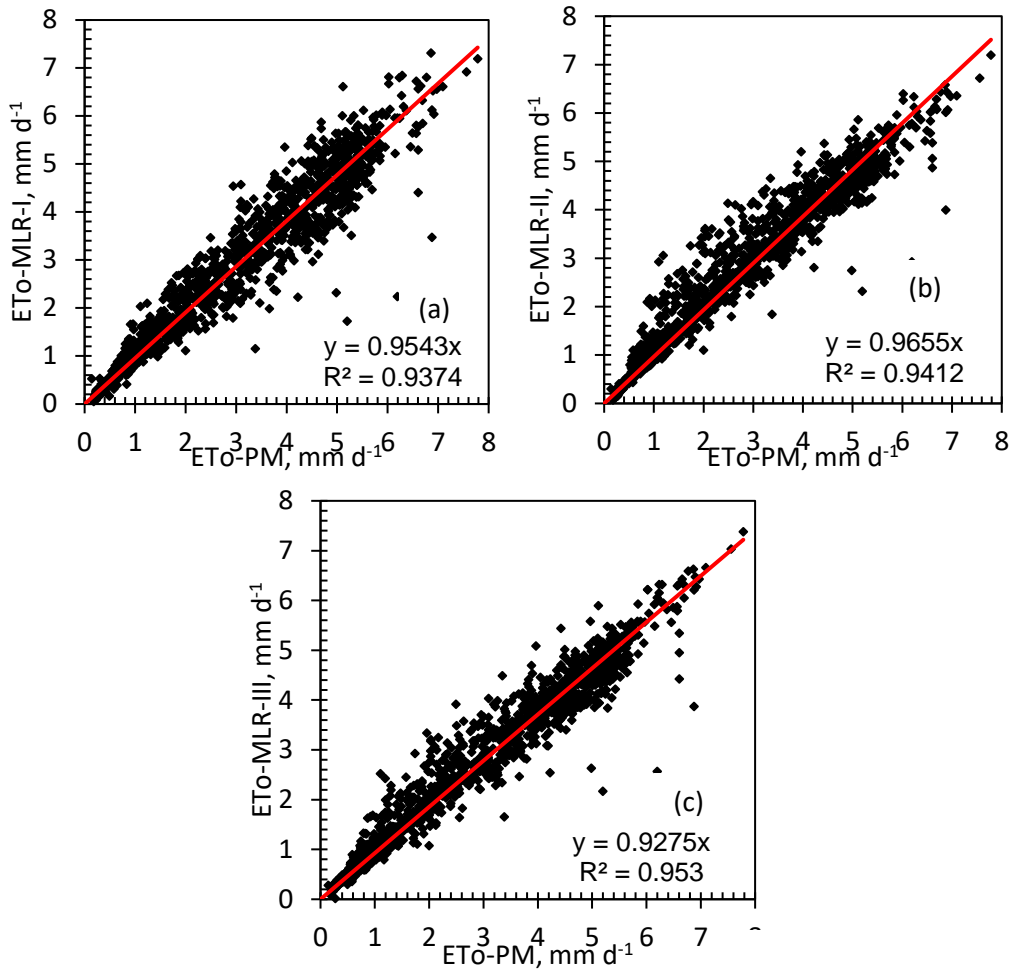
Figure 3 presents the scattering diagrams between  $ET_0$  of Priestley-Taylor method using  $R_s$  estimated using the ANNs models and the measured values of  $R_s$  at Aristotle University Farm, respectively.



**Fig. 3. Scattering diagrams of  $ET_0$ -PrT estimated with  $R_s$  measured and  $ET_0$ -PrT estimated with  $R_s$  computed with Artificial Neural Networks (a. ANN-I; b. ANN-II and c. ANN-III) models at Aristotle University Farm station.**

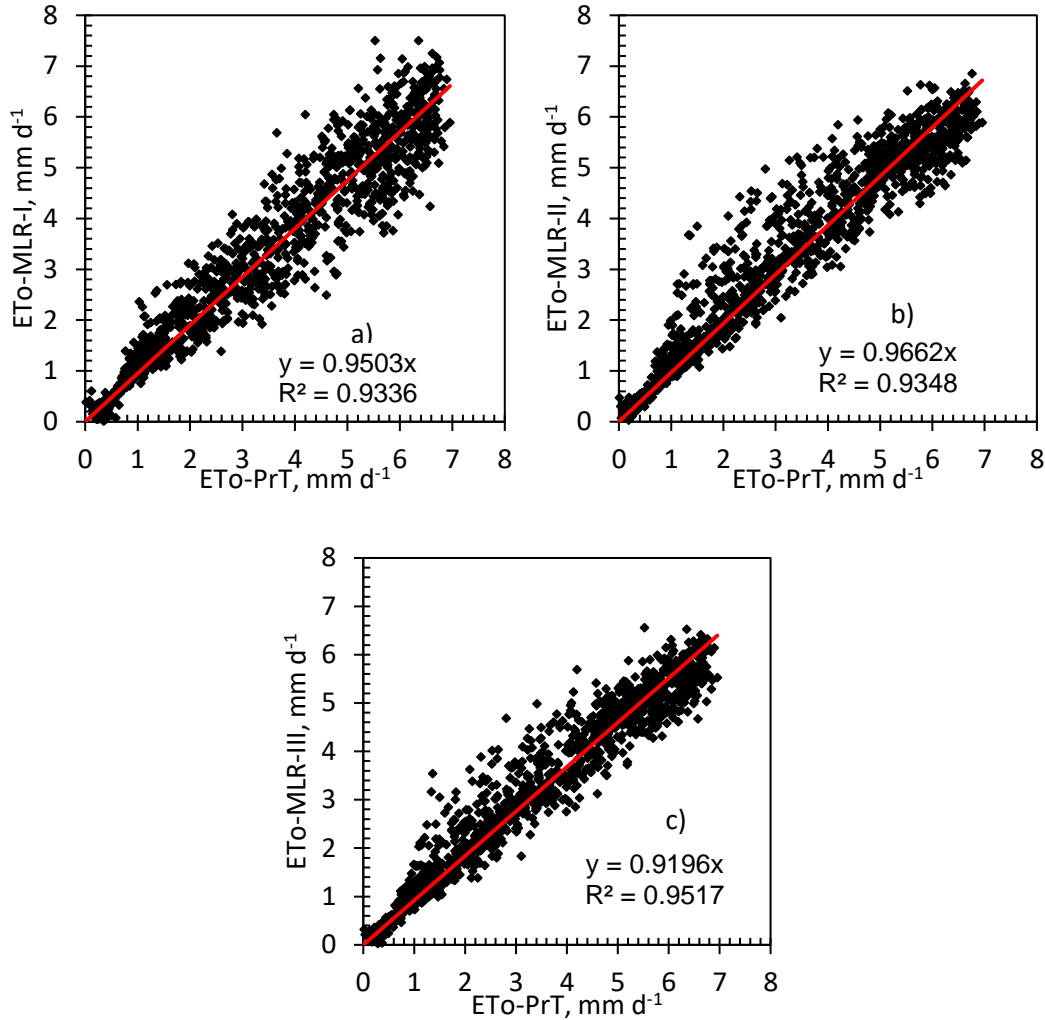
The values of  $R^2$  are very high in these three scatters diagrams (0.926 to 0.954). Underestimation of higher values of  $ET_0$ -PrT observed, with lower using the ANN-I model.

Figures 4 presents the comparison between  $ET_0$  of Penman-Monteith method using  $R_s$  estimated using the MLR models and the measured values of  $R_s$  at Aristotle University Farm, respectively.



**Fig. 4. Scattering diagrams between  $ET_0$  estimated with  $R_s$  measured and  $ET_0$  estimated with  $R_s$  computed with Multi linear regression (a. MLR-I, b. MLR-II and c. MLR-III) models at Aristotle University Farm station.**

Figure 5 presents the comparison between  $ET_0$  of Priestley-Taylor method using  $R_s$  estimated using the MLR models and the measured values of  $R_s$  at Aristotle University Farm, respectively.



**Fig. 5. Scattering diagrams of  $ET_0$ -PrT estimated with  $R_s$  measured and  $ET_0$ -PrT estimated with  $R_s$  computed with Multi linear regression (a. MLR-I, b. MLR-II and c. MLR-III) models at Aristotle University Farm station.**

The values of  $R^2$  are very high in these three scatter diagrams (0.933 to 0.951). Underestimation of higher values of  $ET_0$ -PrT is also observed, with lower values when the MLR-III model is used.

Table 3 presents the statistical properties of different methods to estimate  $ET_0$ , using the indirect methods of  $R_s$  estimation.

The correlation coefficient of the Hargreaves method for  $ET_0$  is 0.932 using both approaches of  $R_s$ .

The  $r$  of ANNs models ranged from 0.910 to 0.978, and of MLR, it ranged from 0.963 to 0.988 for  $ET_0$ -PM method, while it ranged from 0.984 to 0.991 for ANNs and from 0.986 to 0.990 for MLR of  $ET_0$ -PrT method. The MLR models correlated very well with the measured values of  $ET_0$ , followed by the ANN models and Hargreaves method.

The scattering diagrams and the comparison between the estimated values of  $ET_o$ , along with the statistical criteria, show that the evaluated  $ET_o$  with the Penman-Monteith and Priestley-Taylor methods, while using indirect methods to estimate the  $R_s$ , is highly correlated with the values of  $ET_o$  estimated with measurements of  $R_s$ .

**Table 3. Statistical criteria of  $ET_o$  of PM and PrT methods estimation at Aristotle University Farm station using the indirect method of  $R_s$  computing.**

	$ET_o$ -PM				$ET_o$ -PrT			
	Mean mm d <sup>-1</sup>	r	RMSE mm d <sup>-1</sup>	EF	Mean mm d <sup>-1</sup>	r	RMSE mm d <sup>-1</sup>	EF
ANN -I	2.413	0.963	0.410	0.917	2.72	0.984	0.626	0.960
ANN -II	2.566	0.978	0.314	0.952	2.93	0.991	0.450	0.982
ANN -III	2.550	0.973	0.356	0.932	2.90	0.987	0.541	0.972
MLR -I	2.736	0.983	0.371	0.965	2.84	0.986	0.558	0.971
MLR -II	2.788	0.988	0.313	0.975	2.93	0.987	0.529	0.974
MLR -III	2.800	0.985	0.355	0.968	2.78	0.990	0.529	0.971
HG	3.358	0.932	0.889	0.712				
HG local	2.669	0.932	0.693	0.826				

### 3.3. $R_s$ model derivation at Amyntaio Station

The statistical properties of the methods used to estimate  $R_s$  at Amyntaio meteorological station are presented in Table 4. More details and scatter diagrams slightly different were presented at Antonopoulos et al. (2019). The value of  $K_{RS}$  coefficient adjusted to local conditions is  $K_{RS}=0.178$ . The correlation coefficient ( $r$ ), the RMSE and EF of the Hargreaves method for  $R_s$  are 0.908, 4.197 MJ m<sup>-2</sup>d<sup>-1</sup> and 0.688, respectively for  $K_{RS}=0.162$ , and 0.908, 3.857 and 0.782, respectively for  $K_{RS}=0.178$ .

The same procedure was followed to select the ANN models with the daily data sets of Amyntaio station, three different models was examined. The input variables for the 1<sup>st</sup> ANN-I model (ANN 5-6-1) are  $T_{max}$ ,  $T_{min}$ ,  $T_{ave}$ ,  $RH_{av}$ ,  $u_2$ , while in the 2<sup>nd</sup> ANN-II (ANN 4-6-1) are  $R_a$ ,  $(T_{max}-T_{min})$ ,  $(T_{max}-T_{min})^{0.5}$  and  $RH_{av}$ , and in the 3<sup>rd</sup> ANN-III (ANN 2-6-1) model the input variables are  $R_a$ , and  $(T_{max}-T_{min})^{0.5}$ . In Table 4 the statistical properties of three different ANNs models to estimate  $R_s$  at Amyntaio station are presented. The correlation coefficient ( $r$ ) of the ANNs models for  $R_s$  ranged from 0.890 to 0.936, the RMSE ranged from 3.274 to 4.202 MJ m<sup>-2</sup>d<sup>-1</sup> and the EF ranged from 0.734 to 0.848.

The MLR equations, which is based on the available variables of the daily datasets of 2011 to 2015 at Amyntaio station, are given as

$$R_s = 16.1099 + 0.4415T_{max} - 0.5583T_{min} - 0.6654T_{ave} - 0.2045RH_{av} + 0.7657u_2 \quad (11)$$

$$R_s = 4.0126 + 0.4811R_a - 0.0478(T_{max} - T_{min}) + 3.7292(T_{max} - T_{min})^{0.5} - 0.1862RH_{av} \quad (12)$$

$$R_s = -15.9673 + 0.5696R_a + 5.1011(T_{max} - T_{min})^{0.5} \quad (13)$$

The  $R^2$  of these approaches are 0.789, 0.862 and 0.807, respectively. In Table 4 the statistical properties of three different MLRs models to estimate  $R_s$  at Amyntaio station are

presented. The correlation coefficient ( $r$ ) of the MLR models for  $R_s$  ranged from 0.889 to 0.929, the RMSE ranged from 3.408 to 4.210 MJ m<sup>-2</sup>d<sup>-1</sup> and the EF ranged from 0.734 to 0.840.

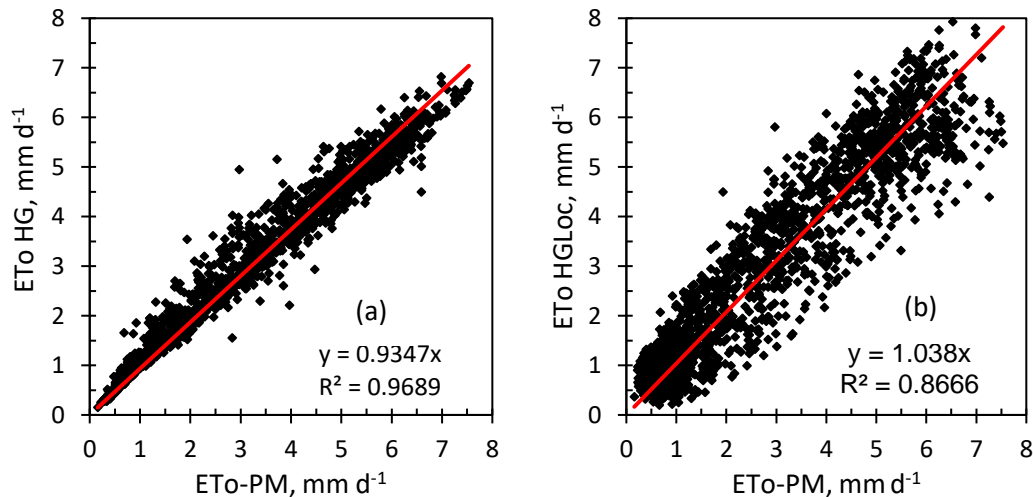
The values of  $R_s$  computed with the ANN-II model correlate better with the measured values of  $R_s$ , followed by the MLR-II model. The other ANN and MLR models, as well as the Hargreaves method, show lower accuracy.

**Table 4. Statistical criteria of Hargreaves, ANN and MLR models to estimate  $R_s$  at AMYNTAIO station**

	$R_s$		$r$	index		ranking		
	Mean MJ m <sup>-2</sup> d <sup>-1</sup>	sd MJ m <sup>-2</sup> d <sup>-1</sup>		RMSE MJ m <sup>-2</sup> d <sup>-1</sup>	EF	$r$	RMSE	EF
Measured	16.899	9.187						
HG	15.457	7.515	0.908	4.197	0.688	4	6	7
HG Local	16.984	8.257	0.908	3.857	0.782	4	4	4
ANN-I	16.629	8.151	0.890	4.202	0.734	6	7	6
ANN-II	16.480	8.409	0.936	3.274	0.848	1	1	1
ANN-III	16.936	8.327	0.909	3.837	0.788	3	3	3
MLR-I	16.891	8.171	0.889	4.210	0.734	7	8	6
MLR-II	16.899	8.531	0.929	3.408	0.840	2	2	2
MLR-III	16.899	8.254	0.898	4.032	0.761	5	5	5

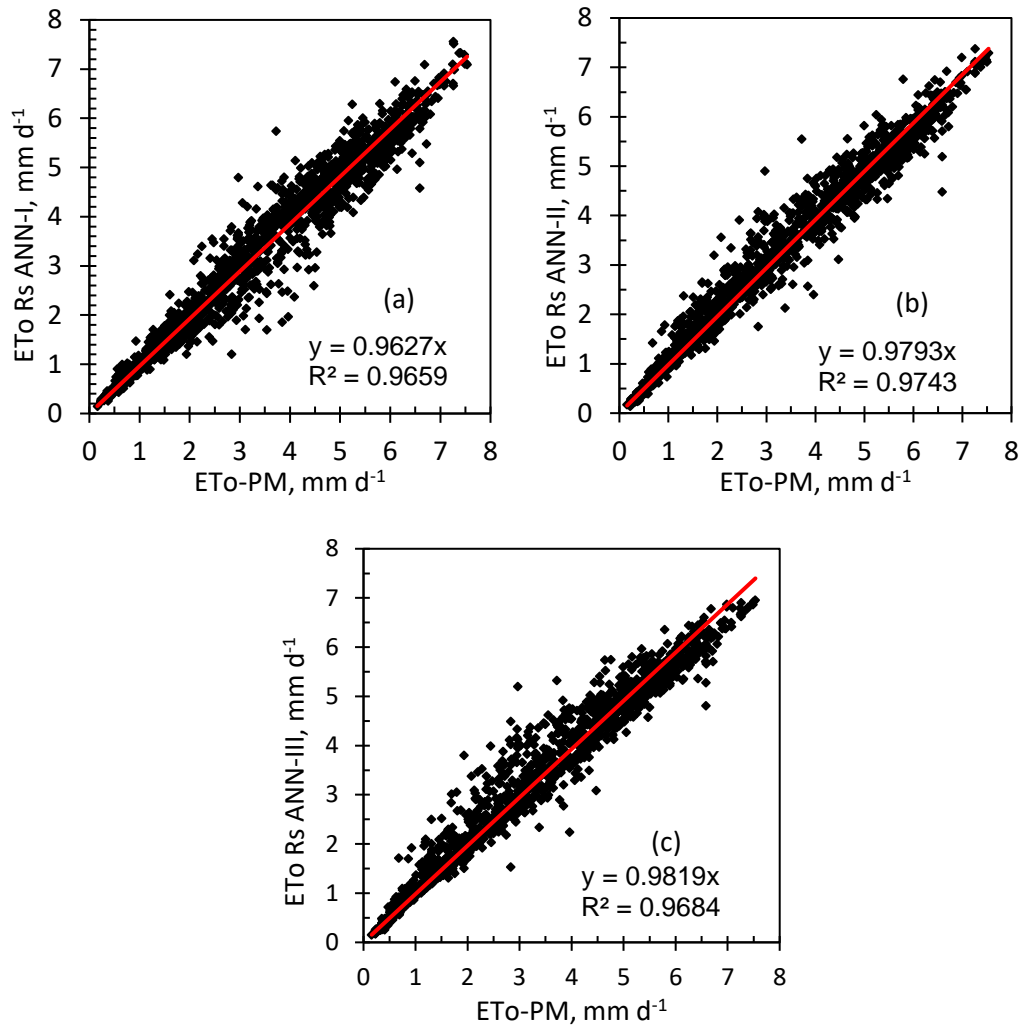
### 3.4 Results of $ET_o$ at Amyntaio Station

Figure 6 shows the comparison of daily  $ET_o$  values estimated using the  $R_s$  values of Hargreaves equations (original and modified to local conditions) and the  $ET_o$  estimated by Penman –Monteith method using the measured values of  $R_s$  at Amyntaio Station.

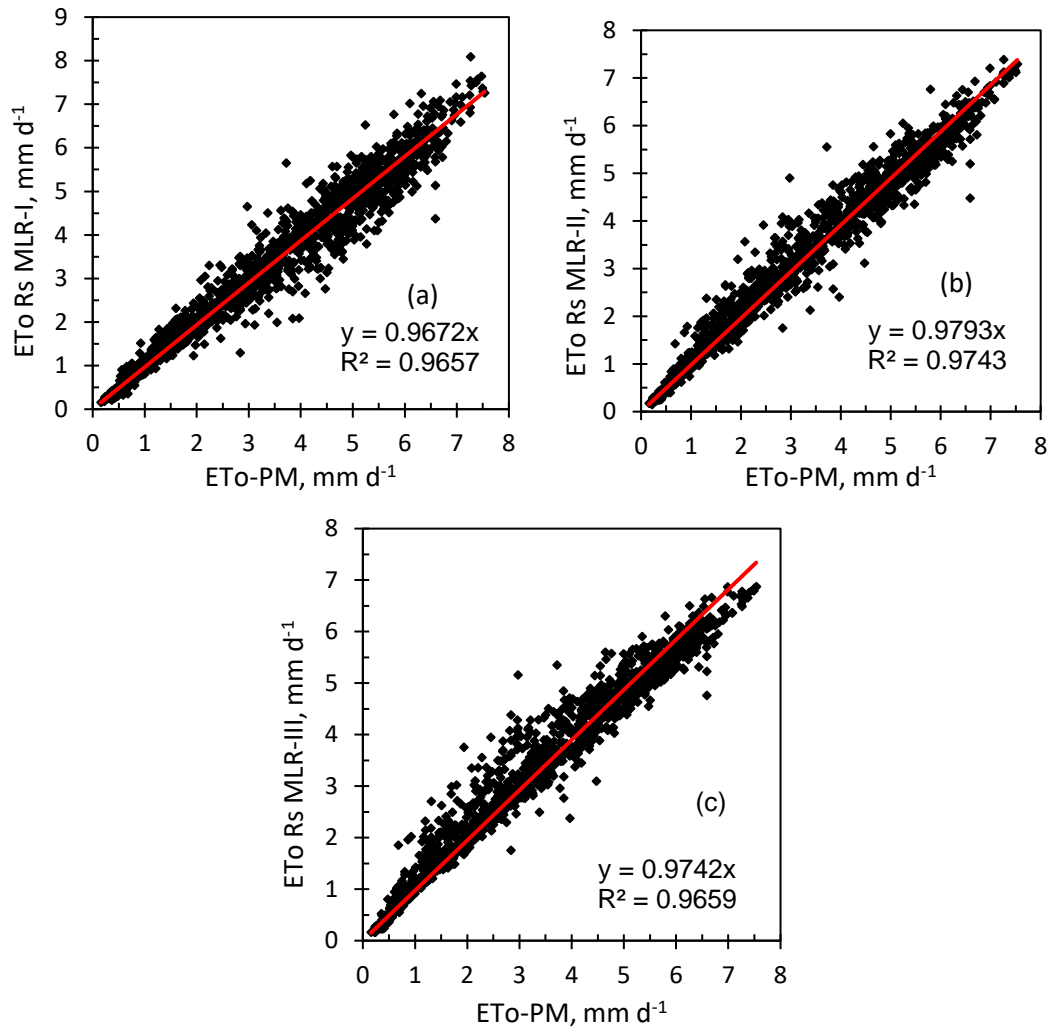


**Fig. 6. Scattering diagrams between  $ET_o$  estimated with Hargreaves (HG) method (a. original and b. local adjustment) against the  $ET_o$  of Penman-Monteith method using  $R_s$  measured values at Amyntaio Station.**

Figures 7 and 8 present the comparison between  $ET_o$ -PM estimated using  $R_s$  measurements and  $ET_o$ -PM estimated with  $R_s$  computed with a) Artificial Neural Networks (ANNs) and b) multilinear regression (MLR) models at Amyntaio Station.

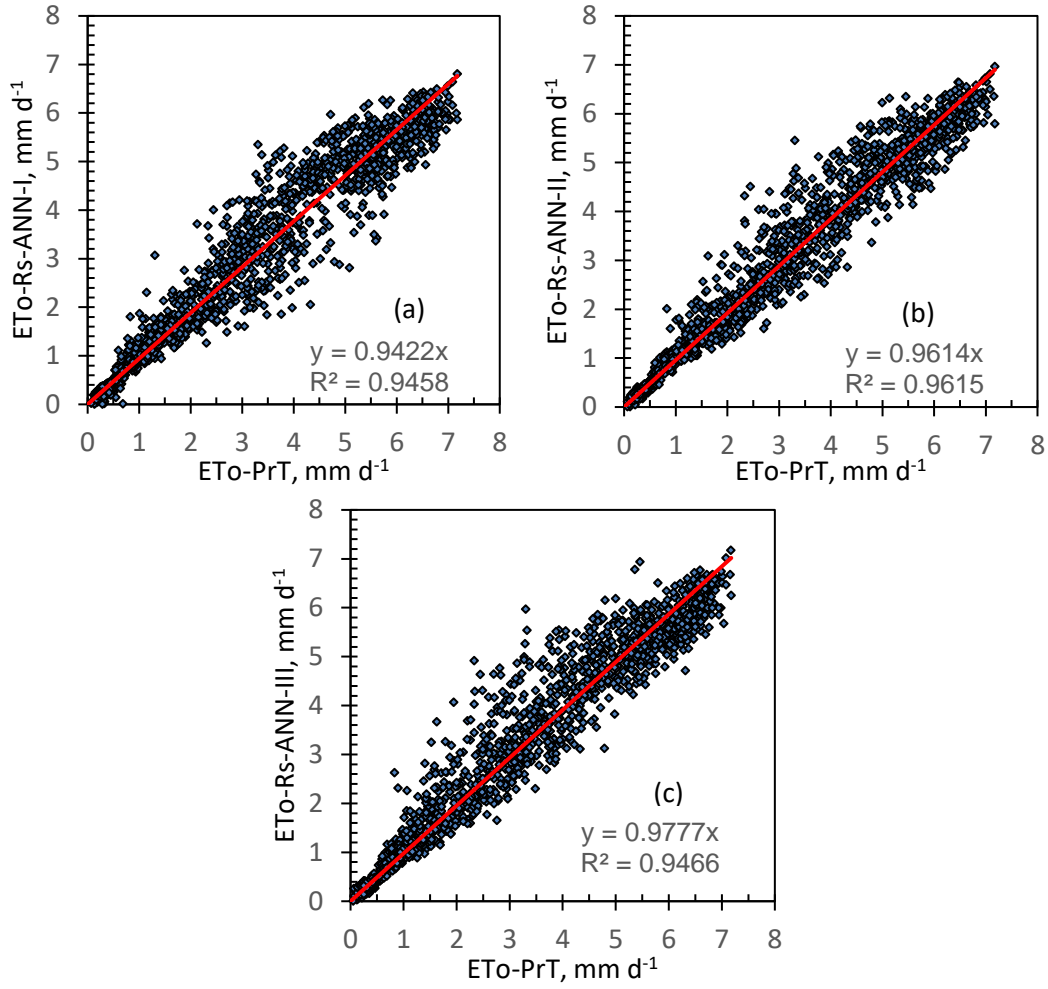


**Fig. 7. Scattering diagrams between  $ET_o$ -PM estimated with  $R_s$  measured and  $ET_o$ -PM estimated with  $R_s$  computed with Artificial Neural Networks (a. ANN-I, b. ANN-II and c. ANN-III) models at Amyntaio station.**



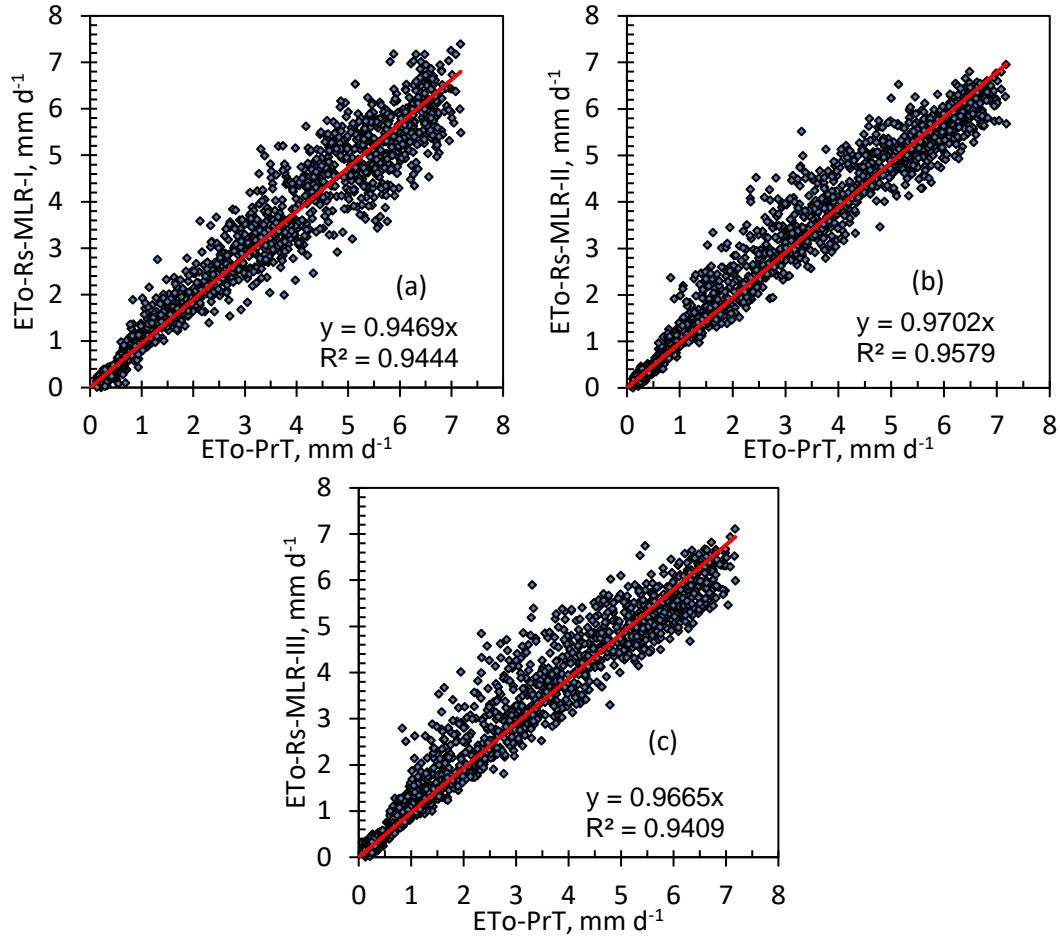
**Fig. 8. Scattering diagrams between  $ET_o$ -PM estimated with  $R_s$  measured and  $ET_o$ -PM estimated with  $R_s$  computed with multi-linear regression (a. MLR-I, b. MLR-II and c. MLR-III) models at Amyntaio station.**

Figures 9 and 10 present the comparison between  $ET_o$  of Priestley-Taylor method estimated using  $R_s$  measurements and  $ET_o$  estimated with  $R_s$  computed with a) Artificial Neural Networks (ANNs) and b) multilinear regression (MLR) models at Amyntaio Station.



**Fig. 9. Scattering diagrams between  $ET_o$ -PrT estimated with  $R_s$  measured and  $ET_o$ -PrT estimated with  $R_s$  computed with Artificial Neural Networks (a. ANN-I, b. ANN-II and c. ANN-III) models at Amyntaio station.**

The values of  $R^2$  are very high in these three scatters diagrams (0.946 to 0.962). Underestimation of higher values of  $ET_o$ -PrT observed, with lower using the ANN-I model.



**Fig. 10. Scattering diagrams between  $ET_o$ -PrT estimated with  $R_s$  measured and  $ET_o$ -PrT estimated with  $R_s$  computed with multi-linear regression (a. MLR-I, b. MLR-II and c. MLR-III) models at Amyntaio station.**

The values of  $R^2$  are very high in these three scatters diagrams (0.941 to 0.958). Underestimation of higher values of  $ET_o$ -PrT is also observed, with lower values when the MLR-I model is used.

The statistical criteria of models to estimate the  $ET_o$  at Amyntaio meteorological station using the  $R_s$  values estimated using the Hargreaves. ANNs and MLRs models are presented in Table 5.

The correlation coefficient for the Hargreaves method for  $ET_o$  is 0.986 for the original equation and 0.937 for the local adjusted equation.

The values of  $r$  for ANNs and MLR models ranged from 0.983 to 0.988 for  $ET_o$ -PM method, while for  $ET_o$ -PrT method it ranged from 0.973 to 0.981 and 0.972 to 0.980, respectively for ANNs and MLR models. The  $ET_o$  values computed using the MLR-II and ANN-II models show high accuracy in correlation with the values of  $ET_o$  estimated using measured  $R_s$ . In general, the  $ET_o$  estimated using the ANN and MLR models, as well as the Hargreaves method, demonstrate high accuracy (with  $r$  ranging from 0.937 to 0.988).

The scattering diagrams, the comparison between the estimated values of  $ET_o$  with the Penman-Monteith method and the statistical criteria show that the three methods describe with high accuracy the  $ET_o$  at Amyntaio station.

**Table 5. Statistical criteria of Hargreaves, ANNs and MLR models to estimate  $ET_o$  at AMYNTAIO station**

	$ET_o$ -PM				$ET_o$ -PrT			
	Mean mm d <sup>-1</sup>	r	RMSE mm d <sup>-1</sup>	EF	Mean mm d <sup>-1</sup>	r	RMSE mm d <sup>-1</sup>	EF
$ET_o$ -PM	2.806							
ANN-I	2.724	0.983	0.373	0.964	2.69	0.973	0.516	0.936
ANN-II	2.788	0.988	0.313	0.975	2.73	0.981	0.429	0.957
ANN-III	2.805	0.985	0.343	0.970	2.80	0.974	0.490	0.945
MLR-I	2.736	0.983	0.371	0.965	2.70	0.972	0.519	0.936
MLR-II	2.788	0.988	0.313	0.975	2.78	0.980	0.436	0.955
MLR-III	2.800	0.985	0.355	0.968	2.80	0.972	0.436	0.954
HG	2.687	0.986	0.385	0.962				
HG Local	3.032	0.937	0.744	0.858				

#### 4. DISCUSSION

The accurate estimation of  $ET_o$  is very interesting in agriculture, engineering, hydrology, ecology and decision makers. It requires measurements of many meteorological parameters, in which the more significant is the solar radiation. It is a meteorological variable which in many stations are not measured or when it measured it is of low accuracy. The reasons are the cost, maintenance and calibration requirements of the measuring equipment [16]. In the Greek territory, many meteorological stations have been established in the last decades (National Observatory of Athens/Meteo.gr). In most of them, solar radiation is not measured. In the cases of lack of solar measurements, the indirect estimation of  $R_s$  is necessary to estimate  $ET_o$ . The machine learning models are the alternative methods that used more recently.

The developed in this work, empirical equations such as Hargreaves, ANNs and MLR models to estimate  $R_s$  using available datasets from our study areas in the Northern Greece region showed that they have the ability to describe it with high accuracy. The models of ANNs and MLR methods that derived using different combination of input variables were evaluated. In these combination the following variables were used:  $T_{max}$ ,  $T_{min}$ ,  $T_{ave}$ ,  $RH_{av}$ ,  $u_2$  in the 1<sup>st</sup>,  $R_a$ ,  $(T_{max}-T_{min})$ ,  $(T_{max}-T_{min})^{0.5}$ ,  $RH_{av}$  in the 2<sup>nd</sup> and  $R_a$ , and  $(T_{max}-T_{min})^{0.5}$  in 3<sup>rd</sup>.

The extraterrestrial radiation ( $R_a$ ) could improve the accuracy of estimations, either using ANN models or MLR methods. The  $R_a$  is incorporated in the Hargreaves equation. Using the  $R_a$  and the factor of  $(T_{max}-T_{min})^{0.5}$ , as input better performance was observed.

##### 4.1 Evaluation of $R_s$ models

The derived ANN models can reasonably estimate the daily radiation, The coefficient of determination (r) ranged from 0.861 to 0.936, the RMSE ranged from 3.271 to 4.451 MJ m<sup>-2</sup> d<sup>-1</sup> and the EF ranged from 0.652 to 0.848, respectively, using the data from the two stations. The results of this work align with the conclusions drawn by Zhang et al. [17]. They concluded that the ANNs models can reasonably estimate the daily radiation, with RMSE

values in the range of 1.24–4.2 MJ m<sup>-2</sup>d<sup>-1</sup> for daily radiation. However it is unclear, whether the improvement in accuracy of ANNs models, when compared to empirical models, is significant.

The statistical criteria for the derived MLR models show that the values of *r* ranged from 0.871 to 0.929, RMSE ranged from 3.408 to 4.210 MJ m<sup>-2</sup> d<sup>-1</sup> and EF ranged from 0.681 to 0.840, respectively, using the data from the two stations.

The *r*, RMSE and EF of Hargreaves method for *R<sub>s</sub>* was 0.893 and 0.908, 3.049 and 4.197 MJ m<sup>-2</sup>d<sup>-1</sup> and 0.732 and 0.688, respectively for each station AUTH and AMIN, when *K<sub>RS</sub>*=0.162. The accuracy of *R<sub>s</sub>* estimation showed a slight improvement when *K<sub>RS</sub>*=0.178 was used.

Using five years of daily data sets, in the present analysis, to derive the *R<sub>s</sub>* models of Hargreaves, ANNs and MLR methods, and comparing them to three years of daily data (Antonopoulos et al. 2019), result in minor changes in the statistical criteria for the same modules of ANNs or MLR models. The percentile changes in *r* ranged from 1.51 to -5.44 % at the AUTH station and from -0.11 to 0.54 % at the Amyntaio station. The changes in RMSE and EF are more significant for the AUTH station data (average 11.61 and -3.17 %) compared to the AMIN station data (average -0.37 and 1.41 %).

Despotovic et al. [16] concluded that the different *R<sub>s</sub>* models, even though they might have better performance with the data used for model development that cannot be recommended for global use. Aladenola, and Madramootoo[47] presented an evaluation of suitability of nine models to estimate *R<sub>s</sub>*, and their effect on *ET<sub>o</sub>* calculated with FAO-56 PM. The estimated *R<sub>s</sub>* when compared with the measured *R<sub>s</sub>*, did not show significant differences. The authors suggested that in Canada, the Samani and Hargreaves-Samani models [29, 30] are recommended for estimating *R<sub>s</sub>*. The conclusion of Zhang et al. [17] (2017), on the non-sunshine duration empirical models which include the difference between maximum and minimum temperature, relative humidity, cloud cover, precipitation, and vapor pressure, summarized that the RMSE values of those models ranged from 2.05 to 4.70 MJ m<sup>-2</sup>d<sup>-1</sup>. Zang et al. [19] summarized that the various empirical models combining different meteorological parameters to estimate *R<sub>s</sub>*, perform well only in areas where the required meteorological data are available. A comprehensive analysis of the related literature reveals that an issue exists where empirical models are site-dependent, and empirical models trained at one site may not be suitable for another site with a different climate. In a study of six different machine-learning algorithms to predict daily solar radiation at 27 European countries. Nematchoua et al. [20] concluded that for all the algorithms, the *r*<sup>2</sup> values range from 0.382 to 0.985, while the RMSE values ranged from 0.145 to 2.126 MJ m<sup>-2</sup> d<sup>-1</sup>.

**Table 6. Changes of average, sd, *r*, RMSE and EF of *R<sub>s</sub>* at AUTH and AMIN stations when using 3 and 5 years daily sets of data.**

	Average <i>R<sub>s</sub></i> , %	sd of <i>R<sub>s</sub></i> , %	<i>r</i> , %	RMSE, %	EF, %
<b>AUTH</b>					
Ave	6.12	0.60	-2.16	11.61	-3.17
max	13.00	5.68	1.51	26.11	5.92
min	2.95	-1.62	-5.44	-9.55	-9.86
<b>AMYNTAIO</b>					
Ave	2.96	2.69	0.27	-0.37	1.41
max	5.80	6.81	0.54	1.36	3.30
min	1.07	1.36	-0.11	-3.30	0.00

Nawab et al. [21] concluded that Artificial Intelligent (AI) methods are more accurate than empirical methods and that the modified sunshine-based models were more accurate compared to empirical methods. Moreover, the artificial neural networks and Hybrid models had the highest accuracy amongst the AI methods.

## **4.2 Evaluation of $ET_o$ methods**

Two of most important methods of  $ET_o$  estimation were evaluated in this work. Both of them, the Penman-Monteith and the Priestley-Taylor methods, are based on the combination of radiation and temperature.

The values of  $r$ , RMSE and EF for  $ET_o$  calculation using the Hargreaves method in relation to  $ET_o$ -PM with  $R_s$  measured are 0.932, 0.889 mm d<sup>-1</sup> and 0.712, for the AUTH station and 0.986, 0.385 mm d<sup>-1</sup> and 0.962, for the AMIN station, respectively.

The results of the present work to calculate  $ET_o$  using the FAO-56 PM equation, while using the derived  $R_s$  from the models in this study, indicate an acceptable level of accuracy.

The values of  $r$ , RMSE and EF for  $ET_o$  calculation obtained using the derived ANNs models ranged from 0.963 to 0.978, 0.314 to 0.410 mm d<sup>-1</sup> and 0.917 to 0.952, respectively, for the AUTH station. Similarly, for the AMIN station, the values ranged from 0.983 to 0.988, 0.313 to 0.373 mm d<sup>-1</sup> and 0.964 to 0.975, respectively.

The statistical criteria obtained by the comparison of  $ET_o$ -PM using MLR models and  $ET_o$ -PM using measured  $R_s$  showed consistency, with values for  $r$ , RMSE and EF ranging from 0.983 to 0.988, 0.313 to 0.371 mm d<sup>-1</sup> and 0.965 to 0.975, respectively for the AUTH station. While for the AMIN station, these values ranged from 0.983 to 0.986, 0.313 to 0.371 mm d<sup>-1</sup> and 0.965 to 0.975, respectively.

The results of present work to calculate  $ET_o$  using the Priestley-Taylor method, while using the derived  $R_s$  from the models in this study, indicate also an acceptable level of accuracy.

The values of  $r$ , RMSE and EF for  $ET_o$ -PrT calculation using the derived ANN models comparing with  $ET_o$ -PrT calculation using measured values of  $R_s$  ranged from 0.973 to 0.991, 0.429 to 0.626 mm d<sup>-1</sup> and 0.936 to 0.982, respectively, for the two stations. The ANN-II model show better values of statistical criteria and the ANN-I the worse values.

The statistical criteria obtained by the comparison of  $ET_o$ -PrT using MLR models and  $ET_o$ -PrT using measured  $R_s$  showed accuracy, with values for  $r$ , RMSE and EF ranging from 0.972 to 0.990, 0.436 to 0.556 mm d<sup>-1</sup> and 0.936 to 0.974, respectively for the two stations. The better values of statistical criteria are showed by the ANN-II model and the worse values of MLR-I.

Similar results have been observed in other studies using ANNs models by different authors, as presented by Terzi and Keskin [48], Diamantopoulou et al. [23], Shiri et al. [49]. The comparison results of Antonopoulos and Antonopoulos [14] found that ANNs models, as well as empirical equations, estimated  $ET_o$  with accuracy. Specifically, the RMSE ranged from 0.574 to 1.33 mm d<sup>-1</sup>, and  $r$  ranged from 0.955 to 0.986 when using daily data from the Amyntaio station and measured  $R_s$  values. These findings align with the results and

conclusions of many other authors that examined empirical equations for  $ET_o$  estimations [3, 8, 10, 11, 23, 50, 51, 52, 53, 54].

Aladenola and Madramootoo [47] examined the effects of nine models to estimate  $R_s$  on the  $ET_o$  computed with FAO-56 PM. They concluded that the effects was highly reduced in calculated  $ET_o$ . In the study of Bellido-Jimenez et al. [55] of  $ET_o$  using a regional machine learning method in Southern Spain got statistical values of RMSE and  $r^2$  of 0.657 to 0.703  $mm\ d^{-1}$  and 0.897 to 0.931, respectively.

The results of the evaluation of the empirical Hargreaves method, multi-linear regression models, and artificial neural networks models using measured solar radiation values showed that these models can effectively be used to estimate solar radiation at stations without direct measurements. When these different models are used to estimate solar radiation and then  $ET_o$ , with the Penman-Monteith and Priestley-Taylor methods, at nearby stations where solar radiation is not being measured, similar results are obtained. These findings suggest that this procedure can be reliably used to estimate  $ET_o$  in such situations.

## 5. CONCLUSION

The reference evapotranspiration ( $ET_o$ ) with the Penman-Monteith and Priestley-Taylor methods estimated using indirect methods to calculate solar radiation ( $R_s$ ) was evaluated. These indirect methods include the Hargreaves method, models based on ANN technology and models using MLR method. Daily meteorological data from two stations in northern Greece were utilized for the development of solar radiation models and  $ET_o$  estimation,

Three different ANNs and MLR models were derived, each using a different number and type of input or independent variables.

The scattering diagrams comparing the estimated and measured values of  $R_s$ , along with the statistical criteria, indicate that the indirect model accurately describes  $R_s$  at the two meteorological stations. The  $r$  and EF values of statistical indexes ranged from 0.860 to 0.871 and 0.650 to 0.681, respectively, while the RMSE values ranged from 4.21 to 4.751  $MJ\ m^{-2}d^{-1}$ . The RMSE values indicated similarity to those reported in other models describing  $R_s$  as summarized by Zang et al. (2017). The inclusion of  $R_a$  and the factor of  $(T_{max}-T_{min})^{1/2}$  in the ANNs and MLR models improved the accuracy of the results. The results of ANNs models, when compared to MLR models using the same input variables, are consistent between them.

The values obtained from  $ET_o$ -PM and  $ET_o$ -PrT methods, when  $R_s$  is indirectly estimated using ANNs and MLR, models, show high accuracy in  $ET_o$  estimation. The statistics of  $ET_o$  estimation at the two stations for both  $ET_o$  methods, showed that the  $r$  and EF values, between  $ET_o$  estimated using the indirect  $R_s$  models and  $ET_o$  estimated using  $R_s$  measured, were greater than 0.963 and 0.918, respectively, while the RMSE values were lower than 0.646  $mm\ d^{-1}$ . The  $ET_o$ -PM using MLR models of  $R_s$  estimation showed better accuracy ( $r>0.983$ ,  $EF>0.964$  and  $RMSE<0.37\ mm\ d^{-1}$ ) compared to ANNs models of  $R_s$  estimation ( $r>0.963$ ,  $EF>0.917$  and  $RMSE<0.41\ mm\ d^{-1}$ ). The  $ET_o$ -PrT produced similar results of statistical indexes using either MLR or ANNs models of  $R_s$  estimation. The inclusion of  $R_a$ , the factor  $(T_{max}-T_{min})^{1/2}$  and relative humidity as input variables in MLR models resulted in higher accuracy. The ANN model with the same input variables and parameters followed in accuracy.

The  $R_s$  and  $ET_o$  of the Hargreaves method were also evaluated in comparison to the measured  $R_s$  and  $ET_o$  of Penman-Monteith method. The result showed high accuracy, with

high values of statistical indexes ( $r$  and  $EF$  greater than 0.893 and 0.722, respectively, and  $RMSE$  lower than  $3.86 \text{ MJ m}^{-2}\text{d}^{-1}$  for  $R_s$ , and  $r$  and  $EF$  greater than 0.932 and 0.826, respectively, and  $RMSE$  lower than  $0.744 \text{ mm d}^{-1}$  for  $ET_o$ ).

Empirical methods for estimating solar radiation, which can subsequently be used to estimate reference evapotranspiration continue to be valuable tools, and remain highly interesting in hydrological and agronomical studies. They provide one of the main components of hydrological balance. The accuracy of reference evapotranspiration with the Penman-Monteith and Priestley-Taylor methods is within an acceptable range when these empirical methods were used as input data in the absence of radiation measurements. The multi-linear regression models are highly accurate and are on par with artificial neural networks. However, achieving accurate results with these methods requires special knowledge from the users and a significant dataset with the same variables used to estimate  $ET_o$ .

## **ACKNOWLEDGEMENTS**

The authors acknowledge Municipality of Amyntaio of Greece and School of Agriculture (Laboratory of General and Agricultural Hydraulics and Land Reclamation) of Aristotle University of Thessaloniki in Greece for providing the data sets of meteorological stations.

## **COMPETING INTERESTS**

There is not any disclose interests that are directly or indirectly related to the work submitted for publication.

## **AUTHORS' CONTRIBUTIONS**

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Vassilis Antonopoulos and Athanasios Antonopoulos. The first draft of the manuscript was written by Vassilis Antonopoulos and the other author commented on previous versions of the manuscript. All authors read and approved the final manuscript.

## **FUNDING**

The authors did not receive support from any organization for the submitted work

## **REFERENCES**

1. Priestley C, Taylor R. On the assessment of surface heat flux and evaporation using large-scale parameters. *Monthly Weather Rev.* 1972; 100 (2): 81-92.
2. Allen RG, Pruitt WO, FAO-24 reference evapotranspiration factors. *J. of Irrig. and Drain.Eng.*, ASCE, 1991;117: 758-773.
3. Gianniou SK, Antonopoulos VZ. Evaporation and energy budget in Lake Vegoritis, Greece. *J. Hydrol.* 2007; 345: 212-223.

4. Yao H. Long-term study of lake evaporation and evaluation of seven estimation methods: Results from Dickie Lake. south-central Ontario. Canada. *J. Water Resour. Prote.* 2009; 2: 59-77.
5. Allen RG, Pereira LS, Raes D, Smith M. Crop evapotranspiration-guidelines for computing crop water requirements, FAO Irrigation and Drainage. Paper 56, 1998.,Rome, Italy.
6. Xu C-Y, Singh VP. Cross Comparison of Empirical Equations for Calculating Potential Evapotranspiration with Data from Switzerland. *Water Resour. Manag.*, 2002;16: 197–219
7. Ampas V, Baltas E, Papamichail D.Comparison of Different Methods for the Estimation of the Reference Crop Evapotranspiration in the Florina Region, *WSEAS Trans, Environ. Development*, 2007;12(2): 1449-1454.
8. Lu J, Sun G, McNulty SG, Amatya DM. A comparison of six potential evapotranspiration methods for regional use in the southeastern United States. *J. Amer. Water Resour. Assoc. (JAWRA)*,2005: 621-633.
9. Xystrakis F, Matzarakis A. Evaluation of 13 Empirical Reference Potential Evapotranspiration Equations on the Island of Crete in Southern Greece. *J. Irrig. Drain Eng.*, 2011, 137(4): 211-222
10. Rácz C, Nagy J, Dobos AC. Comparison of Several Methods for Calculation of Reference Evapotranspiration, *Acta Silv. Lign. Hung.* 2013;9.
11. Efthimiou N, Alexandris S, Karavitis C, Mamassis N. Comparative analysis of reference evapotranspiration estimation between various methods and the FAO56 Penman - Monteith procedure, *European Water*, 2013; 42: 19-34.
12. Djaman K, Baldea AB, Sow A, Mullera B, Irmak S,, N'Diaye MK, Manneha B, Moukoubia YD, Futakuchic K, Saitoc K. Evaluation of sixteen reference evapotranspiration methods under sahelian conditions in the Senegal River Valley. *J. Hydrol.: Regional Studies*, 2015; 3:139–159
13. Aschonitis VG, Demertzi K, Papamichail DM, Colombani N, Mastrociccio M.Revisiting the Priestley-Taylor method for the assessment of reference crop evapotranspiration in Italy, *Italian J. Agrometeorology*.2015; 20 (2): 5-18.
14. Antonopoulos VZ, Antonopoulos AV.Daily reference evapotranspiration estimates by artificial neural networks technique and empirical equations using limited input climate variables. *Computers and Electronics in Agriculture*, 2017;132: 86 - 96,
15. Su Q, Singh VP, Karthikeyan R. Improved reference evapotranspiration methods for regional irrigation water demand estimation. *Agric. Water Manag.*2022; 274: 107979
16. Despotovic M, Nedica V, Despotovic D, Cvetanovic S. Review and statistical analysis of different global solar radiation sunshine models.*Renewable and Sustainable Energy Reviews* 2015; 52: 1869–1880.
17. Zhang J, Zhao L, Deng S, Xu W, Zhang Y. A critical review of the models used to estimate solar radiation.*Renewable and Sustainable Energy Reviews*.2017; 70 : 314–329.
18. Antonopoulos VZ, Papamichail DM, Aschonitis VG, Antonopoulos AV. Solar radiation estimation methods using ANN and empirical models. *Computers and Electronics in Agriculture*. 2019;160: 160 - 167.
19. Zhang H, Jiang X, Cheng L, Zhang F, Wei Z, Sun G. Combined empirical and machine learning modeling method for estimation of daily global solar radiation for general meteorological observation stations. *Renewable Energy*. 2022; 195: 795-808.
20. Nematchoua MK, Orosa JA, Afaifia M. Prediction of daily global solar radiation and air temperature using six machine learning algorithms; a case of 27 European countries. *Ecological Informatics*, 2022; 69: 101643.
21. Nawab F, Abd Hamid AS, Ibrahim A, Sopian K, Fazlizan A, Fauzan MF. Solar irradiation prediction using empirical and artificial intelligence methods: A comparative review. *Heliyon*2023; 9: e17038.

22. Jain SK, Nayak PC, Sudheer KP. Models for estimating evapotranspiration using artificial neural networks and their physical interpretation. *Hydrol. Process.* 2008;22: 2225–2234.
23. Diamantopoulou ML, Georgiou PE, Papamichail DM. Performance evaluation of artificial neural networks in estimation references evapotranspiration with minimal meteorological data. *Global Nest J.* 2011;13: 18-27.
24. Laaboudi A, Mouhouche M, Draoui B. Neural network approach to reference evapotranspiration modeling from limited climatic data in arid regions. *Int. J. Biometeorol.* 2012; 56: 831–841
25. Heddam S. Modelling hourly dissolved oxygen concentration (DO) using dynamic evolving neural- fuzzy inference system (DENFIS)-based approach: case study of Klamath River at Miller Island Boat Ramp. OR. USA. *Environ. Sci. Pollut. Res.* 2014; 21:9212–9227
26. Antonopoulos VZ, Gianniou SK, Antonopoulos AV. Artificial neural networks and empirical equations to estimate daily evaporation: application to Lake Vegoritis, Greece. *Hydrol. Sci. J.* 2016; 61: 2590-2599.
27. Utset A, Farré I, Martínez-Cob A, Cavelo J. Comparing Penman-Monteith and Priestley-Taylor approaches as reference evapotranspiration, Inputs for modeling maize water-use under Mediterranean conditions. *Agric. Water Manage.* 2004; 66: 205-219
28. Bogawski P, Bednorz E. Comparison and validation of selected evapotranspiration models for conditions in Poland (Central Europe). *Water Resour. Manage.* 2014; 28: 5021–5038. DOI 10.1007/s11269-014-0787-8
29. Hargreaves GH, Samani ZA. Reference crop evapotranspiration from temperature. *Trans. ASAE.* 1985; 1(2). 96-99.
30. Hargreaves GH, Samani ZA. Estimating potential evapotranspiration. *J. Irrig. Drain. Eng. ASCE.* 1982; 108 (3): 225–230.
31. Daut I, Irwanto M, Irwan YM, Gomesh N, Ahmad NS. Combination of Hargreaves method and linear regression as a new method to estimate solar radiation in Perlis, Northern Malaysia. *Solar Energy.* 2011; 85 (11): 2871–2880.
32. Razinei T, Pereira LS. Estimation of ETo with Hargreaves-Samani and FAO-PM temperature methods for a wide range of climate in Iran. *Agricultural Water Management,* 2013;121: 1– 18
33. Rivero M, Orozco S, Sellschopp FS, Loera-Palomo R. A new methodology to extend the validity of the Hargreaves-Samani model to estimate global solar radiation in different climates: Case study Mexico. *Renewable Energy.* 2017; 114: 1340–1352.
34. Aschonitis VG, Papamichail D, Demertzi K, Colombani N, Mastrocicco M, Ghirardini A, Castaldelli G, Fano E-A. High-resolution global grids of revised Priestley-Taylor and Hargreaves-Samani coefficients for assessing ASCE-standardized reference crop evapotranspiration and solar radiation. *Earth System Science Data* 2017; 9(2): 615-638.
35. Hargreaves GH. Simplified coefficients for estimating monthly solar radiation in North America and Europe. 1994; Departmental Paper, Dept. of Biol. and Irrig. Engrg., Utah State University, Logan, Utah.
36. Alexandris S, Kerkides P, Liakatas A. Daily reference evapotranspiration estimates by the Copais approach, *Agric. Water Manag.* 2006; 82: 371-386.
37. El-Sebaili AA, Al-Hazmi FS, Al-Ghamdi AA, Yaghmour SJ. Global, direct and diffuse solar radiation on horizontal and tilted surfaces in Jeddah, Saudi Arabia. *Applied Energy.* 2010; 87 (2): 568–576.
38. Li H, Ma W, Lian Y, Wang X, Zhao L. Global solar radiation estimation with sunshine duration in Tibet, China. *Renewable Energy.* 2011; 36 (11): 3141-3145.
39. Besharat F, Dehghan AA, Faghieh AR. Empirical models for estimating global solar radiation: A review and case study. *Renewable and Sustainable Energy Reviews.* 2013; 21: 798–821

40. Valiantzas JD. Modification of the Hargreaves-Samani model for estimating solar radiation from temperature and humidity data. *J. Irrig. Drain. Eng., ASCE*, 2018; 144:06017014.
41. Yadav AK, Chandel SS. Solar radiation prediction using Artificial Neural Network techniques: A review *Renewable and Sustainable Energy Reviews*. 2014; 33: 772–781
42. Kumar M, Raghuwanshi NS, Singh R. Artificial neural networks approach in evapotranspiration modeling: a review, *Irrig. Sci.*, 2011; 29:11–25
43. Kisi O, Sanikhani H, Zounemat-Kermani M, Niazi, F. Long-term monthly evapotranspiration modeling by several data-driven methods without climatic data. *Computers and Electronics in Agriculture*. 2015; 115: 66-77. ISSN 0168-1699.
44. Premalatha N, Valan Arasu A. Prediction of solar radiation for solar systems by using ANN models with different batch propagation algorithms. *J. of Applied Research and Technology*, 2016; 14:206-214.
45. Küçüktopcu E, Cemek E, Cemek B, Simsek H. Hybrid Statistical and Machine Learning Methods for Daily Evapotranspiration Modeling. *Sustainability*. 2023; 15: 5689. <https://doi.org/10.3390/su15075689>
46. Goya P, Kumar S, Sharda R. A review of the Artificial Intelligence (AI) based techniques for estimating reference evapotranspiration: Current trends and future perspectives. *Computers and Electronics in Agriculture*, 2023; 209: 107836
47. Aladenola OO., Madramootoo CA. Evaluation of solar radiation estimation methods for reference evapotranspiration estimation in Canada. *Theoretical and Applied Climatology*, 2014; 118(3):377-385.
48. Terzi O, Keskin ME. Comparison of artificial neural networks and empirical equations to estimate daily pan evaporation. *Irrig. Drain*. 2010; 59: 215–225.
49. Shiri J, Nazemi AH, Sadraddini AA, Landaras G, Kisi O, Fard AF, Marti P. Comparison of heuristic and empirical approaches for estimating reference evapotranspiration from limited inputs in Iran. *Comput. Electron. Agric*. 2014; 108: 230-241.
50. Xu C-Y, Singh VP. Evaluation and Generalization of Radiation-based Methods for Calculating Evaporation, *Hydrol. Processes*. 2000; 14: 339–349.
51. Heydari MM, Aghamajidi R, Beygipoor G, Heydari M. Comparison and evaluation of 38 equations for estimating reference evapotranspiration in an arid region, *Fresenius Environ. Bulletin*. 2014; 23: 1985-1997.
52. Tigkas D, Vangelis H, Tsakiris G. 2020. Implementing Crop Evapotranspiration in RDI for Farm-Level Drought Evaluation and Adaptation under Climate Change Conditions. *Water Resour Manage*. 2020; 34: 4329–4343. <https://doi.org/10.1007/s11269-020-02593-6>
53. Dimitriadou S, Nikolakopoulos KG. Artificial Neural Networks for the Prediction of the Reference Evapotranspiration of the Peloponnese Peninsula, Greece. *Water* 2022; 14: 2027. <https://doi.org/10.3390/w14132027>
54. R JT, Reddy NVS, Acharya UD. Modeling Daily Reference Evapotranspiration from Climate Variables: Assessment of Bagging and Boosting Regression Approaches. *Water Resources Management*. 2023; 37:1013–1032. <https://doi.org/10.1007/s11269-022-03399-4>
55. Bellido-Jimenez, A., Estevez, J., García-Marín, A.P., A regional machine learning method to outperform temperature-based reference evapotranspiration estimations in Southern Spain. *Agric. Water Manag.* 2022; 274: 107955.