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

Abstract

The reference evapotranspiration (ET_o) estimation with Penman-Monteith or Pristley-Taylor methods requires measurements of temperature, radiation, humidity, and wind velocity. In this study, we evaluated the estimations of ET_o by Penman-Monteith (ET_o-PM) and Pristley-Taylor (ET_o-PrT) methods using indirect methods of calculating solar radiation (R_s). These indirect methods include the Hargreaves method, models based on Artificial Neural networks (ANN) technology and models using the multi-linear regression method (MLR). Three different ANN and MLR models were derived. Daily meteorological measurements from two stations in northern Greece were used for the development of solar radiation models and ET_o calculation. The evaluation of the indirect R_s derived models and the ET_o estimation by the two methods was performed with the use of correlation coefficients (r), root mean square error (RMSE), and efficiency (EF) indexes. The statistics of ET_o estimation at the two stations showed that the r and EF values, between the estimated ET_o using the indirect R_s models and estimated ET_o 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 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 $m^{-2}d^{-1}$. 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 Pristley-Taylor methods can accurately predict ET_o using R_s values estimated indirectly through the examined methods and models.

Keynotes: Solar radiation; Reference evapotranspiration; Penman–Monteith method; Pristley-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 (Priestley and Taylor, 1972), the corrected FAO-24 Penman method (Allen and Pruitt, 1991; Gianniou and Antonopoulos, 2007; Yao, 2009), and the FAO-56 Penman-Monteith method (Allen et al., 1998).

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 Xu and Singh (2002), Ampas et al. (2005), Lu et al. (2005), Xystrakis and Matzarakis (2011), Rácz et al. (2013), Efthimiou et al. (2013), Djaman et al. (2015), Aschonitis et al. (2015), Antonopoulos and Antonopoulos (2017), Su et al. (2022).

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 (Despotovic et al., 2015; Zhang et al., 2017; Antonopoulos et al. 2019; Zang et al. 2022; Nematchoua et al. 2022; Nawab et al. 2023).

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 (Jain et al., 2008; Diamantopoulou et al., 2011; Laaboudi et al., 2012; Heddam, 2014; Antonopoulos et al., 2016; Antonopoulos et al., 2019; Nematchoua et al., 2022; Nawab et al., 2023, among others) and climate variables.

In Antonopoulos et al. (2019), 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, $(T_{max}\text{-}T_{min})^{0.5}$, 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 Pristley-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 (2019). 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. Materials 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 (Allen et al. 1998):

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

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

The Priestley-Taylor method (Priestley and Taylor, 1972) of daily reference crop evapotranspiration (ET_o-PrT) is a modification and simplification of the Penman formula. It described by the following form:

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

where λ is the latent heat of vaporization (MJ kg^{-1}), ρ_w is the water density (kg m^{-3}) and α is an empirically derived parameter with an average value of 1.26 (Sene et al. 1991, Aschonitis et al., 2015). This method is a radiation based method. The Priestley-Taylor method has been used to estimate the reference crop evapotranspiration in many works (Utset et al., 2004; Bogawski and Bednorz, 2014; Aschonitis et al., 2015; Antonopoulos et al, 2017).

The Hargreaves method (Hargreaves and Samani, 1985) estimates daily ET_o, with the following equation

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

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

The incoming shortwave solar radiation R_s (MJ m^{-2} d^{-1}), according to Hargreaves and Samani (1982; 1985), 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 (MJ m^{-2} d^{-1}) and TD (equal to T_{max}-T_{min}) is the temperature difference between maximum (T_{max}) and minimum (T_{min}) daily temperature (°C). Hargreaves (1994) recommended using K_{RS}= 0.162 for "interior" locations, and K_{RS} = 0.19 for coastal locations. (Daut et al., 2011; Raziei and Pereira, 2013; Antonopoulos and Antonopoulos, 2017; Rivero et al., 2017; Aschonitis et al. 2017).

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

$$R_s = m_1 + m_2X_1 + m_3X_2 + m_4X_3 + \cdots + m_{n+1}X_n \quad (5)$$

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_{ave}, T_{max}, T_{min}, RH_{av}, u_2) or combinations of them ((TD=T_{max}-T_{min}) and (TD)$^{0.5}$) (Alexandris et al., 2006; El-Sebaii et al., 2010; Li et al., 2011; Besharat et al., 2013; Valiantzas, 2018).

2.3. 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 (Jain et al., 2008; Diamantopoulou et al., 2011; Laaboudi et al., 2012; Yadav and Chandel, 2014; Kumar et al. 2011; Kisi et al, 2015; Premalatha and Valan Arasu, 2016; Antonopoulos et al., 2016; Zhang et al., 2017; Antonopoulos and Antonopoulos, 2017).

In this article, an algorithm of the multi-layer feed forward artificial neural networks and of the back-propagation for optimization was used (Premalatha and Vala Arasu, 2016). 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_{av}, RH_{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 (Jain et al., 2008; Antonopoulos et al. 2016); Antonopoulos and Antonopoulos 2017).

2.4. 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):

$$\mathrm{r} = \left(\sum_{i=1}^{N} (O_\mathrm{i} - O_\mathrm{m})(C_\mathrm{i} - C_\mathrm{m}) \right) / \left(\sqrt{\sum_{i=1}^{N} (O_\mathrm{i} - O_\mathrm{m})^2} \sqrt{\sum_{i=1}^{N} (C_\mathrm{i} - C_\mathrm{m})^2} \right) \quad (6)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (C_\mathrm{i} - O_\mathrm{i})^2} \quad (7)$$

$$\mathrm{EF} = 1 - \left(\sum_{i=1}^{N} (\mathrm{C_i} - O_\mathrm{i})^2 \right) / \left(\sum_{i=1}^{N} (\mathrm{O_i} - O_\mathrm{m})^2 \right) \quad (8)$$

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 -∞.

2.5. 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 (Antonopoulos et al. 2019).

The 1st meteorological station of Aristotle University of Thessaloniki Farm (AUTH) is located in Central Macedonia (40º 37'54''N, 22º 57'27''E, 34 m above sea level) and the 2nd meteorological station of Amyntaio (AMIN) at West Macedonia is located at northern latitude of 40º 46'27''N, 21º39'E, 580 m above sea level.

Table 1 presents the average and standard deviation values of temperature (ºC), relative humidity (%), wind velocity (m s^{-1}), and solar radiation (MJ m^{-2} d^{-1}) 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_2, m sec^{-1}		R_s, MJ $m^{-2}d^{-1}$	
	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_s 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 (Antonopoulos et al., 2019) to evaluate the R_s 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_s (via empirical and ANN models) as inputs for ET_o calculations using the Penman-Monteith, the Pristley-Taylor and Hargreaves equations.

3.1. Results of estimated R_s 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_s estimation. The daily R_s values predicted by the Hargreaves (HG) method using the recommended value of K_{RS} coefficient (K_{RS}=0.162) and the value adjusted to local conditions (K_{RS}=0.158), compared with the R_s 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_s are 0.893, 3.049 MJ $m^{-2}d^{-1}$ and 0.732, respectively for K_{RS}=0.162, and 0.893, 3.032 MJ $m^{-2}d^{-1}$ and 0.722, respectively for K_{RS}=0.158.

The architecture of the ANN model was identified by the trial and error procedure (Antonopoulos and Antonopoulos, 2017; Antonopoulos et al. 2019). 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 1st model, the standard meteorological parameters (T_{max}, T_{min}, T_{ave}, RH_{av}, u_2) 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.

Table 2.

Statistical criteria of ANN model to estimate R_s at Aristotle University Farm station

	R_s		index			Ranking		
	Average MJ $m^{-2}d^{-1}$	sd MJ $m^{-2}d^{-1}$	r	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 { Ra, $(T_{max}-T_{min})$, $(T_{max}-T_{min})^{0.5}$, RH_{av}}; ANN -III{Ra, $(T_{max}-T_{min})^{0.5}$}

MLR –I (T_{max}, T_{min}, T_{ave}, RH_{av}, u_2); MLR –II { Ra, $(T_{max}-T_{min})$, $(T_{max}-T_{min})^{0.5}$, RH_{av}}; MLR -III{Ra, $(T_{max}-T_{min})^{0.5}$}

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.

3.2 Results of ET_o at Aristotle University Farm Station

Figure 1 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 values estimated by Penman – Monteith method using the measured values of R_s at Aristotle University Farm station.

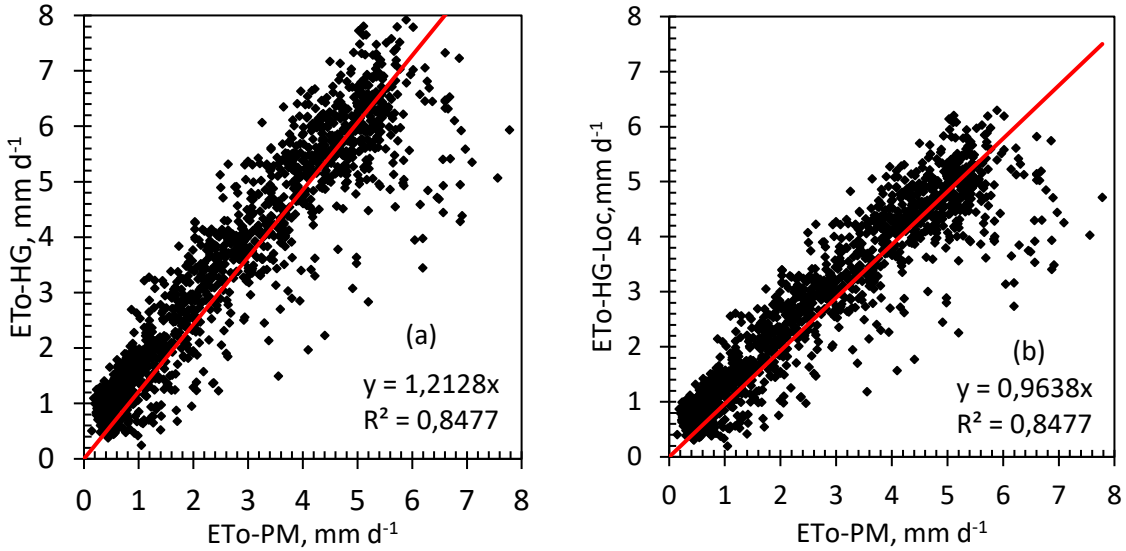


Figure 1. Scattering diagrams of daily ET_o estimated by the Hargreaves (HG) and the ETo values estimated by the Penman – Monteith method using measured values of R_s, a) K_{RS}=0.162; b) K_{RS}=0.158 local adjusted coefficient.

Figures 2 presents the scattering diagrams between ET_o of Penman-Monteith method using R_s estimated using the ANN models and the measured values of R_s at Aristotle University Farm, respectively.

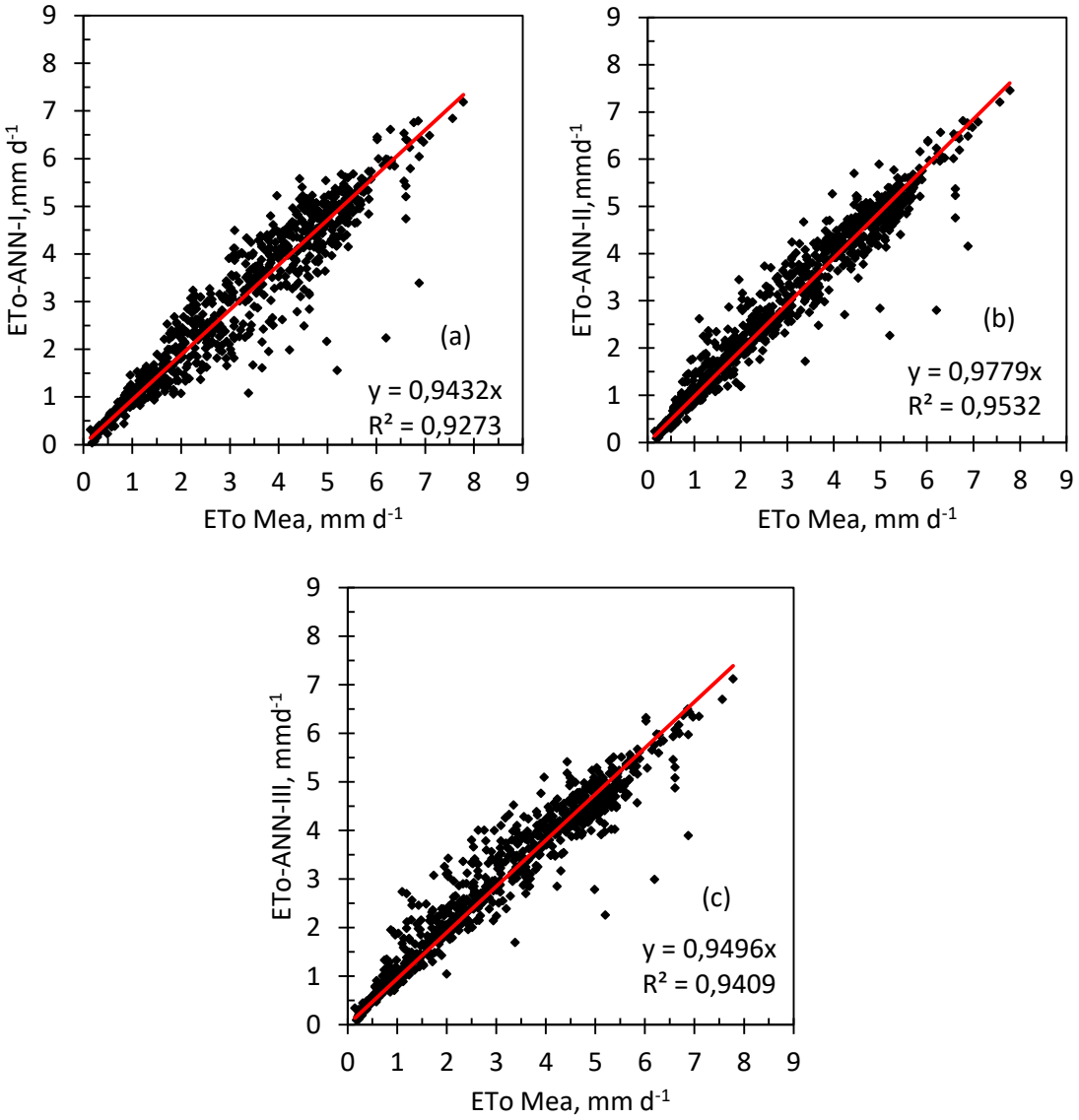


Figure 2. Scattering diagrams between ET_o estimated with R_s measured and ET_o estimated with R_s computed with Artificial Neural Networks (a. ANN-I; b. ANN-II and c. ANN-III) models at Aristotle University Farm station.

Figures 3 presents the scattering diagrams between ET_o of Pristley-Taylor method using R_s estimated using the ANNs models and the measured values of R_s at Aristotle University Farm, respectively.

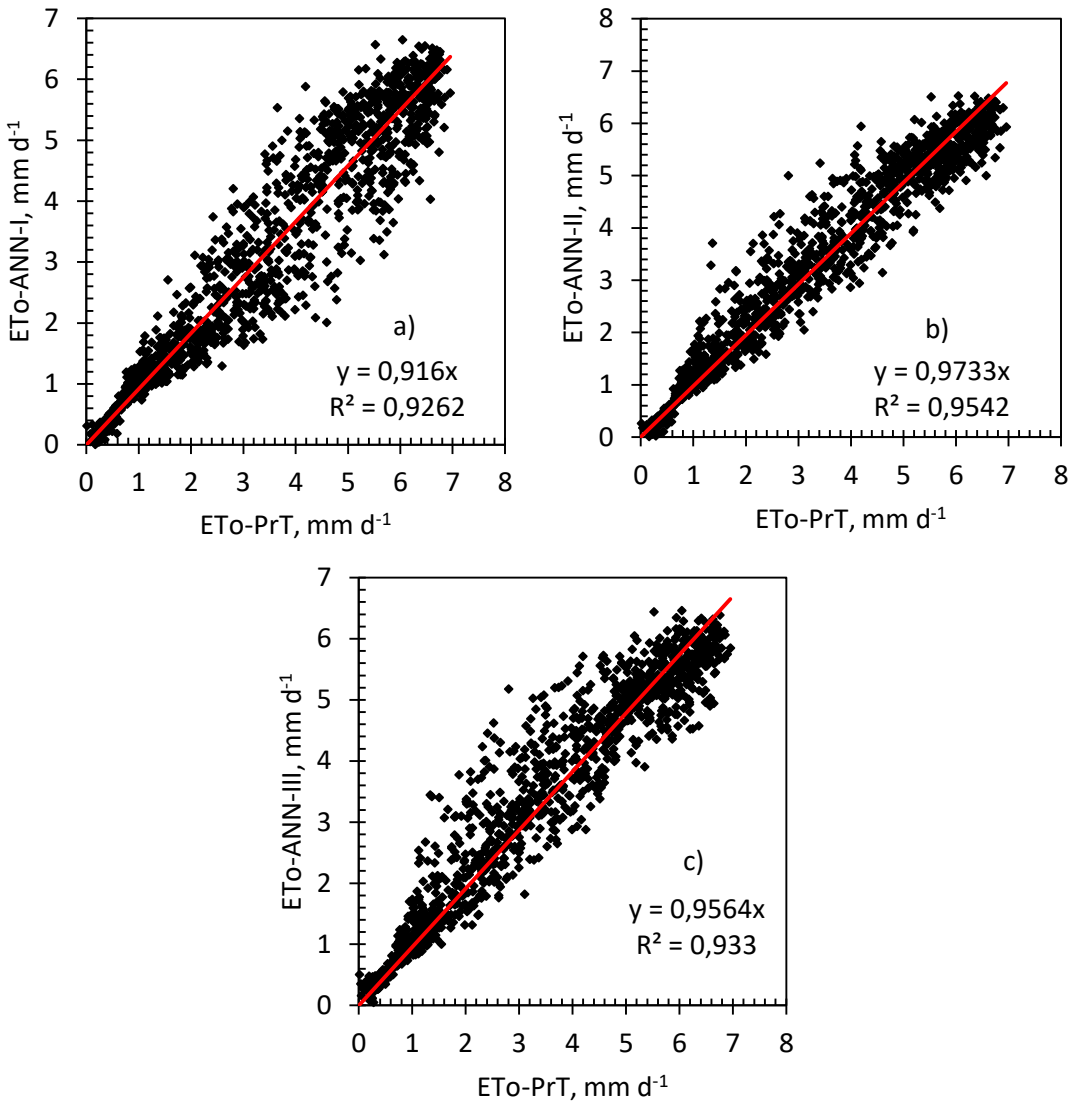


Figure 3. Scattering diagrams of ET_o-PrT estimated with R_s measured and ET_o-PrT estimated with R_s computed with Artificial Neural Networks (a. ANN-I; b. ANN-II and c. ANN-III) models at Aristotle University Farm station.

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

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

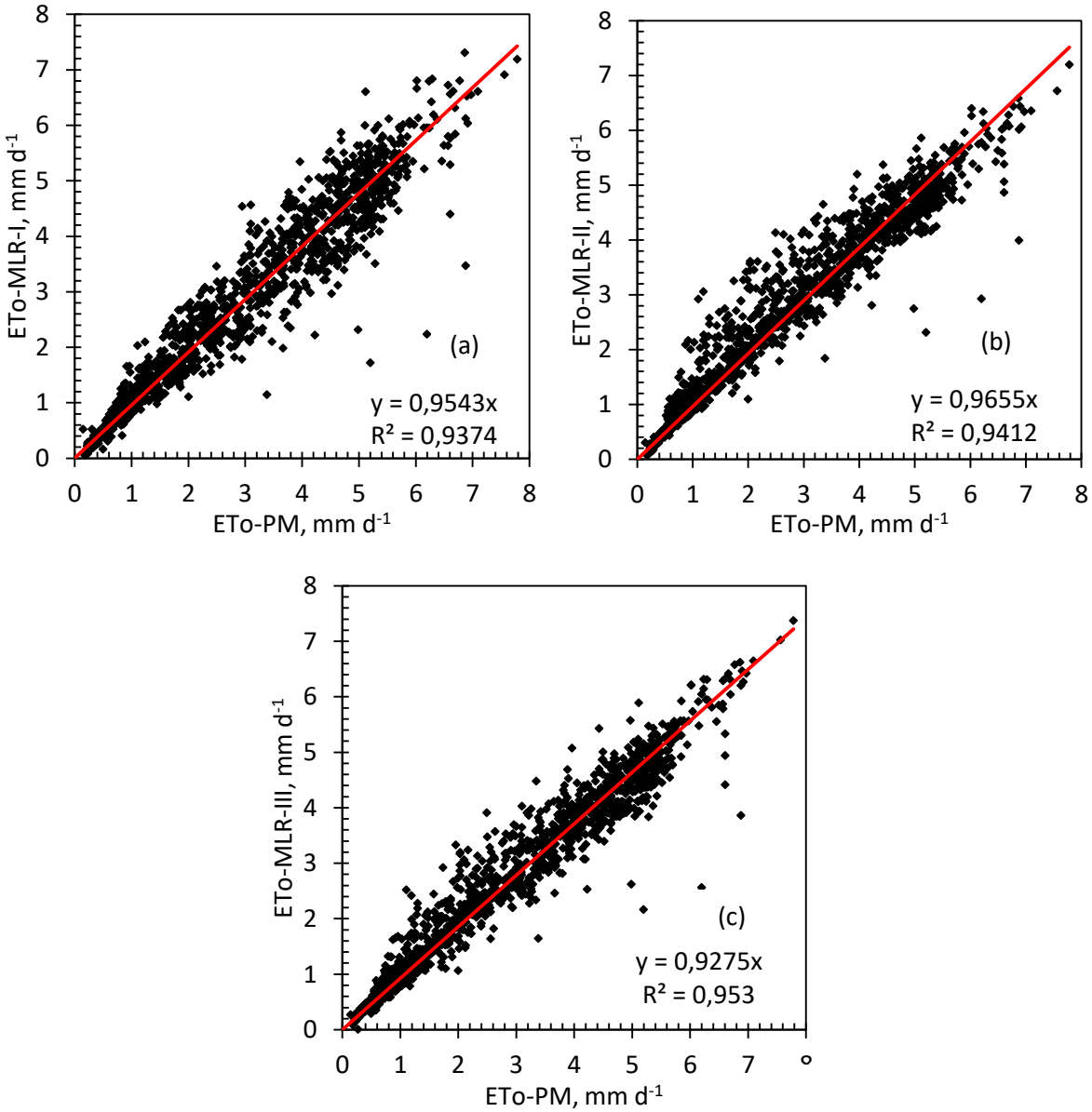


Figure 4. Scattering diagrams between ET_o estimated with R_s measured and ETo estimated with R_s computed with Multi linear regression (a. MLR-I, b. MLR-II and c. MLR-III)) models at Aristotle University Farm station.

Figures 5 presents the comparison between ET_o of Pristley-Taylor method using R_s estimated using the MLR models and the measured values of R_s at Aristotle University Farm, respectively.

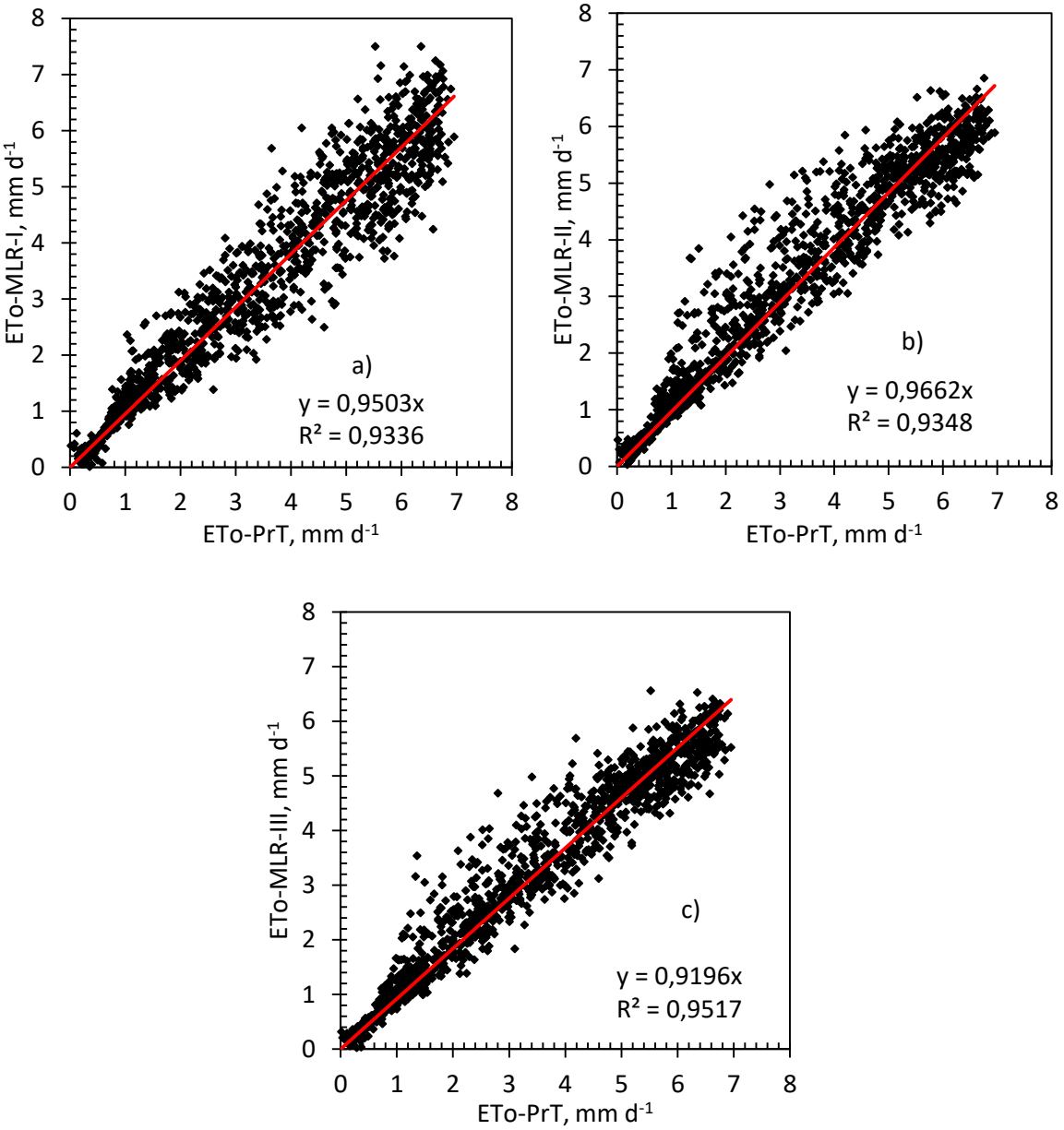


Figure 5. Scattering diagrams of ET_o-PrT estimated with R_s measured and ET_o-PrT estimated with R_s computed with Multi linear regression (a. MLR-I, b. MLR-II and c. MLR-III)) models at Aristotle University Farm station.

The values of R^2 are very high in these three scatters diagrams (0.933 to 0.951). Underestimation of higher values of ET_o-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_o, using the indirect methods of R_s estimation.

The correlation coefficient of the Hargreaves method for ET_o 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_o-PM method, while it ranged from 0.984 to 0.991 for ANNs and from 0.986 to 0.990 for MLR of ET_o-PrT method. The MLR models correlated very well with the measured values of ET_o, 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 Pristley-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.

	ETo-PM				ETo-PrT			
	Ave mm d^{-1}	r	RMSE mm d^{-1}	EF	ave mm d^{-1}	r	RMSE mm d^{-1}	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 $m^{-2}d^{-1}$ 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 1st ANN-I model (ANN 5-6-1) are T_{max}, T_{min}, T_{ave}, RH_{av}, u_2, while in the 2nd 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 3rd 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 $m^{-2}d^{-1}$ 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 $m^{-2}d^{-1}$ 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		index			ranking		
	Average MJ $m^{-2}d^{-1}$	sd MJ $m^{-2}d^{-1}$	r	RMSE MJ $m^{-2}d^{-1}$	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.

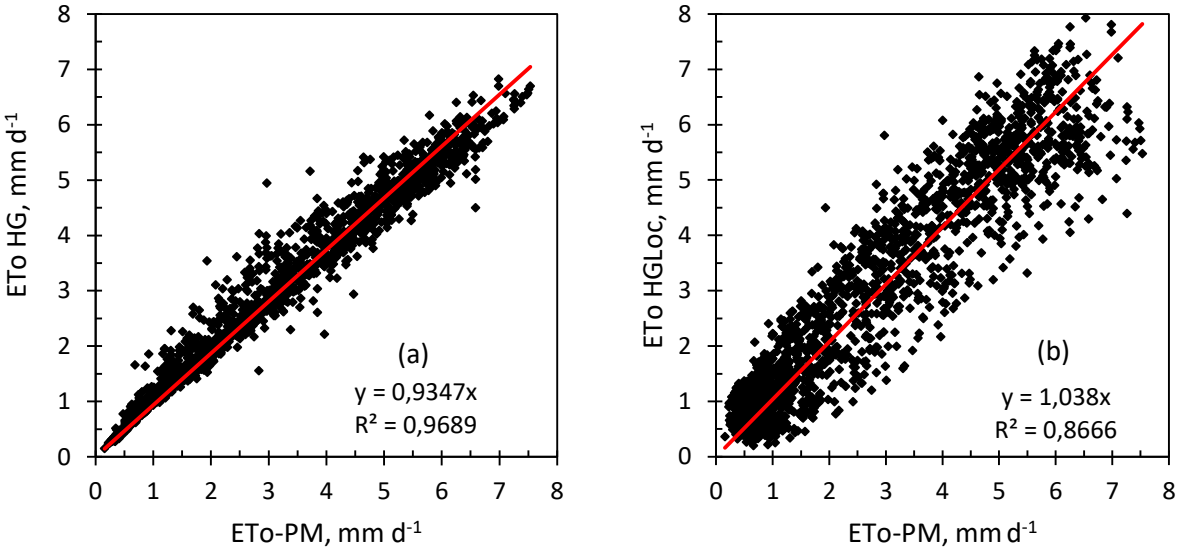
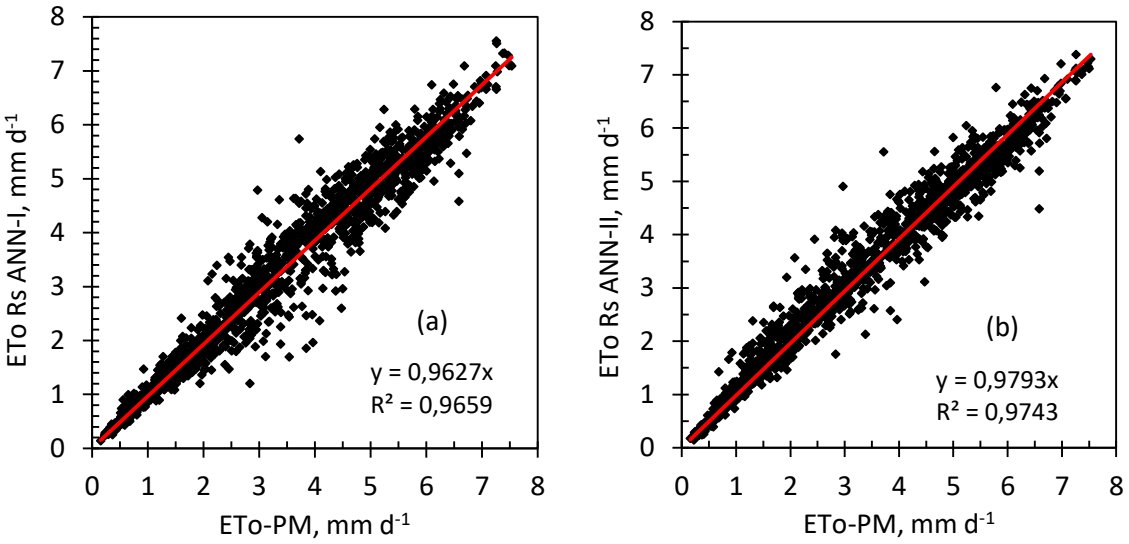
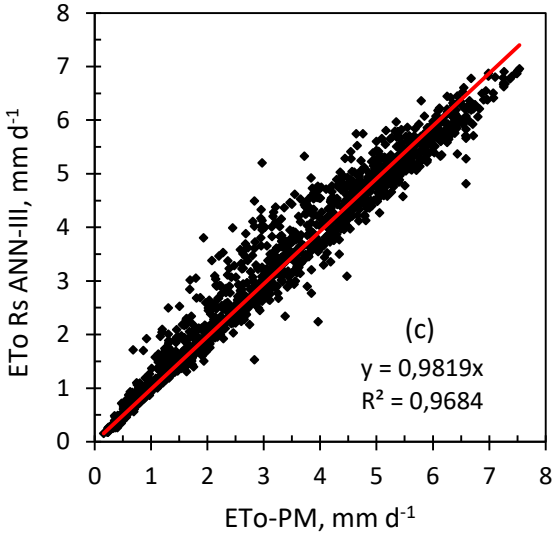


Figure 6. Scattering diagrams between ET_o estimated with Hargreaves (HG) method (a. original and b. local adjustment) against the ET_o of Penman-Monteith method using R_s measured values at Amyntaio Station.

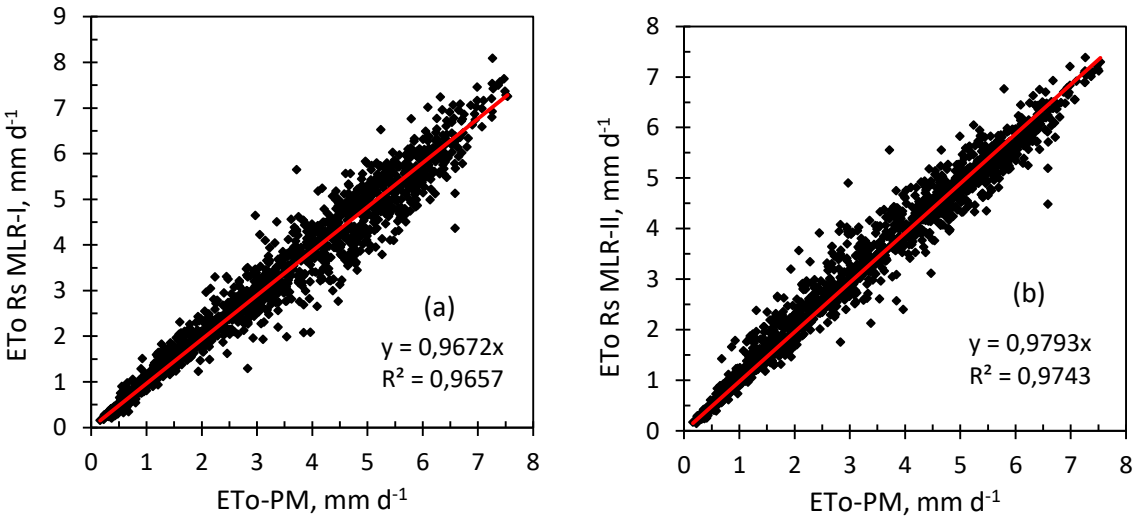
Figures 7 and 8 present the comparison between ET_o-PM estimated using R_s measurements and ET_o-PM estimated with R_s computed with a) Artificial Neural Networks (ANNs) and b) multilinear regression (MLR) models at Amyntaio Station.



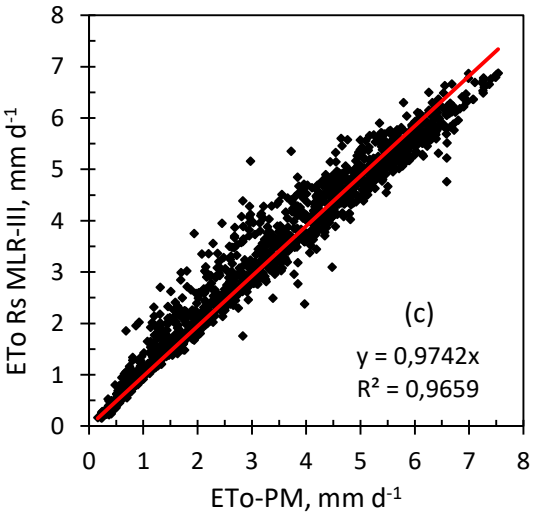


342

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



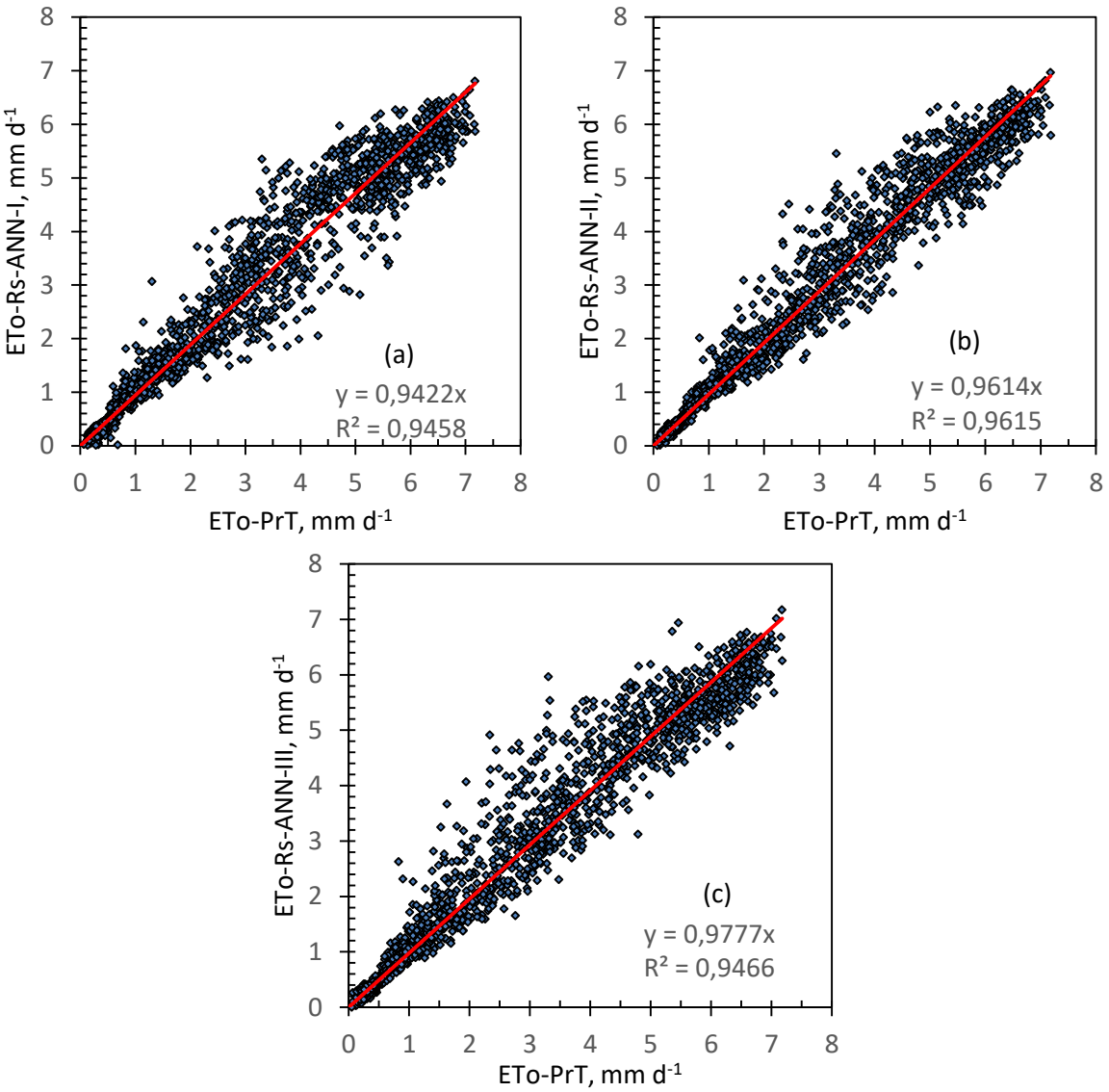
346



347

348 *Figure 8. Scattering diagrams between ET_o-PM estimated with R_s measured and ET_o-PM estimated with*
349 *R_s computed with multi-linear regression (a. MLR-I, b. MLR-II and c. MLR-III)) models at Amyntaio*
350 *station.*
351

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



355
356
357 *Figure 9. Scattering diagrams between ET_o–PrT estimated with R_s measured and ET_o–PrT estimated with*
358 *R_s computed with Artificial Neural Networks (a. ANN-I, b. ANN-II and c. ANN-III) models at Amyntaio*
359 *station.*
360

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

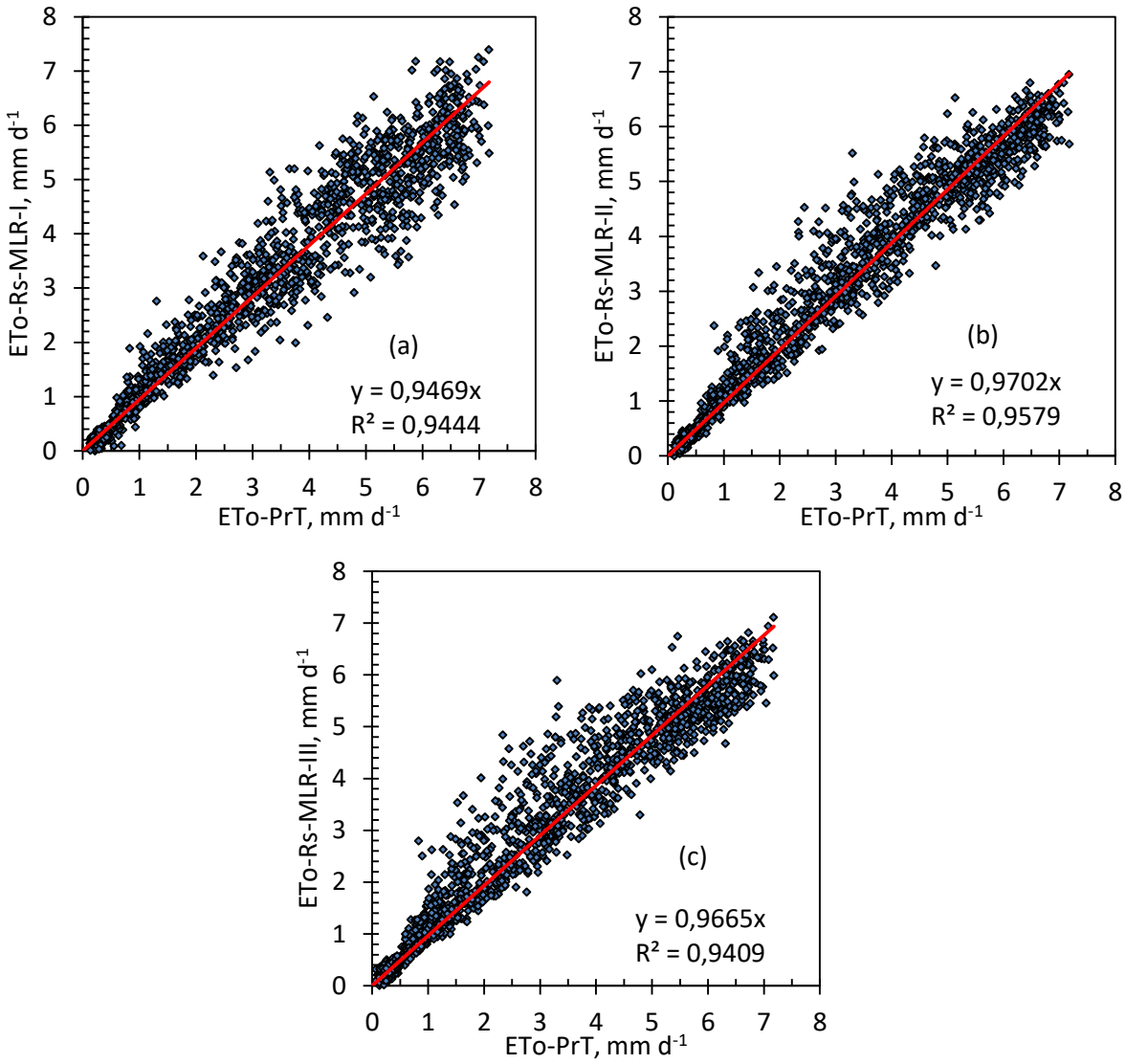


Figure 10. Scattering diagrams between ET_o–PrT estimated with R_s measured and ET_o–PrT estimated with R_s computed with multi-linear regression (a. MLR-I, b. MLR-II and c. MLR-III)) models at Amyntaio station.

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			
	Ave mm d^{-1}	r	RMSE mm d^{-1}	EF	Ave mm d^{-1}	r	RMSE mm d^{-1}	EF
ETo-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 (Despotovic et al., 2015). 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 1st, R_a, (T_{max}-T_{min}), $(T_{max}-T_{min})^{0.5}$, RH_{av} in the 2nd and R_a, and $(T_{max}-T_{min})^{0.5}$ in 3rd.

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^{-2} d^{-1} 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. (2017). They concluded that the ANNs models can reasonably estimate the daily radiation, with RMSE values in the range of 1.24–4.2 MJ $m^{-2}d^{-1}$ 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^{-2} d^{-1} 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_s was 0.893 and 0.908, 3.049 and 4.197 MJ $m^{-2}d^{-1}$ and 0.732 and 0.688, respectively for each station AUTH and AMIN, when K_{RS}=0.162. The accuracy of R_s estimation showed a slight improvement when K_{RS}=0.178 was used.

Using five years of daily data sets, in the present analysis, to derive the R_s 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. (2015) concluded that the different R_s 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 (2014) presented an evaluation of suitability of nine models to estimate R_s, and their effect on ET_o calculated with FAO-56 PM. The estimated R_s when compared with the measured R_s, did not show significant differences. The authors suggested that in Canada, the Samani and Hargeaves-Samani models (1982; 1985) are recommended for estimating R_s. The conclusion of Zhang et al. (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 $m^{-2}d^{-1}$. Zang et al. (2022) summarized that the various empirical models combining different meteorological parameters to estimate R_s, 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. (2022) concluded that for all the algorithms, the r^2 values range from 0.382 to 0.985, while the RMSE values ranged from 0.145 to 2.126 MJ m^{-2} d^{-1}.

Table 6. Changes of average, sd, r, RMSE and EF of Rs at AUTH and AMIN stations when using 3 and 5 years daily sets of data.

AUTH	Average R_s, %	sd of R_s, %	R, %	RMSE, %	EF, %
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
AMYNTAIO					
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. (2023) 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 Pristley-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^{-1} and 0.712, for the AUTH station and 0.986, 0.385 mm d^{-1} 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^{-1} 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^{-1} 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^{-1} 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^{-1} and 0.965 to 0.975, respectively.

The results of present work to calculate ET_o using the Pristley-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^{-1} 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^{-1} 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 (2010), Diamantopoulou et al. (2011), Gocic et al. (2016), Shiri et al. (2014). The comparison results of Antonopoulos and Antonopoulos (2017) 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^{-1}, 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 (Xu and Singh, 2002; Lu et al., 2005; Xystrakis and Matzarakis, 2011; Rácz, et al. 2013; Efthimiou et al. 2013; Bogawski et al. 2014; Heydari et al. 2014; Tigkas et al. 2020).

Aladenola and Madramootoo (2014) 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. (2022) 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 Pristley-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. Conclusions

The reference evapotranspiration (ET_o) with the Penman-Monteith and Pristley-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 $(T_{max}\text{-}T_{min})^{1/2}$ 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 $(T_{max}\text{-}T_{min})^{1/2}$ 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 MJ $m^{-2}d^{-1}$ for Rs, and r and EF greater than 0.932 and 0.826, respectively, and RMSE lower than 0.744 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 Pristley-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.

References

Aladenola, O.O., Madramootoo, C. A., 2014. Evaluation of solar radiation estimation methods for reference evapotranspiration estimation in Canada. Theoretical and Applied Climatology, 118(3):377-385.

Alexandris, S., Kerkides. P., Liakatas, A., 2006. Daily reference evapotranspiration estimates by the Copais approach, Agric. Water Manag., 82, 371-386.

Allen, R.G., Pruitt, W.O., 1991. FAO-24 reference evapotranspiration factors. J. of Irrig. and Drain.Eng., ASCE, 117, 758-773.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration-guidelines for computing crop water requirements, FAO Irrigation and Drainage. Paper 56, Rome, Italy.

Ampas, V., Baltas, E., Papamichail, D., 2007. Comparison of Different Methods for the Estimation of the Reference Crop Evapotranspiration in the Florina Region, WSEAS Trans, Environ. Development, 12(2), 1449-1454.

Antonopoulos, V. Z., Gianniou, S.K., 2003. Simulation of water temperature and dissolved oxygen distribution in Lake Vegoritis, Greece. Ecol. Model., 160, 39-53.

Antonopoulos, V.Z., Antonopoulos, A.V., 2017. Daily reference evapotranspiration estimates by artificial neural networks technique and empirical equations using limited input climate variables. Comput. Electron. Agric., 132. 86 - 96 ,

574 Antonopoulos, V.Z., Gianniou. S.K., Antonopoulos. A.V., 2016. Artificial neural networks and empirical
575 equations to estimate daily evaporation: application to lake Vegoritis. Greece. Hydrol. Sci. J. 61. 2590-
576 2599.
577 Antonopoulos, V.Z., Papamichail, D.M., Aschonitis, V.G., Antonopoulos, A.V.., 2019. Solar radiation
578 estimation methods using ANN and empirical models. Comput. Electron. Agric., 160, 160 - 167 .
579 Aschonitis, V.G., Antonopoulos, V.Z., Papamichail, D.M., 2012. Evaluation of pan coefficient equations
580 in a semi-arid Mediterranean environment using the ASCE standardized Penman-Monteith method.
581 Agr. Sci. 3(1). 58-65.
582 Aschonitis, V.G., Demertzi, K., Papamichail, D.M., Colombani, N., Mastroccico, M., 2015. Revisiting
583 the Priestley-Taylor method for the assessment of reference crop evapotranspiration in Italy, Italian J.
584 Agrometeorology. 20 (2). 5-18.
585 Aschonitis, V.G., Papamichail, D., Demertzi, K., Colombani, N., Mastrocicco, M., Ghirardini, A.,
586 Castaldelli, G., Fano, E.-A., 2017. High-resolution global grids of revised Priestley-Taylor and
587 Hargreaves-Samani coefficients for assessing ASCE-standardized reference crop evapotranspiration
588 and solar radiation. Earth System Science Data 9(2), 615-638.
589 Bellido-Jimenez, A., Estevez, J., García-Marín, A.P., 2022. A regional machine learning method to
590 outperform temperature-based reference evapotranspiration estimations in Southern Spain. Agric.
591 Water Manag., 274, 107955.
592 Besharat, F., Dehghan, A. A. Faghih, A.R., 2013. Empirical models for estimating global solar radiation:
593 A review and case study. Renewable and Sustainable Energy Reviews 21 (2013) 798–821
594 Bogawski, P., Bednorz, E., 2014. Comparison and validation of selected evapotranspiration models for
595 conditions in Poland (Central Europe). Water Resour. Manage. 28. 5021 –5038. DOI 10.1007/s11269-
596 014-0787-8
597 Daut, I., Irwanto, M., Irwan, Y.M., Gomesh, N., Ahmad, N.S., 2011. Combination of Hargreaves method
598 and linear regression as a new method to estimate solar radiation in Perlis, Northern Malaysia. Solar
599 Energy 85 (11), 2871–2880.
600 Despotovic, M., Nedica, V., Despotovic, D., Cvetanovicc, S., 2015. Review and statistical analysis of
601 different global solar radiation sunshine models. Renewable and Sustainable Energy Reviews 52:
602 1869–1880.
603 Diamantopoulou, M.L.. Georgiou, P.E., Papamichail, D.M., 2011. Performance evaluation of artificial
604 neural networks in estimation references evapotranspiration with minimal meteorological data. Global
605 Nest J. 13. 18-27.
606 Djaman, K., Baldea, A.B., Sow, A., Mullera, B., Irmak, S.,, N'Diayea, M.K., Manneha, B., Moukoumbia,
607 Y. D., Futakuchic, K., Saitoc, K., 2015. Evaluation of sixteen reference evapotranspiration methods
608 under sahelian conditions in the Senegal River Valley. J. Hydrol.: Regional Studies, 139–159
609 Efthimiou, N., Alexandris, S., Karavitis, C., Mamassis, N., 2013. Comparative analysis of reference
610 evapotranspiration estimation between various methods and the FAO56 Penman - Monteith
611 procedure, European Water, 42: 19-34.
612 El-Sebaii, A.A., Al-Hazmi, F.S., Al-Ghamdi, A.A., Yaghmour, S.J., 2010. Global, direct and diffuse solar
613 radiation on horizontal and tilted surfaces in Jeddah, Saudi Arabia. Applied Energy 87 (2), 568–-576.
614 Gianniou, S. K., Antonopoulos, V.Z., 2007. Evaporation and energy budget in Lake Vegoritis, Greece. J.
615 Hydrol. 345. 212-223.
616 Jain, S.K., Nayak, P.C., Sudheer, K.P., 2008. Models for estimating evapotranspiration using artificial
617 neural networks and their physical interpretation. Hydrol. Process. 22. 2225–2234.
618 Hargreaves, G.H., 1994. Simplified coefficients for estimating monthly solar radiation in North America
619 and Europe. Departmental Paper, Dept. of Biol. and Irrig. Engrg., Utah State University, Logan, Utah.
620 Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from temperature. Trans.
621 ASAE 1(2). 96-99.
622 Hargreaves, G.H., Samani, Z.A., 1982. Estimating potential evapotranspiration. J. Irrig. Drain. Eng.
623 ASCE 108 (3). 225–230.
624 Heddam, S., 2014. Modelling hourly dissolved oxygen concentration (DO) using dynamic evolving
625 neural- fuzzy inference system (DENFIS)-based approach: case study of Klamath River at Miller
626 Island Boat Ramp. OR. USA. Environ. Sci. Pollut. Res. 21:9212–9227

627 Heydari, M.M., Aghamajidi, R., Beygipoor, G., Heydari, M., 2014. Comparison and evaluation of 38
628 equations for estimating reference evapotranspiration in an arid region, Fresenious Environ. Bulletin,
629 23, 1985-1997.
630 Kisi, O., Sanikhani, H., Zounemat-Kermani, M., Niazi,F,. 2015. Long-term monthly evapotranspiration
631 modeling by several data-driven methods without climatic data. Comput. Electron. Agric. 115. 66-77.
632 ISSN 0168-1699.
633 Kumar, M., Raghuwanshi, N.S., Singh, R., 2011. Artificial neural networks approach in
634 evapotranspiration modeling: a review, Irrig. Sci., 29:11–25
635 Laaboudi, A., Mouhouche, M., Draoui, B., 2012. Neural network approach to reference
636 evapotranspiration modeling from limited climatic data in arid regions. Int. J. Biometeorol. 56. 831–
637 841
638 Li, H., Ma, W., Lian, Y., Wang, X., Zhao, L., 2011. Global solar radiation estimation with sunshine
639 duration in Tibet, China. Renewable Energy 36 (11), 3141-3145.
640 Lu, J., Sun, G., McNulty, S.G., Amatya, D.M., 2005. A comparison of six potential evapotranspiration
641 methods for regional use in the southeastern United States. J. Amer. Water Resour. Assoc. (JAWRA),
642 621-633.
643 Nawab, F., Abd Hamid, A.S., Ibrahim, A., Sopian, K., Fazlizan, A., Fauzan, M.F.,. 2023. Solar irradiation
644 prediction using empirical and artificial intelligence methods: A comparative review. Heliyon 9,
645 e17038.
646 Nematchoua, M.K., Orosa J.A., Afaifia, M., 2022. Prediction of daily global solar radiation and air
647 temperature using six machine learning algorithms; a case of 27 European countries. Ecological
648 Informatics, 69, 101643.
649 Premalatha, N., Valan Arasu, A., 2016. Prediction of solar radiation for solar systems by using ANN
650 models with different bach propagation algorithms. J.of Applied Research and Technology, 14:206-
651 214.
652 Priestley, C., Taylor, R., 1972, On the assessment of surface heat flux and evaporation using large-scale
653 parameters. Monthly Weather Rev. 100 (2). 81-92.
654 Rácz, C., Nagy, J. Dobos, A.C., 2013. Comparison of Several Methods for Calculation of Reference
655 Evapotranspiration, Acta Silv. Lign. Hung. 9.
656 Raziei, T, Pereira, L.S., 2013. Estimation of ETo with Hargreaves-Samani and FAO-PM temperature
657 methods for a wide range of climate in Iran. Agricultural Water Management, 121: 1– 18
658 Rivero, M., Orozco, S., Sellschopp, F.S., Loera-Palomo, R., 2017. A new methodology to extend the
659 validity of the Hargreaves-Samani model to estimate global solar radiation in different climates: Case
660 study Mexico. Renewable Energy 114, 1340–1352.
661 Shiri, J., Nazemi, A.H., Sadraddini, A.A., Landeras, G., Kisi, O., Fard, A.F., Marti, P., 2014. Comparison
662 of heuristic and empirical approaches for estimating reference evapotranspiration from limited inputs
663 in Iran. Comput. Electron. Agric. 108. 230-241.
664 Su, Q., Singh, V.P., Karthikeyan, R., 2022. Improved reference evapotranspiration methods for regional
665 irrigation water demand estimation. Agric. Water Manag., 274: 107979
666 Terzi, O., Keskin, M.E., 2010. Comparison of artificial neural networks and empirical equations to
667 estimate daily pan evaporation. Irrig. Drain. 59. 215–225.
668 Tigkas, D., Vangelis, H. & Tsakiris, G., 2020. Implementing Crop Evapotranspiration in RDI for Farm-Level
669 Drought Evaluation and Adaptation under Climate Change Conditions. *Water Resour Manage* **34**, 4329–
670 4343. https://doi.org/10.1007/s11269-020-02593-6
671 Xystrakis, F., Matzarakis, A., 2011. Evaluation of 13 Empirical Reference Potential Evapotranspiration
672 Equations on the Island of Crete in Southern Greece. J. Irrig. Drain Eng., 2011, 137(4): 211-222
673 Xu, C.-Y., Singh, V.P., 2000. Evaluation and Generalization of Radiation-based Methods for Calculating
674 Evaporation, Hydrol. Processes 14, 339–349.
675 Xu, C.-Y., Singh, V.P., 2002. Cross Comparison of Empirical Equations for Calculating Potential
676 Evapotranspiration with Data from Switzerland. Water Resour. Manag., 16: 197–219

677 Utset, A., Farré, I., Martínez-Cob, A., Cavero, J., 2004. Comparing Penman-Monteith and Priestley-
678 Taylor approaches as referenceevapotranspiration, Inputs for modeling maize water-use under
679 Mediterranean conditions. Agric. Water Manage., 66, 205-219
680 Valiantzas, J.D., 2018. Modification of the Hargreaves-Samani model for estimating solar radiation from
681 temperature and humidity dada. J. Irrig. Drain. Eng., ASCE, 144:06017014.
682 Yadav, A.K., Chandel, S.S., 2014. Solar radiation prediction using Artificial Neural Network techniques:
683 A review Renewable and Sustainable Energy Reviews 33 : 772–781
684 Yao, H., 2009. Long-term study of lake evaporation and evaluation of seven estimation methods: Results
685 from Dickie Lake. south-central Ontario. Canada. J. Water Resour. Prote. 2. 59-77.
686 Zang, H., Jiang, X., Cheng, L., Zhang, F., Wei, Z., Sun, G., 2022. Combined empirical and machine
687 learning modeling method for estimation of daily global solar radiation for general meteorological
688 observation stations. Renewable Energy 195, 795-808.
689 Zhang, J., Zhao, L., Deng, S., Xu, W., Zhang, Y., 2017. A critical review of the models used to estimate
690 solar radiation. Renewable and Sustainable Energy Reviews 70 : 314–329.
691

692

693