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Performance of potential evapotranspiration models in Peninsular Malaysia

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ABSTRACT

Potential evapotranspiration (PET) is an important parameter for the operation of irrigation projects and water resources management. The globally recognized PET estimation model, the FAO-56 Penman–Monteith (FAO-56 PM) model, had been criticized for its requirement of many detailed meteorological variables, but nevertheless has been accepted as the baseline model in many worldwide studies. The performances of different PET models can be found to be excellent for a specific location but may not be representative in other regions. The aim of this study is to select the most suitable PET model to estimate PET in Malaysia. Three radiation-based models and four temperature-based models were compared with the FAO-56 PM model at seven selected meteorological stations in Peninsular Malaysia. The mean bias error, relative error (Re) and normalized root-mean-square error (NRMSE) and coefficient of determination (R^2) were used to evaluate the performances of the PET models. The Re values of Turc models were below 0.2 at all stations, while Priestly–Taylor, Thornthwaite, Thornthwaite-corrected and Blaney–Criddle models were above 0.2. The Makkink and Hargreaves–Samani models were below 0.2 at most of the stations. Thus, the Turc model was recommended as the best model to estimate PET in Peninsular Malaysia.

Key words: Penman–Monteith, potential evapotranspiration, radiation-based model, temperature-based model, Turc model

HIGHLIGHTS

- This study applied various empirical potential evapotranspiration (PET) models to estimate the PET.
- Radiation-based models and temperature-based models were compared with the FAO Penman–Monteith model.
- MBE, Re, NRMSE and R^2 were used to evaluate the performances of PET models.
- The Turc model was found to give superior performance.
- The outcomes can be used as a reference for water resources-related project design.

INTRODUCTION

Potential evapotranspiration (PET) is an index used to represent the environmental demand for evapotranspiration. The changes in PET can affect the crop water requirement, water allocation and food production. Hence, knowledge of PET estimation has been extensively used in water resources management, water balance estimation, agricultural water productivity studies, irrigation studies and agricultural water demand analysis (Tran & Honti 2017; Farzanpour *et al.* 2019; Pan *et al.* 2019). Generally, PET can be measured either directly or indirectly. There are various equipment and methods which are used to measure PET directly, such as lysimeters, Bowen ratio-energy balance system, eddy covariance technique and scintillometers. Considering the high cost and demand for experimental equipment maintenance, indirect methods, such as empirical models or simply deriving by multiplying a coefficient from standard data on pan evaporation, were instead proposed (Paparrizos *et al.* 2017; Landeras *et al.* 2018).

Over the years, a vast number of empirical models have been developed for estimating PET. Empirical models are accordingly sorted into various types, namely temperature-based, radiation-based and combination-based models (Shiri *et al.* 2019; Feng & Tian 2020). Allen *et al.* (1998) suggested that the FAO-56 Penman–Monteith (FAO-56 PM) model can be used as a reference model in estimating PET. Despite the wide applicability and high acceptance of the FAO-56 PM model, a large number of detailed meteorological variables are required for estimating PET. The long and complete series of meteorological variables, such as solar radiation, relative humidity, air temperature and wind speed, are often found to be insufficient, wanting or sparse, especially in developing countries (Lang *et al.* 2017; Shiri 2017). Several researchers have developed models that require less intensive data to estimate PET by using other available meteorological variables.

As an alternative to the FAO-56 PM model, the temperature-based and radiation-based models are particularly useful, as they depend mainly on air temperature and solar radiation as the input data (Shiri *et al.* 2019). The earliest temperature-based model was the Thornthwaite model, which assumed an exponential connection between mean monthly consumption and mean monthly temperature (Thornthwaite 1948). Blaney & Criddle (1950) developed the temperature-based Blaney–Criddle model to estimate PET, which requires only daylight hours and mean monthly temperature as data input. Hargreaves & Samani (1985) developed the Hargreaves–Samani model for estimating PET, which requires only the highest and the lowest temperatures along with extraterrestrial radiation as data input. Makkink (1957) established the Makkink model with only solar radiation as input to estimate PET over a 10-day period under a cool climatic condition in the Netherlands. Turc (1961) presented the Turc model for PET of a 10-day period under general weather conditions in Western Europe. The Turc model employed mean temperature, solar radiation and relative humidity to estimate PET. With only net radiation as input, Priestly & Taylor (1972) proposed the radiation-based Priestly–Taylor model to estimate PET for wet surface area.

Many studies have been carried out to compare the performances of different empirical PET estimation models. To overcome the issues of missing data and low availability of input data, Maeda *et al.* (2011) evaluated the suitability of three temperature-based models, namely the Thornthwaite, Blaney–Criddle and Hargreaves–Samani models at Taita Hills, Kenya. The results revealed that the Hargreaves model showed superior performance. Meanwhile, Lang *et al.* (2017) presented a comparative study of temperature-based, radiation-based PET models and FAO-56 PM model using long-term data from 90 meteorological stations in Southwest China. They found that the radiation-based models performed better than the temperature-based models. The radiation-based Makkink model and Hargreaves–Samani model gave the best performances among the selected models. They concluded that radiation-based models were suitable for low latitude, warm and moist climate. Quej *et al.* (2019) applied seven temperature-based models to estimate PET and compare their performances with the FAO-56 PM model in Mexico. The FAO-56 PM exhibited the best performance followed by the Hargreaves–Samani and Camargo models. They suggested the use of temperature-based models in areas with missing data. Xie & Wang (2020) compared 10 empirical PET estimation models over 10 River Basins in China. The results revealed that the Hamon version1 outperformed the other models in Pearl River Basin and the Hamon version2 was selected as the best model in Huaihe, Yangtze and Yellow River Basins. For the remaining basins, the FAO-56 PM model performed the best.

Studies on determining suitable PET models were also conducted in Malaysia. Tukimat *et al.* (2012) concluded that radiation-based models (Priestley–Taylor model, Makkink model and Turc model) showed superior performance over temperature-based models (Thornthwaite model and Blaney–Criddle model) in estimating PET. The Turc model was suggested to estimate PET due to its simplicity and lower requirements for input parameters. The radiation-based models performed similarly to the Penman–Monteith model, while the estimation of evapotranspiration by temperature-based models had the minimum error throughout the study. Muniandy *et al.* (2016) assessed the best PET model out of the 26 PET-selected models in order to determine the crop coefficients of bitter gourd and chili in Kluang, Malaysia. In terms of statistical performance, they concluded that the Penman, McGuinness & Borden, Szasz and the FAO-56 PM models performed better in PET estimation. Taking it a little further, Muhammad *et al.* (2019) employed a compromise programming and group decision-making approach to rank 31 empirical models for Peninsular Malaysia. The statistical results revealed that the FAO-56 PM model was the most suitable method in PET estimation, followed by radiation-based Priestley and Taylor and the mass transfer-based Dalton and Meyer methods. However, under limited data availability, it was suggested that the Priestley and Taylor can be used to replace the FAO-56 PM model.

In general, as observed from the studies mentioned above, it is difficult to identify the most suitable PET model due to the presence of different topographic and climatic conditions in different areas. It should be noted that each empirical model varies significantly in terms of performance due to different input data requirements and each model was developed specifically for different climatic regions. The major challenge arises in determining the best PET model because, for obvious reasons, a specific model may not be representative for all regions. To ensure a reliable result, it is of great importance to assess and evaluate different PET estimation models at a particular study region to obtain the most suitable PET model. Following this cue in this study, various types of empirical PET models will be applied in Peninsular Malaysia to estimate the PET on daily, monthly and annual time scales. Following that, statistical analysis was performed to evaluate the performance of each PET model. The outcomes of this study are expected to provide a better understanding regarding the selection of suitable estimation models and used as a reference for water resources-related project design and irrigation management.

STUDY AREA AND DATA DESCRIPTION

Peninsular Malaysia (latitude 1–7°N and longitude 100–119°E) was chosen as the study area for this study. Peninsular Malaysia is located near to the equator, and the total area is about 334,671 km^2. The climate of Peninsular Malaysia follows the tropical climate, which is categorized as humid and high temperature throughout the year (Lian *et al.* 2019). The relative humidity is more than 68%, and the daily air temperature ranged from 23 to 34 °C (Fisher *et al.* 2017). This study area has a daylight range of 3.7–8.7 h per day, with high precipitation throughout the year. The monsoon seasons of Malaysia comprise the Northeast monsoon (November–February), Inter-monsoon2 (March–April), Southwest monsoon (May–August) and the Inter-monsoon1 (September–October). During the Northeast monsoon period, the largest amount of rainfall will occur over the east coast region (Ng *et al.* 2015, 2016, 2019). The highest amount of rainfall recorded reached a value of 965–1,394 mm during this monsoon period (Pour *et al.* 2020). It is thus not surprising that states in the east coastal region are susceptible to flooding (Ng *et al.* 2020). The temperature of sea surface is higher, which causes the wind speed to be lower due to higher sea surface heat flux during the Inter-monsoon 2. The climate of Southwest monsoon is warmer and drier due to lower rainfall amounts.

The geographical locations of the selected meteorological stations are illustrated in Figure 1. Table 1 shows the general information for all the meteorological stations used in the study. Six types of daily meteorological data, namely the relative humidity, solar duration, wind speed, minimum air temperature, mean air temperature and maximum air temperature, were collected from Malaysia Meteorological Department (MMD). All the calculated PET values were based on the daily meteorological data.

METHODOLOGY

Data checking and quality control

All the input meteorological data were checked for completeness and quality. A threshold of 10% was adopted for data quality control. The elimination of observed data with more than 10% missing values was implemented to prevent any possible source of error that might result in biased estimations of PET. In the present study, a subjective method was used to evaluate the data quality. For instance, the input variables were checked carried out to ensure that the data consisted of positive values only, the maximum temperature was not lower than the minimum temperature, the maximum temperature was not less than 21 °C (lowest minimum temperature in Peninsular Malaysia), the maximum temperature was not higher than 36 °C and the

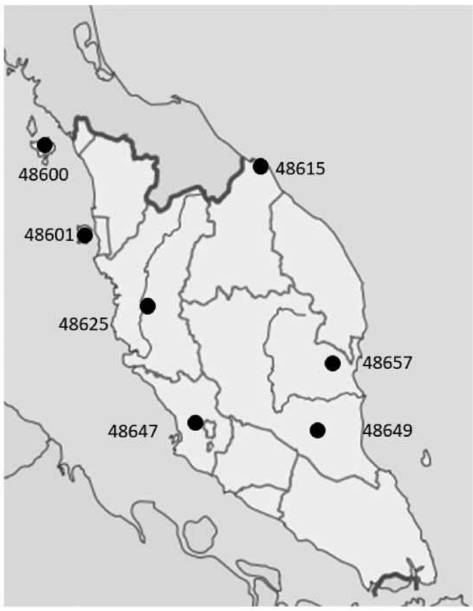

Figure 1 | Geographical location of all the meteorological stations in Peninsular Malaysia used in the study.

Table 1 | List of meteorological stations used in this study

Station code	Station name	Record period	Duration	Latitude (N)	Longitude (E)
48601	Bayan Lepas	2009–2018	10	05° 18′N	100° 16′E
48625	Ipoh	2009–2018	10	04° 34′N	101° 06′E
48615	Kota Bahru	2009–2018	10	06° 10′N	102° 18′E
48657	Kuantan	2009–2018	10	03° 46′N	103° 13′E
48649	Muadzam Shah	2009–2018	10	03° 03′N	103° 05′E
48600	Pulau Langkawi	2009–2018	10	06° 20′N	99° 44′E
48647	Subang	2009–2018	10	03° 08′N	101° 33′E

relative humidity was not higher than 100%. Besides, several methods were adopted to fill up the detected missing data, as shown in the following subsection.

Estimation of missing vapor pressure data

The missing vapor pressure data can be obtained from the minimum temperature. Guidelines provided by the FAO-56 PM stated that the dew point temperature can be used interchangeably with the minimum air temperature for calculating the actual vapor pressure (Upreti & Ojha 2017). However, this guideline is only applicable for the estimation of missing relative humidity data. The equation to estimate missing vapor pressure is expressed as follows (Allen *et al.* 1998):

$$e_a(T_{min}) = 0.6108 \times \exp\left(\frac{17.27 \times T_{min}}{T_{min} + 237.3}\right) \quad (1)$$

where e_a (T_{min}) is the vapor pressure depending on the minimum air temperature (kPa); T_{min} is the minimum air temperature (°C).

Estimation of missing solar radiation data

Solar radiation is one of the climatic parameters that are rarely measured at most of the meteorological stations. The missing solar radiation data were estimated by using the Angstrom method, which is expressed as follows (Allen *et al.* 1998):

$$R_s = \left(a + b\frac{n}{N}\right)R_a \quad (2)$$

where R_a is the extraterrestrial radiation (MJ m^{-2} day^{-1}); N is the average of daylight hours in a day (h); n is the actual sunshine hours in a day (h); R_s is the solar radiation (MJ m^{-2} day^{-1}); a and b are the regression coefficients with values of 0.25 and 0.5, respectively, which were recommended by the FAO-56 PM (Allen *et al.* 1998; Yang *et al.* 2020).

PET models

Seven PET models comprising three radiation-based models (Makkink, Priestly–Taylor and Turc models) and four temperature-based models (Thornthwaite, Thornthwaite-corrected, Blaney–Criddle and Hargreaves–Samani models) were chosen. They were used to estimate PET, and their performances were compared against the reference method, FAO-56 PM model.

FAO Penman–Monteith model

For continuity, the FAO-56 PM model, which is a combination-based model that combines the vapor aerodynamic and fixed bulked surface resistance, is included here. This model requires more input of meteorological variables than the temperature-based and radiation-based models. The required data were solar radiation, air temperature, wind speed and relative humidity. The equation is expressed as follows (Allen *et al.* 1998):

$$PET = \frac{0.480\Delta(R_n - G) + \gamma\frac{900}{T_{mean} + 273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34\,u_2)} \quad (3)$$

where R_n is the net radiation of the crop surface (MJ m^{-2} day^{-1}); Δ is the slope vapor curve (kPa °C^{-1}); T_{mean} is the daily mean air temperature at 2 m height (°C); u_2 is the wind speed at 2 m height (m s^{-1}); G is the soil heat flux density (MJ m^{-2} day^{-1}); e_a is the actual vapor pressure (kPa); e_s is the saturation vapor (kPa) and γ is the psychrometric constant (kPa °C^{-1}).

Makkink model

The Makkink model is a simple radiation-based model for estimating PET by using temperature and radiation data. The equation is expressed as follows (Makkink 1957):

$$PET = 0.61 \frac{\Delta}{\Delta + \gamma} \frac{R_s}{\lambda} - 0.12 \tag{4}$$

where R_s is the solar radiation of the crop surface (MJ m^{-2} day^{-1}); γ is the psychrometric constant (kPa °C^{-1}); Δ is the slope vapor curve (kPa °C^{-1}) and λ is the latent heat of vapor (MJ kg^{-1}).

Priestly–Taylor model

The Priestly–Taylor model is a shortened form of the original Penman (1948) equation. Priestly & Taylor (1972) showed that when the large land area becomes more saturated, the net radiation is the main factor which affects the rate of evapotranspiration. The equation is expressed as follows:

$$PET = 1.26 \frac{\Delta}{\Delta + \gamma} (R_n - G) \frac{1}{\lambda} \tag{5}$$

where R_n is the net radiation of the crop surface (MJ m^{-2} day^{-1}); Δ is the slope vapor curve (kPa °C^{-1}); λ is the latent heat of vapor (MJ kg^{-1}); G is the soil heat flux density (MJ m^{-2} day^{-1}) and γ is the psychrometric constant (kPa °C^{-1}).

Turc model

The Turc model is one of the radiation-based PET models to estimate PET by using mean temperature, solar radiation and relative humidity. The equation is expressed as follows (Turc 1961):

For $RH < 50\%$,

$$PET = 0.013 \left(\frac{T_{mean}}{T_{mean} + 15} \right) (R_s \times 23.8846 + 50) \left(1 + \frac{50 - RH}{70} \right) \tag{6}$$

For $RH > 50\%$,

$$PET = \left(\frac{T_{mean}}{T_{mean} + 15} \right) (R_s \times 23.8846 + 50) \tag{7}$$

where T_{mean} is the daily mean temperature (°C); RH is the relative air humidity (%) and R_s is the solar radiation of the crop surface (MJ m^{-2} day^{-1}).

Thornthwaite model and Thornthwaite-corrected model

The most widely used mean air temperature model is the Thornthwaite model, as shown in Equation (8). The Thornthwaite and Mather (1955) model, as shown in Equation (9), was modified from the original Thornthwaite (1948) model. The equations can be expressed as follows:

$$\mathrm{PET} = 16\left(\frac{10T_{\mathrm{m}}}{I}\right)^{a} \quad (8)$$

$$\mathrm{PET} = 16\left(\frac{L}{12}\right)\left(\frac{N}{30}\right)\left(\frac{10T_{\mathrm{m}}}{I}\right)^{a} \quad (9)$$

$$I = \sum_{i=1}^{12}\left(\frac{T_{\mathrm{m}}}{5}\right)^{1.514} \quad (10)$$

$$a = 6.75 \times 10^{-7}I^3 - 7.71 \times 10^{-5}I^2 + 1.7912 \times 10^{-2}I + 0.49239 \quad (11)$$

where T_{m} is mean air temperature (°C), N is the number of days in the month and L is the average number of daylight hour per day for each month.

Blaney–Criddle model

The Blaney–Criddle model is one of the simplest temperature models used to estimate PET. The model only considers temperature change in a particular region. The equation is expressed as follows (Blaney & Criddle 1950):

$$\mathrm{PET} = p(0.46T_{\mathrm{m}} + 8.128) \quad (12)$$

where p is the mean daily percentage of annual daytime hours due to the latitude of region, and T_{m} is mean air temperature (°C).

Hargreaves–Samani model

The Hargreaves–Samani model requires the only daily maximum and minimum air temperatures that are usually available at most meteorological stations as input. The equation is expressed as follows (Hargreaves & Samani 1985):

$$\mathrm{PET} = 0.0023(T_{\mathrm{m}} + 17.8)\sqrt{(T_{\max} - T_{\min})}R_{\mathrm{a}} \quad (13)$$

where T_{m} is the daily mean temperature (°C), $T_{\min}$ is the daily minimum temperature (°C), $T_{\max}$ is the daily maximum temperature (°C) and R_{a} is the extraterrestrial radiation (MJ m^{-2} day^{-1}).

Evaluation of PET model performance

Four statistical measures, namely the mean bias error (MBE), relative Error (Re), normalized root-mean-square error (NRMSE) and coefficient of determination (R^2), were used to evaluate the accuracy and capability of different PET models. The performances of each model were compared with the FAO-56 PM model, which serves as a reference model for PET estimation.

Normalized root-mean-square error

The NRMSE value is expressed as an absolute value between predicted values and observed values. The predicted values agree perfectly with observed values when NRMSE is equal to zero. The equation of NRMSE is expressed as follows:

$$\mathrm{NRMSE} = \sqrt{\frac{\sum_{i=1}^{N}\frac{(O_i - P_i)^2}{N}}{\bar{O}}} \quad (14)$$

where P_i is the prediction data; O_i is the observation data; i is the indicated data point; N is the total number of data points and $\bar{O}$ is the average observation data.

Coefficient of determination

The R^2 is used to indicate the linear relationship between the PET models and the reference model. R^2 is a measurement of the ability of a model to predict an outcome on the basis of a linear regression approach. In general, a high R^2 value indicated that the prediction model is a good fit for the observation model, and vice versa. The equation is expressed as follows:

$$R^2 = \frac{\sum_{i=1}^{N} (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\left[\sum_{i=1}^{N} (O_i - \bar{O})^2\right]\left[\sum_{i=1}^{N} (P_i - \bar{P})^2\right]}} \tag{15}$$

where P_i is the prediction data; O_i is the observation data; N is the total number of data points; i is the indicated data point; $\bar{O}$ is the mean of observation data and $\bar{P}$ is the mean of prediction data.

Mean bias error

The MBE is used to measure the average magnitude of the error of observed data and predicted data. A low absolute MBE value indicated the higher accuracy of the prediction models. The equation is expressed as follows:

$$\text{MBE} = \sum_{i=1}^{N} \frac{(P_i - O_i)}{N} \tag{16}$$

where P_i is the prediction data; O_i is the observation data; N is the total number of data points and i is the indicated data point.

Relative error

The relative error (Re) is one of the statistical measures to measure the variability of measurement. The predicted values are close to observed values when Re is equal to zero. The equation is expressed as follows:

$$\text{RE} = \frac{\sum_{i=0}^{N} (P_i - O_i)}{\sum_{i=0}^{N} (O_i)} \tag{17}$$

where P_i is the prediction data; O_i is the observation data; N is the total number of data points and i is the indicated data point.

RESULTS

Statistical characteristics of PET values

The maximum, minimum and mean PET values estimated by the FAO-56 PM model over daily, monthly and annual time scales, at all the various meteorological stations, are shown in Table 2. For the daily mean PET estimation, there were five out of seven stations that had exceeded 4 mm/day except for the Kuantan station and the Muadzam Shah station. Similarly,

Table 2 | Daily, monthly and yearly PET values estimated by the FAO-56 PM at seven stations

	Daily PET (mm/day)			Monthly PET (mm/month)			Annual PET (mm/year)		
Station	**Max.**	**Min.**	**Mean**	**Max.**	**Min.**	**Mean**	**Max.**	**Min.**	**Mean**
Bayan Lepas	7.88	0.88	4.29	194.22	102.15	130.70	1,748.2	1,485.3	1,568.4
Ipoh	6.82	1.40	4.11	166.66	94.78	125.03	1,640.4	1,427.2	1,500.3
Kota Bahru	6.71	0.59	4.12	172.19	43.48	125.31	1,639.9	1,407.5	1,503.7
Kuantan	5.91	0.94	3.88	148.48	88.81	118.07	1,485.3	1,346.6	1,416.9
Muadzam Shah	5.45	0.91	3.65	136.55	86.55	111.07	1,362.7	1,297.5	1,332.9
Pulau Langkawi	8.35	1.00	4.32	191.29	99.29	131.57	1,687.3	1,499.8	1,578.8
Subang	8.06	0.97	4.31	166.98	97.74	131.02	1,688.3	1,464.9	1,572.3

the mean monthly PET values exceeded 120 mm/month for all stations except for the Kuantan station and the Muadzam Shah station. For annual mean PET values, the Kuantan and Muadzam Shah stations were below 1,400 mm/year, while the other meteorological stations had exceeded 1,500 mm/year. Figure 2 depicts the annual PET values estimated by using the temperature-based and radiation-based PET models for the seven meteorological stations. The FAO- 56 PM model was

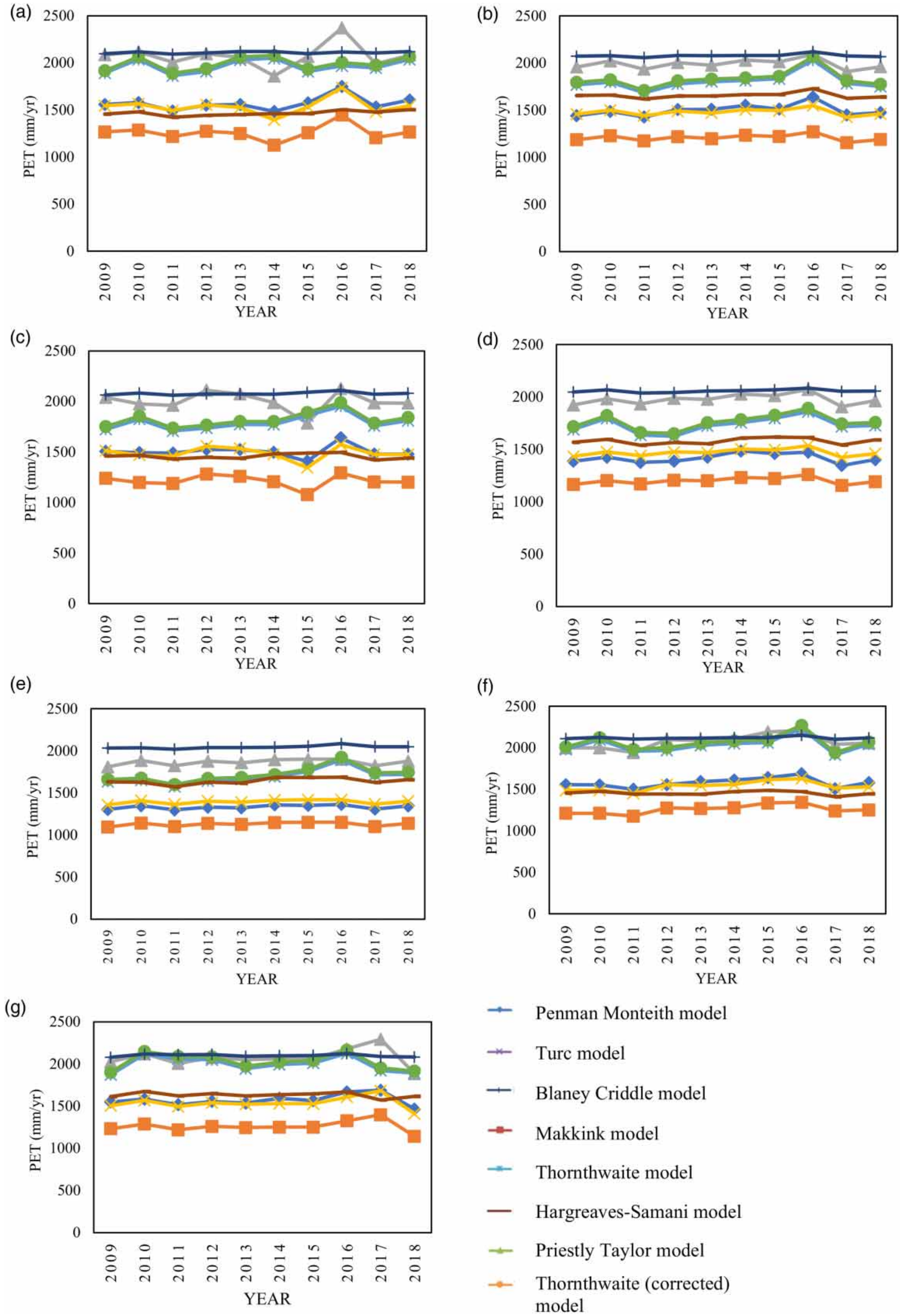

Figure 2 | Annual PET values computed by PET models at seven meteorological stations: (a) Bayan Lepas station; (b) Ipoh station; (c) Kota Bahru station; (d) Kuantan station; (e) Muadzam station; (f) Pulau Langkawi station and (g) Subang station.

used as a reference for the PET estimation. The overestimation of PET occurs when the trend of the PET models was above the trend of the FAO-56 PM model, and vice versa. As depicted in Figure 2, the values obtained by Priestly–Taylor, Blaney–Criddle, Thornthwaite, Thornthwaite corrected and Hargreaves–Samani models were all above the FAO-56 PM model, which indicates the overestimation of PET values. On the other hand, the Makkink model was the only PET model that underestimated the PET values, as the trend produced was below that of the FAO-56 PM model. Hence, the Turc model gave the best performance, as the trend was the closest to the trend of the FAO-56 PM model.

Statistical performances of PET models for daily, monthly and annual series

To understand the relationship between the FAO-56 PM model and the PET models, statistical measures, including Re, MBE, NRMSE and R^2, were applied to the seven PET models at each of the seven meteorological stations. The statistical performances of PET models for daily, monthly and annual series are displayed in Tables 3–5, respectively.

Table 3 | Statistical performances of the radiation-based and temperature-based PET models (daily series)

		Stations						
Statistical measures	**PET models**	**Bayan Lepas**	**Ipoh**	**Kota Bahru**	**Kuantan**	**Muadzam Shah**	**Pulau Langkawi**	**Subang**
Re	PET_{Mak}	0.196	0.195	0.192	0.153	0.153	0.202	0.198
	PET_{PT}	0.322	0.327	0.331	0.397	0.399	0.313	0.32
	PET_{Turc}	0.02	0.014	0.011	0.038	0.046	0.026	0.021
	PET_{HS}	0.066	0.104	0.031	0.115	0.232	0.079	0.038
MBE	PET_{Mak}	−0.844	−0.801	−0.79	−0.592	−0.559	−0.874	−0.851
	PET_{PT}	1.385	1.343	1.365	1.54	1.458	1.353	1.38
	PET_{Turc}	−0.085	−0.059	−0.044	0.148	0.167	−0.114	−0.092
	PET_{HS}	−0.282	0.425	−0.129	0.446	0.845	−0.343	0.164
NRMSE	PET_{Mak}	0.213	0.204	0.208	0.16	0.156	0.227	0.206
	PET_{PT}	0.348	0.34	0.387	0.411	0.413	0.35	0.344
	PET_{Turc}	0.084	0.059	0.085	0.061	0.053	0.104	0.058
	PET_{HS}	0.188	0.163	0.212	0.187	0.263	0.221	0.183

Table 4 | Statistical performance of the radiation-based and temperature-based PET models (monthly series)

		Stations						
Statistical measures	**PET models**	**Bayan Lepas**	**Ipoh**	**Kota Bahru**	**Kuantan**	**Muadzam Shah**	**Pulau Langkawi**	**Subang**
Re	PET_{Mak}	0.196	0.195	0.192	0.153	0.153	0.202	0.198
	PET_{PT}	0.322	0.327	0.331	0.397	0.399	0.313	0.32
	PET_{Turc}	0.02	0.014	0.011	0.038	0.046	0.026	0.021
	PET_{Tho}	0.252	0.203	0.191	0.223	0.271	0.288	0.271
	PET_{Thoc}	0.271	0.221	0.211	0.243	0.291	0.307	0.291
	PET_{BC}	0.345	0.385	0.381	0.452	0.534	0.342	0.336
	PET_{HS}	0.066	0.104	0.031	0.115	0.232	0.079	0.038
MBE	PET_{Mak}	−25.677	−24.369	−24.057	−18.03	−16.999	−26.607	−25.895
	PET_{PT}	42.148	40.876	41.54	46.854	44.359	41.182	41.99
	PET_{Turc}	−2.581	−1.785	−1.345	4.506	5.098	−3.459	−2.802
	PET_{Tho}	32.937	25.37	23.954	26.332	30.127	37.895	35.536
	PET_{Thoc}	35.409	27.69	26.485	28.671	32.283	40.333	38.078
	PET_{BC}	45.084	48.195	47.799	53.425	59.336	45.018	44.027
	PET_{HS}	−8.569	12.945	−3.918	13.579	25.713	−10.43	4.989
NRMSE	PET_{Mak}	0.203	0.199	0.197	0.157	0.154	0.214	0.201
	PET_{PT}	0.33	0.329	0.349	0.398	0.402	0.32	0.325
	PET_{Turc}	0.055	0.04	0.046	0.049	0.048	0.074	0.039
	PET_{Tho}	0.28	0.216	0.236	0.246	0.286	0.308	0.29
	PET_{Thoc}	0.305	0.239	0.261	0.273	0.308	0.335	0.312
	PET_{BC}	0.367	0.396	0.409	0.46	0.54	0.377	0.35
	PET_{HS}	0.116	0.114	0.118	0.131	0.238	0.132	0.094

Table 5 | Statistical performance of the radiation-based and temperature-based PET models (annual series)

		Stations						
Statistical measures	**PET models**	**Bayan Lepas**	**Ipoh**	**Kota Bahru**	**Kuantan**	**Muadzam Shah**	**Pulau Langkawi**	**Subang**
Re	PET_{Mak}	0.196	0.195	0.192	0.153	0.153	0.202	0.198
	PET_{PT}	0.322	0.327	0.331	0.397	0.399	0.313	0.32
	PET_{Turc}	0.02	0.014	0.011	0.038	0.046	0.026	0.021
	PET_{Tho}	0.252	0.203	0.191	0.223	0.271	0.288	0.271
	PET_{Thoc}	0.271	0.221	0.211	0.243	0.291	0.307	0.291
	PET_{BC}	0.345	0.385	0.381	0.452	0.534	0.342	0.336
	PET_{HS}	0.066	0.104	0.031	0.115	0.232	0.079	0.038
MBE	PET_{Mak}	−308.119	−292.46	−288.685	−216.363	−203.988	−319.279	−310.742
	PET_{PT}	505.775	490.515	498.475	562.245	532.303	494.18	503.879
	PET_{Turc}	−30.972	−21.423	−16.137	54.075	61.17	−41.506	−33.62
	PET_{Tho}	395.245	304.444	287.453	315.981	361.521	454.736	426.435
	PET_{Thoc}	424.906	332.284	317.826	344.057	387.396	483.996	456.933
	PET_{BC}	541.003	578.334	573.589	641.099	712.028	540.211	528.32
	PET_{HS}	−102.83	155.343	−47.013	162.943	308.558	−125.161	59.864
NRMSE	PET_{Mak}	0.197	0.196	0.193	0.153	0.153	0.203	0.198
	PET_{PT}	0.325	0.327	0.333	0.397	0.399	0.314	0.322
	PET_{Turc}	0.027	0.025	0.023	0.041	0.046	0.031	0.025
	PET_{Tho}	0.258	0.205	0.197	0.226	0.276	0.29	0.277
	PET_{Thoc}	0.277	0.223	0.217	0.245	0.295	0.308	0.296
	PET_{BC}	0.348	0.387	0.383	0.453	0.534	0.343	0.338
	PET_{HS}	0.074	0.106	0.048	0.116	0.232	0.084	0.058

For daily series (Table 3), the Turc model gave the best performance, as the Re values were relatively low and ranged from 0.011 to 0.046. This indicated that the PET values were close to the FAO-56 PM model. On the contrary, all the Re values of the Priestly–Taylor model were above 0.2 in every station and this implied that the PET values differed largely as compared to the FAO-56 PM model. Similar results can be observed where the NRMSE values for the Turc and Priestly–Taylor models were below and above 0.2, respectively. The results showed that the Turc model performed the best, followed by the Hargreaves–Samani model, the Makkink model and the Priestly–Taylor model. Besides, the MBE results showed that the Makkink model underestimated PET values, while the Priestly–Taylor model showed overestimation at every station. This may due to the average RH being higher than 75% at every station, and reportedly, the Priestly–Taylor models tend to overestimate PET values in humid sites (Suleiman & Hoogenboom 2007; Fisher *et al.* 2011). Although the Turc model mostly showed underestimation in every station, the MBE results were close to zero. This indicated that the estimated PET values were near to the values estimated by the FAO-56 PM model. The Hargreaves–Samani model mostly overestimated the PET values at every station.

For monthly and annual series (Tables 4 and 5), the Re depicted that the PET values estimated with the Turc model at every station were close to the PET values estimated by the FAO-56 PM model. This indicated the superior performance of the Turc model as compared with other PET models. On the other hand, the Re values of the Priestly–Taylor, Thornthwaite, Thornthwaite-corrected and Blaney–Criddle models were above 0.2 at every station, indicating a significant difference with respect to the PET values estimated by the FAO-56 PM model. The NRMSE results were similar to the results of the Re. The Turc model performed the best, followed by the Makkink and Hargreaves–Samani models, while the Priestly–Taylor, Thornthwaite, Thornthwaite-corrected and Blaney–Criddle models gave the worst performances. On the other hand, the MBE results had it that the Makkink model underestimated PET values at every station, while the Priestly–Taylor, Thornthwaite, Thornthwaite-corrected and Blaney–Criddle models showed overestimation at every station.

The R^2 values for the PET models are presented as scatter plots and are shown in Figures 3–5. The radiation-based models gave good performances, as there was a significant positive correlation between the PET values of the radiation-based models and the FAO-56 PM model ($R^2 > 0.8100$). Although all radiation-based models gave approximately similar R^2 values, the Turc model requires the least number of parameters, and therefore easier to be used. Temperature-based models yielded the R^2 value ranging from 0.0097 to 0.5197. This indicated that the temperature-based models and the FAO-56 PM model exhibited

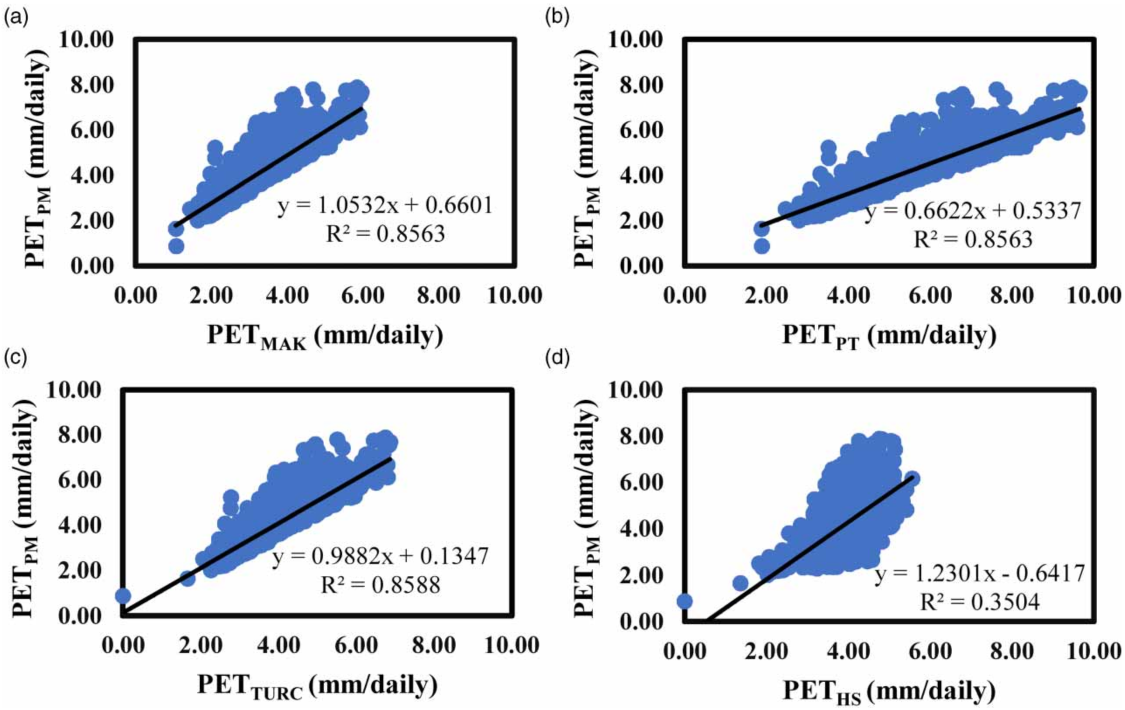

Figure 3 | Daily PET values estimated by the FAO-56 PM (PET_{PM}) model versus various PET models: (a) Makkink model (PET_{MAK}); (b) Priestley–Taylor model (PET_{PT}); (c) Turc model (PET_{TURC}) and (d) Hargreaves–Samani model (PET_{HS}) in the Bayan Lepas station.

a poor relationship due to the weak positive correlation of the PET values. The results are consistent with those in Tukimat *et al.* (2012) who had reported better performances (higher R^2) for the radiation-based methods as compared to the temperature-based methods.

Determination of the best PET estimation models

To determine the best PET method, the statistical performances of each model at every station were ranked from one (best fit) to seven (least fit). The selection of the best PET models was based on the lowest tested scores acquired by summing up the scores of each statistical performance. Table 6 presents an overview of ranking score of statistical performance based on the daily, monthly and annual time scales. For the daily and monthly time scales, it can be observed that the Turc model showed the best performance at every station. The scores obtained by the Makkink model were close to those of the Hargreaves–Samani model. The Makkink model obtained the second-lowest score for four out of seven stations and the third-lowest score for three out of seven stations, while the Hargreaves–Samani model obtained the second-lowest score for three out of seven stations and the third-lowest score for four out of seven stations. The Thornthwaite model obtained the fourth-lowest score for all stations, whereas the Priestly–Taylor model obtained the third-highest score for six out of seven stations. The Thornthwaite-corrected model obtained the second-highest score for six out of seven stations, while the Blaney–Criddle model obtained the highest score for all stations. Similarly for the annual time scale, it was found that the Turc model gave the best fit for six out of seven stations. The Makkink model obtained the second-lowest score at five out of seven stations followed by the Hargreaves–Samani and Thornthwaite models. The Blaney–Criddle model depicted the least fit for all stations.

DISCUSSION

The overall results revealed that the radiation-based PET models gave better performances compared to the temperature-based models. The findings are consistent with those of Tukimat *et al.* (2012), Muniandy *et al.* (2016) and Muhammad *et al.* (2019) who found that the radiation-based models outperformed the temperature-based models in Peninsular Malaysia. Most of the PET models overestimated the PET values. However, the Makkink model obtained a lower PET value than the FAO-56 PM model. Based on the trend analysis pattern and the ranking score for statistical performances, it is evident that the Turc model was the best model for estimating PET values and thus is the best alternative to the FAO-56 PM model. This

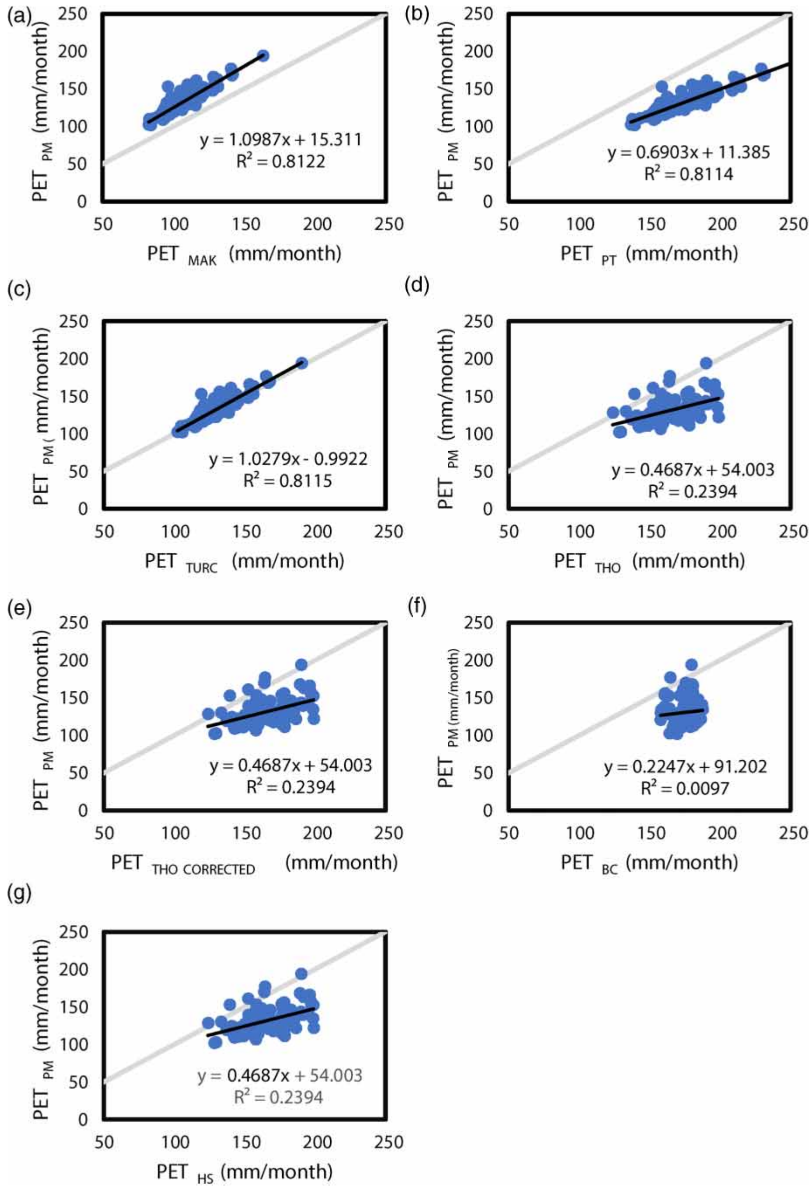

Figure 4 | Scatter plot of monthly PET estimated by the FAO-56 PM (PET_{PM}) model versus various PET models: (a) Makkink model (PET_{MAK}); (b) Priestley–Taylor model (PET_{PT}); (c) Turc model (PET_{TURC}); (d) Thornwaite model (PET_{THO}); (e) Thornwaite-corrected model ($PET_{THO\ CORRECTED}$); (f) Blaney–Criddle model (PET_{BC}) and (g) Hargreaves–Samani model (PET_{HS}) in the Bayan Lepas station.

can be explained by the dominant role of relative humidity, solar radiation and temperature used in the Turc model. According to Jensen *et al.* (1990), the Turc model was suitable to estimate PET, especially under humid regions. This is probably one of the reasons why the Turc model is suited for regions with abundant rainfall in this study area. According to relevant studies and literature, Tukimat *et al.* (2012) and Birara *et al.* (2021) pointed out that the Turc model provided the best performance in estimating PET values under subhumid and humid regions.

Among the temperature-based models, the Hargreaves–Samani model obtained a comparable score with the radiation-based Makkink model at most of the stations. This is because the solar radiation is the most sensitive meteorological parameter for PET estimation, followed by air temperature, relative humidity and wind speed. The Hargreaves–Samani model included extraterrestrial solar radiation as input, while other temperature-based models require air temperature and relative

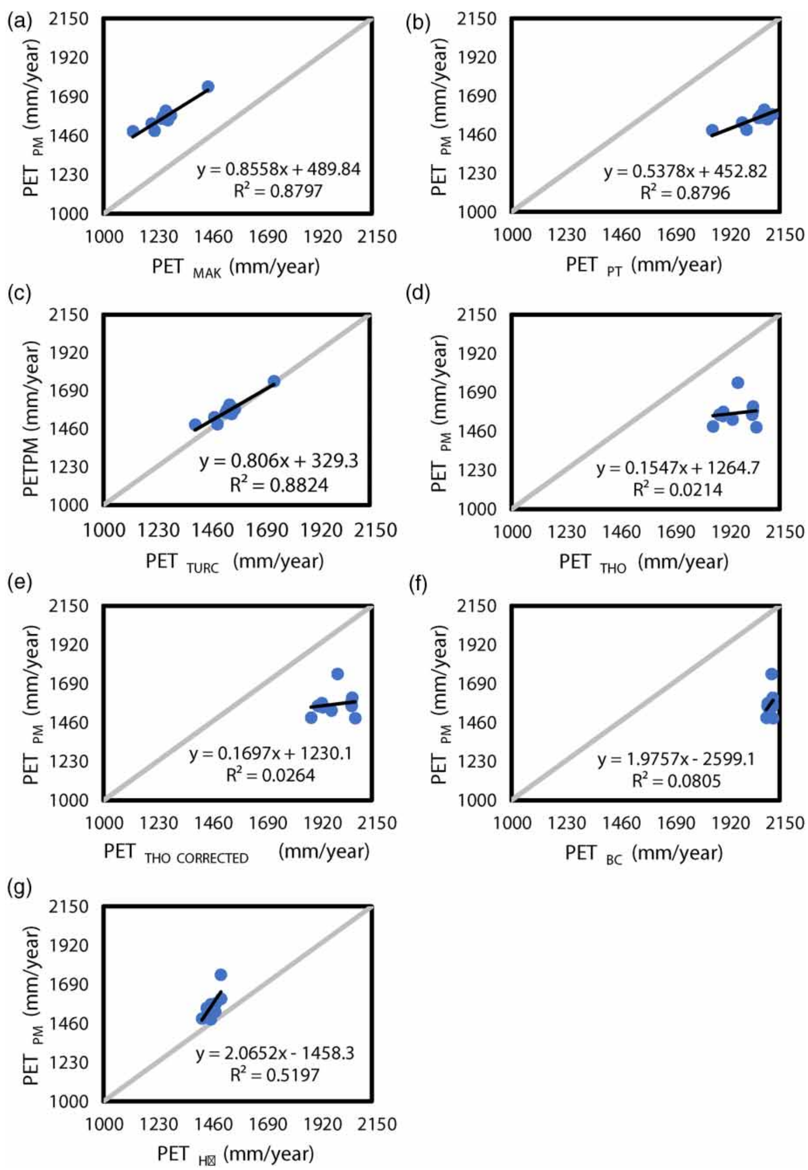

Figure 5 | Scatter plot of Annual PET estimated by the FAO-56 PM (PET_{PM}) model versus various PET models: (a) Makkink model (PET_{MAK}); (b) Priestley–Taylor model (PET_{PT}); (c) Turc model (PET_{TURC}); (d) Thornwaite model (PET_{THO}); (e) Thornwaite-corrected model ($PET_{THO\ CORRECTED}$); (f) Blaney–Criddle model (PET_{BC}) and (g) Hargreaves–Samani model (PET_{HS}) in the Bayan Lepas station.

humidity only (Sentelhas *et al.* 2010). This led to a better performance of the Hargreaves–Samani model. On the other hand, the Blaney–Criddle model demonstrated high discrepancies and provided the least fit at all stations. This can be explained by the fact that the model was established in a humid area and it was always found to overestimate the PET values. The overestimation was due to the high humidity with low wind speeds that force the ratio of the aerodynamic to energy terms below 0.26 (Lee *et al.* 2004).

CONCLUSION

In summary, PET estimation using various estimation models for Peninsular Malaysia was carried out. Three radiation-based and four temperature-based PET models were compared with reference to the FAO-56 PM model based on different time scales at seven meteorological stations across Peninsular Malaysia. All the derived PET values were fitted into four different statistical measures, namely the MBE, Re, NRMSE and R^2. The statistical performances of each model at each

Table 6 | Ranking score of statistical performance based on daily, monthly and annual time scales

Stations	PET models	Time Scale Daily Re	MBE	NRMSE	R^2	Score	Monthly Re	MBE	NRMSE	R^2	Score	Annual Re	MBE	NRMSE	R^2	Score
Bayan Lepas	**PET_{Mak}**	3	3	3	2	**11**	3	3	3	1	**10**	3	3	3	2	**11**
	PET_{PT}	4	4	4	2	**14**	6	6	6	3	**21**	6	6	6	2	**20**
	PET_{Turc}	1	1	1	1	**4**	1	1	1	1	**4**	1	1	1	1	**4**
	PET_{Tho}	-	-	-	-	-	4	4	4	5	**17**	4	4	4	7	**19**
	PET_{Thoc}	-	-	-	-	-	5	5	5	6	**21**	5	5	5	6	**21**
	PET_{BC}	-	-	-	-	-	7	7	7	7	**28**	7	7	7	5	**26**
	PET_{HS}	2	2	2	4	**10**	2	2	2	4	**10**	2	2	2	4	**10**
Ipoh	**PET_{Mak}**	3	3	3	2	**11**	3	3	3	3	**12**	3	3	3	6	**15**
	PET_{PT}	4	4	4	2	**14**	6	6	6	2	**20**	6	6	6	6	**24**
	PET_{Turc}	1	1	1	1	**4**	1	1	1	1	**4**	1	1	1	5	**8**
	PET_{Tho}	-	-	-	-	-	4	4	4	5	**17**	4	4	4	3	**15**
	PET_{Thoc}	-	-	-	-	-	5	5	5	6	**21**	5	5	5	2	**17**
	PET_{BC}	-	-	-	-	-	7	7	7	7	**28**	7	7	7	4	**25**
	PET_{HS}	2	2	2	4	**10**	2	2	2	4	**10**	2	2	2	1	**7**
Kota Bahru	**PET_{Mak}**	3	3	2	2	**10**	4	4	3	2	**13**	4	4	3	2	**13**
	PET_{PT}	4	4	4	2	**14**	6	6	6	2	**20**	6	6	6	2	**20**
	PET_{Turc}	1	1	1	1	**4**	1	1	1	1	**4**	1	1	1	1	**4**
	PET_{Tho}	-	-	-	-	-	3	3	4	5	**15**	3	3	4	6	**16**
	PET_{Thoc}	-	-	-	-	-	5	5	5	6	**21**	5	5	5	5	**20**
	PET_{BC}	-	-	-	-	-	7	7	7	7	**28**	7	7	7	4	**25**
	PET_{HS}	2	2	3	4	**11**	2	2	2	4	**10**	2	2	2	7	**13**
Kuantan	**PET_{Mak}**	3	3	2	2	**10**	3	3	3	3	**12**	3	3	3	1	**10**
	PET_{PT}	4	4	4	2	**14**	6	6	6	2	**20**	6	6	6	3	**21**
	PET_{Turc}	1	1	1	1	**4**	1	1	1	1	**4**	1	1	1	1	**4**
	PET_{Tho}	-	-	-	-	-	4	4	4	5	**17**	4	4	4	6	**18**
	PET_{Thoc}	-	-	-	-	-	5	5	5	6	**21**	5	5	5	5	**20**
	PET_{BC}	-	-	-	-	-	7	7	7	7	**28**	7	7	7	7	**28**
	PET_{HS}	2	2	3	4	**11**	2	2	2	4	**10**	2	2	2	4	**10**
Muadzam Shah	**PET_{Mak}**	2	2	2	2	**8**	2	3	2	1	**8**	2	2	2	2	**8**
	PET_{PT}	4	4	4	2	**14**	6	6	6	1	**19**	6	6	6	2	**20**
	PET_{Turc}	1	1	1	1	**4**	1	1	1	3	**6**	1	1	1	1	**4**
	PET_{Tho}	-	-	-	-	-	4	4	4	6	**18**	4	4	4	6	**18**
	PET_{Thoc}	-	-	-	-	-	5	5	5	5	**20**	5	5	5	5	**20**
	PET_{BC}	-	-	-	-	-	7	7	7	7	**28**	7	7	7	7	**28**
	PET_{HS}	3	3	3	4	**13**	3	2	3	4	**12**	3	3	3	4	**13**

(*Continued*.)

Table 6 | Continued

Stations	PET models	Time Scale Daily Re	MBE	NRMSE	R^2	Score	Monthly Re	MBE	NRMSE	R^2	Score	Annual Re	MBE	NRMSE	R^2	Score
Pulau Langkawi	PET_{Mak}	3	3	3	2	**11**	3	3	3	1	**10**	3	3	3	2	**11**
	PET_{PT}	4	4	4	2	**14**	6	6	5	2	**19**	6	6	6	2	**20**
	PET_{Turc}	1	1	1	1	4	1	1	1	3	**6**	1	1	1	1	**4**
	PET_{Tho}	-	-	-	-	-	4	4	4	5	**17**	4	4	4	6	**18**
	PET_{Thoc}	-	-	-	-	-	5	5	6	6	**22**	5	5	5	5	**20**
	PET_{BC}	-	-	-	-	-	7	7	7	7	**28**	7	7	7	4	**25**
	PET_{HS}	2	2	2	4	**10**	2	2	2	4	**10**	2	2	2	7	**13**
Subang	PET_{Mak}	3	3	3	2	**11**	3	3	3	2	**11**	3	3	3	2	**11**
	PET_{PT}	4	4	4	2	**14**	6	6	6	2	**20**	6	6	6	2	**20**
	PET_{Turc}	1	1	1	1	**4**	1	1	1	1	**4**	1	1	1	1	**4**
	PET_{Tho}	-	-	-	-	-	4	4	4	5	**17**	4	4	4	6	**18**
	PET_{Thoc}	-	-	-	-	-	5	5	5	4	**19**	5	5	5	5	**20**
	PET_{BC}	-	-	-	-	-	7	7	7	7	**28**	7	7	7	4	**25**
	PET_{HS}	2	2	2	4	**10**	2	2	2	6	**12**	2	2	2	7	**13**

station were ranked from the best fit to the least fit. Finally, the best PET model was selected based on the lowest tested scores acquired by summing up the scores of each statistical performance. The statistical results demonstrated that the Turc model gave the best overall performance, whereas the Blaney–Criddle model performed the worst. In general, the assessment of PET estimation models plays a crucial role in defining the water budget and physical processes in tropics. This study is essential for understanding the adaptability of PET models in Peninsular Malaysia and is able to provide guidance when selecting the most appropriate PET models for estimating PET based on the accessibility of meteorological information.

In addition, the assessment of PET models in this study was carried out using only temperature-based and radiation-based PET models, and thus it should be noted that a comprehensive exploration of various other PET estimation approaches may be performed to enhance the use of highly precise models.

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CONFLICT OF INTEREST

The authors declared that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

REFERENCES

Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. 1998 *Crop Evapotranspiration: Guideline for Computing Crop Water Requirements*. Fao Irrigation and Drainage Paper 56. FAO-Food and Agriculture Organization of the United Nations Rome, Rome, Italy.

Birara, H., Mishra, S. K. & Pandey, R. P. 2021 Comparison of methods for evapotranspiration computation in the Tana Basin, Ethiopia. In: *Hydrological Extremes* (A. Pandey, S. Mishra, M. Kansal, R. Singh & V. P. Singh, eds.) Springer, Cham, pp. 405–422.

Blaney, H. F. & Criddle, W. D. 1950 *Determining Water Requirements in Irrigated Areas from Climatological Irrigation Data*. Technical Paper No. 96. US Department of Agriculture, Soil Conservation Service, Washington, DC, p. 48.

Farzanpour, H., Shiri, J., Sadraddini, A. A. & Trajkovic, S. 2019 Global comparison of 20 reference evapotranspiration equations in a semi-arid region of Iran. *Hydrology Research* **50** (1), 282–300.

Feng, K. & Tian, J. 2020 Estimating potential evapotranspiration based on self-optimizing nearest neighbor algorithms: a case study in arid–semiarid environments, Northwest of China. *Environmental Science and Pollution Research* **27** (30), 37176–37187.

Fisher, J. B., Whittaker, R. J. & Malhi, Y. 2011 ET come home: potential evapotranspiration in geographical ecology. *Global Ecology and Biogeography* **20** (1), 1–18.

Fisher, J. B., Melton, F., Middleton, E., Hain, C., Anderson, M., Allen, R., McCabe, M. F., Hook, S., Baldocchi, D., Townsend, P. A. & Kilic, A. 2017 The future of evapotranspiration: global requirements for ecosystem functioning, carbon and climate feedbacks, agricultural management, and water resources. *Water Resources Research* **53** (4), 2618–2626.

Hargreaves, G. H. & Samani, Z. A. 1985 Reference crop evapotranspiration from temperature. *Transactions of the American Society of Agricultural Engineers* **1** (2), 96–99.

Jensen, M. E., Burman, R. D. & Allen, R. G. 1990 *Evapotranspiration and Irrigation Water Requirements*. ASCE Manuals and Reports on Engineering Practices No. 70. New York, p. 332.

Landeras, G., Bekoe, E., Ampofo, J., Logah, F., Diop, M., Cisse, M. & Shiri, J. 2018 New alternatives for reference evapotranspiration estimation in West Africa using limited weather data and ancillary data supply strategies. *Theoretical and Applied Climatology* **132** (3), 701–716.

Lang, D., Zheng, J., Shi, J., Liao, F., Ma, X., Wang, W., Chen, X. & Zhang, M. 2017 A comparative study of potential evapotranspiration estimation by eight methods with FAO Penman–Monteith method in southwestern China. *Water* **9** (10), 734.

Lee, T. S., Najim, M. M. M. & Aminul, M. H. 2004 Estimating evapotranspiration of irrigated rice at the West Coast of the Peninsular of Malaysia. *Journal of Applied Irrigation Science* **39** (1), 103–117.

Lian, C. Y., Huang, Y. F., Ng, J. L., Mirzaei, M., Koo, C. H. & Tan, K. W. 2019 A proposed hybrid rainfall simulation model: bootstrap aggregated classification tree–artificial neural network (BACT-ANN) for the Langat River Basin, Malaysia. *Journal of Water and Climate Change* **11** (4), 1218–1234.

Maeda, E. E., Wiberg, D. A. & Pellikka, P. K. 2011 Estimating reference evapotranspiration using remote sensing and empirical models in a region with limited ground data availability in Kenya. *Applied Geography* **31** (1), 251–258.

Makkink, G. F. 1957 Testing the Penman formula by means of lysimeters. *Journal of Institute of Water Engineering* **11**, 277–288.
Muhammad, M. K. I., Nashwan, M. S., Shahid, S., Ismail, T. B., Song, Y. H. & Chung, E. S. 2019 Evaluation of empirical reference evapotranspiration models using compromise programming: a case study of Peninsular Malaysia. *Sustainability* **11** (16), 4267.
Muniandy, J. M., Yusop, Z. & Askari, M. 2016 Evaluation of reference evapotranspiration models and determination of crop coefficient for *Momordica charantia* and *Capsicum annuum*. *Agricultural Water Management* **169**, 77–89.
Ng, J. L., Abd Aziz, S., Feng, H. Y., Wayayok, A. & Kamal, M. R. 2015 Homogeneity analysis of rainfall in Kelantan, Malaysia. *Jurnal Teknologi* **76** (15), 1–6.
Ng, J. L., Abd Aziz, S., Huang, Y. F., Wayayok, A. & Rowshon, M. K. 2016 Analysis of annual maximum rainfall in Kelantan, Malaysia. In: *III International Conference on Agricultural and Food Engineering*, Vol. 1152, pp. 11–18.
Ng, J. L., Aziz, S. A., Huang, Y. F., Mirzaei, M., Wayayok, A. & Rowshon, M. K. 2019 Uncertainty analysis of rainfall depth duration frequency curves using the bootstrap resampling technique. *Journal of Earth System Science* **128** (5), 113.
Ng, C. K., Ng, J. L., Huang, Y. F., Tan, Y. Y. & Mirzaei, M. 2020 Tropical rainfall trend and analysis. *Water Supply* **20** (7), 2471–2483.
Pan, S., Xu, Y. P., Xuan, W., Gu, H. & Bai, Z. 2019 Appropriateness of potential evapotranspiration models for climate change impact analysis in Yarlung Zangbo River Basin, China. *Atmosphere* **10** (8), 453.
Paparrizos, S., Maris, F. & Matzarakis, A. 2017 Sensitivity analysis and comparison of various potential evapotranspiration formulae for selected Greek areas with different climate conditions. *Theoretical and Applied Climatology* **128** (3–4), 745–759.
Penman, H. L. 1948 Natural evaporation from open water, bare soil and grass. *Proceedings of the Royal Society of London* **193** (1032), 120–145.
Pour, S. H., Wahab, A. K. A. & Shahid, S. 2020 Physical-empirical models for prediction of seasonal rainfall extremes of Peninsular Malaysia. *Atmospheric Research* **233**, 104720.
Priestley, C. H. B. & Taylor, R. J. 1972 On the assessment of the surface heat flux and evaporation using large-scale parameters. *Monthly Weather Review* **100**, 81–92.
Quej, V. H., Almorox, J., Arnaldo, J. A. & Moratiel, R. 2019 Evaluation of temperature-based methods for the estimation of reference evapotranspiration in the Yucatán peninsula, Mexico. *Journal of Hydrologic Engineering* **24** (2), 05018029.
Sentelhas, P. C., Gillespie, T. J. & Santos, E. A. 2010 Evaluation of FAO Penman–Monteith and alternative methods for estimating reference evapotranspiration with missing data in Southern Ontario, Canada. *Agricultural Water Management* **97** (5), 635–644.
Shiri, J. 2017 Evaluation of FAO56-PM, empirical, semi-empirical and gene expression programming approaches for estimating daily reference evapotranspiration in hyper-arid regions of Iran. *Agricultural Water Management* **188**, 101–114.
Shiri, J., Nazemi, A. H., Sadraddini, A. A., Marti, P., Fard, A. F., Kisi, O. & Landeras, G. 2019 Alternative heuristics equations to the Priestley–Taylor approach: assessing reference evapotranspiration estimation. *Theoretical and Applied Climatology* **138** (1), 831–848.
Suleiman, A. A. & Hoogenboom, G. 2007 Comparison of Priestley-Taylor and FAO-56 Penman-Monteith for daily reference evapotranspiration estimation in Georgia. *Journal of Irrigation Drainage Engineering* **133** (2), 175–182.
Thornthwaite, C. 1948 An approach toward a rational classification of climate. *Geographical Review* **38** (1), 55–94.
Thornthwaite, C. W. & Mather, J. R. 1955 The water budget and its use in irrigation. In: *Water, the Yearbook of Agriculture*. (A. Stefferud, ed.) US Department of Agriculture, Washington, DC, pp. 346–358.
Tran, T. H. N. & Honti, M. 2017 Application of different evapotranspiration models to calculate total agricultural water demand in a tropical region. *Periodica Polytechnica Civil Engineering* **61** (4), 904–910.
Tukimat, N. N. A., Harun, S. & Shahid, S. 2012 Comparison of different methods in estimating potential evapotranspiration at Muda Irrigation Scheme of Malaysia. *Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS)* **113** (1), 77–85.
Turc, L. 1961 Estimation of irrigation water requirements, potential evapotranspiration: a simple climatic formula evolved up to date. *Annals of Agronomy* **12**, 13–49.
Upreti, H. & Ojha, C. S. P. 2017 Estimation of relative humidity and dew point temperature using limited meteorological data. *Journal of Irrigation and Drainage Engineering* **143** (9), 05017005.
Xie, R. & Wang, A. 2020 Comparison of ten potential evapotranspiration models and their attribution analyses for ten Chinese drainage basins. *Advances in Atmospheric Sciences* **37** (9), 959–974.
Yang, L., Feng, Q., Adamowski, J. F., Yin, Z., Wen, X., Wu, M., Jia, B. & Hao, Q. 2020 Spatio-temporal variation of reference evapotranspiration in northwest China based on CORDEX-EA. *Atmospheric Research* **238**, 104868.

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