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Evaluation of Reference Evapotranspiration Estimation Methods for the Assessment of Hydrological Impacts of Photovoltaic Power Plants in Mediterranean Climates

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Abstract: Large-scale photovoltaic (PV) power plants may affect the hydrological cycle in all its components. Among the various components, evapotranspiration is one of the most important. As a preliminary step for assessing the impacts of PV plants on evapotranspiration, in this study, we performed an evaluation study of methods for estimating reference evapotranspiration (ETo). FAO and ASCE recommend the Penman–Monteith (PM) method for the estimation of ETo when the data for all involved variables are available. However, this is often not the case, and different empirical methods to estimate ETo, requiring mainly temperature data, need to be used. This study aimed at assessing the performance of different temperature- and radiation-based empirical ETo estimation methods against the standardized PM ETo method in an experimental photovoltaic power plant in Piazza Armerina, Sicily, Italy, where a meteorological station and a set of sensors for soil moisture were installed. The meteorological data were obtained from the Lab from July 2019 to end of January 2022. By taking the ETo estimations from the PM method as a benchmark, the study assessed the performance of various empirical methods. In particular, the following methods were considered: Hargreaves and Samani (HS), Baier and Robertson (BR), Priestley and Taylor (PT), Makkink (MKK), Turc (TUR), Thornthwaite (THN), Blaney and Criddle (BG), Ritchie (RT), and Jensen and Haise (JH) methods, using several performance metrics. The result showed that the PT is the best method, with a Nash–Sutcliffe efficiency (NSE) of 0.91. The second method in order of performance is HS, which, however, performs significantly worse than PT (NSE = 0.51); nevertheless, this is the best among methods using only temperature data. BG, TUR, and THN underestimate ETo, while MKK, BG, RT, and JH showed overestimation of ETo against the PM ETo estimation method. The PT and HS methods are thus the most reliable in the studied site.

Keywords: statistical performance metrics; Penman–Monteith method; empirical methods; PV panels

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1. Introduction

Recently, the solar photovoltaic (PV) plant areas have been increasing globally, as they are seen as a valid source of renewable energy production [1–6]. These PV panels contain directly produced energy from the incoming solar radiation [7–9]. The PV will be influenced and attributed on the amount of solar radiation on the existing local climate system [7,9,10]. This solar radiation also a crucial part of reference evapotranspiration (ETo). Solar radiation highly contributed to the trend and sensitivity of evapotranspiration compared with the other climatological elements [11,12]. Therefore, before we estimate and analyze the impact of PV on evapotranspiration, it is necessary to carefully select which empirical estimations should be applied on the study area.

The ETo process is entirely linked to the exchange of water and energy within land, soil, atmosphere, and biosphere [13–15]. ETo can be estimated by using earth–atmosphere energy balance aerodynamics principles or by more simplistic empirical models [14,16]. The estimation of ETo can be carried out either directly (field water balance approach and soil moisture depletion approach) or indirectly (empirical/statistical methods, micrometeorological methods, and remote sensing methods) [14,17–22]. Empirical estimation of ETo is very helpful to understand the spatiotemporal configuration of hydrological cycle and climatological components and for water use, agricultural, ecological applications, and other developmental projects (including large-scale photovoltaic panels) [14,23,24]. An accurate estimation of ETo is important to improve the understanding of water and energy exchange processes between land and atmosphere that are relevant for many scientific disciplines and agricultural management [13].

Mediterranean climate studies have evaluated the ETo empirical estimation methods against the PM method and filed measurements [19,25–28]. With reference to the Central Spanish Pyrenees, Hess and White (2009) found that the FAO56–PM method offers a more accurate estimation of reference evapotranspiration than the Hargreaves formula against the field lysimeter measurement. From 1995 and 1996, a study on the maize growth seasons at Zaragoza, Spain [29], compared the FAO56–PM with Priestley–Taylor (PT), and the study revealed that PT ETo values were significantly lower than the FAO56–PM calculations.

Katerji and Rana (2000) calculated the ETo by using the FAO56–PM method from hourly and daily data. The result of this study showed that the FAO56–PM was not effective for timescales shorter than 10 days, whereas for greater intervals, it was more accurate. Katerji and Rana (2000) evaluated ten ETo estimation methods in Mediterranean regions by field lysimeter measurements; the results showed that the FAO56–PM is sufficiently accurate for the Mediterranean region at monthly and seasonal temporal-scale analysis, and the second for performance was the Hargreaves–Samani method (1985) [30]. Gharsallah et al. (2013), with reference to two sites in the Padana Plain, Northern Italy, showed that the FAO56–PM provides better results than other indirect estimation methods against lysimeter measurements. The FAO–PM method also showed the highest R^2 (0.96) value compared to radiation-based models of Makkink and Priestley–Taylor, against scintillometer measurements in Sicily [31]. The FAO–PM method is used as a standardized method for comparison of other temperature, radiation, and mixed (radiation and temperature) based methods in different areas of the world [16,24,32–34].

A study in Alentejo, Southern Portugal [35], also evaluated nine ETO estimation empirical methods; the result showed that the HS radiation adjustment coefficient (kRs) produced the best performance against the FAO56–PM. In addition to the ETo empirical estimation methods, machine learning also proved to be helpful to estimate the ETo. A study in Valenzano, Southern Italy, showed that the k-Nearest Neighbor (kNN) machine learning technique had the best performance only when using temperature data input, compared with the Artificial Neural Networks (ANNs) and Adaptive Boosting (AdaBoost) models to predict daily potato crop evapotranspiration against the gravimetric measurement and FAO–PM method [36]. Yamaç and Todorovic (2020) conducted a study that also confirmed that ANN showed the highest performance with temperature, wind speed, solar radiation, and relative humidity data inputs compared with the machine learning techniques against the FAO–PM method and gravimetric measurement. The study in Ranichauri (India) and Dar El Beida (Algeria) compared the artificial neural network (ANN)-embedded grey wolf optimizer (ANN–GWO), multi-verse optimizer (ANN–MVO), particle swarm optimizer (ANN–PSO), whale optimization algorithm (ANN–WOA), and ant lion optimizer (ANN–ALO) hybrid machine learning approaches against the FAO–PM standard; the result showed that the ANN–GWO-1 model with five input variables (Tmin, Tmax, RH, Us, Rs) provided better estimates at both study stations (RMSE = 0.0592/0.0808, NSE = 0.9972/0.9956, PCC = 0.9986/0.9978, and WI = 0.9993/0.9989) [37].

The empirical estimations of ETo have their advantage and disadvantageous. In general, with the exception of the FAO–PM method, they do not need full meteorological data;

rather, they will use either one or two input data. This will be considered as an advantage, especially in developing countries [38,39]. The main disadvantage is over- or underestimation in different climate systems. For instance, Hargreaves–Samani showed both under- and overestimation in Mediterranean climate [40]. The Priestley–Taylor, Thornthwaite, and Blaney–Criddle models showed overestimation by 0.2 mm per day, while the Makkink and Hargreaves–Samani models showed an underestimate 0.2 mm per day in Peninsular of Malaysia [41].

In the Goulburn-Murray Irrigation Area (GMIA) of Southeastern Australia [42], one study evaluated Hargreaves (HAR), improved Hargreaves (IHA), FAO-24 Radiation (RAD), Ritchie-type (RIT), FAO-24 Class-A Pan with pan coefficients of Doorenbos and Pruitt (PEV) and empirical regression coefficient (SEV), combination methods McIlroy (McI), FAO–Penman with wind functions of Watts and Hancock (W–H) and Meyer (M_PY), and the Penman–Monteith (P–M); and the result showed that there were both underestimations and overestimations in the two sample sites. In arid regions across Iran, Irmak (Irmak et al. 2003), Hargreaves–Samani (Hargreaves and Samani 1985), and Hargreaves (1975) equations showed the best performance compared to 13 other commonly applied empirical methods against the FAO–PM method [43]. A study in Southern Manitoba [44]. Assessed the performance of the 14 commonly used ETo estimation methods, and the result showed that Valiantzas-1, Valiantzas-3, Irmak, Valiantzas-2, and Priestley–Taylor models scored the best in regard to performance against the FAO–PM method.

Specifically in Sicily, by using the scintillometer measurements, six ETo empirical estimation methods were compared in Southwest Sicily [45], obtaining the following ranking in respect to performance: FAO–PM, Priestley–Taylor, Makkink (1957), and Turc. Closely similar analyses compared radiation based and aerodynamic-radiation based ETo estimation methods against scintillometer measurements; the result showed that the radiation-based model of Priestley–Taylor had the best performance [31]. In a study conducted in the semi-arid Mediterranean areas of the Belice Basin, Sicily [46], it was reported that the Hargreaves method gave a better performance compared with remote sensing data against the filed measurement.

The abovementioned studies conducted in Sicily used radiation-based methods. However, temperature- and aerodynamics/radiation-based methods still remain poorly evaluated. To test the hypothesis of this study, besides the FAO–PM method, we applied other ETo empirical estimation methods and substituted when there was a lack of data to apply to the FAO–PM method. Therefore, the objective of this study was to evaluate the nine ETo empirical estimation methods, which include temperature-, radiation-, and aerodynamics/radiation-based methods against the FAO56–PM method and to apply the best-performing method for future research work about the impact of PVs infrastructure on evapotranspiration in Ambiens S.r.l. Lab, near Piazza Armerina, Sicily.

2. Study Area and Data

In this study we analyze the data collected at the experimental site in Piazza Armerina, Sicily, Italy, owned by Ambiens S.r.l. The site has the aim at monitoring large-scale PV plants impacts on local hydro-climate and soil in Piazza Armerina, Sicily. A meteorological station has recorded every 10 min temperature (°C), relative humidity (%), air pressure (hPa), wind direction, wind speed (m/s), and solar radiation (w/m^2) from 1 July 2019 to 14 January 2022 for 929 days record data. The sensors that were used to record the variables were a thermo-hygrometer, barometer, anemometer, rain gauge, and pyranometer. The site is located at 37°20′42.19″ N, 14°24′16.11″ E, and has an altitude of 558 m a.s.l (Figure 1).

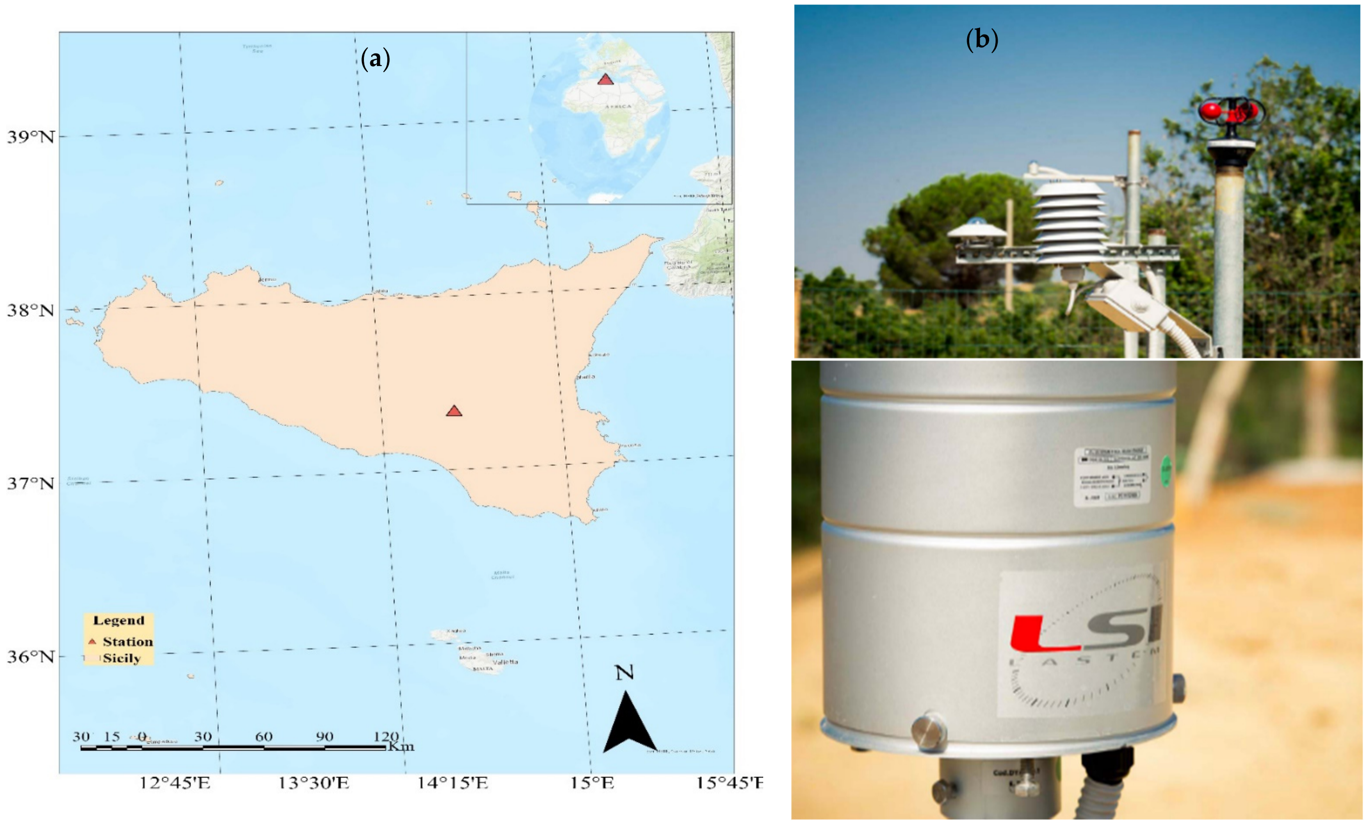

Figure 1. (**a**) Location of the experiment site and (**b**) on-site view of the meteorological station.

The climate of Sicily is typically Mediterranean along the coasts, with hot but not torrid summers, mild and short winters, and moderate annual rainfall (average around 750 mm), occurring mainly from October to March. The annual average temperature along the coast is between 17 and 18.7 °C, with July being the hottest month [47]. It is also characterized by hot and dry summer and mild and rainy winter [48].

The study used maximum, minimum, and mean temperature; solar radiation; relative humidity; and wind speed for the FAO56–PM method and other ETo estimations methods depending on their necessary variables. The data for these variables were obtained from the mentioned meteorological station. The data cover the period from July 2017 to 31 January 2022 for all four meteorological variables.

2.1. The Standardized ETo Estimation (FAO/Penman–Monteith) Method

The FAO–PM has been established as a standard for calculating reference evapotranspiration (ETo) [34]. The method requires air temperature, relative humidity, solar radiation, and wind speed data and is usually reported as the most accurate compared to other empirical ETo estimation methods [23,49–54].

This equation is simplified by integrating the original Penman–Monteith equation and the equations of the aerodynamic and canopy resistance, yielding the following FAO/Penman–Monteith equation:

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34\,U_2)} \quad (1)$$

where ET_o is the reference evapotranspiration (mm day^{-1}), R_n is the net radiation at the crop surface (MJ m^{-2} day^{-1}), G is the soil heat flux density (MJ m^{-2} day^{-1}), T is the air temperature at 2 m height (°C), u_2 is the wind speed at 2 m height (m s^{-1}), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), $e_s - e_a$ is the saturation vapor pressure deficit (kPa), slope vapor pressure curve (kPa °C^{-1}), and g is the psychrometric constant (kPa °C^{-1}). Moreover, 900 and 0.34 are, respectively, the constants by considering the clipped grass reference crop, while for the alfalfa crop, they are 1600 and 0.38, respectively (FAO 1998).

2.2. Selected ETo Estimation Methods

Considering the effectiveness of the Mediterranean climate and Sicily climate, the study selected ten ETo empirical estimation methods, including temperature-, radiation-, and the mixed-based (aerodynamic radiation) methods (Table 1).

Table 1. Selected ETo empirical estimation methods which are compared with against the FAO56–PM method with their equation, reference, and other information.

Method	Model Type	Abbreviation	Formula	Timescale	Parameters
Hargreaves and Samani (1985)	Temp	HS	$0.0023R_a(T_{avg}+17.8)\ (T_{max}-T_{min})^{0.5}$	Daily	T_{max}, T_{min}, φ
Baier and Robertson (1965)	Temp	BR	$0.157T_{max}+0.158(T_{max}-T_{min})+0.109\ R_a-5.39$	Daily	T_{max}, T_{min}, φ
Priestley and Taylor (1972),	Rad	PT	$1.26\cdot\frac{\Delta}{\Delta+\gamma}\frac{R_n-G}{\lambda}$	Daily	T_{max}, T_{min}, φ, T_{avg}
Makkink (1957)	Rad	MAK	$0.61\frac{\Delta}{\Delta+\gamma}\frac{R_s}{2.45}-0.12$	Daily	T_{avg}, R_s
Turc (1961)	Rad	TUR	$0.013\left(\frac{T_{avg}}{T_{avg}+15}\right)\cdot(R_s+50)$	Daily	T_{avg}, R_s
Thornthwaite (1957)	Temp	THN	$16\cdot(10\frac{T_{avg}}{I})^{a}\times\frac{N}{360}$	Monthly	T_{max}, T_{min}, φ
Blaney and Criddle (1950)	Temp	BG	$p\ (0.457T_{avg}+8.128)$	Monthly	T_{avg} and p (FAO document)
Ritchie (1972)	Rad	RT	$\frac{\Delta}{\Delta+\gamma}R_n$	Daily	R_s
Jensen and Haise (1963)	Rad	JH	$R_s(0.0252T_{avg}+0.078)$	Daily	T_{avg}, R_s

Note: Temp, temperature-based method; Rad, radiation-based method; T_{max}, maximum temperature; T_{min}, minimum temperature; T_{avg}, mean temperature; φ, latitude; I, annual heat index, defined as the summation of 12 values of the monthly heat; N, maximum number of sunshine hours in the month (h/d); a, empirical exponent function of the annual heat index, I (a = 6.75 × 10^{-5}I^3 + 7.71 × 10^{-7}I^2 + 1.79 × 10 − 2I + 0.492); Ra, extraterrestrial radiation (MJ m^{-2} day^{-1}); Rs, solar radiation (MJ m^{-2} day^{-1}); p, mean daily percentage of annual daytime hours. For Jensen and Haise (1963), R_S should be changed in mm d^{-1} (Rs mm d^{-1} = 0.408 × Rs in MJ m^{-2} day^{-1}); e^o, mean saturation vapor pressure for a day in KPa; G = soil heat flux density, MJ m^{-2} d^{-1} (for this study the value zero because of its daily analysis); Δ, slope of the vapor pressure curve, kPa·°C^{-1}; γ is psychrometric constant, kPa·°C^{-1}; λ, latent heat of vaporization (MJ kg^{-1}); R_n, net radiation at the crop surface, MJ m^{-2} d^{-1} (Table 1).

2.3. Statistical Analysis

To evaluate the best ETo estimation methods against the FAO–PM international standard method, we considered the following metrics: Nash–Sutcliffe efficiency (NSE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Willmott index (d), Coefficient of Determination (R^2), Mean Absolute Error (MAE), Mean Basis Error (MBE), and Root Mean Square Error (RMSE). The NSE is a widely used and potentially reliable statistic for assessing the goodness of fit of hydrologic models [55]. The NSE ranges from $-\infty$ to 1. When NSE is close to 1, the quality of the method for estimating ETo is perfect. When NSE is less than 0, the estimation is worse than the observed mean, and thus it is not reliable [56].

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2}, \tag{2}$$

$$R^2 = \left\{\frac{\sum_{i=1}^{n}(O_i - \overline{O}\,)\ (P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2} * \sqrt{\sum_{i=1}^{n}(P_i\ - \overline{P})^2}}\right\}^2, \tag{3}$$

$$MAE = \frac{\sum_{i=1}^{n}(|O_i - P_i|)}{n}\ , \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}, \tag{5}$$

$$MBE = \overline{P} - \overline{O}\,. \tag{6}$$

$$AIC = -2lnL + 2k \tag{7}$$

$$BIC = -2lnL + kln\ (n) \tag{8}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P'_i| + |O'_i|)^2} \tag{9}$$

where P_i are the values obtained from the ETo estimation methods to be assessed O_i are the reference ones, derived from the FAO–PM method, $\overline{P}$ and $\overline{O}$, are the respective arithmetic mean and n is sample size. $Additionally,\ P'_i = P_i - \overline{O}$ and $O'_i = O_i - \overline{O}$.

Moreover, in AIC and BIC, n means number of values, L is the maximum value of the likelihood function for the model, and k is the number of free parameters in the model.

3. Results

Assessing ETo empirical estimation methods' performance is essential in relation to discrepancies of performance in different climate systems [29]. Temperature- and radiation-based empirical ETo estimation methods have different performances. Table 2 showed that the average daily ETo value of PM is highly similar to the ETo values of the PT and HS methods, respectively. The NSE values (Table 2) showed that the PT and HS have the best performance over other methods, with values of 0.91 and 0.51, respectively, against the PM ETo method. The other methods showed negative values of NSE. The negative values of NSE imply that the methods are not recommended or not well calibrated against the PM method [55,57,58].

Table 2. Statistical indicators for the performance of the ETo estimation methods against the FAO–PM ETo estimation method.

	PM	HS	BR	PT	MKK	TUR	RIT	JH	THN	BG
average	2.32	2.88	1.65	2.39	2.86	1.26	4.61	3.68	65.36	4.39
NSE		0.51	−1.01	0.91	−0.51	−0.49	−4.42	−4.58	−1.74	−6.44
RMSE (mm/d)		0.80	1.63	0.34	1.41	1.41	2.68	2.72	41.50	2.22
AIC		−681.4	1537.6	−3363.02	1435.9	1474.8	2902.02	3285.2	90.32	19.42
BIC		−674.04	1544.94	−3355.7	1443.3	1482.14	2909.4	3292.6	92.8	21.91
Willmott index		0.651	0.318	0.865	0.499	0.37	0.18	0.034	0.577	0.4514
MAE (mm/d)		0.66	1.30	0.26	0.95	1.20	2.32	1.84	36.34	1.94
MBE (mm/d)		0.56	−0.67	0.06	0.54	−1.06	2.29	1.36	−9.23	1.94
R^2		0.75	0.01	0.94	0.40	0.35	0.94	0.29	0.18	0.42

Note: The THN values are the overall monthly average of ETo, while the BG values are the monthly daily average ETo values; and others empirical methods have daily ETo values.

The AIC values result also confirmed that PT and HS are the lowest values, with −3633.02 and −681.4, respectively, compared with the other ETo empirical estimation method. The AIC and BIC values showed the lowest values, meaning that they are the best models compared with other models [59–61]. Moreover, the BIC value results for PT and HS showed the lowest values, with −3355.7 and −674.04, and this implies that the PT was the best model and the HS was the second best compared with other models against the FAO–PM ETo estimation method. The Willmott Index result also showed that the PT method was the highest, with a value of 0.865, and the second highest was HS, with the value of 0.651, when compared with other ETo empirical estimation methods (Table 2). The highest value of Willmott Index means that the model has the best performance against the standard model [16,32,37,62].

The RMSE values result (Table 2) showed that the PT and HS were the lowest values, with 0.34 mm per day and 0.8 mm per day errors, respectively; the THN also showed that with 41.5 mm per month errors. The JH and RIT illustrated the highest RMSE, with 2.72 mm per day and 2.68 mm per day errors (most likely greater than the daily average PM ETo value). The MAE values of PT, HS, and MKK showed that less than 1 mm per day errors with 0.26, 0.66, and 0.95 mm per day, respectively. Meanwhile, the THN also showed that 36.34 mm per month MAE value. Moreover, the MBE values of PT, MKK, and HS showed values closet to zero value, with 0.06, 0.54, and 0.56 mm per day errors, respectively, against the PM ETo method. While RIT showed the poorest performance of MBE values against the PM ETo method with 2.29 mm per day overestimate error.

The coefficient determination of the ETO estimation methods against the PM ETO estimation method was evaluated. The result (Table 2) showed that the PT, RIT, and HS values highly correlated with the PM ETo with 0.94, 0.94, and 0.75 R^2 values. On the other hand, the BR and THN are the lowest correlation with PM ETo values, with 0.01 (there is no correlation) and 0.18, respectively.

In general, the performance result showed that the PT is the best method compared with other methods against the PM ETo method. The second better ETo estimation method is the HS. This showed that the radiation-based method (PT) is better than the temperature-based methods in the study area. Among temperature-based methods, the HS showed the best performance compared to other methods. The PT confirmed the highest performance: NSE = 0.91, RMSE = 0.34 mm per day error, MAE = 0.26 mm per day error, MBE = 0.06 mm per day error, and R^2 = 0.94; followed by HS NSE = 0.51, RMSE = 0.80 mm per day error, MAE = 0.66 mm per day error, MBE = 0.56 mm per day error, and R^2 = 0.75 (Table 2).

In general, the performance assessment statistical metrics result showed that the PT and HS configured equivalence; TUR, THN, and BR showed underestimations (Figure 2); and RT, BG, JH, and MKK configured an overestimation of ETo against the PM ETo estimation method (Figure 2).

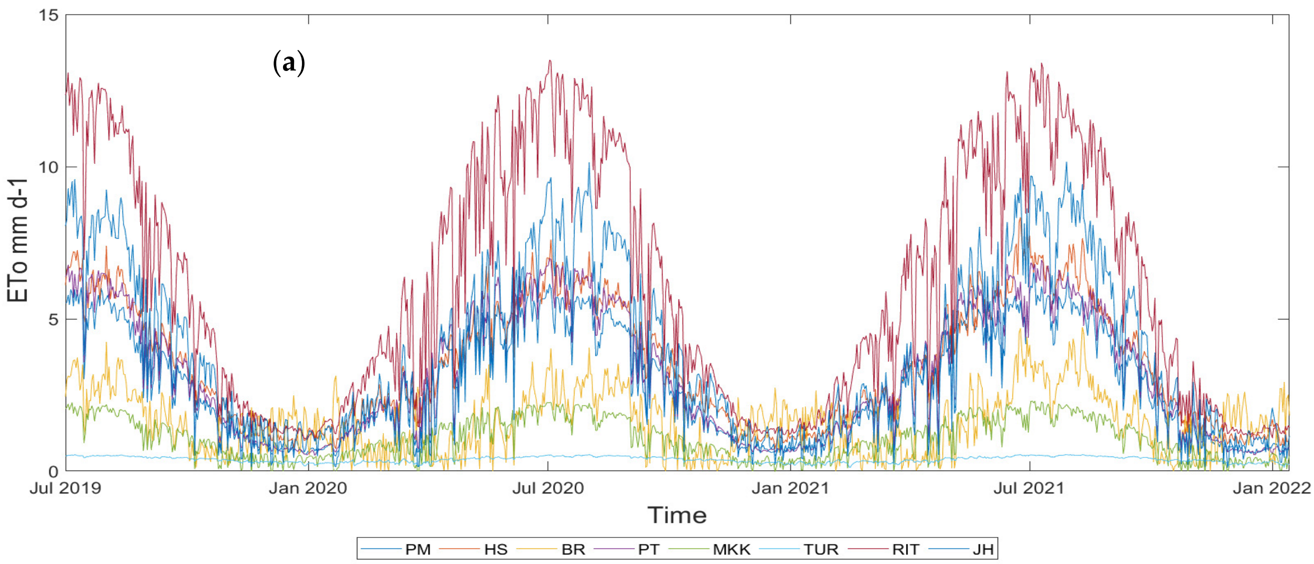

Figure 2. *Cont.*

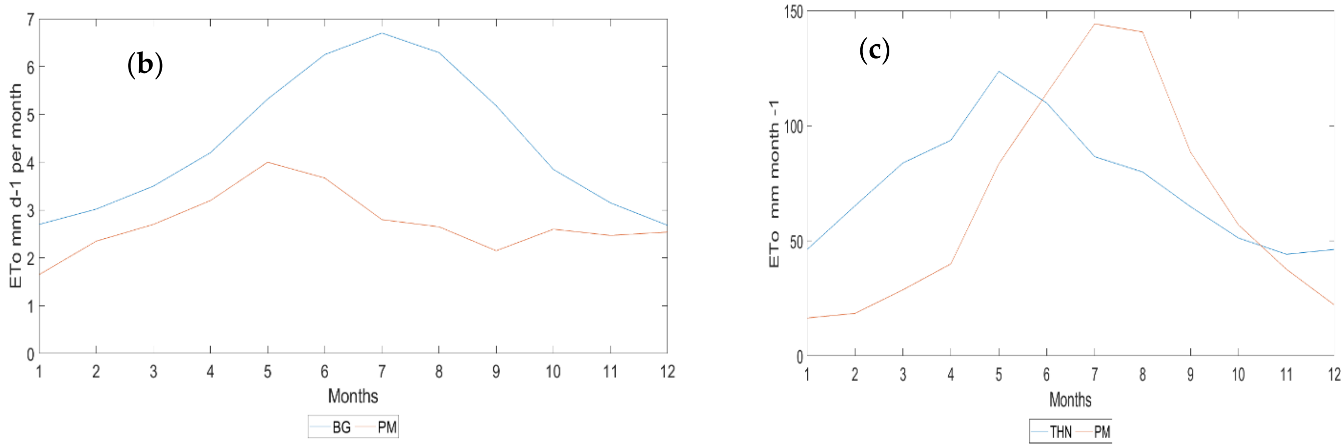

Figure 2. Comparison of PM ETo time-series data to other ETo estimation methods: (**a**) daily ETo in mm for PM, PT, BR, HS, JH, MKK, RIT, and TUR from 1 July 2019 to 14 January 2022; (**b**) average daily ETO per month for PM and BG from 1 July 2019 to 14 January 2022; (**c**) monthly ETo in mm for PM and THN from 1 July 2019 to 14 January 2022. N.B.: BG and THN are calculated based on monthly timescale, and the others were daily scale.

The R^2 is highly supportive the correlation between the observed and estimated model. Table 2 showed that the correlation between the FAO–PM ETo estimation method and other temperature- and radiation-based ETo estimation methods. The result showed that the PT and RIT showed the highest R^2 values (both 0.94) compared with other methods (Table 2). Both RIT and PT are radiation-based models, and net radiation (R_n) was the main input for them. The HS also has the second highest R^2 value (0.75) compared with other ETo estimation methods (the first highest from temperature based ETo estimation methods). Additionally, BR, THN, and JH are the lowest R^2 values 0.01, 0.18, and 0.29, respectively (Table 2). Specifically, BR showed that there is no significant correlation to the PM ETo estimation method. TUR, MKK, and BG estimation methods showed a moderate correlation to the PM ETo estimation method, with R^2 values 0.35, 0.40, and 0.42, respectively (Table 2).

4. Discussion

A. Hargreaves and Samani (1985)

The Hargreaves and Samani (1985) (which we denote as HS in this study) is the second better performance compared to other ETo estimation methods. This method showed good performance against the FAO–PM ETo estimation method [34] in a humid subtropic climate on monthly evapotranspiration. The result showed that the Hargreaves and Samani (1985) method R^2 value was 0.889 and the highest compared to Thornthwaite (1957), Turc (1962), and Priestley–Taylor (1972) against the standard FAO–PM ETo estimation method. It also showed relatively similar values to the PM ETo values in Sichuan Basin and Tibetan Plateau in China compared with the Makkink, Abtew, Priestley–Taylor, Thornthwaite, Hamon, Linacre (Lin), and Blaney–Criddle methods against the standard PM method [33] during a warm, temperate monsoonal summer, on the seasonal and yearly scale. In Southern Italy, namely in Campania, Basilicata, Apulia, Calabria, and Sicily, the Hargreaves and Samani (1985) showed a better performance in regard to MAE and Bias (0.52 and −0.03 mm per day, respectively) values compared with the Makkink ETo method (0.55 and −0.11 mm per day, respectively) values against the PM method with the values [63] in a hot summer Mediterranean climate. The Hargreaves–Samani method showed higher than that obtained by the modified Thornthwaite method against the lysimeter measurement in Shiraz, Iran [64]. It showed also the second performance compared with other temperature-based methods next to the PM temperature-based method, with the values of R^2 = 0.68, NSE = 0.68, MAE = 0. 92 mm d^{-1}, and RMSE = 0.74 mm d^{-1}) [65] in a tropical savanna climate.

B. Baier–Robertson (1965)

The Baier–Robertson (1965) result showed less than the average of the PM method (1.65 mm per day) and underestimated the ETo daily values (Table 2). It showed that the RMSE, MAE, MBE, and R^2 values are 1.63, 0.30, −0.67, 0.01 mm d^{-1}, respectively. This showed that there is also an insignificant correlation between the PM method and the Baier–Robertson (1965). In the central hilly region of Ivan Sedol, eastern hilly region of Sokolac, central of Bugojno, and central of Sarajevo, the Baier–Robertson (1965) showed that underestimation of ETo into daily scale compared with both radiation- and temperature-based empirical methods [66] in a temperate humid climate, humid boreal, and Mediterranean climate.

C. Priestley–Taylor (1972)

This study showed that the Priestley–Taylor method showed that the highest performance compared to all other ETO estimation methods, using different statistical metrics evaluation (Table 2). The Priestley–Taylor showed the highest correlation with the PM ETo method in daily ETo scale compared with the Makkink, de Bruin–Keijman, modified Penman, Hargreaves–Samani, Jensen–Haise, and Blaney–Criddle methods in Northern Greece (Antonopoulos and Antonopoulos 2018) in the Mediterranean climate. In Southwest Sicily olive groves, the Priestley–Taylor showed a better performance next to the PM method against the scintillometer filed measurements in daily ETo [45] in a hot summer Mediterranean climate.

D. Makkink (1957)

The NSE value of the Makkink (1957) showed that negative value (−0.51). It showed that the Makkink (1957) should not be recommended to estimate ETo in the study area because it has a negative NSE value. This method also showed a negative value (−0.2) for NSE and was not considered from the proposed estimation method across different regions of China [56] in monthly and annually ETo. This method overestimated compared to the standard PM method: 2.86 and 2.32 mm daily average ETo (Table 2). In Northern Greece Makkink (3.179 mm per day) also showed a higher daily average value than the PM method (2.824 mm per day) [51]. It also showed negative values (−1.857) for NSE in Southwestern China [33]. The MBE result of the MAK was also lower than the HS in the Southern Italy [63].

E. Turc (1961)

Turc (1961) showed an underestimation and lesser daily average values compared with the standardized PM method and a negative value of NSE (Table 2). For the grassland central part of Serbia, this method also showed underestimated daily ETo values and was lower than the PM method [39] in daily ETo under the warm, temperate humid climate. The index of agreement of the TUR was also the lowest in different regions in the northern and southern areas of Mostar in Bosnia and Herzegovina [66].

F. Thornthwaite (1957)

The Thornthwaite (1957) monthly analysis result showed that the NSE = −1.74 and R^2 = 0.18 (Table 2), and it underestimated compared to the PM method. It showed that there was a poor correlation between the PM method and the Thornthwaite method (1967). This method is also not recommended based on its result of the NSE. In three regions of Southewestern China, it also showed NSE negative values against the PM method in seasonal ETo [33].

G. Blaney and Criddle (1950)

The Blaney and Criddle (1950) overestimated and had the following values: NSE= −6.44, and RMSE = 2.22 mm per day, and R^2 = 0.42 (Table 2). It also showed higher average values than the PM method. It showed a negative NSE value in three regions of Southwestern China [33]. It showed higher average values than the PM method in Northern Greece [51].

The performance of the BG also categorized as bad in Minas Gerais, Brazil against to the PM method [32] in daily ETo under the tropical climate.

H. Ritchie (1972)

The Ritchie (1972) result was highly correlated with the PM method, including the PT, because both used net solar radiation as the main input for their estimation method. Despite the R^2, it showed a lower performance, with a negative NSE value (−4.42), and it is not recommended for ETo estimated in the studied area because of its NSE negative value. It showed overestimated, and the mean daily ETo values were two times those of the PM method's ETo value, 4.61 mm per day. In Northeastern India, it was evaluated in three sites against the PM method; it had higher average values compared with the PM method [16]. Additionally, it showed highest values of R^2 (0.98) in the Jowai site compared to other ETo estimation methods [16] in daily ETo under humid summers, severe monsoons, and mild winter climate. Additionally, it showed highest values of R^2 (0.98) in the Jowai site compared to other ETo estimation methods [16]. It showed also the second highest R^2 (0.98) value compared with the other 22 ETo estimation methods against the PM method in Iran [62] in daily ETo, under a subtropical climate.

I. Jensen and Haise (1963)

The Jensen and Haise (1963) method of this study showed a lower performance on the statistical metrics assessment (Table 2). It showed overestimated and higher mean values (3.68 mm per day) than the PM method. Moreover, it also showed a negative NSE value (−4.58) and is, thus, not suitable for the studied site ETo estimation method (Table 2). In Northern Greece, a similar performance was observed when comparing the temperature- and radiation-based methods [51]. It is considered to be the most unsuitable method when compared with other temperature- and radiation-based methods against the PM method in different parts of Northeastern India [16]. It also showed the second highest value RMSE (1.67 mm per day) next to the original Penman method (2.52) compared with other methods in Uberaba-MG, Brazil [32].

5. Conclusions

The aim of this study was to identify the best ETo estimation methods for the future works that will assess the impact of the PV on evapotranspiration and decide which meteorological instrumentation should be installed under PVs. The study assessed the performance of different ETo estimation methods against the PM method in an experimental PV site in Piazza Armerina, Sicily, Italy. Different statistical performance assessment metrics were considered for the evaluation of both temperature- and radiation-based methods against the PM method. The study assessed the performance of 10 methods based on various statistical metrics, i.e., Nash–Sutcliffe efficiency (NSE), Coefficient of Determination (R^2), Mean Absolute Error (MAE), Mean Basis Error (MBE), and Root Mean Square Error (RMSE). The results showed that the Priestley–Taylor method (1972) (radiation-based) was the best method, with an NSE = 0.91, RMSE = 0.34 mm/d, MAE = 0.26 mm/d, MBE = 0.06 mm/d, and R^2 = 0.94. The AIC, BIC, and Willmott Index results also confirmed that the PT and the HS were the first and second best performing models against the PM method, respectively. The second method which showed the best performance was that of Hargreaves and Samani (1985) (temperature-based), with an NSE = 0.51, MSE = 0.80 mm/d, MAE = 0.66 mm/d, MBE = 0.56 mm/d, and R^2 = 0.75. Baier–Robertson (1965), Turc (1961), and Thornthwaite (1957) showed underestimations, while the Makkink (1957), Blaney–Criddle (1950), Ritiche (1972), and Jensen–Haise (1963) showed overestimation of ETo against the PM ETo estimation method. Hence, the Priestley–Taylor (1972) and Hargreaves–Samani (1985) methods are the most recommended methods if not all variables required for the PM method are available.

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