Selection of Remote Sensing Images And Evapotranspiration Models On Complex Land Surfaces for a Humid Karst Catchment

Rongfei Zhang (rongfei330@cqu.edu.cn)  Chongqing University  https://orcid.org/0000-0001-5445-5869

Research Article

Keywords: Evapotranspiration, Eco-hydrology, Landscape ecology, Ventilated-chambers, Remote sensing models

Posted Date: September 24th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-928797/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License
Selection of remote sensing images and evapotranspiration models on complex land surfaces for a humid karst catchment

Rongfei Zhang¹.².³.⁴*

¹College of Environment and Ecology, Chongqing University, Chongqing, 400045, China;

²Key Laboratory of the Three Gorges Reservoir Region’s Eco-environment, Ministry of Education, Chongqing University, Chongqing 400045, China

³Huanjiang Observation and Research Station for Karst Ecosystem, Key Laboratory of Agro-ecological Processes in Subtropical Region, Institute of Subtropical Agriculture, Chinese Academy of Sciences, Changsha 410125, Hunan, China;

⁴Guangdong Key Laboratory of Integrated Agro-environmental Pollution Control and Management, Guangdong Institute of Eco-Environment & Soil Science, Guangzhou 510650, Guangdong, China

Email: rongfei330@cqu.edu.cn

Key points

1. The PML model using Landsat-8 images performed better than other models.

2. Surface parameters and ET exhibited clear spatial and temporal distributions.

3. Control factors of ET show significantly different effects

ABSTRACT
Evapotranspiration ($ET$) is predominant variable for water management in various types of ecosystems, and $ET$ processes in these ecosystems have been assessed through in-situ measuring and modelling methods. However, it is challenging to measure actual $ET$ and upscale it to regional level. In addition, the accuracy of retrieved parameters from models is usually low for karst landscapes, where the underlying surface is more complex than non-karst landscapes. Due to various porosities and conduits, aquifers in karst landscapes typically show remarkable and rapid responses to precipitation events, leading to serious water stress. Therefore, there is an urgent need to quantify water fluxes to provide reliable evidence for the protection and sustainable management of karst water resources. In this study, five plots were built to observe actual $ET$ based on Thermal Dissipation Probes (TDP), re-designed Ventilated-chamber and Microlysimeters in a karst catchment in southwest China. Then, three models (Penman-Monteith-Leuning, PML; Remote Sensing-Priestley and Taylor, RS-PT; and Hargreaves) were selected to upscale $ET$ estimation to the regional level based on Landsat-8 and MODIS data. The results showed that: 1) The PML model performed better than other models ($p < 0.01$) with higher $R^2$ values (0.72 for MODIS images and 0.87 for Landsat-8 images) and smaller RMSE values (1.4 mm·day$^{-1}$ and 0.8 mm·day$^{-1}$ for MODIS and Landsat-8 images, respectively); 2) Daily $ET$ exhibited significant seasonal variability and different spatial distribution; 3) $ET$ had a slightly positive correlation with DEM; however, ground temperature had a negative correlation with $ET$. By combining remote sensing data and upscaling it to the regional level, this study helps improve the accuracy of measured and estimated $ET$. It suggests that $ET$ is
strongly regulated by vegetation coverage and available energy in subtropical humid karst catchments.

Keywords

Evapotranspiration; Eco-hydrology; Landscape ecology; Ventilated-chambers; Remote sensing models

1 Introduction

Evapotranspiration (ET) process bonds water, energy cycle and carbon cycles, and nearly 70% of the precipitation returns to the atmosphere in the form of $ET$ (Zhang et al., 2016). According to the changing law of the value, $ET$ process for ecosystems can be an important climatic predictor of ecosystem health. Therefore, the mastery of ecosystem $ET$ plays a great role in promoting water resources management (Allen and Breshears, 1998; Anderson et al., 2012; Fisher et al., 2017; Jung et al., 2010; Koster et al., 2004; Seneviratne et al., 2006). Accordingly, $ET$ processes of ecosystems in different climatic zones and geomorphological regions around the world have been estimated through in-situ measuring and modelling methods as shown in Table 1. In detail, in-situ measuring methods conclude Micro-lysimeter, Soil heat pulse, Chamber, Micro Bowen ratio energy balance, Eddy covariance method, Sap flow, Biomass-transpiration relationship, Isotope’s methods, and so on. However, it is difficult to use experimental methods to estimate regional $ET$. Therefore, various models were combined with remote sensing technique, which has been recognized as one of the feasible ways to estimate $ET$ in regional scale, to extend $ET$ estimation level. The basic
idea of remote sensing technique is energy balance in the vertical direction. In 1997, Jackson first put forwards a simplified method that combining the observation data with remote sensing data to fit evaporation and remote sensing data (Jackson et al., 1977). In 1983, Sequin perfected Jackson’s empirical formula (Seguin and Itier, 1983). Since then, Bella established a relationship between daily $ET$ with NDVI and surface temperature by using AVHRR data (Bella et al., 2000). Some scholars established empirical relationship among net radiation, vegetation index, temperature, soil temperature and $ET$. Overall, empirical statistical models are simple to use but relying on the surface observation data too much (Wang and Liang, 2008). In 1948, Penman proposed two formulas: one is to calculate potential evaporation underlying moist surface and the other is to calculate transpiration of single leaves hole (Penman, 1948). Based on the two formulas, Monteith introduced the concept of surface impedance and got the Penman-Monteith (P-M) formula, which is the foundation for the further study about $ET$ of unsaturated underlying surface. In 1972, Priestley put forward Priestley-Taylor (P-T) model to calculate $ET$ based on the equilibrium vaporization and under the premise of the hypothesis of no advection (Priestley and Taylor, 1972). By combining with the feature space of temperature-vegetation index and quadratic linear interpolation, Jiang and Islam (2001) calculated actual P-T coefficient of different underlying surface. In 1963, Bouchet first put forward the relationship theory of actual and potential $ET$ (Bouchet, 1960). Based on the theory, scholars established a series of calculation models of actual $ET$, such as the Advection-Aridity model put forward by Brutsaert, the CRAE (Complementary Relationship Areal Evapotranspiration) model
proposed by Morton, the Granger model established by Granger through combining heat balance principle and aerodynamics based on Dolton evaporation law. In 1981, Jackson presented CWSI (Crop Water shortage Index) (Jackson et al., 1981). Due to the exponential model error in sparse vegetation area is too big, Moran improved the model by using vegetation index and temperature trapezoidal method. SEBAL (Surface Energy Balance Algorithm for Land) model was put forward based on land surface energy balance equation to estimate regional ET by analyzing the net radiation flux. These kinds of remote sensing ET models can be divided into single-layer model and double-layer model out of different exchange ways of surface and near surface atmosphere turbulence heat flux (Bastiaanssen et al., 1998; Kustas et al., 1989).

Insert Table 1 here

Though various models have been combined with remote sensing images to estimate regional ET in many landscapes, however, it is challenging to measure actual ET and the accuracy of retrieved parameters of models is usually low for karst landscapes, which cover 10% of the earth’s land surface and supply water resources for approximately 25% of the world’s population (Hartmann et al., 2014a). The underlying surface features of karst landscape are more complicated than plain or plateau landscapes, leading to poorer parameters values estimation. For example, Luo et al. (2019) calculated the spatial distribution of soil moisture for a karst catchment and found that the models did not perform well in highly heterogeneous landscapes ($R^2 = 0.36$). Therefore, accurate ET estimation based models for karst landscapes is more difficult than in regions with a uniform underlying surface. Aquifers in karst landscapes
typically exhibit significant and rapid responses to precipitation events (Hartmann et al., 2014a), due to various porosities (such as micropores, small fissures and fractures, large fractures and conduits) (Bakalowicz, 2005) and low water retention in thin soil (Liu et al., 2016). Moreover, severe rocky desertification has occurred in many fragile karst ecosystems, mainly due to deforestation and agricultural intensification in recent years (Yang et al., 2016). When rainfall is low, water stress and water shortages occur frequently and rapidly, and there is an urgent need to quantify water fluxes to provide reliable evidence for the protection and sustainable management of karst water resources.

Therefore, this study aims to: 1) Construct and compare remote sensing models to estimate $ET$ at the regional level for karst landscapes; and 2) Characterize $ET$ processes and impact controls for karst ecosystems.

2 Materials and methods

2.1 Study Area

Being typical karst landscape in southwestern China, SANCHEA (Fig.1b) Basin (103°30′–105°54′E, 25°36′–27°18′N) covers approximately 7265 km². It is located in the Wumeng Mountains, the transition region between Yunnan Plateau and Guizhou Plateau. The average elevation of upstream is greater than 2000 m. Midstream elevations range from 1800 m to 2400 m and downstream areas are less than 1200 m. Perennial mean precipitation and annual mean temperature of study area are 1336 mm·year⁻¹ and 13 – 15 °C, respectively. With obvious humid subtropical monsoon
climate characteristic, approximately 80% of precipitation during a year falls between
May and October. The vegetation types are diverse in the basin, where is dominated by
deciduous broad-leaved forest and evergreen broad-leaved forest. HOUZHAI Basin
(Fig.1c) is located in the southeastern corner of SANCHA Basin. It covers
approximately 81 km². The elevation ranges from 1220 to 1531 m. The three major soil
types are lime soil, yellow loam and rice soil in the catchment (Zhang et al., 2017).

Insert Figure 1 here

2.2 Field measurements

In-situ monitoring was carried out in HOUZHAI Basin (Fig.2). Five cover types
were selected to monitor actual ET as shown in Table 2. TDP (Thermal dissipation
probes, FLGS-TDP XM1000, Dynamax, USA), connected to a CR 1000 datalogger,
were used for forest, orchard and shrub-grass and burned patch to monitor transpiration
of trees and shrub. Micro-lysimeters were used to measure soil evaporation. Ventilated-
chambers were used to monitor ET for low vegetation, such as grass, shrub, crop and
soil. Two micro-meteorological stations (HOBO U30-NRC made by USA Onset
Computer Corporation) were set to monitor meteorological factors, i.e. air temperature
\( (T_a) \), precipitation \( (PRCP) \), relative humidity \( (RH) \), photosynthetic active radiation
\( (PAR) \) and wind speed \( (WS) \). One is inside the forest, and the other is outside. Time-
domain reflectometry probes (CS625) were used to automatic continuous monitor \( \theta \)
once every five minutes. LAI (Leaf Area Index) was measured using LAI-2200C (LI-
COR LTD., U.S.) once every 10-15 days.
2.3 Sap flow, ventilated chamber, and micro-lysimeters

Sap flow for trees and shrubs was monitored using the TDP system to calculate transpiration. Two thermocouple probes of the TDP system were implanted in the sapwood of the tree trunk (Granier, 1985; Granier et al., 2000). Then, the temperature difference ($T_d$) was recorded by these two thermocouples. When transpiration happens in the stem of trees or shrubs, the sap flow in the conduit will make the heated probe cool and increase $T_d$ between the reference probe and the heated probe. When the sap flow stops at midnight, the temperature difference reaches its maximum ($T_{dm}$) (Bosch et al., 2014). The formula to calculate sap is below (Granier et al., 2000):

$$SF = S_a \times 0.119(T_{dm} - T_d)^{1.231} \times 3600 \ [cm^3 \cdot cm^{-2} \cdot hr^{-1}]$$

(1)

where $T_{dm}$ is the mean value of the temperature difference between 23:00 pm and 3:00 am of the next morning (Cramer et al., 1999), and $S_a$ is the area of trees’ sapwood.

Ventilated chambers are able to measure actual $ET$ for crops, shrub, grass, small trees and plantations (Reicosky and Peters, 1977). Its ability to accurate real-time monitoring actual $ET$ for different ecosystems in-site makes the ventilated chamber well known (Greenwood et al., 1982; Greenwood et al., 1985a; Greenwood et al., 1985b). The ventilated chambers made in previous studies were fixed in soil and they were difficult to move and operate. Therefore, we redesigned the ventilated chambers, which were easily portable (Patent No.: ZL 201410756225.X). The redesigned ventilated
chamber has two pipelines connecting the outside air. One is an outlet near the top connected to an aspirator pump by PVC tubing and the other is inlet hole connected with a PVC tube. There are two sensors were inserted in these two pipelines to log the temperature and humidity of air flux. The chamber frames were made by stainless-steel, and covered by lightfast and transparent doors. Then, the chamber can be lifted and placed on the ground with a pedestal. \( ET \) (mm·day\(^{-1}\)) was estimated according to the following equations:

\[
AH = \frac{217 \times RH \cdot 6.1078e^{17.269t}}{T_a} \ (g/m^3) \tag{2}
\]

\[
ET = \sum_{i=1}^{n} V \cdot AH_{\text{outlet}} \cdot t - \sum_{i=1}^{n} V \cdot AH_{\text{inlet}} \cdot t \tag{3}
\]

where \( V \) is the flow rate of the pump (m\(^3\)·min\(^{-1}\)) and \( AH \) is absolute humidity (g·m\(^{-3}\)).

For ecosystems with installed \( TDP \) and ventilated chambers, \( ET \) can be estimated as follows:

\[
ET = \frac{T_{\text{sum}}}{A} + ET_v \tag{4}
\]

where \( T_{\text{sum}} \) (kg·day\(^{-1}\)) is tree transpiration, \( ET_v \) is the \( ET \) measured by the ventilated chamber in the understory and \( A \) (m\(^2\)) is the cover area of the trees.

In this study, Micro-lysimeters were used to measure soil evaporation. The Micro-lysimeters were made by PVC cylinders, the size is 9.5 cm inner diameter x 20 cm depth PVC cylinders, and the outer diameter of the PVC cylinders was 10 cm (Boast and Robertson, 1982). The Micro-lysimeters were encased by outer PVC cylinders of slightly larger diameter but of the same depth as the inner PVC cylinders (Balwinder-
Singh et al., 2014). Each cylinder held a undisturbed soil core, which was performed with minimum soil disturbance so that the obtained soil core remained (Allen, 1990). In every plot, there are three Micro-lysimeters were set under vegetation near the ventilated chamber. The cylinders were weighed every two hours from 06:00 to 20:00 to determine water loss.

2.4 Remote sensing data and model construction

Landsat-8 and MODIS images of SANCHA and HOUZHAI Basins were used in this study. Landsat-8 images were obtained from [http://glovis.usgs.gov/](http://glovis.usgs.gov/), and MODIS products were downloaded from [http://ladsweb.nascom.nasa.gov/data/search.html](http://ladsweb.nascom.nasa.gov/data/search.html). DEM data were obtained from the geospatial data cloud ([http://www.gscloud.cn/](http://www.gscloud.cn/)), with a spatial resolution is 90 m. Before retrieving relevant surface parameters, radiation calibration and atmospheric correction were performed on the Landsat-8 data to maintain the same spatial resolution as the visible light and near infrared band. The original MODIS leaf area product data were re-projected using MRT (MODIS Reprojection Tool) software to convert to the krasovsky-albert equivolume projection, then resampled to a spatial resolution of 1 km. After that, remote sensing images were spliced and cut based on the boundary of the study area map. To improve the quality of MODIS-LAI data, the Savitzky-Golay (S-G) filter was used to reduce noise in the MOD152A products. Then, the image time sequence was reconstructed. Using TIMESAT software, the original LAI was smoothed and the key step was setting relevant parameters (including the sliding window size, fitting peak parameters and iteration times), according to the vegetation growth pattern.
The PML (Penman-Monteith-Leuning), RS-PT (Remote sensing- Priestley and Taylor) and Hargreaves models were selected and compared to simulate \( ET \). The PML model was optimized by the PM model (Penman-Monteith) to describe the biophysics of evaporation \( E \) from land surfaces. It can be expressed as equation (5). \( ET \) is the sum of \( ET \) from plant canopy \( (ET_c) \) and \( E \) of bare soil \( (E_s) \). Then, \( \lambda ET \), \( G_c \) and \( G_s \) can be expressed as equations (6) - (8) (Leuning et al., 2008):

\[
\lambda E = \frac{\varepsilon A + \left( \frac{\rho c_p}{\gamma} \right) D_a G_a}{\varepsilon + 1 + \frac{G_a}{G_s}}
\]  

(5)

\[
\lambda ET = \frac{\varepsilon A_c + \left( \frac{\rho c_p}{\gamma} \right) D_a G_a}{\varepsilon + 1 + \frac{G_a}{G_s}} + \frac{f \varepsilon A_S}{\varepsilon + 1}
\]  

(6)

\[
G_c = \frac{g_{sx}}{k_Q} \ln \left[ \frac{Q_h + Q_{50}}{Q_h \exp(-k_Q L) + Q_{50}} \right] \left[ \frac{1}{1 + \frac{D_a}{D_{50}}} \right]
\]  

(7)

\[
G_s = G_c \left[ \frac{1 + \frac{G_a}{G_c}}{1 - \frac{f (e + 1)(1 - f)G_c}{G_a} + \frac{f G_a}{\varepsilon G_i}} \right]
\]  

(8)

where \( \lambda (\lambda = 2.45, \text{MJkg}^{-1}) \) is the latent heat of \( E \), \( \varepsilon = \frac{S}{\gamma} \), \( \gamma (\gamma = 0.66 \text{hPa} \cdot \text{°C}^{-1}) \) is the psychrometric constant and \( S \) (kPa \cdot °C^{-1}) is the slope of the curve relating saturation water vapor pressure and \( T_d \). \( A \) (W\cdot m^{-2}) denotes the available energy absorbed by the surface \((Rn - G, \text{net absorbed radiation minus soil heat flux})\). \( D_a \) (Pa) denotes the water vapor pressure of the air, \( G_a \) (m\cdot s^{-1}), \( G_c \) (m\cdot s^{-1}) and \( G_s \) (m\cdot s^{-1}) denote the aerodynamic conductance, canopy conductance and the surface conductance, respectively. Parameter \( f \) denotes the soil moisture index, \( g_{sx} \) is stomatal conductance. \( A_c \) (W\cdot m^{-2}) and \( A_s \) (W\cdot m^{-2}) are the available energy absorbed by the canopy and soil, respectively. The fraction of the total available energy absorbed by the canopy and by the soil are given
respectively by \( A_c/A = 1 - \tau \) and \( A_s/A = \tau \), where \( \tau = \exp (-k_A \cdot LAI) \), \( k_A \) is an extinction coefficient for available energy and \( LAI \) (m\(^2\)·s\(^{-2}\)) is leaf area index. \( Q_h = 0.8 \, A \), and fixed values are \( Q_{50} = 30 \, \text{W} \cdot \text{m}^{-2} \), \( G_a = 0.033 \), \( k_Q = 0.6 \), \( D_{50} = 1.0 \, \text{kPa} \).

The PT model used to calculate \( ET \) can be expressed as equation (9) (Utset et al., 2004). Because interception loss can be responsible for approximately 13-22% of the evaporation component of total \( ET \) losses in various ecosystems, therefore, it should be taken into account when estimating \( ET \) over large land masses. The modified RS - PT model can be expressed as equation (10) - (13).

\[
\lambda ET = \alpha [\frac{\Delta (R_n - G)}{\Delta + \gamma}] \quad (9)
\]

\[
\lambda ET = \lambda T_c + \lambda E_s + \lambda E_{ic} + \lambda E_{ws} \quad (10)
\]

\[
\lambda T_c = (1 - F_{wet})f_v f_T \alpha \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (11)
\]

\[
\lambda E_s = (1 - f_{wet})f_{sm} \alpha \frac{\Delta}{\Delta + \gamma} (R_{ns} - G) \quad (12)
\]

\[
\lambda E_{ic} = f_{wet} \alpha \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (13)
\]

\[
\lambda E_{ws} = f_{wet} \alpha \frac{\Delta}{\Delta + \gamma} (R_{ns} - G) \quad (14)
\]

where \( \alpha \) is a dimensionless coefficient ranging from 1.08 ± 0.01 and 1.34 ± 0.05, with average of 1.26 according to empirical data from numerous sites around the world.
(Priestley and Taylor, 1972), \( T_{opt} = 25^\circ C, \alpha_g = 0.18 \). \( \lambda \) is the latent heat of vaporization of water (\( \lambda = 2.45, \text{MJ} \cdot \text{kg}^{-1} \)), \( R_n \) is the net radiation (\( \text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1} \)), \( \gamma \) is the psychrometric constant (\( \gamma = 0.66 \text{hPa} \cdot ^\circ C^{-1} \)). (Ding et al., 2013; Pereira, 2004; Utset et al., 2004). \( T_c, E_s, E_{ic} \) and \( E_{ws} \) denote vegetation transpiration, soil evaporation, vegetation interception and wet soil surface evaporation, respectively. Parameter \( f_v \) is fraction of green vegetation (\( f_v = \frac{NDVI_{max} - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \)), \( f_t \) is the plant temperature constraint (\( f_t = \exp\left[-\left(\frac{T_a - T_{opt}}{T_{opt}}\right)^2\right] \)), \( f_{sm} \) is soil moisture constraint (\( f_{sm} = \left(1 - \frac{1}{DT/DT_{max}}\right) \)), \( f_{wet} \) is the relative surface wetness (\( f_{wet} = f_{sm} \)). \( G \) is the soil heat flux (\( G = \alpha_g R_n (1 - f_v) \), \( \text{W} \cdot \text{m}^{-2} \)), \( R_{nc} \) and \( R_{ns} \) are net radiation to the vegetation (\( R_{nc} = R_n f_v \)) and net radiation to the soil (\( R_{ns} = R_n (1 - f_v) \)), respectively (Fisher et al., 2008; Qiaozhen et al., 2011).

The Hargreaves model was firstly proposed by Hargreaves to estimate \( ET \). The model only requires measurements of the maximum and minimum air temperature data, and it can be expressed as (Zanetti et al., 2019):

\[
ET = 0.0023 \frac{R_a}{\lambda} \sqrt{(T_{a_{max}} - T_{a_{min}})(T_{a_{mean}} + 17.8)}
\]

\[
R_n = k_{Rs} R_a \sqrt{(T_{a_{max}} - T_{a_{min}})}
\]

where \( R_n \) (\( \text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1} \)) is the solar radiation, \( \lambda \) is the latent heat of vaporization of water (\( \lambda = 2.45, \text{MJ} \cdot \text{kg}^{-1} \)). \( R_a \) (\( \text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1} \)) is the extraterrestrial radiation with a value of approximately 1367 \( \text{W} \cdot \text{m}^{-2} \) (Allen et al., 1998), \( k_{Rs} (\text{^\circ C}^{-0.5}) \) is the adjustment coefficient. The value of \( k_{Rs} \) falls within the range of 0.16 – 0.19. For interior regions more than 20 km from the ocean, the value is 0.16. \( T_{a_{max}} \) (\( \text{^\circ C} \)), \( T_{a_{min}} \) (\( \text{^\circ C} \)) and \( T_{a_{mean}} \) (\( \text{^\circ C} \)) denote the max temperature, the min temperature and the mean temperature, respectively (Zanetti et al., 2019).
Evaluation of Model Performance

Taylor diagrams were used to evaluate model performance, which are polar-style graphs (Yao et al., 2017). Taylor diagrams include the centered root-mean-square error \((RMSE)\), the correlation coefficient \((R)\) and the standard deviation \((STD)\) between observed and modeled \(ET\). In addition, the determination efficiency \((R^2)\) was used in model evaluation (Gupta et al., 2009; Hartmann et al., 2013). These indices were calculated by the following equations:

\[
R^2 = \left[ \frac{\sum_{t=1}^{n} (Q^t_m - \overline{Q}_m)(Q^t_o - \overline{Q}_o)}{\sqrt{\sum_{t=1}^{n} (Q^t_m - \overline{Q}_m)^2 \sum_{t=1}^{n} (Q^t_o - \overline{Q}_o)^2}} \right]^2 \tag{17}
\]

\[
RMSE = \sqrt{\frac{\sum_{t=1}^{n} (Q^t_m - Q^t_o)^2}{n}} \tag{18}
\]

where \(n\) is the number of data sets, \(r\) is the linear correlation coefficient between simulations and observations, \(Q^t_m\) is the modeled value, \(Q^t_o\) is observed data \(\overline{Q}_m\) is average modelled value, and \(\overline{Q}_o\) is the average observed value.

3 Results

3.1 Performance of different models

Fig.2a - f show the relationships between observed and simulated daily \(ET\) by different models based on MODIS and Landsat-8 images. Fig.3 shows the Taylor diagrams for observed and simulated daily \(ET\) from the different models using MODIS and Landsat-8 images. As shown in Fig.2a – f and Fig.3, Landsat-8 images (the average
$R^2$ and RMSE are 0.81, 0.9 mm·day$^{-1}$, respectively) were more suitable for simulating
daily ET than MODIS images (the average $R^2$ and RMSE are 0.68, 1.3 mm·day$^{-1}$, respectively) for all three models. The PML model ($p < 0.01$) had a higher $R^2$ (0.72 for MODIS images and 0.87 for Landsat-8 images) and lower RMSE (1.4 mm·day$^{-1}$ and 0.8 mm·day$^{-1}$ for MODIS and Landsat-8 images, respectively), and therefore performed better than the other models. The Hargreaves model performed ?? ($R^2 = 0.65$ for MODIS images and $R^2 = 0.77$ for Landsat-8 images) than any other model using two kinds of images.

**Insert Figure 2 here**

**Insert Figure 3 here**

**3.2 Spatial-temporal distribution of ET**

Fig.4a – f show the spatial distribution of daily ET in different seasons for HOUZHAI Basin. As shown in Fig.4, daily ET exhibited marked seasonal variability. Mean daily ET in HOUZHAI Basin during the growing period (May, June and August: Mean = 3.77 mm·day$^{-1}$) is obvious higher than in the non-growing period (December, March and April: Mean = 1.6 mm·day$^{-1}$). As shown in Fig.5a - f, mean daily ET in SANCHAEHE River Basin also exhibited seasonal variability. The mean daily ET was 1.7 mm·day$^{-1}$, 3.6 mm·day$^{-1}$, 2.6 mm·day$^{-1}$ and 0.8 mm·day$^{-1}$ in spring (February), summer (May and August), autumn (September and October) and winter (December), respectively.

**Insert Figure 4 here**
As shown in Fig.6, the monthly ET of HOUZHAI Basin exhibited noticeable seasonal variability and strongly affected by vegetation cover type. Monthly ET values for cropland, forest and orchards in June and August were all greater than 100 mm·month$^{-1}$; however, monthly ET for shrub-grass never reached 85 mm·month$^{-1}$. The six-month average ET values were 84.5 mm·month$^{-1}$, 95.5 mm·month$^{-1}$, 89.5 mm·month$^{-1}$, 69.5 mm·month$^{-1}$ and 54.4 mm·month$^{-1}$ for cropland, forest, orchard, fired patch and shrub-grass, respectively. As shown in Fig.7a - b, Annual average ET were 634.7 mm·year$^{-1}$ and 589 mm·year$^{-1}$ for HOUZHAI Basin and SANCHA River Basin, respectively. The distribution of annual average ET exhibited marked regional differences. As shown in Fig.6a, annual ET for the eastern HOUZHAI Basin is clearly higher than in the western part. The values in the eastern part mainly ranged from 600-750, and values in the west mainly ranged from 500-650. Fig.7b shows the distribution of annual ET for SANCHA Basin. On the whole, values in the south-central region were higher than in the northern region. The distribution of ET was not uniform, which may have been related to the underlying surface cover types.

3.3 Relationship between ET and retrieved surface parameters

As shown in Fig.8, the surface parameters values exhibited distinct seasonality. The average NDVI (Fig.8a-d) was 0.15 in April (spring), then it rose to 0.37 and 0.55
in June and August (summer), respectively. However, it was only 0.1 in December (winter). Similar seasonality was observed in the seasonal variability process of Gs, Rn and GTa. The average Gs was 0.025 m·s$^{-1}$, 0.034 m·s$^{-1}$, 0.042 m·s$^{-1}$ and 0.016 m·s$^{-1}$ for April, June, August and December, respectively. The values of Rn mainly ranged from 114 - 500 W·m$^{-2}$ on 14 April and the average April value was 254 W·m$^{-2}$. Values ranged from 281 – 610 W·m$^{-2}$ and 207-630 W·m$^{-2}$ on 15 June and 11 August, respectively. The average values were 477 W·m$^{-2}$ and 485 W·m$^{-2}$ for the two months, respectively. GTa values ranged from 289-307 K, 300-315 K, 303-317 K and 282-298 K on 14 April, 15 June, 11 August and 17 December, respectively. Average GTa value was 295 K, 308 K, 311 K and 287 K for April, June, August and December, respectively.

As shown in Fig. 9, ET had a slight positive correlation with DEM, and $R^2$ was 0.18 and 0.11 on 14 April and 18 June, respectively. There was a clear positive correlation between ET and LAI, Gs and Rn. $R^2$ for the three controls were greater than 0.60 and 0.54 on 14 April and 18 June, respectively. However, GTa exhibited a negative correlation with ET, and $R^2$ was 0.61 and 0.74 on 14 April and 18 June, respectively.

4. Discussion

As a key parameter for retrieving ET, GTa is essential in constructing various models. Compared with SPOT, Gaofen and Sentinel remote sensing images and data, only MODIS and Landsat data contain thermal infrared bands, which is the basis for
retrieving GTa (Bhattacharya et al., 2010; Bourras, 2006; Shen et al., 2016). Therefore, MODIS and Landsat-8 were selected as remote sensing data in this study. As shown in Fig. 2 and Fig. 3, PML models using Landsat-8 images performed slightly better than those using MODIS data. This may be because the spatial resolution of Landsat-8 images (30 m) is higher than those of MODIS data (1000 m). More validation data observed in experimental spots can be identified and corresponded with satellite data. Consequently, more samples decreased the systematic error and increased the accuracy of the models based on Landsat-8 images. The RS-PT model didn't perform as well as the PML model in our study, which may have been related to the complex and varied surface. For the five ecosystems, crop rotation and deciduous trees create high variability in stomatal resistance over the course of the year. Consequently, simulated values for canopy resistance ($r_c$) and canopy surface resistance ($r'_c$) might be imprecise (Irmak et al., 2013; Whitley et al., 2009). In other words, values of the calibrated 'α' parameter for ecosystems were difficult to unify and specify. The Hargreaves model also performed slightly poorer than the PML model. This may have been because $k_{Rs}$ was readjusted in our study and the parameter was influenced by wind speed at 2 m height (Martinez-Cob and Tejero-Juste, 2004). However, there were only two meteorological stations in experimental plots and, previous studies have demonstrated that wind speed is usually not reliable at many stations (Shiri et al., 2013). As a result, the parameter of $k_{Rs}$ was less precise in this study.

In our study, daily ET for both HOUZHAI (Fig. 4) and SANCHAHE (Fig. 5) Basins both exhibited seasonality. This finding was similar to previous studies in
various climatic zones, including cold climates, temperate climates, tropical systems and arid/semi-arid regions (Li et al., 2012; Parka et al., 2008; Shao et al., 2012; Tanaka et al., 2008; Yang and Zhou, 2011). During the study period, the annual mean potential ET was approximately 1102 mm·year\(^{-1}\), which is similar with those results in the same bioclimatic zone (Chen et al., 2015; Tian et al., 2018; Yao et al., 2014). For example, annual potential ET mainly ranged from 950-1350 mm·year\(^{-1}\) in southwestern China over eight years (2008-2016) (Tian et al., 2018). The annual potential ET calculated by Yao et al. (2014) from 1982-2010 was between 800-1400 mm·year\(^{-1}\) in the same zone. Chen et al. (2015) calculated 50-year (1956-2006) actual annual ET for Guangdong Province, which was in a similar latitude as our study area, and results showed that actual annual ET was within 600-1200 mm·year\(^{-1}\). In our study, actual annual ET was lower than in Sichuan and Guangdong provinces, with annual ET values of 634.7 mm·year\(^{-1}\) and 589 mm·year\(^{-1}\) for HOUZHAH and SANCHAE Basins, respectively. Previous studies have demonstrated that ET was mainly related to temperature, precipitation, solar radiation, soil water content (SWC) and leaf area index (LAI) (Parka et al., 2008; Shao et al., 2012; Tanaka et al., 2008; Yang and Zhou, 2011). In our study, the basins were located in the transition region between Yunnan plateau and Guizhou plateau. The average elevation is higher than in Sichuan and Guangdong provinces, and average daily temperatures were much lower than those regions. Consequently, annual ET was also lower. Daily ET was highest during the growing seasons. In our study, annual ET in forest, orchard and cropland was always higher than in fired patch and shrub-grass ecosystems. The vegetation coverage and density of conducting tissue (e.g.
LAI) both contributed to ET seasonality and the differing spatial distributions (Dickinson et al., 1991; Ge et al., 2011; Kite, 2000; Kite and Droogers, 2000; Tanaka et al., 2008). Moreover, this region is generally underdeveloped, overpopulated and characterized by severe rocky desertification (Hartmann et al., 2014b; Nie et al., 2012; Yang et al., 2017). The water retention capacity of the thin soil layer is low, and water flows away through surface runoff and crevasses. Therefore, the upper limit of ET was constrained (Liu et al., 2016).

The values for soil moisture index ($f$) and stomatal conductance ($g_{sx}$) in the PML model were 0.017 m·s$^{-1}$ and 1, respectively. Previous studies have demonstrated that $g_{sx}$ often falls the range of 0 – 0.020 m·s$^{-1}$, and $f$ ranges from 0 – 1. When the value of $f$ is closer to 1, the climate is wetter (Leuning et al., 2008). NDVI reflects vegetation coverage and its values range between -1 and 1. Where vegetation is denser, the value of NDVI is closer to 1. As shown in Fig. 7, the evolution of retrieved NDVI was consistent with seasonality and vegetation growth in this study. This demonstrated that the retrieved NDVI was trustable (Rocchini, 2009). Previous studies concluded that $G_{s}$ was related to NDVI and values in the karst areas of southwestern China mainly ranged from 0.020 – 0.040 during the growing seasons (Xu et al., 2018). The results were similar to our study. Compared with the North China plain, where vegetation cover is lower, $G_{s}$ was higher in our study (Hu et al., 2018). GTa and Rn exhibited clear spatial distributions in our study. This may have been because towns, asphalt roads and artificial buildings have a strong capacity to absorb heat during the day, so GTa and Rn were higher in towns than mountain areas and croplands where the canopy density of
vegetation was much higher (Fu and Weng, 2016; He et al., 2014; Li and Wang, 2019; Rigden and Li, 2017; Wang et al., 2019). In our study, $ET$ had slight positive correlations with DEM, LAI, Gs and Rn. In essence, the DEM effect was influenced by vegetation, because NDVI values at high elevations were higher than that at lower elevation. By the same principle, the distribution of LAI was consistent with NDVI and elevation in the study area. On the contrary, GTa was higher in towns where vegetation is sparse, and it was negatively correlated with $ET$. Previous studies showed that the main controlling environmental factors for $ET$ differed with vegetation type (such as crops, grass and trees), climate (such as water and energy availability) and landscapes (such as plains, plateaus and karst depressions) (Beven, 1979; Coleman and Decoursey, 1976; Gong et al., 2006; Nouri et al., 2017; Sharifi and Dinpashoh, 2014). Overall, $ET$ is more strongly controlled by energy availability as the climate becomes wetter, and more controlled by water availability as the climate becomes drier.

5. Conclusions

In this study, five plots were built to observe actual $ET$ using refitted ventilated-chamber, thermal dissipation probes and micro-lysimeters in a subtropical humid karst catchment. Then, three models (Penman-Monteith-Leurning, PML; Remote Sensing-Priestley and Taylor, RS-PT; and Hargreaves) were selected to upscale $ET$ estimation to the regional level using Landsat-8 and MODIS data. The results showed that the PML model performed the best, probably due to the fact that the spatial resolution of Landsat-8 images (30 m) was higher than the MODIS data (1000 m). Additional validation data observed in experimental spots were identified and corresponded with
satellite data. Vegetation coverage and the density of conducting tissue (e.g. LAI) both contributed to ET seasonality and the spatial distribution differences.

Acknowledgments

This study was supported by the GDAS' Project of Science and Technology Development (2020GDASYL-20200103078) and Natural Science Youth Foundation of Guangdong Province (2020A1515111060). We thank anonymous reviewers and the editorial team.

Data Availability Statement

All data and models are available from the authors upon request.

Ethical Approval

The authors declare no conflict of interest.

Consent to Participate

The authors consent to participate.

Consent to Publish

The authors consent to publish.

Authors Contributions

Rongei Zhang: Conceptualization, Methodology, Software, Validation, Writing-Original Draft, Review & Editing, Resources, Project administration, funding acquisition.

Funding
This study is supported by GDAS' Project of Science and Technology Development (2020GDASYL-20200103078), Natural Science Youth Foundation of Guangdong Province (2020A1515111060) and National Natural Science Foundation of China (42101036).

Additional information

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Reference

Allen, C.D. and Breshears, D.D., 1998. Drought-induced shift of a forest-woodland ecotone: Rapid landscape response to climate variation. Proceedings of the National Academy of Sciences of the United States of America, 95(25): 14839-14842.

Allen, R.G., Pereira, L.S. and Raes, D., 1998. Crop evapotranspiration—Guidelines for computing crop water requirements. FAO Irrig and Drain Paper No. 56, Rome.

Allen, S.J., 1990. Measurement and Estimation of Evaporation from Soil under Sparse Barley Crops in Northern Syria. Agr Forest Meteorol, 49(4): 291-309.

Anderson, R.G., Jin, Y.F. and Goulden, M.L., 2012. Assessing regional evapotranspiration and water balance across a Mediterranean montane climate gradient. Agr Forest Meteorol, 166: 10-22.

Bakalowicz, M., 2005. Karst groundwater: a challenge for new resources. Hydrogeol J, 13(1): 148-160.

Balwinder-Singh, Eberbach, P.L. and Humphreys, E., 2014. Simulation of the evaporation of soil water beneath a wheat crop canopy. Agr Water Manage, 135: 19-26.

Bastiaanssen, W.G.M. et al., 1998. A remote sensing surface energy balance algorithm for land (SEBAL) -2. Validation. J Hydrol, 212(1-4): 213-229.

Bella, D.L., Kwon, Y.H., Hirschberger, L.L. and Stipanuk, M.H., 2000. Post-transcriptional regulation of cysteine dioxygenase in rat liver. Adv Exp Med Biol, 483: 71-85.

Beven, K., 1979. Sensitivity Analysis of the Penman-Monteith Actual Evapotranspiration
Bhattacharya, B.K., Mallick, K., Patel, N.K. and Parihar, J.S., 2010. Regional clear sky evapotranspiration over agricultural land using remote sensing data from Indian geostationary meteorological satellite. Journal of Hydrology, 387(1-2): 65-80.

Boast, C.W. and Robertson, T.M., 1982. A Micro-Lysimeter Method for Determining Evaporation from Bare Soil - Description and Laboratory Evaluation. Soil Sci Soc Am J, 46(4): 689 - 696.

Bosch, D.D., Marshall, L.K. and Teskey, R., 2014. Forest transpiration from sap flux density measurements in a Southeastern Coastal Plain riparian buffer system. Agricultural and Forest Meteorology, 187: 72-82.

Bouchet, R.J., 1960. Evapotranspiration Potentielle Dun Couvert Vegetal - Sa Signification Et Sa Mesure a Partir De Levaporation Sous Abri. Cr Hebd Acad Sci, 251(12): 1231-1233.

Bourra, D., 2006. Comparison of five satellite-derived latent heat flux products to moored buoy data. Journal of Climate, 19(24): 6291-6313.

Chen, X.Z. et al., 2015. 50-year evapotranspiration declining and potential causations in subtropical Guangdong province, southern China. Catena, 128: 185-194.

Coleman, G. and Decoursey, D.G., 1976. Sensitivity and Model Variance Analysis Applied to Some Evaporation and Evapotranspiration Models. Water Resour Res, 12(5): 873-879.

Cramer, V.A., Thorburn, P.J. and Fraser, G.W., 1999. Transpiration and groundwater uptake from farm forest plots of Casuarina glauca and Eucalyptus camaldulensis in saline areas of southeast Queensland, Australia. Agricultural Water Management, 39(2-3): 187-204.

Dickinson, R.E., Henderson-Sellers, A., Rosenzweig, C. and Sellers, P.J., 1991. Evapotranspiration Models with Canopy Resistance for Use in Climate Models - a Review. Agricultural and Forest Meteorology, 54(2-4): 373-388.

Ding, R.S., Kang, S.Z., Li, F.S., Zhang, Y.Q. and Tong, L., 2013. Evapotranspiration measurement and estimation using modified Priestley-Taylor model in an irrigated maize field with mulching. Agr Forest Meteorol, 168: 140-148.

Fisher, J.B. et al., 2017. The future of evapotranspiration: Global requirements for ecosystem functioning, carbon and climate feedbacks, agricultural management, and water resources. Water Resour Res, 53(4): 2618-2626.

Fisher, J.B., Tu, K.P. and Baldocchi, D.D., 2008. Global estimates of the land-atmosphere water flux based on monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites. Remote Sensing of Environment, 112(3): 901-919.

Fu, P. and Weng, Q.H., 2016. A time series analysis of urbanization induced land use and land cover change and its impact on land surface temperature with Landsat imagery. Remote
Sensing of Environment, 175: 205-214.

Ge, Z.M. et al., 2011. Impacts of changing climate on the productivity of Norway spruce dominant stands with a mixture of Scots pine and birch in relation to water availability in southern and northern Finland. Tree Physiol, 31(3): 323-338.

Gong, L.B., Xu, C.Y., Chen, D.L., Halldin, S. and Chen, Y.Q.D., 2006. Sensitivity of the Penman-Monteith reference evapotranspiration to key climatic variables in the Changjiang (Yangtze River) basin. Journal of Hydrology, 329 (3-4): 620-629.

Granier, A., 1985. A New Method of Sap Flow Measurement in Tree Stems. Annales Des Sciences Forestieres, 42(2): 193-200.

Granier, A., Biron, P. and Lemoine, D., 2000. Water balance, transpiration and canopy conductance in two beech stands. Agr Forest Meteorol, 100(4): 291-308.

Greenwood, E.A.N., Beresford, J.D., Bartle, J.R. and Barron, R.J.W., 1982. Evaporation from Vegetation in Landscapes Developing Secondary Salinity Using the Ventilated-Chamber Technique. Evaporation from a Regenerating Forest of Eucalyptus Wandoo on Land Formerly Cleared for Agriculture. J Hydrol, 58(3-4): 357-366.

Greenwood, E.A.N., Klein, L., Beresford, J.D. and Watson, G.D., 1985a. Differences in Annual Evaporation between Grazed Pasture and Eucalyptus Species in Plantations on a Saline Farm Catchment. Journal of Hydrology, 78(3-4): 261-278.

Greenwood, E.A.N., Klein, L., Beresford, J.D., Watson, G.D. and Wright, K.D., 1985b. Evaporation from the Understorey in the Jarrah (Eucalyptus-Marginata Don Ex Sm) Forest, Southwestern Australia. J Hydrol, 80(3-4): 337-349.

Gupta, H.V., Kling, H., Yilmaz, K.K. and Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. J Hydrol, 377(1-2): 80-91.

Hartmann, A., Barbera, J.A., Lange, J., Andreo, B. and Weiler, M., 2013. Progress in the hydrologic simulation of time variant recharge areas of karst systems - Exemplified at a karst spring in Southern Spain. Adv Water Resour, 54: 149-160.

Hartmann, A., Goldscheider, N., Wagener, T., Lange, J. and Weiler, M., 2014a. Karst water resources in a changing world: Review of hydrological modeling approaches. Rev Geophys, 52(3): 218-242.

Hartmann, A. et al., 2014b. Modeling spatiotemporal impacts of hydroclimatic extremes on groundwater recharge at a Mediterranean karst aquifer. Water Resour Res, 50(8): 6507-6521.

He, F. et al., 2014. Simulating global and local surface temperature changes due to Holocene anthropogenic land cover change. Geophysical Research Letters, 41(2): 623-631.
Hu, X.L., Shi, L.S., Lin, L., Zhang, B.Z. and Zha, Y.Y., 2018. Optical-based and thermal-based surface conductance and actual evapotranspiration estimation, an evaluation study in the North China Plain. Agr Forest Meteorol, 263: 449-464.

Irmak, S., Mutiibwa, D., Payero, J., Marek, T. and Porter, D., 2013. Modeling soybean canopy resistance from micrometeorological and plant variables for estimating evapotranspiration using one-step Penman-Monteith approach. Journal of Hydrology, 507: 1-18.

Jackson, R.D., Idso, S.B., Reginato, R.J. and Pinter, P.J., 1981. Canopy Temperature as a Crop Water-Stress Indicator. Water Resour Res, 17(4): 1133-1138.

Jackson, R.D., Reginato, R.J. and Idso, S.B., 1977. Wheat Canopy Temperature - Practical Tool for Evaluating Water Requirements. Water Resour Res, 13(3): 651-656.

Jiang, L. and Islam, S., 2001. Estimation of surface evaporation map over southern Great Plains using remote sensing data. Water Resour Res, 37(2): 329-340.

Jung, M. et al., 2010. Recent decline in the global land evapotranspiration trend due to limited moisture supply. Nature, 467(7318): 951-954.

Kite, G., 2000. Using a basin-scale hydrological model to estimate crop transpiration and soil evaporation. Journal of Hydrology, 229 (1-2): 59-69.

Kite, G. and Droogers, P., 2000. Comparing evapotranspiration estimates from satellites, hydrological models and field data - Preface. Journal of Hydrology, 229 (1-2): 1-2.

Koster, R.D. et al., 2004. Regions of strong coupling between soil moisture and precipitation. Science, 305(5687): 1138-1140.

Kustas, W.P. et al., 1989. Determination of Sensible Heat-Flux over Sparse Canopy Using Thermal Infrared Data. Agr Forest Meteorol, 44 (3-4): 197-216.

Leuning, R., Zhang, Y.Q., Rajaud, A., Cleugh, H. and Tu, K., 2008. A simple surface conductance model to estimate regional evaporation using MODIS leaf area index and the Penman-Monteith equation. Water Resources Research, 44 (10): 652-655.

Li, D. and Wang, L., 2019. Sensitivity of Surface Temperature to Land Use and Land Cover Change-Induced Biophysical Changes: The Scale Issue. Geophysical Research Letters, 46(16): 9678-9689.

Li, Z., Zheng, F.L. and Liu, W.Z., 2012. Spatiotemporal characteristics of reference evapotranspiration during 1961-2009 and its projected changes during 2011-2099 on the Loess Plateau of China. Agr Forest Meteorol, 154: 147-155.

Liu, M.X., Xu, X.L., Wang, D.B., Sun, A.Y. and Wang, K.L., 2016. Karst catchments exhibited higher degradation stress from climate change than the non-karst catchments in southwest China: An ecohydrological perspective. J Hydrol, 535: 173-180.
Luo, W. et al., 2019. UAV based soil moisture remote sensing in a karst mountainous catchment. Catena, 174: 78-89.

Martinez-Cob, A. and Tejero-Juste, M., 2004. A wind-based qualitative calibration of the Hargreaves ET0 estimation equation in semiarid regions. Agricultural Water Management, 64 (3): 251-264.

Nie, Y.P., Chen, H.S., Wang, K.L. and Yang, J., 2012. Water source utilization by woody plants growing on dolomite outcrops and nearby soils during dry seasons in karst region of Southwest China. J Hydrol, 420: 264-274.

Nouri, M., Homae, M. and Bannayan, M., 2017. Quantitative Trend, Sensitivity and Contribution Analyses of Reference Evapotranspiration in some Arid Environments under Climate Change. Water Resour Manag, 31(7): 2207-2224.

Parka, H., Yamazaki, T., Yamamoto, K. and Ohta, T., 2008. Tempo–spatial characteristics of energy budget and evapotranspiration in the eastern Siberia. Agr Forest Meteorol, 148(12): 1990-2005.

Penman, H.L., 1948. Natural Evaporation from Open Water, Bare Soil and Grass. Proc R Soc Lon Ser-A, 193(1032): 120-133.

Pereira, A.R., 2004. The Priestley-Taylor parameter and the decoupling factor for estimating reference evapotranspiration. Agr Forest Meteorol, 125(3-4): 305-313.

Priestley, C.H.B. and Taylor, R.J., 1972. Assessment of Surface Heat-Flux and Evaporation Using Large-Scale Parameters. Mon Weather Rev, 100(2): 81-95.

Qiaozhen, M., Zhao, M. and Steven, W., 2011. Improvements to a MODIS global terrestrial evapotranspiration algorithm. Remote Sensing of Environment, 115(8): 1781-1800.

Reicosky, D.C. and Peters, D.B., 1977. Portable Chamber for Rapid Evapotranspiration Measurements on Field Plots. Agronomy Journal, 69 (4): 729-732.

Rigden, A.J. and Li, D., 2017. Attribution of surface temperature anomalies induced by land use and land cover changes. Geophysical Research Letters, 44 (13): 6814-6822.

Rocchini, D., 2009. Commentary on Krishnaswamy et al. - Quantifying and mapping biodiversity and ecosystem services: Utility of a multi-season NDVI based Mahalanobis distance surrogate. Remote Sensing of Environment, 113(5): 904-906.

Seguin, B. and Tier, B., 1983. Using Midday Surface-Temperature to Estimate Daily Evaporation from Satellite Thermal Data. Int J Remote Sens, 4 (2): 371-383.

Seneviratne, S.I., Luthi, D., Litschi, M. and Schar, C., 2006. Land–atmosphere coupling and climate change in Europe. Nature, 444(7108): 205-209.

Shao, Q.X., Traylen, A. and Zhang, L., 2012. Nonparametric method for estimating the effects of
climatic and catchment characteristics on mean annual evapotranspiration. Water Resour
Res., 8.

Sharifi, A. and Dinpashoh, Y., 2014. Sensitivity Analysis of the Penman-Monteith reference Crop
Evapotranspiration to Climatic Variables in Iran. Water Resources Management, 28(15):
54 65-54 76.

Shen, H.F., Huang, L.W., Zhang, L.P., Wu, P.H. and Zeng, C., 2016. Long-term and fine-scale
satellite monitoring of the urban heat island effect by the fusion of multi-temporal and
multi-sensor remote sensed data: A 26-year case study of the city of Wuhan in China.
Remote Sensing of Environment, 172: 109 -125.

Shiri, J., Nazemi, A.H., Sadraddini, A.A., Landeras, G. and Martí, P., 2013. Global cross-station
assessment of neuro-fuzzy models for estimating daily reference evapotranspiration.
Journal of Hydrology, 4 80(4 ); 4 6- 57.

Tanaka, N. et al., 2008. A review of evapotranspiration estimates from tropical forests in Thailand
and adjacent regions. Agricultural and Forest Meteorology, 14 8(5): 807-819.

Tian, Y., Zhang, K.J., Xu, Y.P., Gao, X.C. and Wang, J., 2018. Evaluation of Potential
Evapotranspiration Based on CMADS Reanalysis Dataset over China. Water, 10(9).

Utset, A., Farre, I., Martinez-Cob, A. and Cavero, J., 2004. Comparing Penman-Monteith and
Priestley-Taylor approaches as reference-evapotranspiration inputs for modeling maize
water-use under Mediterranean conditions. Agr Water Manage, 66(3): 205-219.

Wang, C.Y., Li, Y.B., Myint, S.W., Zhao, Q.S. and Wentz, E.A., 2019. Impacts of spatial clustering
of urban land cover on land surface temperature across Koppen climate zones in the
contiguous United States. Landscape and Urban Planning, 192.

Wang, K.C. and Liang, S.L., 2008. An improved method for estimating global evapotranspiration
based on satellite determination of surface net radiation, vegetation index, temperature,
and soil moisture. J Hydrometeorol, 9 (4 ); 712-727.

Whitley, R., Medlyn, B., Zeppel, M., Macinnis-Ng, C. and Eamus, D., 2009. Comparing the
Penman-Monteith equation and a modified Jarvis-Stewart model with an artificial neural
network to estimate stand-scale transpiration and canopy conductance. J Hydrol, 373(1-2):
256-266.

Xu, J.M., Wu, B.F., Yan, N.N. and Tan, S., 2018. Regional Daily ET Estimates Based on the Gap-
Filling Method of Surface Conductance. Remote Sensing, 10(4).

Yang, F.L. and Zhou, G.S., 2011. Characteristics and modeling of evapotranspiration over a
temperate desert steppe in Inner Mongolia, China. J Hydrol, 39 6(1-2): 139 -14 7.

Yang, J. et al., 2016. Effects of Napier grass management on soil hydrologic functions in a karst
landscape, southwestern China. Soil & Tillage Research, 157: 83- 9 2.
Yang, J. et al., 2017. Effects of “Grain for Green” program on soil hydrologic functions in karst landscapes, southwestern China. Agr Ecosyst Environ, 247: 120-129.

Yao, Y.J., Zhao, S.H., Zhang, Y.H., Jia, K. and Liu, M., 2014. Spatial and Decadal Variations in Potential Evapotranspiration of China Based on Reanalysis Datasets during 1982-2010. Atmosphere, 5(4): 737-754.

Yao, Y.Y. et al., 2017. Improving global terrestrial evapotranspiration estimation using support vector machine by integrating three process-based algorithms. Agr Forest Meteorol, 242: 55-74.

Zanetti, S.S., Dohler, R.E., Cecilio, R.A., Pezzopane, J.E.M. and Xavier, A.C., 2019. Proposal for the use of daily thermal amplitude for the calibration of the Hargreaves-Samani equation. Journal of Hydrology, 571: 193-201.

Zhang, M., Zhou, Y., Tian, X. and Huang, X., 2017. Study on spatial heterogeneity and reserve estimation of soil organic carbon in a small karst catchment. Acta Ecologica Sinica, 37(22): 7647-7659.

Zhang, Y.Q. et al., 2016. Multi-decadal trends in global terrestrial evapotranspiration and its components. Sci Rep-Uk, 6.
Table 1. Comparison of relevant studies for ET observation methods and models for different various ecosystems in various landscapes.

Table 2. Baseline information for the five land cover types

Fig.1 Study area. Photo (d) shows the ventilated chamber; (e) and (h) show Thermal Dissipation Probes (TDPs); (f) shows a micro-lysimeter; (g) shows a meteorological station.

Fig.2 Relationships (linear regression) between observed and simulated ET using different models based on MODIS and Landsat-8 images. Fig.2a-c are based on MODIS images and Fig.2d-f are based on Landsat-8 images. Note that $R^2$ and RMSE denote the coefficient of determination and root-mean-square error, respectively.

Fig.3 Taylor diagrams of observed and simulated daily ET using different models based on MODIS and Landsat-8 images. Dotted circular lines connecting the x and y axes
represent the standard deviations (STD), dotted radial lines are the correlation coefficient values (R), and the green curves denote RMSE values.

Fig.4 Spatial-temporal distribution of daily ET for HOUZHAI Basin.

Fig.5 Spatial-temporal distribution of daily ET for HOUZHAI Basin.

Fig.6 Monthly ET for different vegetation cover types

Fig.7 Spatial distribution of annual ET for HOUZHAI and SANCHAHERiver Basins

Fig.8 Spatial distribution of surface parameters in different seasons. Fig.7a-d, Fig.7e-h, Fig.7i-l and Fig.7m-p represent NDVI, ground surface conductance, net radiation and ground temperature, respectively. NDVI, Gs, Rn and GTa are normalized vegetation index, ground surface conductance, net radiation and ground temperature, respectively.

Fig.9 Correlation analysis between control factors and ET in different seasons. $R^2$ and $P$ are the coefficient of determination and p-value, respectively.
Table 1. Comparison of relevant studies for ET observation methods and models for different various ecosystems in various landscapes.

| Methods               | Vegetation Types | Reference          | Location/Landscape/Climate                      |
|-----------------------|------------------|--------------------|-------------------------------------------------|
| Micro-lysimeter       | Soil of cropland | Yu et al. (2016)   | Northwest China/Loess plateau/Semi-arid         |
| Soil heat pulse       | Bare soil        | Heitman et al. (2008) | Central US/Plain/Temperate                     |
| Chamber               | Shrubs           | Stannard and Weltz (2006) | Southwest US/Piedmont plain/Arid desert       |
| Micro Bowen ratio     | Vines            | Holland et al. (2013) | Southeast US/Coastal plain/Subtropical climate |
| Method                      | Species                  | Authors                | Region/Climate                  |
|-----------------------------|--------------------------|------------------------|---------------------------------|
| Eddy covariance method      | Wheat                    | Denmead et al.         | Southeast Australian/Temperate humid climate/Coastal lowland |
| Sap flow                    | Woodland                 | Zeppel et al.          | Australia/Liverpool plains/Temperate |
| Biomass-transpiration       | Tomato                   | Ben-Gal et al.         | Israel/Valley/Mediterranean climate |
| Isotopes                    | Savanna                  | Wang et al.            | Kenya/Plateau/Tropical savanna climate |
| One-source model            | Cotton, grapes and olive trees | Bastiaanssen         | Turkey/Irrigated basin/Mediterranean climate |
| Two-source model            | Cherry orchard           | Juhasz and Hrotko     | Hungary/Plain/Continental temperate climate |
| Ts-VI model                 | NA                       | Verhoef                | NA (2007)                        |
| Empirical model             | Whole-ecosystems         | Yan and Shugart        | American/Various landscapes and climate |
| Method | Observation | Study Area | Results |
|--------|-------------|------------|---------|
| Pemnan-Montheith equation | Micro-lysimeter, Sap flow, Ventilated chamber | East of American/Plain/Temperate continental climate | Whole-ecosystems |
| Assimilation method and temporal upscaling | Forest, Orchard, Cropland, shrub-grass and Fired patch | Southwest China/karst landscape/humid subtropical monsoon | Chinese/Various landscapes and climate |
| | | | Cai et al. (2007) |
| | | | Crow et al. (2008) |
| | | | PML, RS-PT, Hargreave models |
Table 2. Baseline information for the five land cover types

| Types    | Vegetation species                                                                 | ET measurement | Data spacing (min) | Experimental spacing (day) | Growth stage |
|----------|-----------------------------------------------------------------------------------|----------------|-------------------|-----------------------------|--------------|
| Forest   | Quercus fabri Hance/Albizia julibrissin Durazz./Toona sinensis/Platycarya strobilacea | TDP            | 5                 | Continuous                 | Mar-Nov      |
|          | Sieb.et Zucc./Kalopanax septemlobus (Thunb.)                                       |                |                   |                             |              |
|          | Koidz./Populus adenopoda Maxim.                                                   |                |                   |                             |              |
| Environment            | Vegetation                        | Ventilated-Chamber | Total Duration | Season       |
|------------------------|-----------------------------------|--------------------|----------------|--------------|
| Grass and soil         | Ventilated-Chamber                | 5                  | 10-15          |              |
| **Orchard**            |                                   |                    |                |              |
| Bare soil              | Ventilated-Chamber                | 5                  | 10-15          | NA           |
| Maize                  | Ventilated-Chamber                | 5                  | 10-15          | Mar-Jun      |
| **Cropland**           |                                   |                    |                |              |
| Oilseed rape           | Ventilated-Chamber                | 5                  | 10-15          | Dec-Mar      |
| **Shrub-grass**        |                                   |                    |                |              |
| Grass                  | Ventilated-Chamber                | 5                  | 10-15          |              |
| **Burned patch**       |                                   |                    |                |              |
| Grass and soil         | Ventilated-Chamber                | 5                  | 10-15          |              |

*Toona sinensis/Pyrus, i, f/Catalpa bungei C. A. Mey.*

*Coriaria nepalensis*

*Wall/Pyracantha fortuneana* (Maxim.) Li

*Populus adenopoda* Maxim.
Fig.1 Study area. Photo (d) shows the ventilated chamber; (e) and (h) show Thermal Dissipation Probes (TDPs); (f) shows a micro-lysimeter; (g) shows a meteorological station.
Fig. 2 Relationships (linear regression) between observed and simulated ET using different models based on MODIS and Landsat-8 images. Fig.2a-c are based on MODIS images and Fig.2d-f are based on Landsat-8 images. Note that $R^2$ and RMSE denote the coefficient of determination and root-mean-square error, respectively.
Fig. 3 Taylor diagrams of observed and simulated daily ET using different models based on MODIS and Landsat-8 images. Dotted circular lines connecting the $x$ and $y$ axes represent the standard deviations ($STD$), dotted radial lines are the correlation coefficient values ($R$), and the green curves denote $RMSE$ values.
**Fig. 4** Spatial-temporal distribution of daily ET for HOUZHAI Basin.
Fig. 5 Spatial-temporal distribution of daily ET for HOUZHAI Basin.
Fig. 6 Monthly ET for different vegetation cover types
Fig. 7 Spatial distribution of annual ET for HOUZHAI and SANCHEHERiver Basins
Fig. 8 Spatial distribution of surface parameters in different seasons. Fig. 7a-d, Fig. 7e-h, Fig. 7i-l and Fig. 7m-p represent NDVI, ground surface conductance, net radiation and ground temperature, respectively. NDVI, Gs, Rn and GTa are normalized vegetation index, ground surface conductance, net radiation and ground temperature, respectively.
Fig. 9 Correlation analysis between control factors and $ET$ in different seasons. $R^2$ and $P$ are the coefficient of determination and p-value, respectively.