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INVESTIGATION ON THE VALIANTZAS' EVAPOTRANSPIRATION MODELS FOR PENINSULAR MALAYSIA

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Abstract: The search for an accurate evapotranspiration (ET) continues when the world has responsibility to cope with the water scarcity issue, population outgrown and uncertain change of weather. Measuring actual evapotranspiration (ET_a) can be tedious and requires a lot of time and cost. Therefore, numbersof empirical ETmodels have been developed to overcome this problem. The Valiantzas' modelsare quite familiar to the hydrologist community as it has been developed based on Penman evaporation equation. This paper presents the evaluation on the selected six Valiantzas' models by comparing to Food and Agricultural Organization Penman-Montieth (FAO-PM) empirical model in estimating ET in the Peninsular Malaysia. Seventeen meteorological stations around Peninsular Malaysia with data gathered from 1987 till 2003 were tested. The performance for each model was evaluated by root mean square error (RMSE), coefficient of determination (R^2), percentage error (PE) and mean bias error (MBE). All the six models showed good agreement to FAO-PM with R^2> 0.90. The PETval2 model which gave R^2 of 0.97 was the best performer with the lowest RMSE, PE and MBE of 0.26, 5.5% and 0.14,respectively. The good and sensible performance on the ET estimation displayed by Valiantzas' model may promise an accurate method for calculation on the water management for irrigation and catchment studies.

Keywords: Potential evapotranspiration, empirical model, comparison, tropical climate, Peninsular Malaysia

INTRODUCTION

The importance of evapotranspiration (ET) in hydrological cycle is undeniable. With an accurate estimation of ET a well balance water resources system can be obtained. The increasing trend on the hydrological and climatology research studies indicate that the world is striving in coping with global warming and climate change issues. Climate change is expected to alter ET in complex ways, notably by increasing the evaporation demand of the atmosphere, influencing the characteristics of the precipitation and changing the vegetation (Turner *et al*., 2017). The understanding on how the of potential evapotranspiration (ET_p) in managing water resources for domestic, agricultural and industrial uses while adapting to the climate change alteration is really important. The effect of climate change may vary which depending on the climate region. An increasing of temperature does not always cause ET to increase. Moonen *et al.* (2002) showed parallel trend of maximum temperature and ET. On the other hand, (Chattopadhyay & Hulme, 1997; Lofgren, Hunter, & Wilbarger, 2011) revealed that with the increasing of temperature, ET trends tend to decrease.

Although actual evapotranspiration (ET_a)gives maximum precision of ET(Abdullah & Malek, 2016; Benli *et al*., 2006; Cruz-Blanco *et al.*, 2014; Djaman *et al*., 2016; Shiri *et al*., 2013), this method is known for its complexity. Number of methods have been developed for estimating ET such as bowen ratio energy balance system (Malek & Bingham, 1993; Spittlehouse & Black, 1980; Todd *et al*., 2000), eddy covariance flux partitioning (Amazirh *et al*., 2017; Anderson *et al*., 2017; Wang & Wang, 2017), empirical models (Allen *et al*., 1998; Irmak *et al*., 2003; Makkink, 1957; Penman, 1948; Thornthwaite, 1948; Valiantzas, 2013a; Xu & Singh, 2000), Extreme Learning Machines (Abdullah *et al*., 2015; Feng *et al*., 2016; Feng *et al.*, 2017; Gocic *et al.*, 2016; Taormina & Chau, 2015; Torres *et al*., 2011) and artificial neural network (Adamala *et al*., 2014; Antonopoulos & Antonopoulos, 2017; Falamarzi *et al.*, 2014; Kumar *et al*, 2002; Wandera *et al*., 2017; Yassin *et al.*, 2016). Every method has its own pros and cons and yet empirical model method seems to be the easiest way in computing ET_p since it only requires meteorological data. Researchers have agreed that FAO-PM is the best empirical model to compute ET but it is also agreeable that this model is data demanding and not applicable at certain región (Ahooghalandari *et al.*, 2016; Almorox *et al.*, 2015; Tabari *et al.*, 2013; Tomas-Burguera *et al.*, 2017; Yeh, 2017). With that many empirical models been developed that are more site specific and their data inputs are based on the available data of that region. The outcome of these models may differ which depends on the climate regions that it needs rigorous local calibration in order to use it (Paparrizos *et al.*, 2016). Foroud *et al.* (1989) found that wind speed plays the most important factor in estimating ET in the southern Alberta while Vicente-Serrano *et al.* (2014) claimed that ET has strong sensitivity to relative humidity along the whole year. A study by Gong *et al.* (2006) in Changjiang (Yangtze River) basin and Zuo *et al.* (2012) in Wei River basin found that shortwave radiation and relative humidity showed a significant effect on ET. These two studies proved that even for the same state, the influential variable on ET can be different. A sensitivity analysis by Ahmad *et al*. (2017) on meteorological data from 17 stations around Peninsular Malaysia revealed that radiation and temperature have significant effect on ET whereas relative humidity is the least influential variable. In fact according to Samani (2000), temperature and solar radiation are the most important parameter in estimating ET.

The most popular empirical model is FAO-PM where it gives prediction close to ET_a and yet the model is data-driven which is not applicable in most of the region. One of the well-known model after FAO-PM model is Valiantzas' model. It has modified the Penman's radiation-aerodynamic combination equation by eliminating the wind speed data which is rarely available and out of question on its precision (Valiantzas, 2013b). The improved Penman's equation was then derived to estimate reference evapotranspiration that are made to account for the impact of humidity on the aerodynamics as shown in **Eqs (1)** and **(2)**. It has been recognized as the accessible model for calibration purposes over FAO-PM (Valipour, 2015).

$$E_{rad} \approx 0.051(1-\alpha)R_s\sqrt{T+9.5} - 2.4\left(\frac{R_s}{R_a}\right)^2 - \frac{0.048}{2}(T+20)\left(1-\frac{RH}{100}\right) \tag{1}$$

$$E_{aero} \approx 0.048(T+20)\left(1-\frac{RH}{100}\right)f_u \tag{2}$$

where T is mean temperature (°C), α is reflection coefficient or albedo with typical value for a grass cover is 0.23, R_a is extra-terrestrial radiation (MJ m^{-2} d^{-1}), RH is relative humidity (%) and ($f_u = 1+0.54u$) as the original Penman's formula includes wind speed. To make sure that this model can be used at both low and high relative humidity regions, W_{aero} has been introduced as calibrated coefficient for RH higher than 65% and lower or equal to 65%.

This paper presents the investigation on the selected six Valiantzas' empirical models performance in estimating ET in Peninsular Malaysia and identifying the best performing estimation model.

MATERIALS AND METHODS

The investigation was carried out on the selected six Valiantzas' empirical models to assess the performance on the ET estimation. Then the best model would be

Table 1. Information on the meteorological stations

No.	ID	Station	Latitude (N)	Longitude (E)	Mean Sea Level (MSL) (m)
			6° 12'	100° 44'	4.0
			3° 58'	102° 21'	59.5
3	48601	Bayan Lepas (BL)	5° 18'	100° 16'	2.8
4	48632	Cameron Highlands (CH)	4° 28'	101° 22'	1545.0
5	48604	Chuping (Chu)	6° 29'	100° 16'	21.7
6	48672	Kluang (Klu)	2° 01'	103° 19'	88.1
7	48615	Kota Bharu (KB)	6° 10'	102° 17'	4.6
8	47616	Kuala Krai (KKrai)	5° 32'	102° 12'	68.3
9	48618	Kuala Terengganu Airport (KT)	5° 23'	103° 06'	5.2
10	48657	Kuantan (Ktn)	3° 47'	103° 13'	15.3
11	48665	Melaka (Mlk)	2° 16'	102° 15'	8.5
12	48674	Mersing (Ms)	2° 27'	103° 50'	43.6
13	48649	MuadzamSyah (Mdz)	3° 03'	103° 05'	33.3
14	48679	Senai (Sn)	1° 38'	103° 40'	37.8
15	48620	Sitiawan (Stwn)	4° 13'	100° 42'	7.0
16	48647	Subang (Sbg)	3° 07'	101° 33'	16.5
17	48653	Temerloh (TM)	3° 28'	102° 23'	39.1

identified based on the statistical characteristics. The FAO-PM model was chosen as the benchmark model for the performance assessment. The models were tested using the recorded meteorological data for 17 stations in Peninsular Malaysia which were obtained from Malaysia Meteorological Department (MMD) from year 1987 to 2003.The details of the stations are presented in **Table 1**.

The available meteorological data from all stations comprised of the maximum (T_{max}), mínimum (T_{min}) and average (T_{avg}) temperature, solar radiation (R_s), wind speed (u) and relative humidity (RH). These data were the input parameters for the ET models. The range of value for parameters of solar radiation, maximum temperature, minimum temperature, average temperature, relative humidity and wind speed used in this study were 1.49to30.46MJ m^{-2} day^{-1}, 18.1°to38.4°C, 12.7° to 27.7°C, 16.1° to 31.6°C, 61.8% to 99.9% and 0.07 to 1.65 ms^{-1}, respectively. The meteorological data for the studied stations are as shown in **Table 2**.

Although there were more than 50 empirical models available in estimating ET_p, only 6 prominent Valiantzas' models were selected based on its input variables can easily obtained from MMD. The equations of the 6 Valiantzas' models and FAO-PM model are as described in **Table 3**. The models' input parameters are also shown on the right column of the table. It was assumed that the most ideal model was expected from the model that required fewer parameters and capable to yield closest agreement to FAO-PM model result.

In which T_{max} is maximum temperature (°C), T_{min} is minimum temperature (°C), T_{avg} is average temperature (°C), RH is relative humidity (%), u is wind speed (ms^{-1}), R_s is solar radiation (MJ m^{-2} day^{-1}), R_a is extraterrestrial radiation (MJ m^{-2} day^{-1}), ϕ is the latitude (rad) and z is elevation of the site (m).

The performance of each Valiantzas' model against the FAO-PM model (as a benchmark model) is evaluated based on root mean square (RMSE), coefficient of determination (R^2), percentage error (PE) and mean bias error (MBE) which are defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (3)$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}(P_i - \overline{P})(O_i - \overline{O})^2\right]}{\sum_{i=1}^{n}(P_i - \overline{P})^2 \sum_{i=1}^{n}(O_i - \overline{O})^2} \quad (4)$$

$$PE = \left|\frac{\overline{P} - \overline{O}}{\overline{O}}\right| \times 100\% \quad (5)$$

$$MBE = \frac{\sum_{i=1}^{n}(P_i - O_i)}{n} \quad (6)$$

where P_i and O_i are predicted and observed values respectively, $\bar{P}$ and $\bar{O}$ are the mean value of P_i and O_i, and n is the total number of data. The result of Valiantzas' models was assumed as predicted value and the result of FAO-PM method was assumed as the observed value.

Table 2. Statistical characteristics of meteorological data

	T_{max} (°C)	T_{min} (°C)	T_{avg} (°C)	RH (%)	u (ms^{-1})	R_s ($MJ\ m^{-2}\ day^{-1}$)
			AS			
Min	28.2	19.6	25.2	63.4	1.65	6.10
Max	36.7	26.4	31.5	98.9	11.59	30.46
Mean	32.6	23.7	28.1	82.2	6.51	18.32
Std. Dev	1.70	1.00	0.98	6.41	1.79	4.33
			BE			
Min	27.4	18.9	24.5	75.4	0.22	6.21
Max	36.8	25.2	31.0	99.4	9.65	27.03
Mean	32.6	22.8	27.7	86.5	4.97	17.48
Std. Dev	1.71	0.92	1.04	4.03	1.69	4.07
			BL			
Min	28.4	21.8	25.4	61.8	0.15	5.29
Max	34.5	27.7	30.5	95.2	2.47	28.58
Mean	31.5	24.4	28.0	80.8	1.26	17.82
Std. Dev	1.16	0.96	0.89	5.96	0.42	4.48
			CH			
Min	18.1	12.7	16.1	78.9	0.07	1.49
Max	27.0	17.4	21.9	99.9	3.44	27.96
Mean	22.5	15.4	19.0	91.1	1.40	14.14
Std. Dev	1.59	0.78	0.93	4.33	0.74	4.56
			CHU			
Min	28.4	21.6	25.4	65.1	0.07	6.36
Max	37.1	25.9	31.4	98.0	2.69	27.65
Mean	32.8	23.7	28.3	82.6	1.09	18.37
Std. Dev	1.66	0.80	0.99	6.45	0.60	3.74
			KB			
Min	26.5	21.1	23.9	70.4	0.15	4.43
Max	36.4	26.7	30.9	92.8	3.14	28.04
Mean	31.5	23.9	27.7	81.5	1.59	18.43
Std. Dev	1.66	0.97	1.08	3.98	0.51	4.62
			KKRAI			
Min	27.2	20.3	23.9	73.7	0.07	5.26
Max	38.4	25.0	31.6	99.1	1.05	29.63
Mean	32.8	22.6	27.7	86.4	0.46	17.38
Std. Dev	1.99	0.86	1.15	4.62	0.22	4.13
			KLU			
Min	27.5	21.0	24.7	72.9	0.07	4.25
Max	36.0	25.3	30.6	100.0	2.09	25.90
Mean	31.9	23.1	27.5	86.5	0.79	15.97
Std. Dev	1.55	0.76	0.95	4.90	0.44	4.11
			KT			
Min	27.2	20.7	24.6	72.3	0.07	3.35
Max	35.8	26.4	31.0	93.9	2.99	30.28
Mean	31.6	23.8	27.7	83.0	1.49	17.79
Std. Dev	1.61	0.96	1.02	3.94	0.53	5.31
			KTN			
Min	26.1	19.5	23.7	72.7	0.07	2.63
Max	36.7	26.6	31.0	98.2	3.07	27.19
Mean	32.0	23.3	27.6	84.4	1.49	16.39
Std. Dev	1.85	0.98	1.17	4.41	0.58	4.49
			MDZ			
Min	27.3	19.7	24.4	74.0	1.42	3.27
Max	37.3	25.0	31.0	98.3	10.92	26.11
Mean	32.4	22.8	27.6	85.7	6.15	16.36
Std. Dev	1.87	0.82	1.03	4.22	1.70	4.25

Table 3. Statistical characteristics of meteorological data (to be continue)

				MLK		
Min	28.9	21.2	25.2	70.2	0.07	5.35
Max	35.6	26.1	30.8	95.2	2.77	28.62
Mean	32.2	23.6	27.9	82.7	1.15	17.22
Std. Dev	1.30	0.85	0.87	4.80	0.52	4.20
				MS		
Min	26.4	20.9	23.9	75.3	0.60	2.20
Max	35.0	25.6	30.0	98.4	3.66	29.91
Mean	30.9	23.3	27.1	86.7	2.05	17.02
Std. Dev	1.67	0.91	0.92	4.39	0.58	5.10
				SBG		
Min	29.1	21.2	25.8	65.1	0.07	4.89
Max	36.2	26.7	31.2	94.7	2.09	26.45
Mean	32.8	23.9	28.3	80.1	1.11	15.80
Std. Dev	1.33	0.93	0.89	5.20	0.38	3.88
				SN		
Min	27.7	20.2	24.6	72.6	0.07	2.47
Max	35.9	24.8	30.3	99.6	2.17	28.44
Mean	32.1	22.8	27.5	86.1	0.98	15.30
Std. Dev	1.48	0.75	0.85	4.67	0.43	4.55
				STWN		
Min	29.3	20.1	25.4	74.8	0.07	6.16
Max	35.2	25.6	30.3	95.5	1.80	27.81
Mean	32.3	23.3	27.8	84.6	0.89	17.40
Std. Dev	1.15	0.84	0.77	3.63	0.32	3.89
				TM		
Min	27.1	19.7	24.8	71.8	0.97	4.13
Max	37.5	25.3	31.4	98.4	11.14	27.86
Mean	33.0	23.0	28.0	84.3	5.70	17.00
Std. Dev	1.75	0.86	1.07	4.60	1.92	4.04

RESULTS AND DISCUSSION

Results of the ET estimation based on the Valiantzas' were assessed based on minimum errors and the FAO-PM was decided as the benchmark. The model ranking was identified and **Fig. 1** plots the ranking of six Valiantzas'models based on their performance in ET estimation. Summary of model performance is tabulated in **Table 4**. It is obvious that PETval2 consistently gives a sensible performance when tested at 12 out of 17 stations followed by PETval4, PETval6, PETval3, and PETval5. The error values indicated in **Table 4** confirm that the difference in performance among these five models is not large. The PETval1 clearly displays a poor performance amongst Valianstzas' models.

It appeared that all the Valiantzas' models overestimate ET_p. The PETval1 has overestimated by 0.58 while others by in the range of 0.14 to 0.2.The PETval1 model took T_{min} into consideration and this was possibly the cause of over estimation of ET_p as Malaysia minimum temperature is not the prominent paremeter affecting ET. On the other hand the other five Valiantzas' models disregarded the T_{min} variable in the ET_p estimation. The PETval2 shared the similar values of MBE and R^2 as PETval4. Since the PE and RMSE for PETval2 was much lower than PETval4, then PETval2 was chosen as the best model. The PETval1 yielded a poor performance when compared to the other models where the RMSE was 0.68, PE was 16.4 and MBE was 0.58. The other models are scattered between rank 1 to rank 6. It is not unusual as the performance of each model varies depending on the area topography. Though it is under the same region.

Fig. 2(a) to **2(d)** illustrate the comparison of mean daily ET_p for group of stations based on their range of elevations. **Fig. 2(a)** represents stations that are within the range 4 MSL to 10 MSL, **Fig. 2(b)** varies between 15 MSL to 22 MSL, **Fig. 2(c)** from 39 MSL to 44 MSL and **Fig. 2(d)** between 59 MSL to 1545 MSL. Mostly the ET_p values of all methods were above 4 mm day^{-1} for elevation of4 MSL to 10 MSL. The results of mean daily PET were in the range of 3 mm day^{-1}to 5 mm day^{-1} for **Fig. 2(a)** to **Fig. 2(c)** for all estimation methods that indicated the elevation between 4 MSL to 60 MSL gave

Table 4. Description on the ET models used in the study

Model	Equation	Parameter
FAO Penman-Montieth (FAO-PM)	$FAO-PM=\dfrac{0.408(R_n-G)+\gamma\dfrac{900}{T_a+273}u_2(e_s-e_a)}{\Delta+\gamma(1+0.34u_2)}$	T_{max}, T_{min}, T_{avg}, RH, u, R_s, ϕ, z
Valiantzas1 (PETval1)	$ET=0.0393R_s\sqrt{\lvert T_{avg}+9.5\rvert}-0.19R_s^{0.6}\varphi^{0.15}+0.0061(T_{avg}+20)(1.12T_{avg}-T_{min}-2)^{0.7}$	T_{min}, T_{avg}, u, R_s, ϕ
Valiantzas2 (PETval2)	$ET=0.0393R_s\sqrt{\lvert T_{avg}+9.5\rvert}-2.4(T_{avg}+20)\left(1-\frac{RH}{100}\right)+W_{aero}0.066(T_{avg}+20)\left(1-\frac{RH}{100}\right)u^{0.6}$ $W_{aero}=0.78\ \text{when}RH>65\%$; $W_{aero}=1.067\ \text{when}RH\leq 65\%$	T_{avg}, RH, u, R_s
Valiantzas3 (PETval3)	$ET=0.0393R_s\sqrt{\lvert T_{avg}+9.5\rvert}-0.19R_s^{0.6}\varphi^{0.15}+0.048(T_{avg}+20)\left(1-\frac{RH}{100}\right)u^{0.7}$	T_{avg}, RH, u, R_s, ϕ
Valiantzas4 (PETval4)	$ET=0.0393R_s\sqrt{\lvert T_{avg}+9.5\rvert}-2.4\left(\frac{R_s}{R_a}\right)^2-0.024(T_{avg}+20)\left(1-\frac{RH}{100}\right)+0.1W_{aero}(T_{avg}+20)\left(1-\frac{RH}{100}\right)$	T_{avg}, RH, R_s, R_a
Valiantzas5 (PETval5)	$ET=0.0393R_s\sqrt{\lvert T_{avg}+9.5\rvert}-0.19R_s^{0.6}\varphi^{0.15}+0.078(T_{avg}+20)\left(1-\frac{RH}{100}\right)$	T_{avg}, RH, R_s, ϕ
Valiantzas6 (PETval6)	$ET=0.051(1-\alpha)R_s\sqrt{T_{avg}+9.5}-2.4\left(\frac{R_s}{R_a}\right)^2+0.048(T_{avg}+20)\left(1-\frac{RH}{100}\right)(0.5+0.536u)+0.00012z$	T_{avg}, RH, R_s, R_a, u, z $\alpha = 0.25$

Table 5. Evaluation on the statistical performance for each Valianstzas' model

	PETval1	PETval2	PETval3	PETval4	PETval5	PETval6
RMSE	0.68	0.26	0.46	0.29	0.44	0.37
R^2	0.98	0.97	0.96	0.97	0.97	0.95
PE	16.4	5.5	9.8	7.0	9.8	7.6
MBE	0.58	0.14	0.21	0.14	0.19	0.26

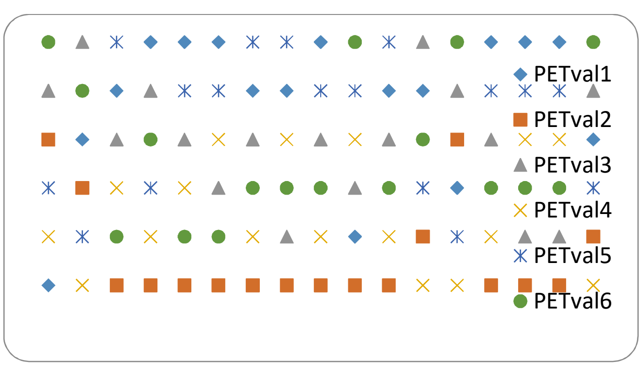

Fig. 1 Performance ranking of ET models

almost similar pattern of ET_p. The highest elevation station CH with 1545 MSL yielded the lowest ET_p estimation followed by second highest elevation station KLU with 88.1 MSL, where both stations consistently yielded similar results for all methods of estimation. The elevation higher than 1000 MSL tends to lower the estimation but the results of all methods are still similar.

Erro! Fonte de referência não encontrada. illustrates the mean daily ET_p for all stations according to corresponding month that predicted by the six ET estimation models. In average, it can be seen that all the Valiantzas' models have overestimated ET_p. PETval1 model gave the highest error in overestimation of the ET_p while PETval4 was the lowest error in overestimation and followed by PETval2 and others. Results in **Fig. 3** suggest that the models PET2val2, PETval3, PETval4, PETval5 and PETval6 are reliable to be adopted as the models for ET_p estimation in Peninsular Malaysia. The overestimation or underestimation value is simply illustrated the diversion of results from the observed values. In agreement to previous study by Sentelhas *et al.* (2010) the results obtained have overestimated when the $R_s$was lower than 20 MJ m^{-2} day^{-1}.

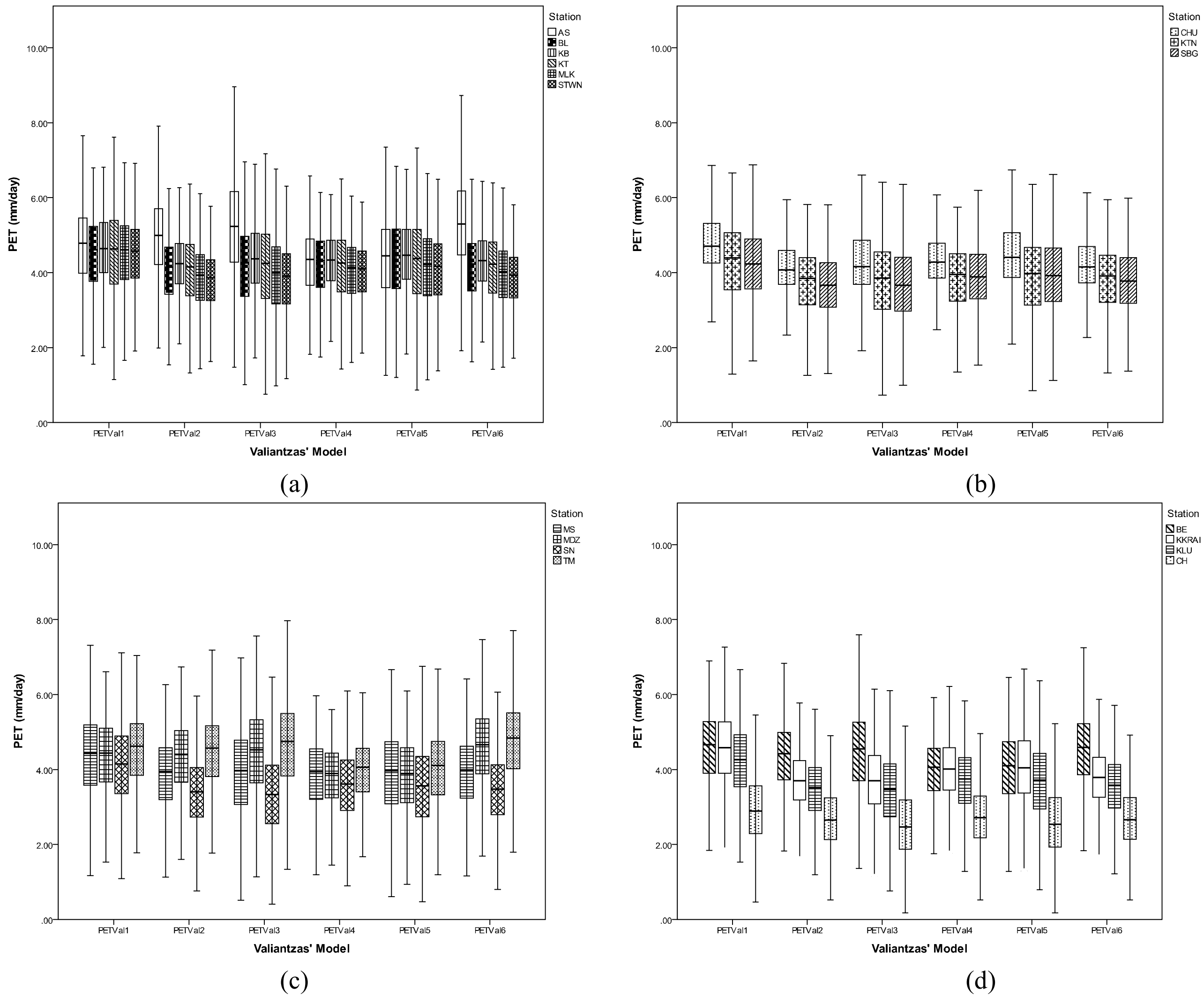

Fig. 2 Comparison of mean daily ET_p based on different groups of station

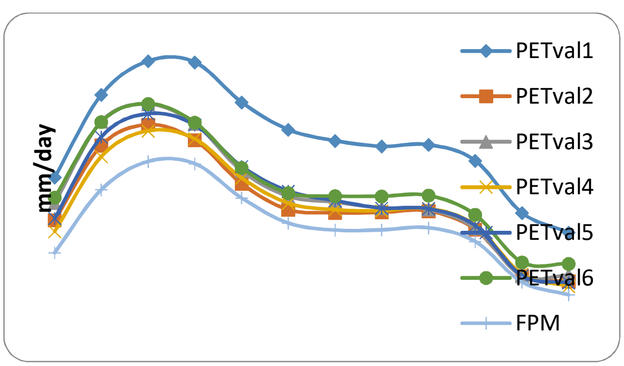

Fig. 3 Mean Daily ET_p for the Valiantzas' models

CONCLUSION

In this study, six Valiantzas' models were applied to estimate the $ET_p$with 14-year dataset (1987 to 2003) for selected 17 meteorological stations in Peninsular Malaysia by deduced their results with FAO-PM ET_p estimation. The most reliable Valiantzas' models after FAO-PM was discussed in this paper. All Valiantzas' methods have core input variables of T_{mean}, R_s and RH. In general the Valiantzas' models performed well under tropical climate wherePETval2model with T_{mean}, R_s, u and RH is the best candidate followed by PETval4 (T_{mean}, R_s, R_a, RH). The accuracy of the results was influenced by the variables in the model. Although PETval3 (T_{mean}, R_s, u, RH, ϕ) has similar input variables as PETval2, the coefficient for relative humidity in PETval2 may have induced the discrepancy in the results. Since Peninsular Malaysia does not has distinct topographical variation, the altitude becomes less influential variable and can be neglected in analysis. Hence, the finding suggests theValiantzas' model can be calibrated by using only the radiation and temperature variables to produce a better ET_p estimation. The results show that it is possible to use any Valiantzas' model for ET_p estimation under humid tropic climate as the difference in performance is not so significant. However in the authors' point of view, it is better to use an authentic model for a region with uncritical elevation and topography factors.

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