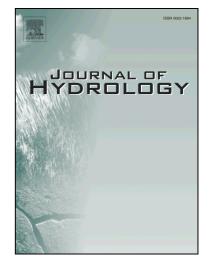
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Evaluation of six potential evapotranspiration models for estimating crop potential and actual evapotranspiration in arid regions

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Abstract

Using potential evapotranspiration (PET) to estimate crop actual evapotranspiration (AET) is a critical approach in hydrological models. However, which PET model performs best and can be used to predict crop AET over the entire growth season in arid regions still remains unclear. The six frequently-used PET models, i.e. Blaney-Criddle (BC), Hargreaves (HA), Priestley-Taylor (PT), Dalton (DA), Penman (PE) and Shuttleworth (SW) models were considered and evaluated in the study. Five-year eddy covariance data over the maize field and vineyard in arid northwest China were used to examine the accuracy of PET models in estimating daily crop AET.

Results indicate that the PE, SW and PT models underestimated daily ET by less than 6% with RMSE lower than 35 W m⁻² during the four years, while the BC, HA and DA models under-predicted daily ET approximately by 10% with RMSE higher than 40 W m⁻². Compared to BC, HA and DA models, PE, SW and PT models were more reliable and accurate for estimating crop PET and AET in arid regions. Thus the PE, SW and PT models were recommended for predicting crop evapotranspiration in hydrological models in arid regions.

Key words: Actual evapotranspiration; Canopy conductance; Crop coefficient; Evapotranspiration; Penman model; Potential evapotranspiration

1. Introduction

The potential evapotranspiration (PET) can be defined as the rate at which evapotranspiration (ET) would occur from a large area completely and uniformly covered with growing vegetation which has access to unlimited water supply, and without advection or heating effects, while the actual ET (AET) is the actual evapotranspiration of the land surface (McVicar *et al.*, 2012; McMahon *et al.*, 2013). PET rather than AET is a common input for hydrological models, such as HYDRUS, SWAP, SWAT, MODFLOW-2000. PET provides the upper limit of land surface ET, while the estimation of AET in hydrological models is generally based on PET and crop coefficient (Douglas *et al.*, 2009). PET models can be grouped into four categories: (1) combination (Penman, 1948; Shuttleworth, 1993); (2) radiation (Priestley and Taylor, 1972); (3) temperature-based (Blaney and Criddle, 1950); (4) mass-transfer (Dalton, 1802; Xu and Singh, 2002). How to choose the appropriate PET model to estimate land AET is critical for determining the watershed ET.

Until recently, several cross comparisons between these PET models in estimating PET under different climate conditions and underlying surface types, have been conducted by scientists (see **Table 1**), such as McKenney and Rosenberg (1993), Xu and Singh (2002), Lu *et al.* (2005), Sumner and Jacobs (2005), Douglas *et al.* (2009), Donohue *et al.* (2010), Bormann (2011), Fisher *et al.* (2011) and Tabari *et al.* (2013). Most of these studies concluded that the fully-physically based combination models are most optimal, and the radiation-based PET models usually performed better than the temperature-based and mass transfer-based models. Additionally, many studies also suggested that the PET models should be recalibrated using the local data to improve accuracy, and model improvement was still required.

However, the PET is not identical to the reference crop water requirement (ET_0) . Many studies used the ET₀ estimated by FAO-56 PM model to evaluate the reliability of PET models, which is

not appropriate and should be corrected. These issue has been clarified in McMahon et al. (2012). A lot of studies took the Penman method as the standard method to evaluate the reliability of other PET methods for the lack of the measured AET data (see **Table 1**). The Penman model is an estimating method but not a measuring approach for PET. Thus these comparisons were not entirely reliable. Furthermore, the previous studies mainly focused on PET of open water, marsh, forest, grassland and etc., but paid little attention to agricultural crops in arid regions (**Table 1**). Thus which models can be used to estimate crop PET and AET in arid regions, is still uncertain and needed to be investigated.

In order to explore the question, we conducted a cross comparison between FAO-Blaney-Criddle (PET_{BC}), Hargreaves (PET_{HA}), Priestley-Taylor (PET_{PT}), Dalton (PET_{DA}), Penman (PET_{PE}) and Shuttleworth (PET_{SW}) models. The five-year eddy covariance AET data for maize and vineyard were used to examine the model performance, aiming to explore the optimum PET models for estimating crop AET in arid regions.

2. Models

2.1 BC model (FAO-Blaney-Criddle)

The BC method for estimating potential evapotranspiration can be expressed as (Blaney-Criddle, 1950; Xu and Singh, 2002):

$$PET = kp(0.46T_a + 8.13) \tag{1}$$

where *PET* is the potential evapotranspiration from a reference crop (W m⁻²), T_a the average daily air temperature (°C), *p* the percentage of total daytime hours for the used period (daily or monthly) out of total daytime hours of the year (365×12), *k* the monthly consumptive use coefficient, depending on vegetation type, location and season and for the growing season. The values of *k* were

calibrated by the measured data of maize in 2007 and that of vineyard in 2008, respectively.

2.2 HA model (Hargreaves)

The HA method for estimating potential evapotranspiration can be expressed as (Hargreaves and Samani, 1982; Xu and Singh, 2002):

$$PET = aR_s TD^{0.5}(T_a + 17.8)$$
⁽²⁾

where *a* is the parameter which should be calibrated by the measured data, R_s the solar radiation (W m⁻²), *TD* the difference between maximum and minimum daily temperature (°C).

2.3 PT model (Priestley-Taylor)

The PT approach for estimating evaporation from an extensive wet surface under conditions of minimum advection is described as (Priestley and Taylor, 1972):

$$PET = \alpha \frac{\Delta}{\Delta + \gamma} (R_n - G) \tag{3}$$

where *PET* is the potential evapotranspiration (W m⁻²), Δ the slope of the saturation water vapour pressure versus temperature curve (KPa K⁻¹), γ the psychrometric constant (KPa K⁻¹), R_n the net radiation (W m⁻²), *G* the soil heat flux (W m⁻²), α is an empirically determined dimensionless correction. In our study, the values of α were calibrated by the measured data of maize in 2007 and that of vineyard in 2008, respectively.

2.4 DA model (Dalton)

The classical DA equation for estimating free water evaporation can be described as (Dalton, 1802; Xu and Singh, 2002):

$$PET = 0.44(1+0.27U_2)(e_s - e_a) \tag{4}$$

where *PET* is the potential evapotranspiration (W m⁻²), U_2 the mean daily wind speed at 2 m (m s⁻¹),

 e_s the saturation vapor pressure (kPa), and e_a the actual vapor pressure (kPa).

2.5 PE model (Penman)

The PE equation for calculating PET can be expressed as (Penman, 1948):

$$PET = \frac{\Delta(R_n - G) + C_p \rho_a VPD / r_a}{\Delta + \gamma}$$
(5)

where *PET* is the potential evapotranspiration (W m⁻²), Δ the slope of the saturation water vapour pressure versus temperature curve (KPa K⁻¹), R_n the net radiation (W m⁻²), *G* the soil heat flux (W m⁻²), C_p the specific heat of dry air at constant pressure (J kg⁻¹ K⁻¹), ρ_a the air density (kg m⁻³), *VPD* the water vapor pressure deficit (KPa), γ the psychrometric constant (KPa K⁻¹), r_a the aerodynamic resistance (s m⁻¹). The aerodynamic resistance r_a can be calculated as (Paulson, 1970; Businger *et al.*, 1971; Massman, 1992):

$$r_{a} = \frac{\left[\ln(z/z_{0}) - \psi_{h}\right]\left[\ln(z/z_{0}) - \psi_{m}\right]}{k^{2}u}$$
(6)

where z is the reference height (m), z_0 the roughness length of the crop relative to momentum transfer (m), k the von Karman constant (0.41), ψ_h the stability correction function for heat and water transfer, ψ_m the stability correction function for momentum transfers. The stability correction functions are followed by the models of Paulson (1970) and Businger *et al.* (1971). *u* is the wind speed at the reference height (m s⁻¹). According to Monteith (1965), z_0 can be estimated as 0.13 h_c , where h_c is the mean canopy height (m).

2.6 SW model (Shuttleworth)

The SW method for calculating PET can be expressed as (Shuttleworth, 1993; Donohue *et al.*, 2010):

$$PET = \frac{\Delta}{\Delta + \gamma} (R_n - G) + \frac{\gamma}{\Delta + \gamma} 6.43(1 + 0.536U_2) VPD$$
(7)

where *PET* is the land potential evapotranspiration (W m⁻²), Δ the slope of the saturation water vapour pressure versus temperature curve (KPa K⁻¹), γ the psychrometric constant (KPa K⁻¹), R_n the net radiation (W m⁻²), *G* the soil heat flux (W m⁻²), U_2 the mean daily wind speed at 2 m (m s⁻¹) and *VPD* the saturation water vapor pressure deficit (kPa). The estimation of *PET* followed the procedure described in Chapter 4 in Handbook of Hydrology (Shuttleworth, 1993).

2.7 Evaluation of model performance

The performance of the models was based on a linear regression between estimated (E_i) and observed (O_i) values of λET . Furthermore, relative mean bias error (MBE), root mean square error (RMSE) and a paired T statistic analysis were included (Eberbach and Pala, 2005). These statistical parameters are described as follows (Poblete-Echeverri'a and Ortega-Farias, 2009):

$$MBE = \frac{1}{n} \sum_{i=1}^{n} (E_i - O_i) / \frac{1}{n} \sum_{i=1}^{n} O_i$$
(8)

$$RMSE = \{\frac{1}{n} \sum_{i=1}^{n} (\lambda ET_i - O_i)^2 \}^{1/2}$$
(9)

3. Materials and methods

3.1 Experimental site and description

The long-term and continuous experiments were conducted at Shiyanghe Experimental Station for Water-saving in Agriculture and Ecology of China Agricultural University, located in Wuwei City, Gansu Province of northwest China (N 37°52', E 102°50', elevation 1581 m) (McVicar and Korner, 2013). The experimental site is located in a typical continental temperate climate zone where mean annual temperature is 8 °C d⁻¹, annual accumulated temperature (>0 °C) 3550 °C, annual

precipitation 164 mm, mean annual pan evaporation approximate 2000 mm, the average annual duration of sunshine 3000 hours, and the average number of frost free days 150 d. These climate data ranged from 1950 to 2010. The groundwater table is 40-50 m below the ground surface. The soil is desert soil (Siltigic-Orthic Anthrosols) and soil texture is sandy loam, with a mean dry bulk density of 1.43 g cm⁻³ and volumetric soil water content at a field capacity of 0.29 cm³ cm⁻³ (Li *et al.*, 2013a, b; Li *et al.*, 2015).

Measurements in the maize field: Spring maize was planted with row spacing of 40 cm and plant spacing of 30 cm. The plant density was about 66,000 plants per hectare, and the total area was about 39 hectares. Crops were also extensively cultivated in the surrounding fields. The experimental field was irrigated with a total amount of 320mm, 420mm, 320mm, 350mm and 350mm in 2007, 2008, 2011, 2012 and 2013, respectively. Border irrigation was adopted to deliver water in the field. The precipitation was 153, 71, 220, 130 and 80 mm during the whole growing stage in the five years. The main root was located at depth of 0~60 cm.

An open-path eddy covariance (EC) system was installed in the northwest of the maize field. The sensors were 1.0 m above the maize canopy. Maize is the principal crop cultivated in the surrounding region, and its planting area is large enough to provide adequate fetch length for EC measurement. The EC system consisted of a 3-D sonic anemometer/thermometer (model CSAT3), a Krypton hygrometer (model KH20) and a temperature and humidity sensor (model HMP45C). Model CSAT3 and KH20 measured vertical fluctuations of wind, temperature and water vapour density at 0.1 s intervals, and temperature and humidity at 10 min intervals. Net radiation (R_n) was measured by a net radiometer (model NR-LITE, Kipp & Zonen, Delft, Netherlands) at a height of 1.5 m above the canopy. Two soil heat flux plates (model HFP01, Hukseflux, Netherlands) were used to measure soil heat flux. All the sensors were connected to a data logger (model CR5000,

Campbell Scientific Inc., USA), and the 10-min statistics were computed. The long-term and continuous measurements over the crop season were made from 2007~2008, and 2011~2013. The measurements of soil water content, leaf area index and other parameters have been introduced in detail in Li *et al.* (2013a, b).

Measurements in the vineyard: The long-term and continuous flux measurements were also conducted in a vineyard with a length of 1650 m and a width of 1400 m during 2008~2012. Vine trees (Vitis vinifera L. cv Merlot Noir) were cultivated in 1999 with row spacing of 270 cm and plant spacing of 100 cm. Height of trellis for grapevine was 1.5 m. The soil texture of the vineyard is sandy loam, with a mean dry bulk density of 1.47 g cm⁻³, porosity of 52%, field capacity ranged from 0.28~0.35 cm³ cm⁻³ for the 0-100 cm layers (Li *et al.*, 2015).

Another eddy covariance system (Campbell Scientific Inc., USA) was installed at 4.2 m above the ground at the northwest of the vineyard and adequate fetch can be met. Measurements were made continuously from May to October in every year. The net radiometer (model NR-LITE, Kipp & Zonen, Delft, Netherlands) was 4.5 m above the ground. Four soil heat flux plates (model HFP01, Hukseflux, Netherlands) were used to measure soil heat flux. Leaf area index was measured in 10 days interval by AM300 portable leaf area meter (ADC BioScientific Ltd., UK), respectively. Soil moisture was measured by the portable device (Diviner 2000, Sentek Pty Ltd., Australia). Fifteen PVC access tubes were evenly installed in the soil in the ditch, shaded and non shaded parts of the ridge, respectively. Furthermore, soil samples for 0-50 mm and 50-100 mm layers near each PVC access tube were taken using an auger to measure soil water content (Li *et al.*, 2015).

3.2 Eddy covariance data corrections

The strict procedures for correcting the eddy covariance measurements included: (1) 10-min interval for eddy flux computation (Twine *et al.*, 2000); (2) The signal asynchrony correction (Wolf

et al., 2008); (3) The oxygen-correction proposed by Tanner and Greene (1989); (4) Planar fit method for coordinate rotation (Finnigan *et al.*, 2003; Paw *et al.*, 2000); (5) Density correction according to the method of Webb *et al.* (1980); (6) Filling data gaps using the mean diurnal variation (MDV) method (Falge *et al.*, 2001; Li *et al.*, 2015).

In this study, sum of maize and vineyard ($\lambda ET + H$) accounted for about 85%~95% during the five years. For the daytime EC-based data, the measured energy budget components were forced to close using "Bowen-ratio closure" method proposed by Twine *et al.* (2000), assuming that Bowen-ratio is correctly measured by the EC system. In order to control the data quality, we only used the daytime eddy covariance data to validate the model (8:00~17:00), because the daytime eddy covariance data are more reliable than the data during the other time periods (Li *et al.*, 2015).

4. Results

4.1 Comparison of potential evapotranspiration using six PET models with the actual crop evapotranspiration

To reveal the relationship between potential evapotranspiration (PET) and crop actual evapotranspiration (AET) on the field scale, we use the five-year eddy covariance data to examine the correlation between maize AET and PET. The PET was estimated by six models simultaneously, such as the FAO-Blaney-Criddle (BC, PET_{BC}), Hargreaves (HA, PET_{HA}), Priestley-Taylor (PT, PET_{PT}), Dalton (DA, PET_{DA}), Penman (PE, PET_{PE}) and Shuttleworth (SW, PET_{SW}) models, in order to explore the optimal PET models.

<Figure **1** here please >

Fig. 1 shows the comparison of maize daytime PET_{BC} , PET_{HA} , PET_{PT} , PET_{DA} , PET_{PE} and PET_{SW} against the AET measured by eddy covariance (ET_{EC}) during the stage of maize LAI higher than 2 in 2007, 2008, 2011, 2012 and 2013. The figure indicates that the SW, PE and PT models

yielded the linear regression equations with high determination coefficient in all the five years (R^2 >0.70), while the BC, HA and DA models yielded low R^2 in all years (R^2 <0.70). Furthermore, the line slopes for SW and PE models were close to 1, while the values for HA and DA models deviated from 1 significantly. Thus it can be inferred that PET_{SW} , PET_{PE} and PET_{PT} showed the high and linear correlation with maize AET, while PET_{BC} , PET_{HA} and PET_{DA} deviated from maize AET remarkably.

<Figure 2 here please >

To identify the relationship between PET and AET at the field scale, we used another long-term data in a vineyard to examine the relationship. Similar to Fig.1, the vineyard PET using the six models was also compared to the AET using eddy covariance in 2008, 2009, 2010, 2011 and 2012 (**Fig. 2**). Results indicate that PET_{PT} , PET_{SW} , PET_{PE} and PET_{HA} showed a linear correlation with AET during all the five years (R^2 >0.40), while PET_{BC} and PET_{DA} deviated with AET significantly in all years (R^2 <0.20).

The above results indicate that the PET using SW, PE and PT models existed significantly linear and positive relationship with AET at the field scale, either over the maize felid or the vineyard. These results were in line with the previous studies (Roderick and Farquhar, 2002; Yang *et al.*, 2007; Szilagyi and Jozsa, 2009; Huntington *et al.*, 2011; Han *et al.*, 2014). In a latest paper of Han *et al.* (2014), they indicated that the correlation between actual and potential evaporation was mainly determined by the relative degree of variability in the radiation term and aerodynamic term of PET, and further affected by water availability. The correlation was always positive under conditions with high radiation ET variability and low aerodynamic ET variability. In our study, the crop AET was mainly driven by radiation and without water-stress, thus AET showed a significantly linear and positive relationship with PET.

4.2 Relationship between the ratio of AET to PET with canopy conductance

To parameterize the crop coefficient, which is the ratio of AET to PET, the study also investigated the response patterns of AET/PET to crop variable. Since canopy conductance can represent the crop development well, thus we analyzed the relationship between AET/PET and canopy conductance using the long-term data of maize and vineyard, respectively.

<Figure **3** here please >

Fig.3a shows that a parabola relationship existed between maize AET/PET using BC model and canopy conductance during all the years ($R^2 = 0.40$). However, the AET/PET estimated by HA model shows a weak parabola function with canopy conductance (**Fig.3b**, $R^2 = 0.10$). Different with BC and HA models, the AET/PET estimated by DA model existed a significantly linear function against canopy conductance in all years (**Fig.3d**, $R^2 = 0.80$). As for the PT, PE and SW models, AET/PET existed significantly hyperbolic function with canopy conductance during all the years (**Fig.3c, e** and **f**, $R^2 > 0.60$). Thus we can parameterize AET/PET using the function of canopy conductance.

<Figure 4 here please 2

The response patterns of vineyard AET/PET using the six PET models to canopy conductance during 2008-2012, are depicted in **Fig.4**. Similar to Fig.3, the AET/PET using BC and HA models showed a weak parabola function with canopy conductance (**Fig.4a**, **b**, $R^2 < 0.50$), while the AET/PET using DA method owned a significantly linear relationship with canopy conductance (**Fig.4d**, $R^2 = 0.90$), and that using PT, PE and SW models existed significantly hyperbolic relation relative to canopy conductance during all the years (**Fig.4c**, **e and f**, $R^2 > 0.60$).

The above results indicate that the crop coefficient using PT, PE and SW models all showed significantly hyperbolic relationship with canopy conductance in all the years, either for maize or

vineyard. These results agree well with McNaughton and Spriggs (1989), Steduto and Hsiao (1998b), and Suyker and Verma (2008). They revealed a similar relationship between AET/PET and canopy conductance by the modeling analysis. Thus AET/PET can be parameterized by canopy conductance for their close correlation. In the later section, the crop coefficient model parameterized by canopy conductance will be combined with PET models, in order to estimate crop AET.

4.3 Comparison of crop coefficient models combined with PET methods in estimating AET

In order to evaluate the performance of the crop coefficient models systematically, comparisons between models in calculating actual ET (AET) over the maize field and vineyard were also conducted. We used the measured data of maize in 2007 and that of vineyard in 2008 to calibrate crop coefficient (AET/PET) models, and used the data from the other four years to examine the model performance.

<Figure 5 and Table 2 here please >

Under the full canopy condition of maize, the SW method combined with the hyperbolic model of crop coefficient yielded accurate estimations with the eddy covariance measurements during the four years (**Fig.5f**). **Table 2** indicates that the model yielded a mean error less than 4% with high \mathbb{R}^2 ranged 0.66~0.96, low MBE over -4%~4% and RMSE over 29~36 W m⁻² during 2008~2013. For the whole data series, the method underestimated ET by 6% with a \mathbb{R}^2 of 0.81 and a RMSE of 31 W m⁻² for the four years. The paired T test indicates that the *P*-values for the four years were remarkably higher than 0.05, revealing that $\mathrm{ET}_{\mathrm{SW}}$ agreed well with $\mathrm{ET}_{\mathrm{EC}}$ (**Table 2**).

Similar to the SW model, the Penman model and Priestley-Taylor model with the hyperbolic model of crop coefficient also performed well during the dense canopy stage. The Penman estimations matched well with the eddy covariance measurements during the four years (**Fig.5e**).

The method under-predicted ET by less than 5% with R^2 ranged 0.84~0.95, low MBE over -2%~3% and RMSE over 27~36 W m⁻² during 2008~2013. For the entire years, the model averagely underestimated ET by 1% with a R^2 of 0.92, a MBE of 1% and a RMSE of 32 W m⁻² (**Table 2**). The PT model also produced accurate estimations during all the years (**Fig.5 c**). The approach yielded high R^2 , low MBE and RMSE for all the season (**Table 2**).

<Figure 6 here please >

For the other three methods, such as BC model, HA model and DA model, all methods yielded the RMSE higher than 45 W m^{-2} , especially for the HA and DA approaches (**Fig.6a**). These methods presented great errors in estimating actual ET under the full canopy stage.

The 4-year average MBE for the six PET methods was also compared in **Fig.6b**. Except for the BC and HA approaches, the other methods yielded MBE ranged from -3% to 3%. Especially the MBE for PT, PE and SW methods were close to zero, suggesting that the model results agreed well with the measured AET. Similar to **Fig.6a**, BC and HA models presented the largest MBE against other approaches. These results reveal that all the models can give accurate estimations under the dense canopy stage, except for BC, HA and DA methods.

The P-values determined by the paired T test were also depicted in **Fig.6c**. Results show that the PT, PE and SW approaches generated high P-values which were remarkably higher than the significant level value of 0.05. These indicate that the three models showed high accuracy compared with other models.

In order to examine the PET models combined with the crop coefficient models extensively, we used another 5-years eddy covariance data from 2008 to 2012 in a vineyard to evaluate the model precision. The data in 2008 was used to calibrate model parameters, and the other four-year data were adopted to test model performance.

<Figure 7, 8 and Table 3 here please >

Similar to the results of maize, the Shuttleworth model, the Penman model and Priestley-Taylor model with the hyperbolic model of crop coefficient also performed well during all the years (**Fig.7c, e and f**). The three approaches estimated AET with R^2 higher than 0.75, MBE less than 5% and RMSE less than 37 W m⁻² during 2009~2012 (**Fig.8, Table 3**). The P-values were higher than 0.01, which reveals the good agreement between the estimated ET and the measured value (**Table 3**). As for the BC and HA models, the methods yielded great errors with the higher RMSE and MBE relative to other methods. (**Fig.8, Table 3**).

The above results reveal that the SW, PE and PT models combined with the hyperbolic model of crop coefficient performed satisfactorily either over the maize field or the vineyard, while the BC and HA models yielded great errors in simulating maize and vineyard AET.

5. Discussion

5.1 Evaluation of PE, SW and PT models in estimating daily crop AET in arid regions

Results indicate that the Penman (PE) and Shuttleworth (SW) models performed superiorly against the other PET models in estimating daily crop AET in the arid regions (**Table 2** and **3**). The SW model is a modified version of Penman model after considering SI units (Donohue *et al.*, 2010). The PE and SW models, which consider the radiation and aerodynamic drive simultaneously, can produce more reliable estimation of AET in many cases. Thus the PE and SW models were taken as the most reliable approaches to calculate PET on the watershed scale (McKenney and Rosenberg. 1993; Oudin et al., 2005; Donohue *et al.*, 2010).

However, the PE and SW models are quart-meteorological-variables models whereas others approaches are only bi-meteorological-variables models and tri-meteorological-variables. These may limit the application of the methods due to data availability. Additionally, the precision of the

models to accurately estimate actual evapotranspiration is highly sensitive to the estimation of crop coefficient. How to estimate crop coefficient determines the model performance. The traditional single or double crop coefficient methods may not be appropriate for estimating the sparse vegetation AET (Zhao *et al.*, 2015), because it is difficult to quantify the variation of land process. Different with the traditional crop coefficient methods, our study proposed a dynamic crop coefficient equation based on the long-term measurement. The crop coefficient equation combined with PET model can simulate daily crop AET accurately in all the years. These provide new methods for estimating land AET by remote sensing.

Similar with PE and SW methods, the PT method also performed satisfactorily in predicting daily crop AET during all the years. The PT method is generally used to calculate ET over free water surface, and its estimation is approximate to the atmosphere evaporation demand. The high accuracy of the model is mainly attributed to the predominant contribution of radiation drive on land ET. Our results agreed well with Xu and Singh (2002), Douglas *et al.* (2009), Xystrakis and Matzarakis (2011), Tabari *et al.* (2013). These studies all indicate that the radiation-based PET models performed better than temperature-based and mass-transfer models (**Table 1**).

However, different with the previous studies, we found that setting PT coefficient as a constant was not reliable and we develop a dynamic PT coefficient equation using the long-term measured data, which can represent the variation of crop growth well. Thus the PT model combined with the dynamic coefficient equation calculated the daily AET reliably in the study. These provide an important scientific basis for developing PT methods in hydrology.

5.2 Evaluation of BC, HA and DA models in estimating daily crop AET in arid regions

Different with the previous models, the BC, HA and DA methods produced large errors in estimating AET in all the years. Thus the three models were not suitable for estimating daily crop

AET in arid regions. The BC model only considers the temperature control, and the HA method includes the radiation and temperature controls, while the DA method only takes account of the aerodynamic effect on PET. These simplifications restricted the temperature-based and mass transfer PET models in arid regions.

These results were consistent with the previous studies (See **Table 1**, Xu and Singh, 2002; Lu *et al.*, 2005; Tabari *et al.*, 2013), which infer that the temperature-based and mass transfer PET models were not suitable in the humid Switzerland, Southeastern United States, and humid region of Iran. Our study also reveals that these models were not the optimum choice for calculating AET in arid regions.

6. Conclusion

Based on the validation by the long-term measured data, it can be concluded that PE, SW and PT models with the dynamic coefficient equations were suitable for estimating daily crop AET while the BC, HA and DA models had large errors in predicting AET in arid regions.

The study developed the crop coefficient method, confirmed the reliability of PE, SW and PT models, which provided an important insight for modifying the present hydrological models in arid regions.

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Figure legends

- **Fig.1** Comparison of daytime maize potential evapotranspiration (PET) estimated by the (a) FAO-Blaney-Criddle (PET_{BC}), (b) Hargreaves (PET_{HA}), (c) Priestley-Taylor (PET_{PT}), (d) Dalton (PET_{DA}), (e) Penman (PET_{PE}) and (f) Shuttleworth (PET_{SW}) models with the actual maize evapotranspiration (AET) measured by eddy covariance (ET_{EC}) in 2007, 2008, 2011, 2012 and 2013
- **Fig.2** Comparison of daytime vineyard potential evapotranspiration (PET) estimated by the (a) FAO-Blaney-Criddle (PET_{BC}), (b) Hargreaves (PET_{HA}), (c) Priestley-Taylor (PET_{PT}), (d) Dalton (PET_{DA}), (e) Penman (PET_{PE}) and (f) Shuttleworth (PET_{SW}) models with the actual vineyard evapotranspiration (AET) measured by eddy covariance (ET_{EC}) in 2008, 2009, 2010, 2011 and 2012
- Fig.3 The response patterns of maize crop coefficient (AET/PET) estimated by the (a) FAO-Blaney-Criddle (BC), (b) Hargreaves (HA), (c) Priestley-Taylor (PT), (d) Dalton (DA), (e) Penman (PE) and (f) Shuttleworth (SW) models with the canopy conductance (g_c) in 2007, 2008, 2011, 2012 and 2013. Maize g_c was obtained by the re-arranged Penman-Monteith equation
- Fig.4 The response patterns of vineyard crop coefficient (AET/PET) estimated by the (a) FAO-Blaney-Criddle (BC), (b) Hargreaves (HA), (c) Priestley-Taylor (PT), (d) Dalton (DA), (e) Penman (PE) and (f) Shuttleworth (SW) models with the canopy conductance in 2008, 2009, 2010, 2011 and 2012. Vineyard g_c was obtained by the re-arranged Penman-Monteith equation

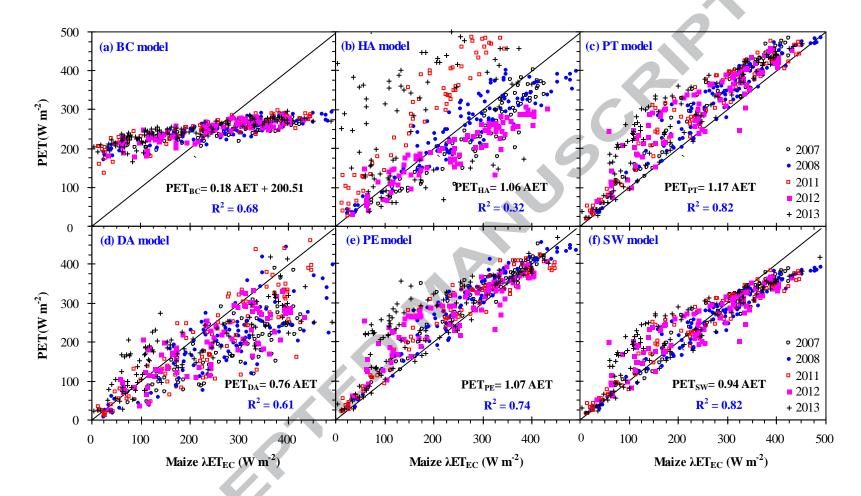
Fig.5 Comparison of daytime maize evapotranspiration estimated by the (a) FAO-Blaney-Criddle

(ET_{BC}), (b) Hargreaves (ET_{HA}), (c) Priestley-Taylor (ET_{PT}), (d) Dalton (ET_{DA}), (e) Penman (ET_{PE}) and (f) Shuttleworth (ET_{SW}) models with the actual maize evapotranspiration measured by eddy covariance (ET_{EC}) in 2008, 2011, 2012 and 2013

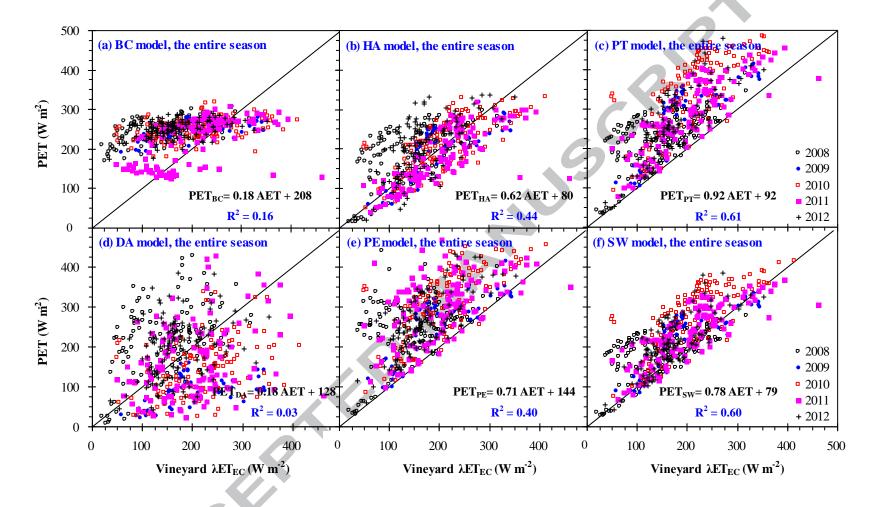
- Fig.6 Comparison of the (a) mean root mean square error (RMSE), (b) relative mean bias error (MBE) and (c) P value (paired T statistic result) yielded by the six PET models in estimating maize AET during the four years
- Fig.7 Comparison of vineyard evapotranspiration estimated by the (a) FAO-Blaney-Criddle (ET_{BC}),
 (b) Hargreaves (ET_{HA}), (c) Priestley-Taylor (ET_{PT}), (d) Dalton (ET_{DA}), (e) Penman (ET_{PE}) and
 (f) Shuttleworth (ET_{SW}) models with the actual evapotranspiration measured by eddy covariance (ET_{EC}) in 2009, 2010, 2011 and 2012
- Fig.8 Comparison of the (a) mean root mean square error (RMSE), (b) relative mean bias error (MBE) and (c) P value (paired T statistic result) produced by the six PET models in estimating vineyard AET during the four years

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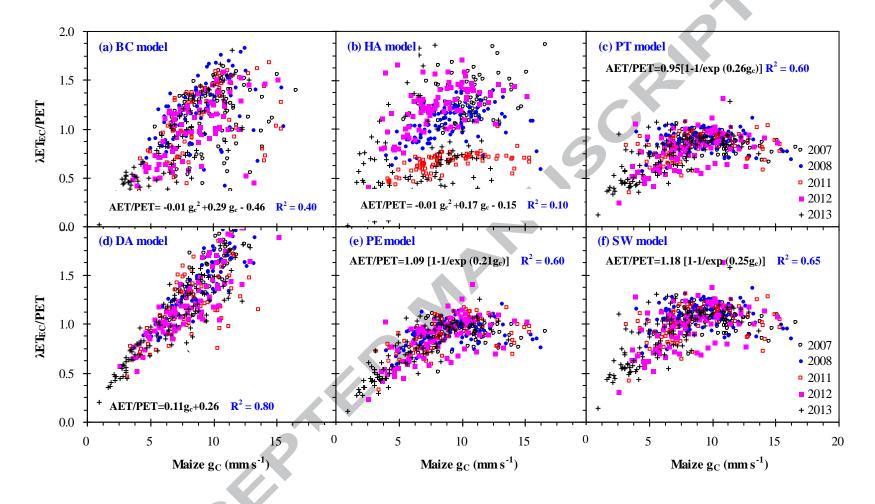
- **Fig.1** Comparison of daytime maize potential evapotranspiration (PET) estimated by the (a) FAO-Blaney-Criddle (PET_{BC}), (b) Hargreaves (PET_{HA}), (c)
- 2 Priestley-Taylor (PET_{PT}), (d) Dalton (PET_{DA}), (e) Penman (PET_{PE}) and (f) Shuttleworth (PET_{SW}) models with the actual maize
- 3 evapotranspiration (AET) measured by eddy covariance (ET_{EC}) in 2007, 2008, 2011, 2012 and 2013



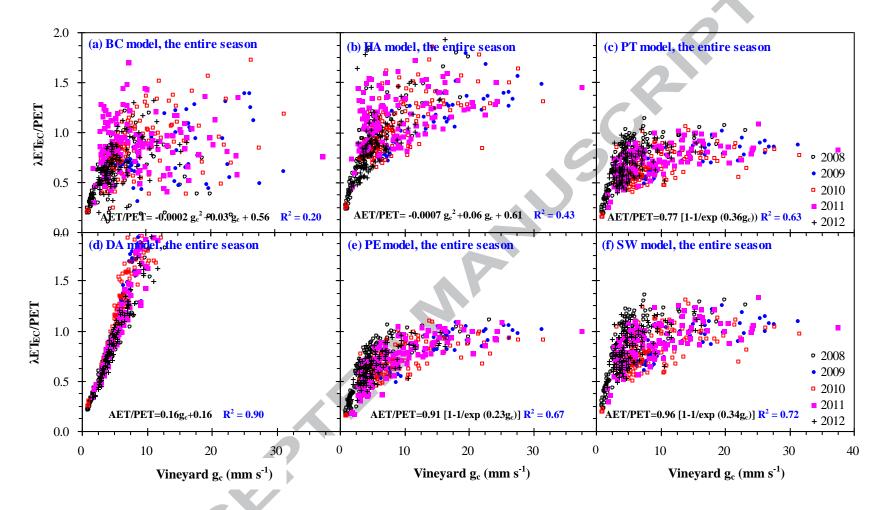
- 5 Fig. 2 Comparison of daytime vineyard potential evapotranspiration (PET) estimated by the (a) FAO-Blaney-Criddle (PET_{BC}), (b) Hargreaves (PET_{HA}),
- 6 (c) Priestley-Taylor (PET_{PT}), (d) Dalton (PET_{DA}), (e) Penman (PET_{PE}) and (f) Shuttleworth (PET_{SW}) models with the actual vineyard
- 7 evapotranspiration (AET) measured by eddy covariance (ET_{EC}) in 2008, 2009, 2010, 2011 and 2012



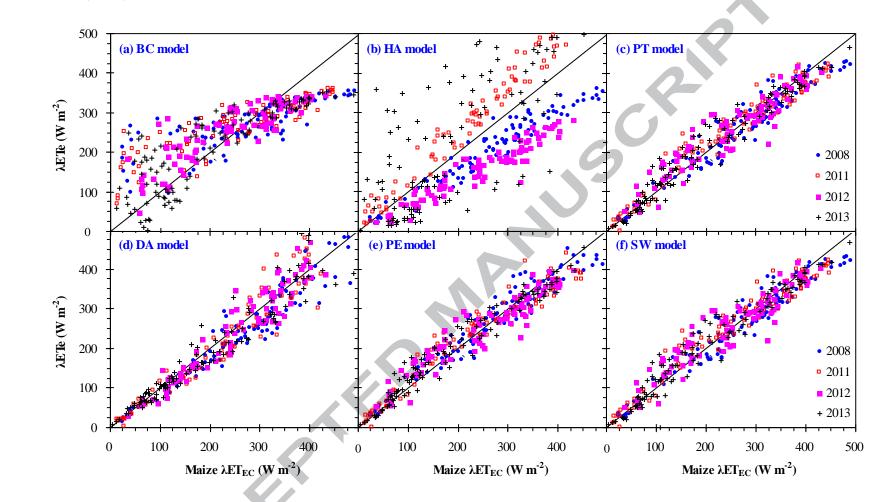
- 9 Fig.3 The response patterns of maize crop coefficient (AET/PET) estimated by the (a) FAO-Blaney-Criddle (BC), (b) Hargreaves (HA), (c)
- 10 Priestley-Taylor (PT), (d) Dalton (DA), (e) Penman (PE) and (f) Shuttleworth (SW) models with the canopy conductance (g_c) in 2007, 2008,
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- 13 Fig.4 The response patterns of vineyard crop coefficient (AET/PET) estimated by the (a) FAO-Blaney-Criddle (BC), (b) Hargreaves (HA), (c)
- 14 Priestley-Taylor (PT), (d) Dalton (DA), (e) Penman (PE) and (f) Shuttleworth (SW) models with the canopy conductance in 2008, 2009, 2010,
- 15 2011 and 2012. Vineyard g_c was obtained by the re-arranged Penman-Monteith equation



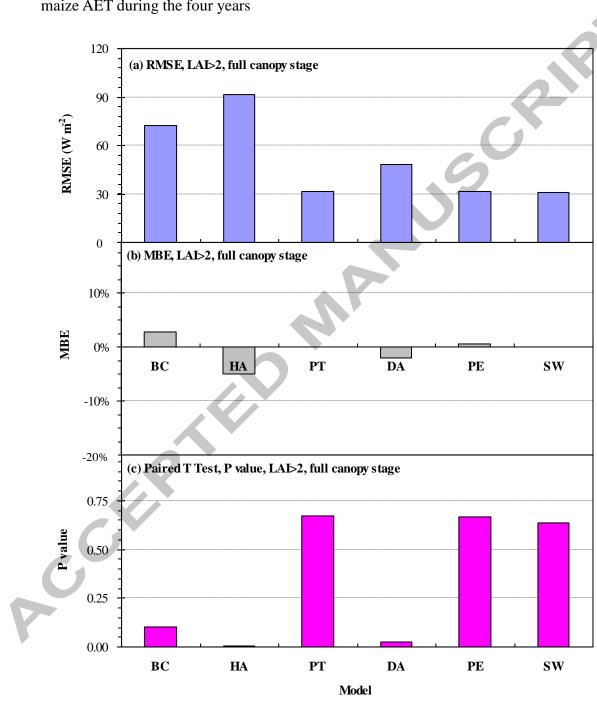
- 17 **Fig.5** Comparison of daytime maize evapotranspiration estimated by the (a) FAO-Blaney-Criddle (ET_{BC}), (b) Hargreaves (ET_{HA}), (c) Priestley-Taylor
- 18 (ET_{PT}), (d) Dalton (ET_{DA}), (e) Penman (ET_{PE}) and (f) Shuttleworth (ET_{SW}) models with the actual maize evapotranspiration measured by eddy



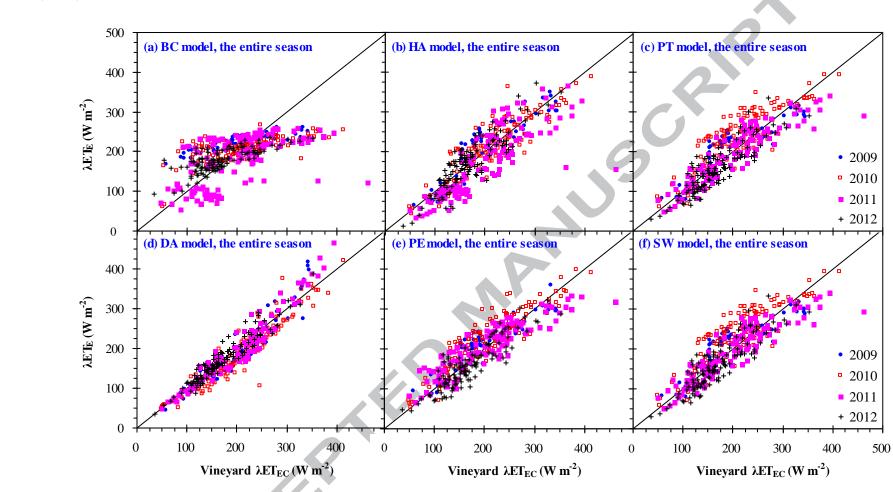
19 covariance (ET_{EC}) in 2008, 2011, 2012 and 2013

Fig.6 Comparison of the (a) mean root mean square error (RMSE), (b) relative mean bias error 21

(MBE) and (c) P value (paired T statistic result) yielded by the six PET models in estimating 22



- Fig.7 Comparison of vineyard evapotranspiration estimated by the (a) FAO-Blaney-Criddle (ET_{BC}), (b) Hargreaves (ET_{HA}), (c) Priestley-Taylor (ET_{PT}),
- 26 (d) Dalton (ET_{DA}), (e) Penman (ET_{PE}) and (f) Shuttleworth (ET_{SW}) models with the actual evapotranspiration measured by eddy covariance



27 (ET_{EC}) in 2009, 2010, 2011 and 2012

Fig.8 Comparison of the (a) mean root mean square error (RMSE), (b) relative mean bias error (MBE) and (c) P value (paired T statistic result)

produced by the six PET models in estimating vineyard AET during the four years

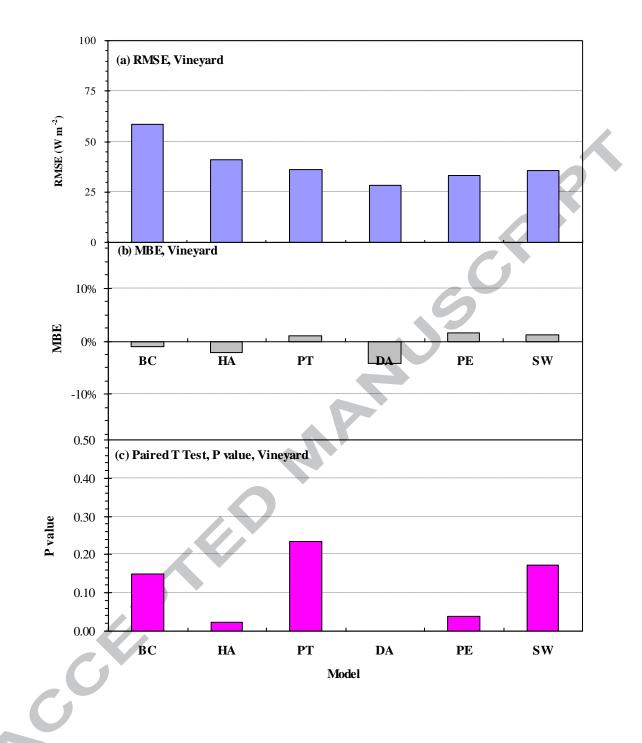


Table 1 A review of studies on the reliability of PET models at different climate conditions and regions

Authors	Climate	Location	Validation methods	PET models	Conclusions			
McKenney and Rosenberg, 1993.		North American Great Plains, USA	Eight alternative PET estimation methods	Thornthwaite, Blaney-Criddle, Hargreaves, Samani-Hargreaves, Jensen-Haise, PT, Penman	The PET methods differed in their sensitivities to temperature and other climate inputs. The degree of agreement among the methods was affected by location and by time of year			
Abtew, 1996	Humid	Florida, USA	PET models VS lysimeters measurements	The Turc method, PT and Penman methods	The PM method was well suited to estimate ET from cattails, marsh, and an open water/algae system, but that calibrated radiation-based models also provided reasonable estimates			
Federer et al., 1996		USA	Five PET models <i>VS</i> Four AET approaches	Thornthwaite, Hamon, Jensen-Haise, Turc, and Penman methods	No methods were consistently low or high. Use of 5-day or monthly input data did not greatly degrade results			
Vörösmarty et al., 1998		The conterminous US	Eleven PET models VS Watershed Water Balances	Thornthwaite, Hamon, Turc, Jensen and Haise, Penman PT, McNaughlon and Black, SW, SW day-night	Predictions made by macro-scale hydrology models can be sensitive to the specific PET method applied and this sensitivity results in bias relative to measured components of the terrestrial water cycle			
Jacobs <i>et al</i> ., 2004	Humid	Central Florida, USA	PET models VS Eddy covariance measurements	The Turc method, Hargreaves and Makkink models	The calibrated PM model gave good results for PET the PT and the PE models overestimated PET, and that the Turc and Makkink methods performed nearly as well as the PM method			

Lu et al., 2005HumidOutdin et al., 2005Different climatesSumner and Jacobs, 2005HumidZhou et al., 2006Yeiß and climatesWeiß and Menzel, 2008Different climatesDouglas et al., 2009Different climates	Southeastern United States France, USA and Australia Florida, USA The Mekong River basin Global scale Florida,	PETmodelsVSWatershedWaterBalances estimationPETmodelsVSPETmodelsVSPETmodelsVSPETmodelsVSPETmodelsVSPETmodelsVSPETmodelsVSpertion dataVSPETmodelsVSpertion dataVSpertion dataVSpertion dataVS	Thornthwaite, Hamon, and Hargreaves-Samani,Turc, Makkink, and PT methods The Penman method The modified PT, reference evapotranspiration and pan evaporation models Shuttleworth–Wallace model Priestley Taylor, Kimberly Penman, and Hargreaves	 PT, Turc and Hamon methods performed better than the other PET methods Temperature-based PET estimates perform as well as more physically-based PET methods Both PM and a modified PT methods required seasonal calibration parameters The PET and the reference evapotranspiration (RET) are vegetation-type-dependently correlated very well. The PT estimations were closest to available pan evaporation data
2005 climates Sumner and Jacobs, 2005 Humid Zhou <i>et al.</i> , 2006 Veiß and Different Menzel, 2008 climates Douglas <i>et al.</i> , Different	and Australia Florida, USA The Mekong River basin Global scale	covariance measurements PET models <i>VS</i> pan evaporation data PET models <i>VS</i> pan	The modified PT, reference evapotranspiration and pan evaporation models Shuttleworth–Wallace model Priestley Taylor, Kimberly	more physically-based PET methods Both PM and a modified PT methods required seasonal calibration parameters The PET and the reference evapotranspiration (RET) are vegetation-type-dependently correlated very well. The PT estimations were closest to available pan
Humid Jacobs, 2005 Zhou <i>et al.</i> , 2006 Weiß and Different Menzel, 2008 climates Douglas <i>et al.</i> , Different	The Mekong River basin Global scale	covariance measurements PET models <i>VS</i> pan evaporation data PET models <i>VS</i> pan	evapotranspiration and pan evaporation models Shuttleworth–Wallace model Priestley Taylor, Kimberly	seasonal calibration parameters The PET and the reference evapotranspiration (RET) are vegetation-type-dependently correlated very well. The PT estimations were closest to available pan
2006 Weiß and Different Menzel, 2008 climates Douglas <i>et al.</i> , Different	River basin Global scale	evaporation data PET models VS pan	Priestley Taylor, Kimberly	are vegetation-type-dependently correlated very well. The PT estimations were closest to available pan
Menzel, 2008 climates Douglas <i>et al.</i> , Different				•
	Florida			
	American	PET models VS EC [*] or BREB* measurements	The Turc method and the Priestley–Taylor method	The PT performance appears to be superior to the other two methods for estimating PET for a variety of land covers in Florida at a daily scale
Donohue et al., Typical 2010 arid climat	Australia	PET models vs pan evaporation dynamics	Penman, Priestley–Taylor, Morton point, Morton areal and Thornthwaite methods	The four-variable Penman formulation produced the most reasonable estimation of potential evaporation dynamics against PT, Morton point, Morton areal and Thornthwaite
Fisher <i>et al.</i> , 2011	Global scale	R		The choice of ET model and input data is likely to have a bearing on model fits and predictions when used in analyses of species richness and related

Authors	Climate	Location	Validation methods	PET models	Conclusions
					phenomena at geographical scales of analysis
Our study	Typical arid climate	Arid northwest China	SixPETmodels VS Five-year EC^* measurements		The PE, SW and PT models combined with the dynamic coefficient equations are reliable to estimate daily crop ET, while the BC, HA and DA methods are not suitable in the arid regions

*EC represents eddy covariance, BREB means Bowen Ratio Energy Balance, PE represents Penman, PT means Priestley-Taylor, SW means Shuttleworth, BC means

FAO-Blaney-Criddle, HA means Hargreaves, DA means Dalton

Table 2 Statistical results of daytime maize ET estimated by the (a) FAO-Blaney-Criddle (ET_{BC}), (b) Hargreaves (ET_{HA}), (c) Priestley-Taylor (ET_{PT}),

(d) Dalton (ET_{DA}), (e) Penman (ET_{PE}) and (f) Shuttleworth (ET_{SW}) models with the actual evapotranspiration measured by eddy covariance

(ET_{EC}) in 2009, 2011, 2012 and 2013

NL	M. J.I	X 7	Descrite		D ²	Ŧ		MDE	D	
No	Model	Year	Regression equation	n	R ²	\overline{E}	\overline{O}	MBE	Р	RMSE(W m ⁻²)
		2008	$\lambda ET_{BC} = 0.88 \ \lambda ET_{EC}$	103	-0.67	268	274	-2%	0.41	81
		2011	$\lambda ET_{BC}=0.93\;\lambda ET_{EC}$	91	0.01	258	246	5%	0.17	79
1	BC	2012	$\lambda ET_{BC}=0.98\;\lambda ET_{EC}$	89	0.40	252	237	6%	0.03	57
		2013	$\lambda ET_{BC} {=} 0.95 \; \lambda ET_{EC}$	109	0.61	203	196	4%	0.25	67
		Total	$\lambda ET_{BC} = 0.93 \lambda ET_{EC}$	392	0.25	244	237	3%	0.10	72
		2008	$\lambda ET_{HA} = 0.76 \; \lambda ET_{EC}$	103	0.92	211	274	-23%	0.00	74
		2011	$\lambda ET_{HA} = 1.24 \; \lambda ET_{EC}$	91	0.97	307	246	25%	0.00	74
2	HA	2012	$\lambda ET_{HA} = 0.61 \; \lambda ET_{EC}$	89	0.91	153	237	-35%	0.00	96
		2013	$\lambda ET_{HA} = 1.12 \; \lambda ET_{EC}$	109	0.55	230	196	17%	0.00	115
		Total	$\lambda ET_{HA} = 0.89 \ \lambda ET_{EC}$	392	0.58	226	237	-5%	0.01	92
		2008	$\lambda ET_{PT} = 0.94 \ \lambda ET_{EC}$	103	0.93	261	274	-5%	0.00	32
		2011	$\lambda ET_{PT} = 0.98 \ \lambda ET_{EC}$	91	0.94	245	246	0%	0.72	30
3	РТ	2012	$\lambda ET_{PT} = 1.00 \lambda ET_{EC}$	89	0.85	246	237	4%	0.07	37
		2013	$\lambda ET_{PT} = 1.00 \; \lambda ET_{EC}$	109	0.94	201	196	3%	0.05	28
		Total	$\lambda ET_{PT} = 0.99 \lambda ET_{EC}$	392	0.92	237	237	0%	0.67	31
(C	5								

No	Model	Year	Regression equation	n	\mathbf{R}^2	\overline{E}	\overline{O}	MBE	Р	RMSE(W m ⁻²)
		2008	$\lambda ET_{DA}=0.92\;\lambda ET_{EC}$	103	0.91	251	274	-8%	0.00	41
		2011	$\lambda ET_{DA} = 1.08 \; \lambda ET_{EC}$	91	0.82	258	246	5%	0.16	76
4	DA	2012	$\lambda ET_{DA} = 0.99 \; \lambda ET_{EC}$	89	0.92	235	237	-1%	0.20	33
		2013	$\lambda ET_{DA}=0.98\;\lambda ET_{EC}$	109	0.92	192	196	-2%	0.28	37
		Total	$\lambda ET_{DA} = 0.97 \lambda ET_{EC}$	392	0.87	232	237	-2%	0.02	48
		2008	$\lambda ET_{PE}=0.98\;\lambda ET_{EC}$	103	0.93	272	274	-1%	0.55	30
		2011	$\lambda ET_{PE} = 0.96 \; \lambda ET_{EC}$	91	0.93	242	246	-2%	0.23	33
5	PE	2012	$\lambda ET_{PE} = 0.97 \; \lambda ET_{EC}$	89	0.84	241	237	2%	0.61	36
		2013	$\lambda ET_{PE} = 1.00 \; \lambda ET_{EC}$	109	0.95	202	196	3%	0.02	27
		Total	$\lambda ET_{PE} = 0.99 \ \lambda ET_{EC}$	392	0.92	239	237	1%	0.67	32
		2008	$\lambda ET_{SW} = 0.90 \; \lambda ET_{EC}$	103	0.92	262	274	-4%	0.00	31
		2011	$\lambda ET_{SW}=0.93\;\lambda ET_{EC}$	91	0.90	245	246	0%	0.72	29
6	SW	2012	$\lambda ET_{SW}=0.96 \; \lambda ET_{EC}$	89	0.66	246	237	4%	0.08	36
		2013	$\lambda ET_{SW} = 1.00 \; \lambda ET_{EC}$	109	0.96	200	196	2%	0.14	29
		Total	$\lambda ET_{SW} = 0.94 \lambda ET_{EC}$	392	0.81	237	237	0%	0.64	31

Table 3 Statistical results of daytime vineyard ET estimated by the (a) FAO-Blaney-Criddle (ET_{BC}), (b) Hargreaves (ET_{HA}), (c) Priestley-Taylor

 (ET_{PT}) , (d) Dalton (ET_{DA}) , (e) Penman (ET_{PE}) and (f) Shuttleworth (ET_{SW}) models with the actual evapotranspiration measured by eddy

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No	Model	Year	Regression equation	n	\mathbf{R}^2	\overline{E}	\overline{O}	MBE	Р	RMSE(W m ⁻²)
		2009	$\lambda ET_{BC}{=}0.97\lambda ET_{EC}$	89	-0.03	227	208	9	0.00	60
		2010	$\lambda ET_{BC} = 0.88 \; \lambda ET_{EC}$	125	-1.85	205	213	-3	0.17	59
1	BC	2011	$\lambda ET_{BC} = 0.83 \ \lambda ET_{EC}$	126	0.02	181	202	-10	0.00	69
		2012	$\lambda ET_{BC} = 0.98 \ \lambda ET_{EC}$	115	-0.93	179	170	5	0.02	41
		Total	$\lambda ET_{BC} = 0.91 \lambda ET_{EC}$	445	-0.24	196	198	-1	0.49	58
		2009	$\lambda ET_{HA} = 1.06 \; \lambda ET_{EC}$	89	0,80	223	208	7	0.00	36
		2010	$\lambda ET_{HA} = 0.98 \; \lambda ET_{EC}$	125	0.79	210	213	-1	0.43	35
2	HA	2011	$\lambda ET_{HA} = 0.87 \; \lambda ET_{EC}$	126	0.67	176	202	-13	0.00	55
		2012	$\lambda ET_{HA} = 1.02 \; \lambda ET_{EC}$	115	0.79	172	170	2	0.36	31
		Total	$\lambda ET_{HA} = 0.97 \lambda ET_{EC}$	445	0.74	194	198	-2	0.02	41
		2009	$\lambda ET_{PT} = 1.00 \lambda ET_{EC}$	89	0.76	214	208	3	0.10	33
		2010	$\lambda ET_{PT} = 1.08 \ \lambda ET_{EC}$	125	0.72	235	213	10	0.00	44
3	РТ	2011	$\lambda ET_{PT} = 0.93 \ \lambda ET_{EC}$	126	0.79	193	202	-5	0.00	34
		2012	$\lambda ET_{PT}=0.94\lambda ET_{EC}$	115	0.78	160	170	-6	0.00	31
		Total	$\lambda ET_{PT} = 1.00 \lambda ET_{EC}$	445	0.76	200	198	1	0.23	36

covariance (ET_{EC}) in 2009, 2010, 2011 and 2012

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No	Model	Year	Regression equation	n	\mathbf{R}^2	\overline{E}	\overline{O}	MBE	Р	RMSE(W m ⁻²)
		2009	$\lambda ET_{DA}=0.97\;\lambda ET_{EC}$	89	0.97	198	208	-5	0.00	31
		2010	$\lambda ET_{DA} = 0.91 \; \lambda ET_{EC}$	125	0.88	191	213	-10	0.00	34
4	DA	2011	$\lambda ET_{DA} = 1.01 \ \lambda ET_{EC}$	126	0.91	201	202	-1	0.57	29
		2012	$\lambda ET_{DA} = 1.01 \ \lambda ET_{EC}$	115	0.91	171	170	1	0.36	17
		Total	$\lambda ET_{DA} = 0.97 \ \lambda ET_{EC}$	445	0.88	190	198	-4	0.00	29
		2009	$\lambda ET_{PE} = 1.00 \; \lambda ET_{EC}$	89	0.82	215	208	3	0.03	28
		2010	$\lambda ET_{PE} = 1.05 \; \lambda ET_{EC}$	125	0.78	228	213	7	0.00	36
5	PE	2011	$\lambda ET_{PE} = 0.96 \; \lambda ET_{EC}$	126	0.64	204	202	1	0.60	37
		2012	$\lambda ET_{PE} = 0.93 \; \lambda ET_{EC}$	115	0.79	159	170	-6	0.00	29
		Total	$\lambda ET_{PE} = 1.00 \lambda ET_{EC}$	445	0.77	201	198	2	0.04	33
		2009	$\lambda ET_{SW} = 1.00 \ \lambda ET_{EC}$	89	0.76	214	208	3	0.09	32
		2010	$\lambda ET_{SW} = 1.07 \; \lambda ET_{EC}$	125	0.73	234	213	10	0.00	43
6	SW	2011	$\lambda ET_{SW}=0.94\;\lambda ET_{EC}$	126	0.80	194	202	-4	0.01	34
		2012	$\lambda ET_{SW}=0.94\;\lambda ET_{EC}$	115	0.79	160	170	-6	0.00	30
		Total	$\lambda ET_{SW} = 1.00 \ \lambda ET_{EC}$	445	0.77	200	198	1	0.17	35
)							

- > AET showed significantly linear and positive correlation with PET on field scale
- > Crop coefficient existed remarkably hyperbolic function with canopy conductance
- A hyperbolic model was used to parameterize crop coefficient
- SW, PE and PT models combined with crop coefficient model estimated AET accurately

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