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Performance of Daily FAO56-PM ET_0 Model Estimates under limited data conditions at Arid Jodhpur District of Rajasthan

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ABSTRACT: This study was conducted for arid Jodhpur district to compare performance of standard FAO56-PM model with derived individual meteorological parameters, their combinations and complete dataset estimates and to decide the minimum meteorological parameters required to compute at par FAO56-PM estimates. The performance of 33 cases of derived individual parameters & their combinations in comparison to complete dataset FAO56-PM estimates was evaluated on the basis of statistical indices and ranking based on summative form of Global performance indicator values. Solar radiation was found most important parameter, followed by relative humidity and wind speed. The saturation vapour pressure estimated using mean air temperature showed least influence on FAO56-PM estimates while, missing relative humidity data obtained by considering dew point temperature 3°C lesser than minimum air temperature extended good results. The missing solar radiation data can be estimated accurately by maximum and minimum air temperature while, long-term average wind speed of study area in absence of wind speed data extended better FAO56-PM estimates. The minimum & maximum and/or mean air temperature along with long-term average wind speed are minimum meteorological data requirement to compute at par FAO56-PM estimates.

Key words: Arid, data limiting, FAO56-PM, missing data, reference evapotranspiration

Introduction

Several studies revealed that by year 2025, more than two third of world's population will be forced to live in very typical water scarcity conditions. It is also expected that with change in climatic conditions, occurrence of extreme weather conditions will be increased (Alcamo *et al*., 1997; Alcamo *et al*., 2000; Rijsberman, 2004). The population of India is expected to stabilize around 1640 million by the year 2050. As a result, gross per capita water availability will decline from nearly 1820 m^3/yr in 2001 to as low as approximately 1140 m^3/yr in 2050 (Gupta and Deshpande, 2004). Evapotranspiration (ET) being a basic component of hydrological cycle is considered as dominant cause of loss of water across the globe as it consists of about 62% precipitation that moves back to the atmosphere (Watson and Burnett, 1995; Dingman, 2002). The study on evapotranspiration is essential for a very large number of scientific and management issues including agricultural climatology (Midgley *et al*., 2002), crop simulation models (Ababaei, 2014), hydro-informatics (Vazquez and Hampel, 2014), hydrology (Buytaert *et al*., 2006; Senay *et al*., 2009) and water resources management (Kisi and Cengiz, 2013) etc.

Reference evapotranspiration (ET_0) gives value of evaporative demand of atmosphere for a grass as reference evapotranspiring surface with no shortage of water and it can be measured either directly (lysimeter or water balance approach), or indirectly (meteorological data). Lysimeter tests are tedious, cumbersome and costlier and are, therefore, generally not preferred. According to Kavazanjian *et al*. (2006), lysimeter conditions may not represent actual field conditions truly as geo-membrane present at the bottom of lysimeter can cut off heat flux and moisture from downside. The estimation of reference evapotranspiration by standard FAO56-PM model requires air temperature, actual vapour pressure, net radiation, and wind speed. In case, if one or more of these weather parameters are not recorded or inaccurate data is available, then they can be estimated using minimum available data (Allen *et al*., 1998). In absence of sunshine hours, solar radiation values can be determined by using minimum and maximum temperature (Hargreaves and Samani, 1985; Allen, 1996) while vapour pressure can be computed by using minimum air temperature. For non-availability of wind speed data, either its long-term average value observed at study area or default value (2 m/sec) should be considered (Allen *et al*., 1998; Trajkovic and Kolakovic, 2009).

Except air temperature and rainfall, all other weather parameters are not recorded at most of the meteorological stations situated in developing countries (Gavilan *et al*., 2006) due to which it becomes very difficult to apply FAO56-PM model. Thus, it is essentially required to evaluate the performance of alternative procedures to compute at par FAO56-PM esimates. Several researchers (Todorovic *et al.*, 2013; Córdova *et al.*, 2015; Majidi *et al.*, 2015; Andrade and Riveiro, 2016; Barreiros *et al.*, 2017; Burgera *et al.*, 2017; Da Cunha *et al.*, 2017; Djaman *et al*., 2017; Paredes *et al.*, 2017a; Paredes *et al.*, 2017b; Da Silva *et al.*, 2018; Ferreira *et al*., 2018; Koudahe *et al.*, 2018; Vincete *et al.*, 2018; Quej *et al.*, 2019) across the globe evaluated performance of FAO56-PM model with missing meteorological parameters & their combinations. However, due to absence of such research work for Indian arid conditions, present study was undertaken for Jodhpur district of Rajasthan with two specific objectives, (i) to compare performance of standard FAO56-PM model with derived individual meteorological parameters & their combinations and complete dataset estimates, and (ii) to decide minimum meteorological parameters required to compute at par FAO56-PM estimates.

Materials and Methods

The study was carried out for arid Jodhpur (26.23°E longitude, 73.02°N latitude and altitude of 231 m above m.s.l.) district of Rajasthan using 25 years (1992-2016) daily meteorological dataset consisting of air temperature (maximum and minimum), relative humidity (maximum and minimum), wind speed and bright sunshine hours collected from IMD, Pune. The quality control of dataset was ensured by removing days with missing and inconsistent data.

Reference Evapotranspiration and Estimation of Missing Meteorological Parameters

a. Reference evapotranspiration: In this study, standardized Penman-Monteith method, suggested by Food and Agriculture Organization (FAO) in its paper No. 56 (FAO56-PM) was used as "standard" to compute ET_0 values. The recommended form of FAO56-PM model (Allen *et al.*, 1998) is:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma(\frac{900}{T_{mean}+273})U_2(e_s - e_a)}{\Delta + \gamma(1+0.34U_2)} \quad (1)$$

Where, ET_0 = reference evapotranspiration (mm/day), = slope of saturated vapour pressure curve (kPa/), R_n = net radiation at crop surface (MJ/m^2/day), G = soil heat flux density (MJ/m^2/day), = psychrometric constant (kPa/), T_{mean} = mean daily air temperature (), U_2 = wind speed at 2 m height (m/sec), e_s = saturated vapour pressure (kPa), e_a = actual vapour pressure (kPa), e_s-e_a = vapour pressure deficit (kPa).

b. Solar radiation (R_s): The difference between maximum air temperature (T_{max}) and minimum air temperature (T_{min}) at a given location can be used efficiently as an indicator of fraction of extra-terrestrial radiation (R_a), which reaches to earth's surface. Hargreaves and Samani (1985) utilized this principle for computing ET_0 estimates using air temperature data alone. The mathematical expression for calculating R_s values is:

$$R_s = k_{RS}\left[\sqrt{(T_{max} - T_{min})}\right] \times R_a \quad (2)$$

Where, R_s = solar radiation (MJ/m^2/day), k_{RS} = adjustment coefficient (1/°C$^{0.5}$), T_{max} = maximum air temperature (°C), T_{min} = minimum air temperature (°C), R_a = extra-terrestrial radiation (MJ/m^2/day).

As study area is in interior region, value of k_{RS} was taken as 0.16 in accordance with Allen *et al.* (1998).

c. Relative humidity: When observed value of relative humidity is not available, actual vapour pressure (e_a) can be estimated by taking dew point temperature (T_{dew}) at par with minimum air temperature (T_{min}) with assumption that at sunrise when air temperature is close to minimum temperature, air is nearly saturated with water vapour and relative humidity is nearly 100%. In case when T_{dew} is represented by T_{min}, it is expressed as:

$$e_a = e^0(T_{min}) = 0.6108 \exp\left\{\frac{17.27 \times T_{min}}{T_{min}+237.3}\right\} \quad (3)$$

Where, e_a = actual vapour pressure (kPa), T_{min} = minimum temperature (°C).

The equivalence of T_{dew} to T_{min} is valid for locations where crop cover of meteorological stations is well-watered, however, for arid regions, air may not be saturated at minimum temperature and, thereby, T_{min} might be more than T_{dew} which require further calibration to estimate dew point temperature. In such cases, value of T_{dew} may be obtained by considering its value 2-3 °C lesser than that of T_{min} (Allen *et al.*, 1998). Keeping above recommendation into consideration, actual vapour pressure (e_a) in present study was calculated by taking dew point temperature k° less then minimum temperature for two values of k (i.e., 2, 3) as:

$$e_a = 0.6108 \times \exp\left\{\frac{[17.27 \times (T_{min} - k)]}{(T_{min} - k) + 237.3}\right\} \quad (4)$$

Where, e_a = actual vapour pressure (kPa), T_{min} = minimum temperature (°C).

Therefore, two cases for determining missing actual vapour pressure (e_a) values considered in this study were:

Case	Value of k	T_{dew} calculation	Designated as
1	2	$T_{dew} = T_{min} - 2$	e_a(k2)
2	3	$T_{dew} = T_{min} - 3$	e_a(k3)

d. Saturation vapour pressure: The values of mean saturation vapour pressure (designated as "e_{sB}") were calculated by using mean air temperature (T_{mean}) as:

$$e_{sB} = 0.6108 \times \exp\left\{\frac{17.27 \times T_{mean}}{T_{mean}+237.3}\right\} \quad (5)$$

Where, e_{sB} = mean saturation vapour pressure (kPa), T_{mean} = mean air temperature (°C).

e. Wind speed: In absence of wind speed data for any location, two approaches are normally used, (i) long-term average wind speed of study area (Majidi *et al.*, 2015; Koudahe *et al.*, 2018), and (ii) default wind speed value as 2 m/sec (Allen *et al.*, 1998). Considering the above, value of long-term average wind speed (U_l) in present study was taken as 3.17 m/sec while, default wind speed (U_d) was taken as 2.00 m/sec in accordance with Allen *et al*. (1998), Paredes *et al*. (2017a, b), and Vincete *et al*. (2018).

Statistical indices and ranking

The performance of FAO56-PM model with derived individual meteorological parameters & their combinations against complete dataset requiring FAO56-PM model was assessed by statistical indices namely, agreement index (D), coefficient of determination (R^2), standard error of estimate (SEE), and weighted root mean square difference (WRMSD) while, their ranking on individual- and overall-basis was done using Global performance indicator (GPI) as a tool. The pertinent details of statistical indices and GPI is presented hereunder as:

a. Agreement index (D): This index measures degree of model prediction error in between "0.00" and "1.00" with value "1.00" indicating perfect agreement (Willmott, 1984; Legates and McCabe, 1999). It is expressed mathematically as:

$$D = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{P}| + |O_i - \bar{O}|)^2} \tag{6}$$

b. Coefficient of determination (R^2): It is defined as ratio of explained variance to total variance and is a measure of linear covariance between two variables. It is an indicator of degree of closeness of predicted values to observed ones and varies in between "0.00" and "1.00". Mathematically, it is expressed (Nagelkerke, 1991; Moriasi *et al.*, 2015) as:

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sum_{i=1}^{n}(P_i - \bar{P})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2}\right]^2 \tag{7}$$

c. Standard error of estimate (SEE): It is the measure of accuracy and precision of estimations and gives equal weightage to absolute difference between standard and comparison methods. The smaller SEE value shows better estimate and its "0.00" value shows perfect correlation. The mathematical expression for SEE (Kumar *et al.*, 2002) is:

$$SEE = \left[\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n-1}\right]^{0.5} \tag{8}$$

d. Weighted root mean square difference (WRMSD): This index shows measure of difference between predicted and observed values. A weightage of 70% and 30% is given to general and peak values, respectively. It is the combination of root mean square difference (RMSD) and adjusted RMSD (ARMSD) in which 67% weightage in given to RMSD values and 33% weightage is given to ARMSD values. The WRMSD represents ability of model to estimate ET_0 accurately giving 47% weightage to all ET_0 values, 20% weightage to peak ET_0 and 33% weightage to adjusted ET_0 (Trajkovic and Kolakovic, 2009), and is expressed as:

$$WRMSD = 0.70 \times (0.67 \times RMSD + 0.33 \times AMRSD + 0.30 \times (0.67 \times pRMSD + 0.33 \times pARMSD) \tag{9}$$

Where, WRMSD = weighted root mean square difference (mm/day), RMSD = root mean square difference, ARMSD = adjusted root mean square difference, pRMSD = root mean square difference for peak period (mm/period), pARMSD adjusted root mean square difference for the peak period (mm/period).

The values for RMSD and ARMSD were computed using following mathematical expressions suggested by Jensen *et al.* (1990) as:

$$RMSD = \left[\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}\right]^{0.5} \tag{10}$$

$$ARMSD = \left[\frac{\sum_{i=1}^{n}(O_i - b \times P_i)^2}{n}\right]^{0.5} \tag{11}$$

The linear regression through origin between ET_0 estimated by derived meteorological parameters & their combinations versus those estimated with complete dataset was also conducted to get linear relationship as:

$$O_i = b \times P_i \tag{12}$$

Where, b = regression coefficient.

In Eqs. (6)-(12), P_i and O_i are predicted and observed values of ET_0 (mm/day), calculated by the FAO56-PM model using derived meteorological parameters & their combinations and those with complete dataset, respectively. The mean values of predicted and observed values of ET_0 (mm/day) are represented by $\bar{P}$ $\bar{O}$ and, respectively with n as total number of observations.

e. Global performance indicator (GPI): The summative form of GPI was used to give final ranking to derived individual meteorological parameters & their combinations. To remove influence of any particular index, all statistical indices were normalized between "0.00" (minimum) and "1.00" (maximum). The highest GPI value indicate most accurate result (Despatovic *et al*., 2015). The mathematical expression for summative form of GPI is:

$$GPI = \sum_{i=0}^{n}(X_i - X_{ij}) \times a_i \tag{13}$$

Where, X_i and X_{ij} are median of individual statistical index "i" and value of statistical index "i" for parameter "j", respectively with value of a_i equal to (-)1 for R^2 and (+)1 for all other considered statistical indices.

Results and Discussion

The comparative performance of FAO56-PM model with derived individual meteorological data & their combinations against complete dataset in terms of statistical indices (D, R^2, SEE, WRMSD) is shown in **Table 1** while, their overall ranking is presented in **Table 2**.

Table 1: Performance of daily FAO56-PM ET_0 estimates with individual derived meteorological parameters & their combinations against complete meteorological dataset

S. No.	Derived parameter(s)	Statistical indices				GPI	Rank
		D	R^2	SEE	WRMSD		
	Individual derived meteorological parameters						
1	R_s	0.9936	0.9982	0.6328	0.5315	0.8989	2
2	$e_a(k2)$	0.7512	0.9802	3.3754	2.9366	-0.1135	4
3	$e_a(k3)$	0.7854	0.9877	3.0972	2.7001	-0.0197	3
4	e_{sB}	0.9969	0.9987	0.4144	0.3094	1.0234	1
5	U_l	0.6178	0.6464	2.9704	3.3941	-0.7301	5
6	U_d	0.5794	0.7270	3.4567	4.0649	-0.7478	6
	Combinations of two derived individual meteorological parameters						
1	$e_a(k2)$-R_s	0.8673	0.9297	2.3502	2.2276	0.4256	3
2	$e_a(k3)$-R_s	0.8952	0.9471	2.0986	2.0049	0.5058	2
3	e_{sB}-R_s	0.9986	0.9982	0.2867	0.2552	1.1699	1
4	U_l-R_s	0.7361	0.7311	2.7220	2.9829	0.0348	9
5	U_d-R_s	0.6977	0.7958	2.8733	3.4223	0.1371	7
6	$e_a(k2)$-e_{sB}	0.7121	0.9898	3.7561	3.2780	0.3668	5
7	$e_a(k3)$-e_{sB}	0.7411	0.9938	3.4791	3.0447	0.4228	4
8	$e_a(k2)$-U_l	0.5590	0.5482	4.1572	4.5182	-0.6249	13
9	$e_a(k3)$-U_l	0.5635	0.5805	3.9966	4.4028	-0.5023	11
10	e_{sB}-U_l	0.6456	0.7545	2.8774	3.4464	0.1567	6
11	$e_a(k2)$-U_d	0.5553	0.6957	4.7066	4.9361	-0.5023	12
12	$e_a(k3)$-U_d	0.5601	0.7128	4.5869	4.8633	-0.4325	10
13	e_{sB}-U_d	0.6010	0.8081	3.5489	4.1628	0.0715	8
	Combinations of three derived individual meteorological parameters						
1	$e_a(k2)$-R_s-U_l	0.6653	0.6253	3.2175	3.6908	-0.4964	8
2	$e_a(k3)$-R_s-U_l	0.6768	0.6449	3.1093	3.6045	-0.3934	7
3	e_{sB}-R_s-U_l	0.7816	0.8183	2.4973	2.8694	0.3683	4
4	$e_a(k2)$-R_s-U_d	0.7974	0.8395	2.2658	2.5912	0.5828	3
5	$e_a(k3)$-R_s-U_d	0.8050	0.8475	2.2039	2.5556	0.6226	2
6	e_{sB}-R_s-U_d	0.8978	0.9259	1.7064	2.1979	0.9184	1
7	$e_a(k2)$-e_{sB}-U_l	0.5752	0.7410	4.3817	4.8137	-0.6967	10
8	$e_a(k3)$-e_{sB}-U_l	0.5824	0.7611	4.2072	4.6858	-0.5380	9
9	$e_a(k2)$-e_{sB}-U_d	0.5949	0.7585	3.6821	4.0981	-0.1645	6
10	$e_a(k3)$-e_{sB}-U_d	0.6023	0.7766	3.5736	4.0263	-0.0592	5
	Combinations of four derived individual meteorological parameters						
1	$e_a(k2)$-e_{sB}-R_s-U_l	0.8073	0.8734	2.2160	2.5709	-0.2854	3
2	$e_a(k3)$-e_{sB}-R_s-U_l	0.8191	0.8816	2.1255	2.5146	0.4610	1
3	$e_a(k2)$-e_{sB}-R_s-U_d	0.7791	0.8839	2.4378	2.7411	-0.3979	4
4	$e_a(k3)$-e_{sB}-R_s-U_d	0.7878	0.8897	2.3660	2.7031	0.1381	2

Where, R_s = solar radiation (MJ/m²/day), $e_a(k2)$ = actual vapour pressure (kPa) estimated by taking dew point temperature 2° less than minimum temperature, $e_a(k3)$ = actual vapour pressure (kPa) estimated by taking dew point temperature 3° less than minimum temperature, e_{sB} = saturation vapour pressure (kPa) estimated by using mean temperature, U_l = long-term average wind speed (m/sec) of study area, U_d = default wind speed (m/sec), D = agreement index, R^2 = coefficient of determination, SEE = standard error of estimate, WRMSD = weighted root mean square difference.

Derived individual meteorological parameters

The performance of FAO56-PM model with individual derived meteorological parameters against complete dataset estimates in terms of statistical indices and ranking **(Table 1)** shows that all derived parameters produced good results as value of D, R^2, SEE and WRMSD varied in the range of 0.5794 (U_d) to 0.9969 (e_{sB}), 0.6464 (U_l) to 0.9987 (e_{sB}), 0.4144 (e_{sB}) to 3.4567 mm/day (U_d), and 0.3094 (e_{sB}) to 4.0649 mm/day (U_d), respectively. The ranking showed that e_{sB} performed best, followed by R_s and $e_a(k3)$ while, U_d was adjudged last.

Combinations of two derived individual meteorological parameters

Among 13 combinations of two derived individual parameters **(Table 1)**, combination e_{sB}-R_s extended best value of D and R^2 with corresponding value as 0.9986 and 0.9982. The highly accepted lowest value of SEE and WRMSD as 0.2867 mm/day and 0.2552 mm/day was also observed with combination e_{sB}-R_s. The ranking of 13 combinations on the basis of GPI values **(Table 1)** revealed that combination e_{sB}-R_s, followed by e_a(k3)-R_s and e_a(k2)-R_s secured top three positions, respectively while, with lowest value of GPI (-0.6249), combination e_a(k2)-U_l was adjudged last.

Combinations of three derived individual meteorological parameters

The results of performance of FAO56-PM ET_0 estimates with combinations of three derived individual meteorological parameters against complete dataset FAO56-PM model in terms of statistical indices **(Table 1)** revealed that combination e_{sB}-R_s-U_d produced highest value of D and R^2, followed by combinations e_a(k3)-R_s-U_d and e_a(k2)-R_s-U_d with corresponding values as 0.8978 and 0.9259, 0.8050 and 0.9611, and 0.7974 and 0.8475. The combination e_{sB}-R_s-U_d performed best in terms of lowest SEE and WRMSD values, followed by e_a(k3)-R_s-U_d and e_a(k2)-R_s-U_d with respective values of 1.7064 mm/day and 2.1979 mm/day; 2.2039 mm/day and 2.5556 mm/day; and 2.2658 mm/day and 2.5912 mm/day. The WRMSD followed same pattern as observed in case of SEE as e_{sB}-R_s-U_d produced lowest value, followed by combinations e_a(k3)-R_s-U_d and e_a(k2)-R_s-U_d. Highest error in terms of SEE and WRMSD values was obtained with e_a(k2)-e_{sB}-U_l as 4.8137 mm/day and 4.8137 mm/day, respectively while, remaining combinations showed intermediate results. The ranking of combinations **(Table 1)** shows that e_{sB}-R_s-U_d topped the tally while, e_a(k3)-R_s-U_d and e_a(k2)-R_s-U_d ranked at second and third positions with corresponding GPI values of 0.9184, 0.6226, and 0.5828. The combination e_a(k2)-e_{sB}-U_l ranked last with GPI value of -0.6967.

Combinations of four derived individual meteorological parameters

The performance of combinations of four derived individual parameters against complete dataset FAO56-PM **(Table 1)** shows that combination e_a(k3)-e_{sB}-R_s-U_l produced highest value of D as 0.8191 while, e_a(k2)-e_{sB}-R_s-U_d extended its lowest value (0.7791). The highest value of R^2 was obtained with e_a(k3)-e_{sB}-R_s-U_d, followed by e_a(k2)-e_{sB}-R_s-U_d and e_a(k3)-e_{sB}-R_s-U_l with corresponding values as 0.8897, 0.8839, and 0.8816. The statistical indices related to errors (SEE, WRMSD) showed same trend as lowest values of both SEE and WRMSD were obtained with combination e_a(k3)-e_{sB}-R_s-U_l having values as 2.1255 mm/day and 2.5146 mm/day, respectively while, combination e_a(k2)-e_{sB}-R_s-U_d produced maximum value for these errors with corresponding values of 2.4378 mm/day and 2.7411 mm/day. The combination e_a(k3)-e_{sB}-R_s-U_l with highest GPI (0.4610) ranked first, followed by e_a(k3)-e_{sB} R_s-U_d and e_a(k2)-e_{sB}-R_s-U_l with GPI values of 0.1381 and -0.2854, respectively while, combination e_a(k2)-e_{sB}-R_s-U_d with lowest GPI value (-0.3979) performed worst.

Overall ranking of derived meteorological parameters & their combinations

The pertinent results related to overall ranking of all 33 cases **(Table 2)** shows that combination e_{sB}-R_s ranked first with highest GPI (1.0103), followed by e_{sB} and R_s with corresponding GPI values of 0.9748 and 0.8842. The last rank was assigned to combination e_a(k2)-U_l with lowest GPI value of -0.7834.

Effect of derived individual meteorological parameters & their combinations on FAO56-PM estimates

The FAO56-PM model uses several meteorological parameters, and in case of non-availability of one or more of them, ET_0 estimates are greatly influenced. On the basis of obtained results, effect of derived values of solar radiation, relative humidity, and wind speed on ET_0 estimates for arid Jodhpur district of Rajasthan is summarized as:

i. Solar radiation: The missing solar radiation data derived from measured minimum and maximum air temperature data showed minimum effect on FAO56-PM model estimates. Missing R_s data in combination with other missing parameters also showed less errors and good correlation with FAO56-PM estimates. Thus, it can be inferred that even with non-availability of solar radiation data, FAO56-PM model at arid regions can be efficiently applied to get accurate results using observed values of minimum and maximum air temperature.

ii. Relative humidity: In absence of observed values of relative humidity, it was found that e_a(k3) produced much closer results to complete meteorological dataset FAO56-PM model estimates and thus, it is recommended to consider value of dew point temperature (T_{dew}) 3°C lesser than minimum air temperature (T_{min}) to obtain at par FAO56-PM model ET_0 values.

iii. Saturation vapour pressure: With saturation vapour pressure estimated using mean air temperature data (e_{sB}), FAO56-PM model yielded almost identical results in comparison to those obtained with complete meteorological dataset.

iv. Wind speed: The use of long-term average wind speed value (U_l) in place of default wind speed (U_d) extended relatively good results and similar behaviour was obtained when U_l values were used in combination with other missing meteorological parameters.

Table 2 : Normalized value of statistical indices and overall ranking of individual derived meteorological parameters & their combinations

S. No.	Derived parameter(s)	Statistical indices				GPI	Rank
		D	R^2	SEE	WRMSD		
	Individual derived meteorological parameters						
1	R_s	0.9887	0.9989	0.0783	0.0590	0.8842	3
2	$e_a(k2)$	0.4419	0.9589	0.6988	0.5728	0.2568	10
3	$e_a(k3)$	0.5191	0.9756	0.6359	0.5223	0.3097	6
4	e_{sB}	0.9962	1.0000	0.0289	0.0116	0.9748	2
5	U_l	0.1410	0.2180	0.6072	0.6706	-0.1894	24
6	U_d	0.0544	0.3969	0.7172	0.8139	-0.1772	23
	Combinations of two derived individual meteorological parameters						
1	$e_a(k2)$-R_s	0.7038	0.8468	0.4669	0.4214	0.2662	7
2	$e_a(k3)$-R_s	0.7667	0.8855	0.4099	0.3738	0.3464	4
3	e_{sB}-R_s	1.0000	0.9989	0.0000	0.0000	1.0103	1
4	U_l-R_s	0.4079	0.4060	0.5510	0.5827	-0.1242	21
5	U_d-R_s	0.3212	0.5496	0.5852	0.6766	-0.0220	19
6	$e_a(k2)$-e_{sB}	0.3537	0.9802	0.7849	0.6458	0.2072	14
7	$e_a(k3)$-e_{sB}	0.4191	0.9891	0.7223	0.5959	0.2632	8
8	$e_a(k2)$-U_l	0.0083	0.0000	0.8757	0.9107	-0.7834	33
9	$e_a(k3)$-U_l	0.0185	0.0717	0.8394	0.8861	-0.6608	31
10	e_{sB}-U_l	0.2037	0.4579	0.5861	0.6817	-0.0022	18
11	$e_a(k2)$-U_d	0.0000	0.3274	1.0000	1.0000	-0.6612	32
12	$e_a(k3)$-U_d	0.0108	0.3654	0.9729	0.9844	-0.5914	30
13	e_{sB}-U_d	0.1031	0.5769	0.7381	0.8348	-0.0876	20
	Combinations of three derived individual meteorological parameters						
1	$e_a(k2)$-R_s-U_l	0.2481	0.1711	0.6631	0.7340	-0.4626	28
2	$e_a(k3)$-R_s-U_l	0.2741	0.2147	0.6386	0.7155	-0.4022	26
3	e_{sB}-R_s-U_l	0.5105	0.5996	0.5001	0.5585	0.0418	17
4	$e_a(k2)$-R_s-U_d	0.5461	0.6466	0.4478	0.4990	0.1651	16
5	$e_a(k3)$-R_s-U_d	0.5633	0.6644	0.4338	0.4914	0.1873	15
6	e_{sB}-R_s-U_d	0.7726	0.8384	0.3212	0.4150	0.3410	5
7	$e_a(k2)$-e_{sB}-U_l	0.0449	0.4280	0.9265	0.9739	-0.5059	29
8	$e_a(k3)$-e_{sB}-U_l	0.0611	0.4726	0.8870	0.9465	-0.4107	27
9	$e_a(k2)$-e_{sB}-U_d	0.0893	0.4668	0.7682	0.8210	-0.2003	25
10	$e_a(k3)$-e_{sB}-U_d	0.1060	0.5070	0.7437	0.8056	-0.1369	22
	Combinations of four derived individual meteorological parameters						
1	$e_a(k2)$-e_{sB}-R_s-U_l	0.5685	0.7219	0.4365	0.4947	0.2336	13
2	$e_a(k3)$-e_{sB}-R_s-U_l	0.5951	0.7401	0.4160	0.4827	0.2577	9
3	$e_a(k2)$-e_{sB}-R_s-U_d	0.5048	0.7452	0.4867	0.5311	0.2340	12
4	$e_a(k3)$-e_{sB}-R_s-U_d	0.5245	0.7580	0.4704	0.5230	0.2516	11

Where, R_s = solar radiation (MJ/m^2/day), $e_a(k2)$ = actual vapour pressure (kPa) estimated by taking dew point temperature 2° less than minimum temperature, $e_a(k3)$ = actual vapour pressure (kPa) estimated by taking dew point temperature 3° less than minimum temperature, e_{sB} = saturation vapour pressure (kPa) estimated by using mean temperature, U_l = long-term average wind speed (m/sec) of study area, U_d = default wind speed (m/sec), D = agreement index, R^2 = coefficient of determination, SEE = standard error of estimate, WRMSD = weighted root mean square difference.

Conclusion

Present study on comparative performance of FAO56-PM ET_0 estimates obtained with derived individual meteorological parameters and their combinations against complete dataset using statistical indices and ranking based on summative form of GPI revealed that the saturation vapour pressure computed using mean air temperature (e_{sB}) has least influence on FAO56-PM model estimates and it can be used successfully with availability of mean air temperature data alone. Similarly, among different combinations of two, three and four derived individual parameters, e_{sB}-R_s, e_{sB}-R_s-U_d and $e_a(k3)$-e_{sB}-R_s-U_l combinations showed best performance. However, to get ET_0 values at par with standard FAO56-PM model, solar radiation was found the most important meteorological parameter, followed by relative humidity and wind speed. The study further revealed that in absence of reliable relative humidity data, it will be appropriate to use dew point temperature 3°C lesser than minimum air temperature to compute actual vapour pressure. Likewise, the effect of unavailability of solar radiation data was found least on performance of FAO56-PM model which can be accurately estimated by maximum and minimum air temperature. From the study, it was also found that in absence of wind speed data, long-term average wind speed of study area can be used effectively. In nutshell, it can be concluded that air temperature (minimum and maximum and/or mean) and long-term average wind speed data are the minimal meteorological data required for estimating ET_0 values with FAO56-PM model at arid regions.

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