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Reference Evapotranspiration Evaluation Using Solar Radiation Estimated by ANN and Empirical Models

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Authors' contributions

This work was carried out in collaboration between both authors, both authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by authors VZA and AVA. The first draft of the manuscript was written by authors VZA and the other author commented on previous versions of the manuscript. Both authors read and approved the final manuscript.

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ABSTRACT

Aims: The reference evapotranspiration (ET_o) 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_o by Penman-Monteith (ET_o-PM) and Priestley-Taylor (ET_o-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_o calculation.

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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_o 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_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 $m^{-2}d^{-1}$.
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_o 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. 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 [5]:

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

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 [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 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 [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

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

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 [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 (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 [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

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

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 $(TD)^{0.5}$) [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_{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 [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):

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

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

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

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 -∞.

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

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 1st 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^{-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.

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 [18] 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 Priestley-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 [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 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.

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

Fig. 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.

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

	R_s		index			Ranking		
	Mean 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, $(T_{max}-T_{min})^{0.5}$}

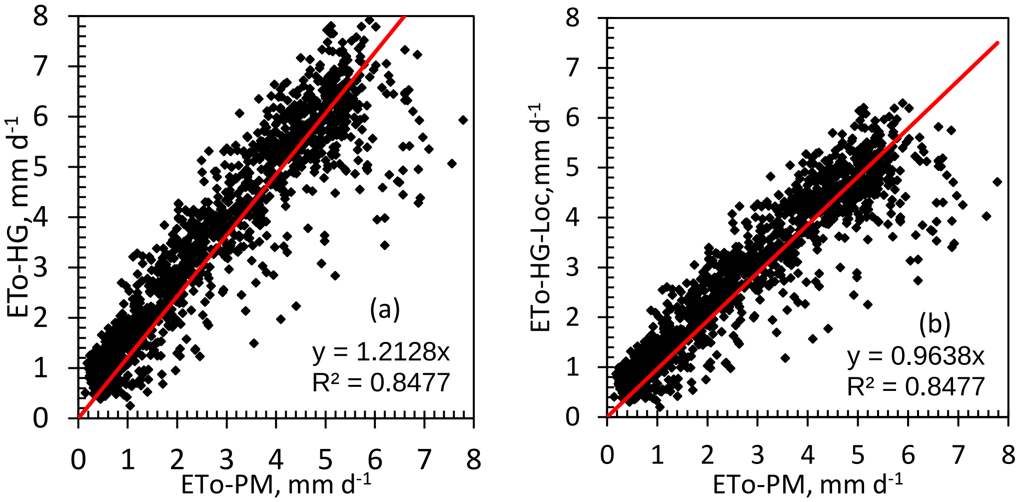


Fig. 1. Scattering diagrams of daily ET_o estimated by the Hargreaves (HG) and the ETo values estimated by the Penman – Monteith method using measured values of R_s, a) K_{RS}=0.162; b) K_{RS}=0.158 local adjusted coefficient

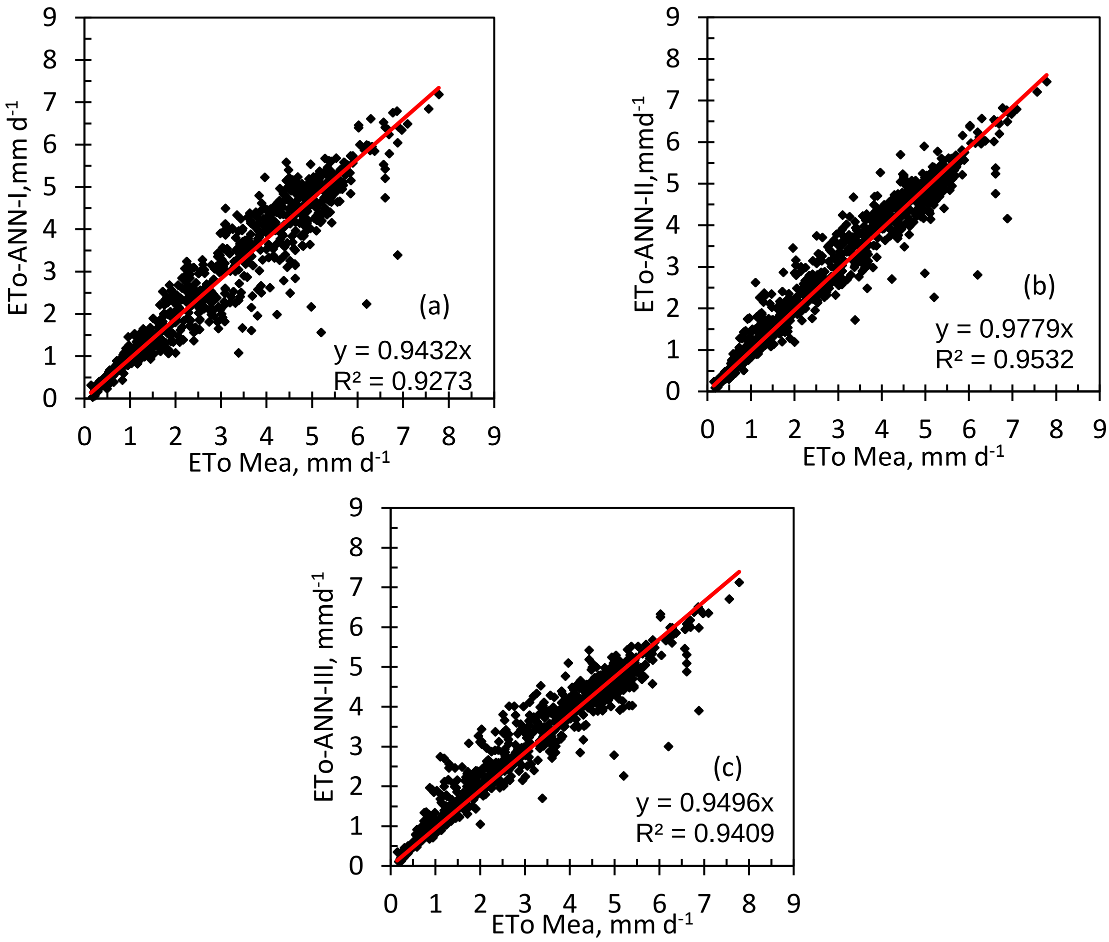


Fig. 2. Scattering diagrams between ET_o estimated with R_s measured and ET_o estimated with R_s computed with Artificial Neural Networks (a. ANN-I; b. ANN-II and c. ANN-III) models at Aristotle University Farm station

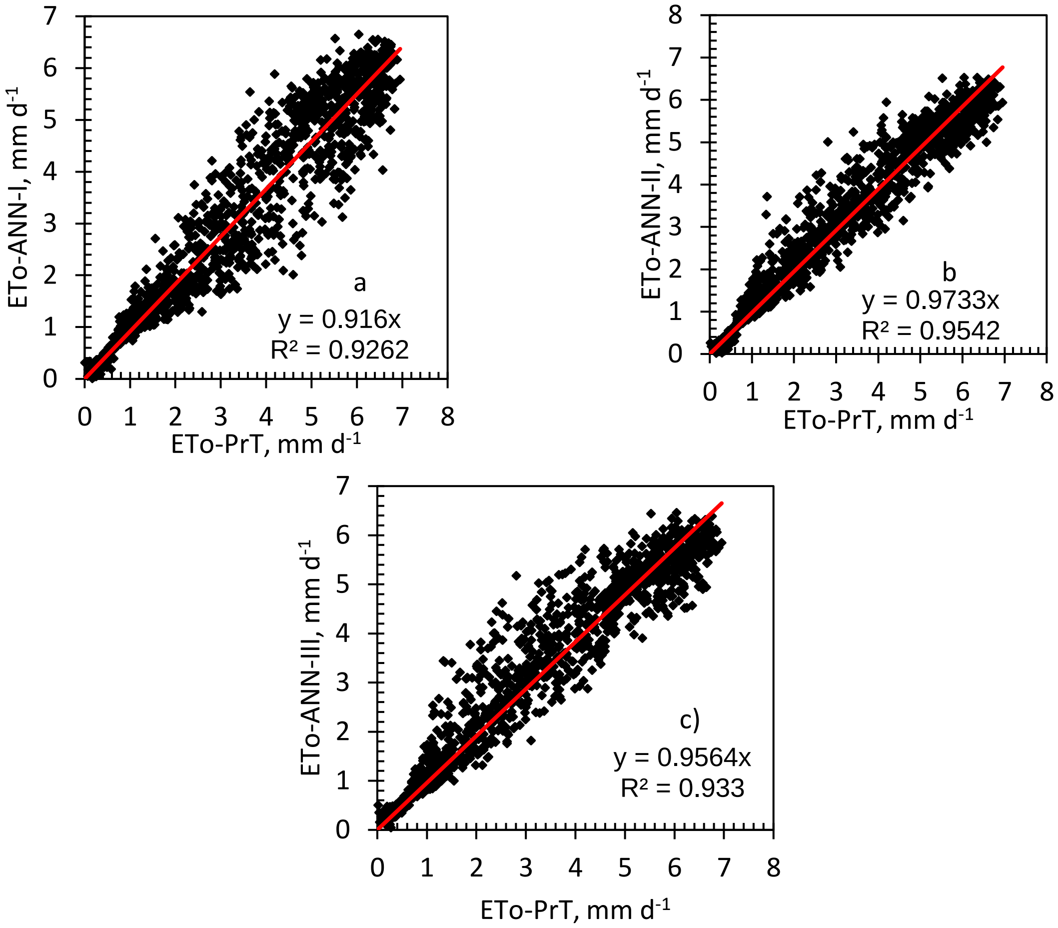


Fig. 3. Scattering diagrams of ET_o-PrT estimated with R_s measured and ET_o-PrT estimated with R_s computed with Artificial Neural Networks (a. ANN-I; b. ANN-II and c. ANN-III) models at Aristotle University Farm station

Fig. 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.

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

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

Fig. 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.

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

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 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

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.

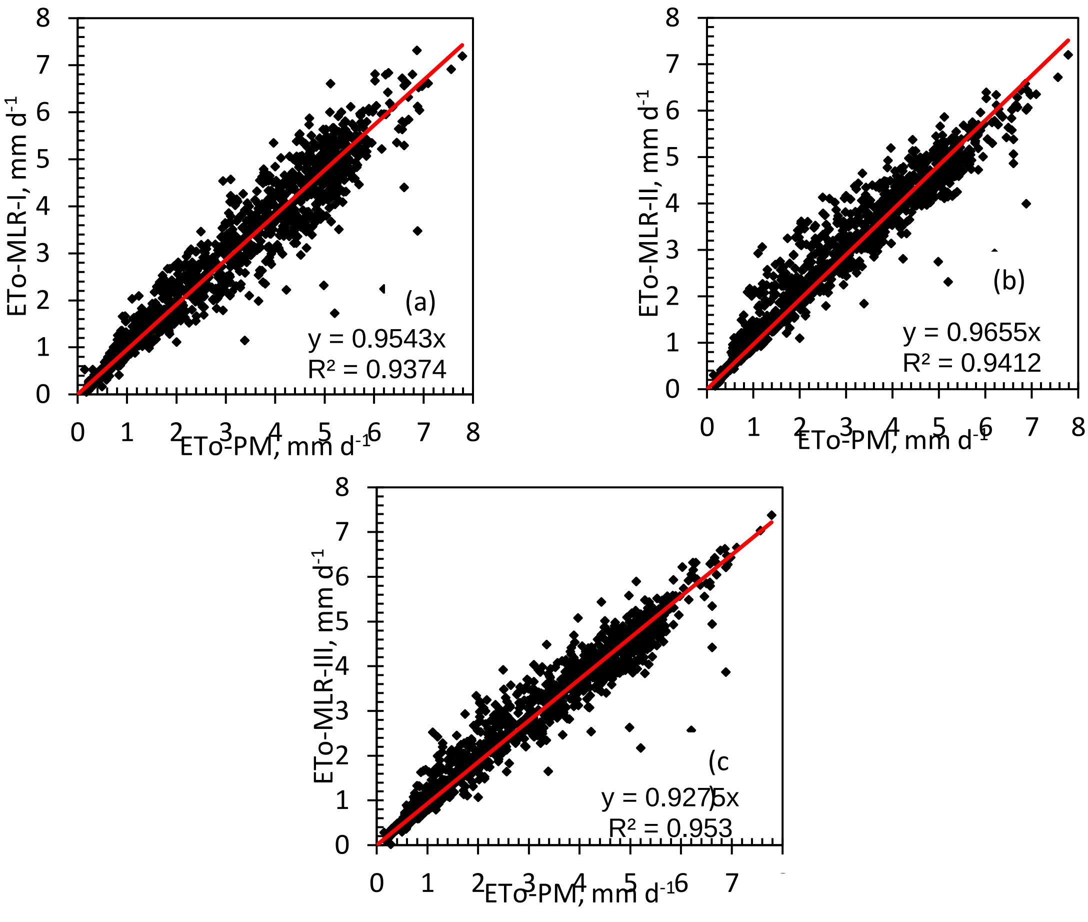


Fig. 4. Scattering diagrams between ET_o estimated with R_s measured and ETo estimated with R_s computed with Multi linear regression (a. MLR-I, b. MLR-II and c. MLR-III)) models at Aristotle University Farm station

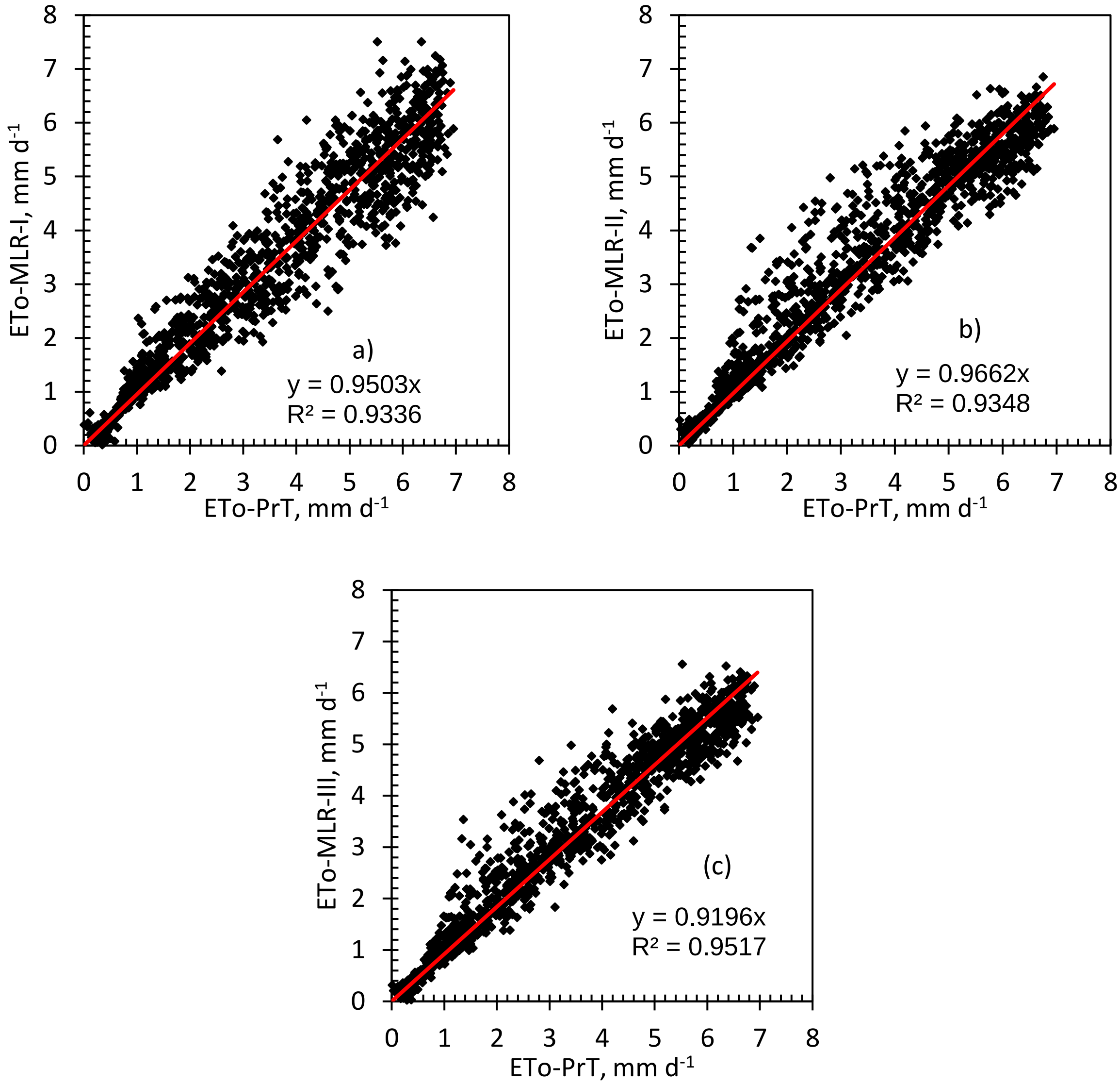


Fig. 5. Scattering diagrams of ET_o-PrT estimated with R_s measured and ET_o-PrT estimated with R_s computed with Multi linear regression (a. MLR-I, b. MLR-II and c. MLR-III)) models at Aristotle University Farm station

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^{-1}	**r**	**RMSE mm d^{-1}**	**EF**	**Mean 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				

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**		
	Mean 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

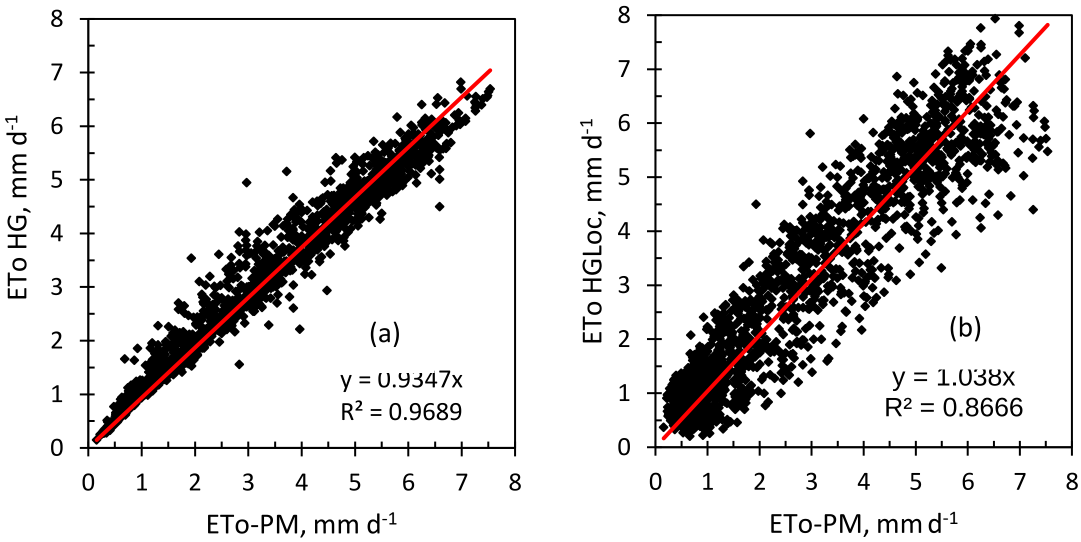


Fig. 6. Scattering diagrams between ET_o estimated with Hargreaves (HG) method (a. original and b. local adjustment) against the ET_o of Penman-Monteith method using R_s measured values at Amyntaio Station

3.4 Results of ET_o at Amyntaio Station

Fig. 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.

Figs. 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.

Figs. 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.

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.

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.

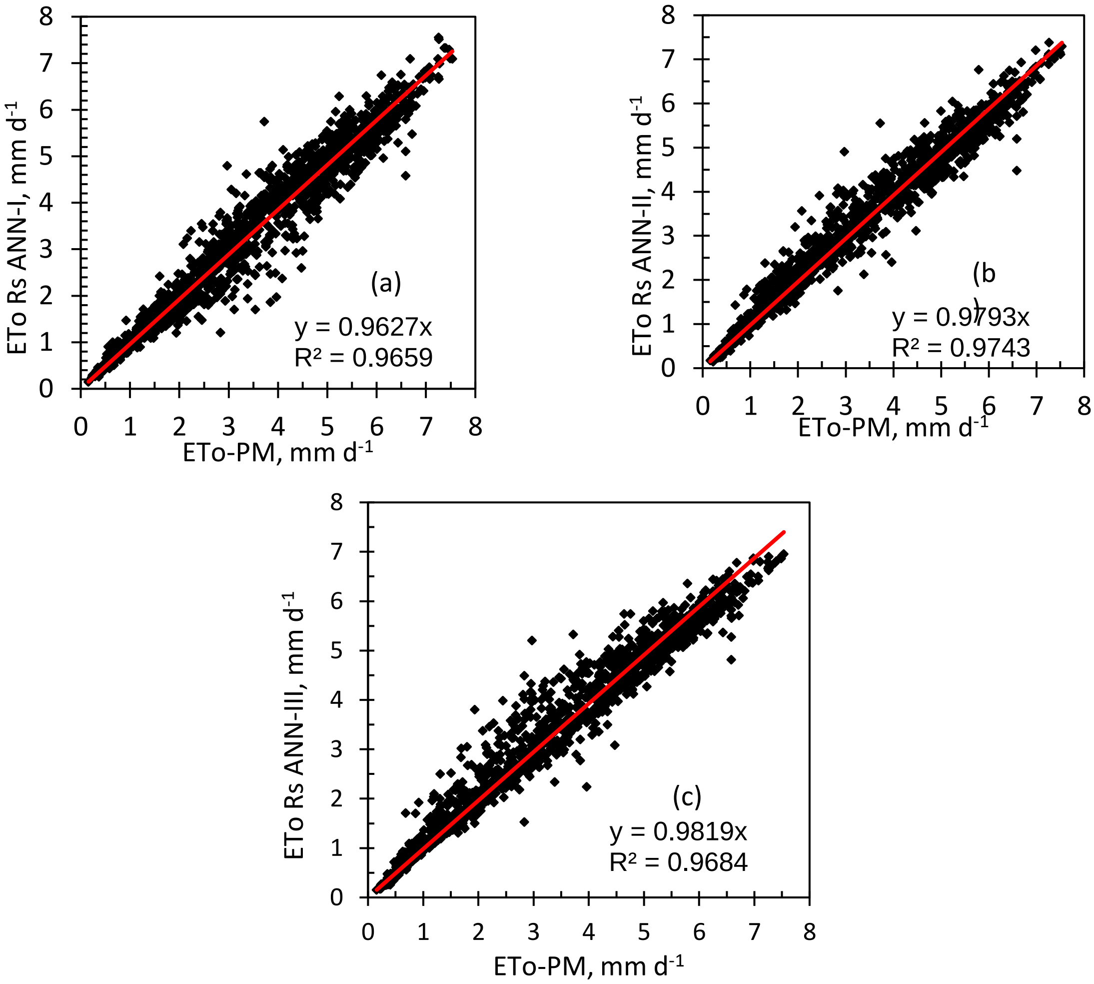


Fig. 7. Scattering diagrams between ET_o-PM estimated with R_s measured and ET_o-PM estimated with R_s computed with Artificial Neural Networks (a. ANN-I, b. ANN-II and c. ANN-III) models at Amyntaio station

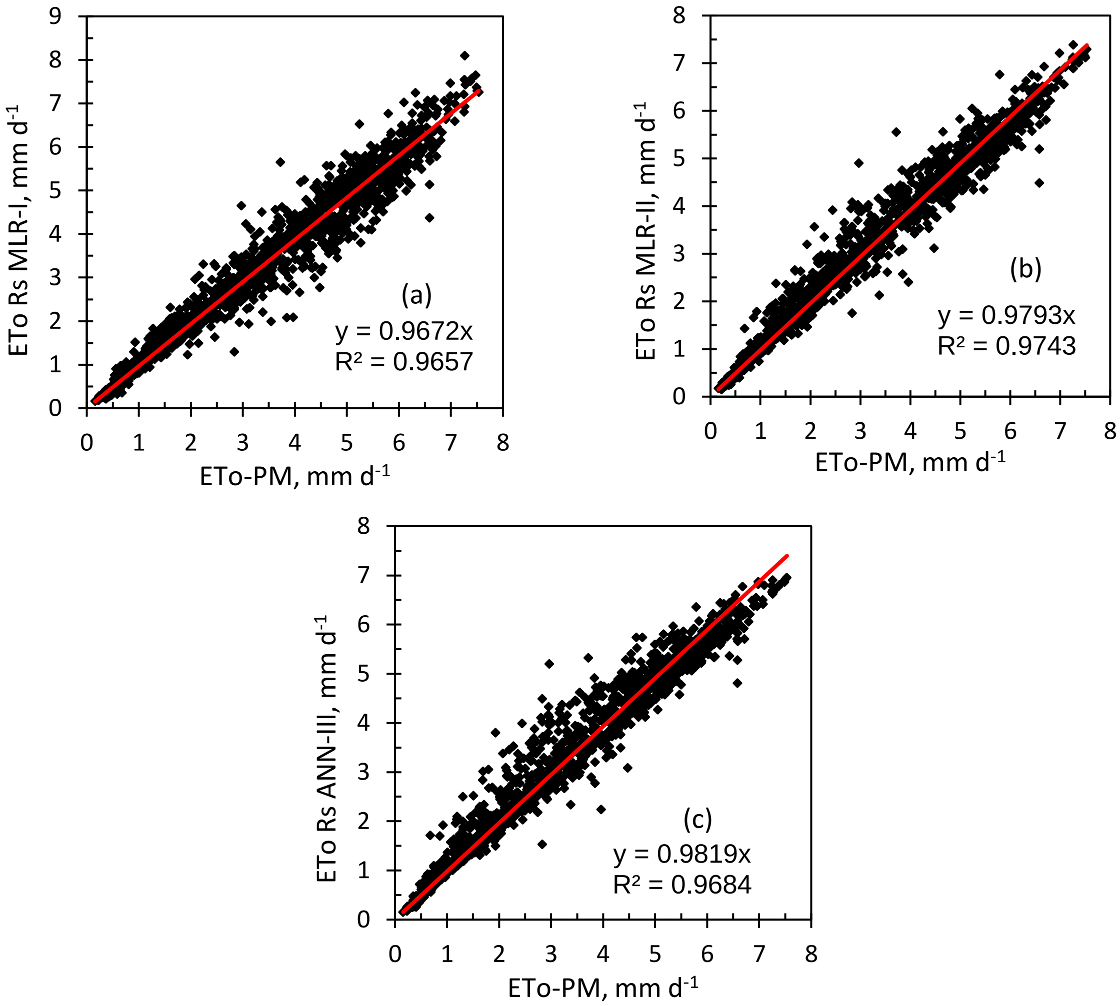
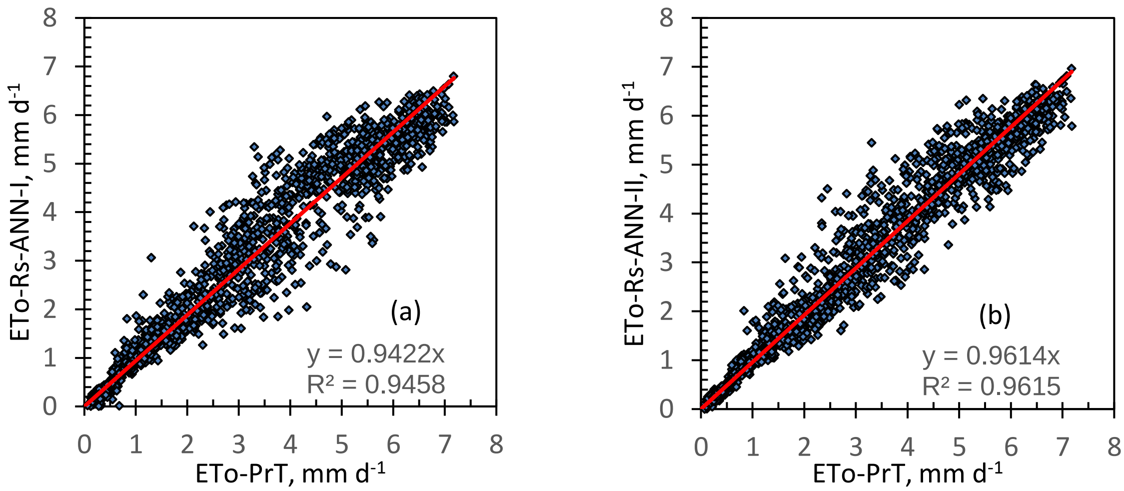


Fig. 8. Scattering diagrams between ET_o-PM estimated with R_s measured and ET_o-PM estimated with R_s computed with multi-linear regression (a. MLR-I, b. MLR-II and c. MLR-III)) models at Amyntaio station



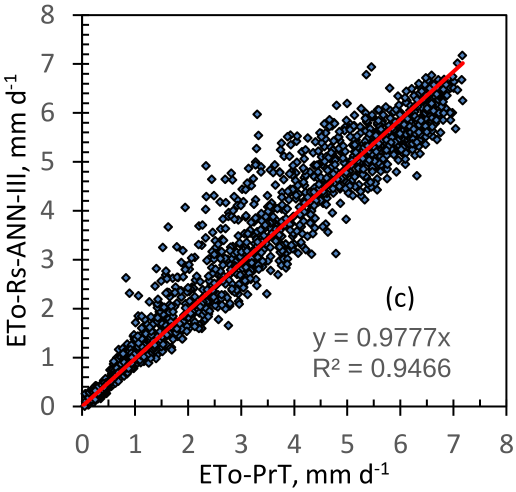


Fig. 9. Scattering diagrams between ET_o–PrT estimated with R_s measured and ET_o–PrT estimated with R_s computed with Artificial Neural Networks (a. ANN-I, b. ANN-II and c. ANN-III) models at Amyntaio station

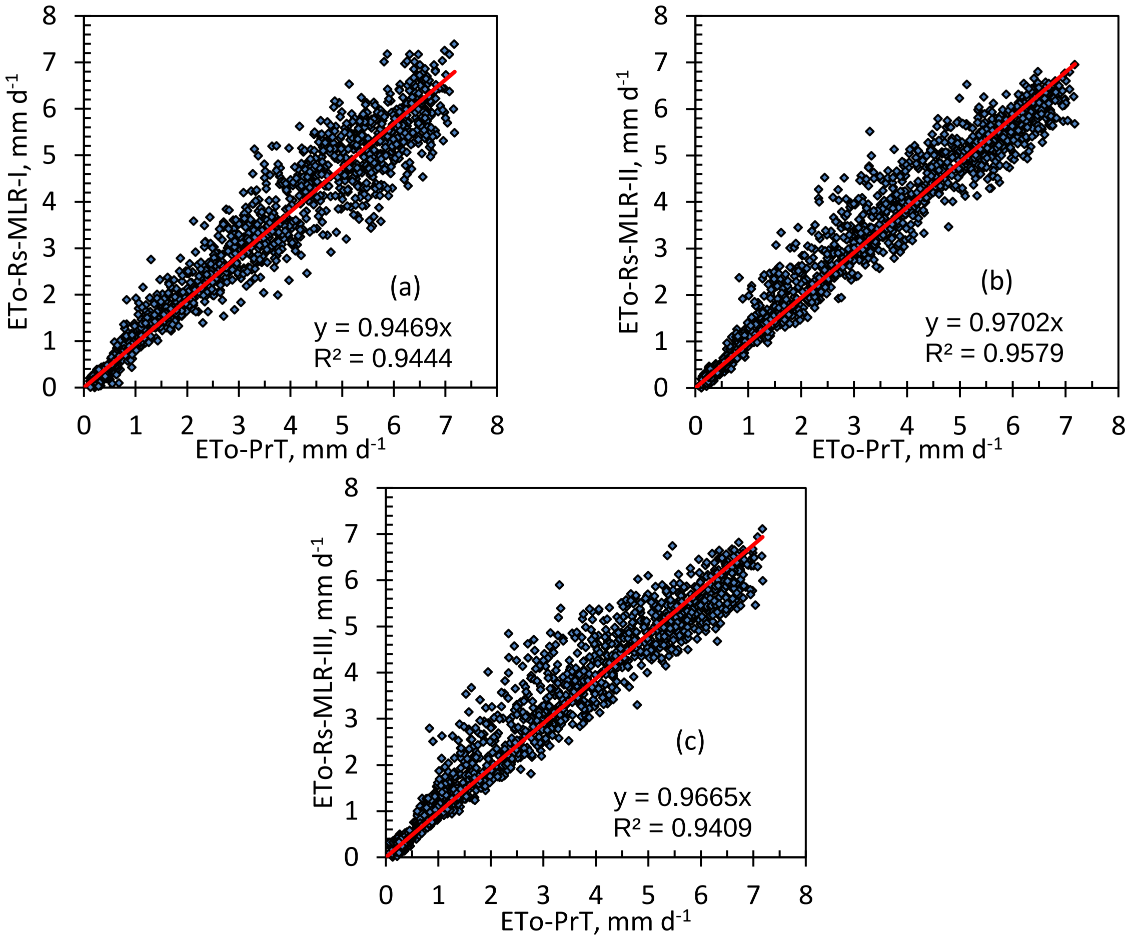


Fig. 10. Scattering diagrams between ET_o–PrT estimated with R_s measured and ET_o–PrT estimated with R_s computed with multi-linear regression (a. MLR-I, b. MLR-II and c. MLR-III)) models at Amyntaio station

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^{-1}	r	RMSE mm d^{-1}	EF	Mean 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				

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.

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 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. [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 $m^{-2}d^{-1}$ 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 (Table 6). 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_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 [47] 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 [29,30] are recommended for estimating R_s. 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 $m^{-2}d^{-1}$. Zang et al. [19] 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. [20] 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}.

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^{-1} and 0.712, for the AUTH station and 0.986, 0.385 mm d^{-1} and 0.962, for the AMIN station, respectively.

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

	Average R_s, %	sd of R_s, %	r, %	RMSE, %	EF, %
AUTH					
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

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 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^{-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 [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^{-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 [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 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 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.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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