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

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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>

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Selection of remote sensing images and evapotranspiration models on complex land surfaces for a humid karst catchment

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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 Micro-lysimeters 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 ($1.4 \text{ mm} \cdot \text{day}^{-1}$ and $0.8 \text{ mm} \cdot \text{day}^{-1}$ 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

63 idea of remote sensing technique is energy balance in the vertical direction. In 1997,
64 Jackson first put forwards a simplified method that combining the observation data with
65 remote sensing data to fit evaporation and remote sensing data (Jackson et al., 1977).
66 In 1983, Seguin perfected Jackson's empirical formula (Seguin and Itier, 1983). Since
67 then, Bella established a relationship between daily *ET* with NDVI and surface
68 temperature by using AVHRR data(Bella et al., 2000). Some scholars established
69 empirical relationship among net radiation, vegetation index, temperature, soil
70 temperature and *ET*. Overall, empirical statistical models are simple to use but relying
71 on the surface observation data too much (Wang and Liang, 2008). In 1948, Penman
72 proposed two formulas: one is to calculate potential evaporation underlying moist
73 surface and the other is to calculate transpiration of single leaves hole (Penman, 1948).
74 Based on the two formulas, Monteith introduced the concept of surface impedance and
75 got the Penman-Monteith (P-M) formula, which is the foundation for the further study
76 about *ET* of unsaturated underlying surface. In 1972, Priestley put forward Priestley-
77 Taylor (P-T) model to calculate *ET* based on the equilibrium vaporization and under the
78 premise of the hypothesis of no advection (Priestley and Taylor, 1972). By combining
79 with the feature space of temperature-vegetation index and quadratic linear
80 interpolation, Jiang and Islam (2001) calculated actual P-T coefficient of different
81 underlying surface. In 1963, Bouchet first put forward the relationship theory of actual
82 and potential *ET* (Bouchet, 1960). Based on the theory, scholars established a series of
83 calculation models of actual *ET*, such as the Advection-Aridity model put forward by
84 Brutsaert, the CRAE (Complementary Relationship Areal Evapotranspiration) model

85 proposed by Morton, the Granger model established by Granger through combining
86 heat balance principle and aerodynamics based on Dolton evaporation law. In 1981,
87 Jackson presented CWSI (Crop Water shortage Index) (Jackson et al., 1981). Due to the
88 exponential model error in sparse vegetation area is too big, Moran improved the model
89 by using vegetation index and temperature trapezoidal method. SEBAL (Surface
9 0 Energy Balance Algorithm for Land) model was put forward based on land surface
9 1 energy balance equation to estimate regional *ET* by analyzing the net radiation flux.
9 2 These kinds of remote sensing *ET* models can be divided into single-layer model and
9 3 double-layer model out of different exchange ways of surface and near surface
9 4 atmosphere turbulence heat flux (Bastiaanssen et al., 1998; Kustas et al., 1989).

9 5 **Insert Table 1 here**

9 6 Though various models have been combined with remote sensing images to
9 7 estimate regional *ET* in many landscapes, however, it is challenging to measure actual
9 8 *ET* and the accuracy of retrieved parameters of models is usually low for karst
9 9 landscapes, which cover 10% of the earth's land surface and supply water resources for
100 approximately 25% of the world's population (Hartmann et al., 2014a). The underlying
101 surface features of karst landscape are more complicated than plain or plateau
102 landscapes, leading to poorer parameters values estimation. For example, Luo et al.
103 (2019) calculated the spatial distribution of soil moisture for a karst catchment and
104 found that the models did not perform well in highly heterogeneous landscapes ($R^2 =$
105 0.36). Therefore, accurate *ET* estimation based models for karst landscapes is more
106 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, SANCHA (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 SANCHI 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 θ once every five minutes. LAI (Leaf Area Index) was measured using LAI-2200C (LI-COR LTD., U.S.) once every 10-15 days.

Insert Table 2 here

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):

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

(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 Sa 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 ($\text{mm} \cdot \text{day}^{-1}$) was estimated according to the following equations:

$$AH = \frac{217 \times RH \cdot 6.1078 e^{\frac{17.269t}{237.3+t}}}{Ta} \quad (\text{g}/\text{m}^3) \quad (2)$$

$$ET = \sum_{i=1}^n V \cdot AH_{outlet} \cdot t - \sum_{i=1}^n V \cdot AH_{intlet} \cdot t \quad (3)$$

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

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

$$ET = \frac{T_{sum}}{A} + ET_v \quad (4)$$

where T_{sum} ($\text{kg} \cdot \text{day}^{-1}$) 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 $\times$ 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 SANCHI and HOUZHAI Basins were used in this study. Landsat-8 images were obtained from <http://glovis.usgs.gov/>, and MODIS products were downloaded from <http://ladsweb.nascom.nasa.gov/data/search.html>.

DEM data were obtained from the geospatial data cloud (<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, λET , G_c and G_s can be expressed as equations (6) - (8) (Leuning et al., 2008):

$$\lambda E = \frac{\varepsilon A + \left(\frac{\rho c_p}{\gamma}\right) D_a G_a}{\varepsilon + 1 + \frac{G_a}{G_s}} \quad (5)$$

$$\lambda ET = \frac{\varepsilon A_c + \left(\frac{\rho c_p}{\gamma}\right) D_a G_a}{\varepsilon + 1 + \frac{G_a}{G_s}} + \frac{f \varepsilon A_s}{\varepsilon + 1} \quad (6)$$

$$G_c = \frac{g_{sx}}{k_Q} \ln \left[\frac{Q_h + Q_{50}}{Q_h \exp(-k_Q L) + Q_{50}} \right] \left[\frac{1}{1 + \frac{D_a}{D_{50}}} \right] \quad (7)$$

$$G_s = G_c \left[\frac{1 + \frac{\tau G_a}{(\varepsilon + 1) G_c} \left[f - \frac{(\varepsilon + 1)(1 - f) G_c}{G_a} \right] + \frac{G_a}{\varepsilon G_i}}{1 - \tau \left[f - \frac{(\varepsilon + 1)(1 - f) G_c}{G_a} \right] + \frac{G_a}{\varepsilon G_i}} \right] \quad (8)$$

where λ ($\lambda = 2.45$, $\text{MJ} \cdot \text{kg}^{-1}$) is the latent heat of E , $\varepsilon = \frac{S}{\gamma}$, γ ($\gamma = 0.66 \text{ hPa} \cdot ^\circ\text{C}^{-1}$) is the psychrometric constant and S ($\text{kPa} \cdot ^\circ\text{C}^{-1}$) is the slope of the curve relating saturation water vapor pressure and T_a . A ($\text{W} \cdot \text{m}^{-2}$) denotes the available energy absorbed by the surface ($R_n - G$, net absorbed radiation minus soil heat flux). D_a (Pa) denotes the water vapor pressure of the air, G_a ($\text{m} \cdot \text{s}^{-1}$), G_c ($\text{m} \cdot \text{s}^{-1}$) and G_s ($\text{m} \cdot \text{s}^{-1}$) 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 ($\text{W} \cdot \text{m}^{-2}$) and A_s ($\text{W} \cdot \text{m}^{-2}$) 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

231 respectively by $A_C/A = 1 - \tau$ and $A_S/A = \tau$, where $\tau = \exp(-k_A \cdot LAI)$, k_A is an extinction
 232 coefficient for available energy and LAI ($\text{m}^2 \cdot \text{s}^{-2}$) is leaf area index. $Q_h = 0.8 A$, and fixed
 233 values are $Q_{50} = 30 \text{ W} \cdot \text{m}^{-2}$, $G_a = 0.033$, $k_Q = 0.6$, $D_{50} = 1.0 \text{ kPa}$.

234 The PT model used to calculate ET can be expressed as equation (9) (Utset et al.,
 235 2004). Because interception loss can be responsible for approximately 13-22% of the
 236 evaporation component of total ET losses in various ecosystems, therefore, it should be
 237 taken into account when estimating ET over large land masses. The modified RS - PT
 238 model can be expressed as equation (10) - (13).

$$239 \quad \lambda ET = \alpha \left[\frac{\Delta(R_n - G)}{\Delta + \gamma} \right] \quad (9)$$

$$240 \quad \lambda ET = \lambda T_c + \lambda E_s + \lambda E_{ic} + \lambda E_{ws}$$

$$241 \quad (10)$$

$$242 \quad \lambda T_c = (1 - F_{wet}) f_v f_T \alpha \frac{\Delta}{\Delta + \gamma} R_{nc}$$

$$243 \quad (11)$$

$$244 \quad \lambda E_s = (1 - f_{wet}) f_{sm} \alpha \frac{\Delta}{\Delta + \gamma} (R_{ns} - G)$$

$$245 \quad (12)$$

$$246 \quad \lambda E_{ic} = f_{wet} \alpha \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (13)$$

$$247 \quad \lambda E_{ws} = f_{wet} \alpha \frac{\Delta}{\Delta + \gamma} (R_{ns} - G)$$

$$248 \quad (14)$$

249 where α is a dimensionless coefficient ranging from 1.08 ± 0.01 and 1.34 ± 0.05 , with
 250 average of 1.26 according to empirical data from numerous sites around the world

251 (Priestley and Taylor, 1972), $T_{opt} = 25^{\circ}\text{C}$, $a_g = 0.18$. λ is the latent heat of vaporization
 252 of water ($\lambda = 2.45$, $\text{MJ}\cdot\text{kg}^{-1}$), R_n is the net radiation ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$), γ is the psychrometric
 253 constant ($\gamma = 0.66$ $\text{hPa}\cdot^{\circ}\text{C}^{-1}$;) (Ding et al., 2013; Pereira, 2004; Utset et al., 2004). T_c ,
 254 E_s , E_{ic} and E_{ws} denote vegetation transpiration, soil evaporation, vegetation interception
 255 evaporation and wet soil surface evaporation, respectively. Parameter f_v is fraction of
 256 green vegetation ($f_v = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$), f_t is the plant temperature constraint (f_t
 257 $= \exp\left[-\left(\frac{T_a - T_{opt}}{T_{opt}}\right)^2\right]$), f_{sm} is soil moisture constraint ($f_{sm} = \left(\frac{1}{DT}\right)^{DT/DT_{max}}$), f_{wet} is the
 258 relative surface wetness ($f_{wet} = f_{sm}^4$). G is the soil heat flux ($G = a_g R_n (1 - f_v)$, $\text{W}\cdot\text{m}^{-2}$),
 259 R_{nc} and R_{ns} are net radiation to the vegetation ($R_{nc} = R_n f_v$) and net radiation to the soil
 260 ($R_{ns} = R_n (1 - f_v)$), respectively (Fisher et al., 2008; Qiaozhen et al., 2011).

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

$$264 \quad ET = 0.0023 \frac{R_a}{\lambda} \sqrt{(Ta_{max} - Ta_{min})} (Ta_{mean} + 17.8) \quad (15)$$

$$265 \quad R_n = k_{Rs} R_a \sqrt{(Ta_{max} - Ta_{min})} \quad (16)$$

266 where R_n ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$) is the solar radiation, λ is the latent heat of vaporization of water
 267 ($\lambda = 2.45$, $\text{MJ}\cdot\text{kg}^{-1}$). R_a ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$) is the extraterrestrial radiation with a value of
 268 approximately $1367 \text{ W}\cdot\text{m}^{-2}$ (Allen et al., 1998), k_{Rs} ($^{\circ}\text{C}^{-0.5}$) is the adjustment coefficient.
 269 The value of k_{Rs} falls within the range of $0.16 - 0.19$. For interior regions more than 20
 270 km from the ocean, the value is 0.16. Ta_{max} ($^{\circ}\text{C}$), Ta_{min} ($^{\circ}\text{C}$) and Ta_{mean} ($^{\circ}\text{C}$) denote the
 271 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:

$$R^2 = \left[\frac{\sum_{t=1}^n (Q_m^t - \bar{Q}_m)(Q_o^t - \bar{Q}_o)}{\sqrt{\sum_{t=1}^n (Q_m^t - \bar{Q}_m)^2} \sqrt{\sum_{t=1}^n (Q_o^t - \bar{Q}_o)^2}} \right]^2 \quad (17)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (Q_m^t - Q_o^t)^2}{n}} \quad (18)$$

where n is the number of data sets, r is the linear correlation coefficient between simulations and observations, Q_m^t is the modeled value, Q_o^t is observed data, $\bar{Q}_m$ is average modelled value, and $\bar{Q}_o$ 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 SANCHAE 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

Insert Figure 5 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 SANCHI 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 SANCHI 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.

Insert Figure 6 here

Insert Figure 7 here

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 $0.025 \text{ m}\cdot\text{s}^{-1}$, $0.034 \text{ m}\cdot\text{s}^{-1}$, $0.042 \text{ m}\cdot\text{s}^{-1}$ and $0.016 \text{ m}\cdot\text{s}^{-1}$ for April, June, August and December, respectively. The values of Rn mainly ranged from 114 - 500 $\text{W}\cdot\text{m}^{-2}$ on 14 April and the average April value was 254 $\text{W}\cdot\text{m}^{-2}$. Values ranged from 281 – 610 $\text{W}\cdot\text{m}^{-2}$ and 207-630 $\text{W}\cdot\text{m}^{-2}$ on 15 June and 11 August, respectively. The average values were 477 $\text{W}\cdot\text{m}^{-2}$ and 485 $\text{W}\cdot\text{m}^{-2}$ 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.

Insert Figure 8 here

Insert Figure 9 here

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_s^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 SANCHAE (Fig. 5) Basins both exhibited seasonality. This finding was similar to previous studies in

376 various climatic zones, including cold climates, temperate climates, tropical systems
377 and arid/semi-arid regions (Li et al., 2012; Parka et al., 2008; Shao et al., 2012; Tanaka
378 et al., 2008; Yang and Zhou, 2011). During the study period, the annual mean potential
379 *ET* was approximately 1102 mm·year⁻¹, which is similar with those results in the same
380 bioclimatic zone (Chen et al., 2015; Tian et al., 2018; Yao et al., 2014). For example,
381 annual potential *ET* mainly ranged from 950-1350 mm·year⁻¹ in southwestern China
382 over eight years (2008-2016) (Tian et al., 2018). The annual potential *ET* calculated by
383 Yao et al. (2014) from 1982-2010 was between 800-1400 mm·year⁻¹ in the same zone.
384 Chen et al. (2015) calculated 50-year (1956-2006) actual annual *ET* for Guangdong
385 Province, which was in a similar latitude as our study area, and results showed that
386 actual annual *ET* was within 600-1200 mm·year⁻¹. In our study, actual annual *ET* was
387 lower than in Sichuan and Guangdong provinces, with annual *ET* values of 634.7
388 mm·year⁻¹ and 589 mm·year⁻¹ for HOUZHAI and SANCHAE Basins, respectively.
389 Previous studies have demonstrated that *ET* was mainly related to temperature,
39 0 precipitation, solar radiation, soil water content (*SWC*) and leaf area index (*LAI*) (Parka
39 1 et al., 2008; Shao et al., 2012; Tanaka et al., 2008; Yang and Zhou, 2011). In our study,
39 2 the basins were located in the transition region between Yunnan plateau and Guizhou
39 3 plateau. The average elevation is higher than in Sichuan and Guangdong provinces, and
39 4 average daily temperatures were much lower than those regions. Consequently, annual
39 5 *ET* was also lower. Daily *ET* was highest during the growing seasons. In our study,
39 6 annual *ET* in forest, orchard and cropland was always higher than in fired patch and
39 7 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 $0.017 \text{ m}\cdot\text{s}^{-1}$ and 1, respectively. Previous studies have demonstrated that g_{sx} often falls the range of $0 - 0.020 \text{ m}\cdot\text{s}^{-1}$, 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). G_{Ta} and R_n 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 G_{Ta} and R_n 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

4 4 2 satellite data. Vegetation coverage and the density of conducting tissue (e.g. *LAI*) both
4 4 3 contributed to *ET* seasonality and the spatial distribution differences.

4 4 4 **Acknowledgments**

4 4 5 This study was supported by the GDAS' Project of Science and Technology
4 4 6 Development (2020GDASYL-20200103078) and Natural Science Youth Foundation
4 4 7 of Guangdong Province (2020A1515111060). We thank anonymous reviewers and the
4 4 8 editorial team.

4 4 9 **Data Availability Statement**

4 50 All data and models are available from the authors upon request.

4 51 **Ethical Approval**

4 52 The authors declare no conflict of interest.

4 53 **Consent to Participate**

4 54 The authors consent to participate.

4 55 **Consent to Publish**

4 56 The authors consent to publish.

4 57 **Authors Contributions**

4 58 Rongei Zhang: Conceptualization, Methodology, Software, Validation, Writing-
4 59 Original Draft, Review & Editing, Resources, Project administration, funding
4 60 acquisition.

4 61 **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

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69 4 CAPTIONS

69 5 TABLES

69 6 **Table 1.** Comparison of relevant studies for *ET* observation methods and models for
69 7 different various ecosystems in various landscapes.

69 8 **Table 2.** Baseline information for the five land cover types

69 9 FIGURES

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

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

707 **Fig.3** Taylor diagrams of observed and simulated daily *ET* using different models based
708 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 SANCHAI River 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.

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733   **Table 1.** Comparison of relevant studies for *ET* observation methods and models for
734   different various ecosystems in various landscapes.

		Methods	Vegetation Types	Reference	Location/Landscape/Climate
Previous studies	Observation	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 energy balance	Vines	Holland et al. (2013)	Southeast US/Coastal plain/Subtropical climate

Model	Eddy covariance method	Wheat	Denmead et al. (1996)	Southeast Australian/Temperate humid climate/Coastal lowland
	Sap flow	Woodland	Zeppel et al. (2008)	Australia/Liverpool plains/Temperate
	Biomass-transpiration relationship	Tomato	Ben-Gal et al. (2003)	Israel/Valley/Mediterranean climate
	Isotopes	Savanna	Wang et al. (2012)	Central Kenya/Plateau/Tropical savanna climate
	One-source model	Cotton, grapes and olive trees	Bastiaanssen (2000)	Turkey/Irrigated basin/Mediterranean climate
	Two-source model	Cherry orchard	Juhasz and Hrotko (2014)	Hungary/Plain/Continental temperate climate
	Ts-VI model	NA	Murray and Verhoef (2007)	NA
	Empirical model	Whole-ecosystems	Yan and Shugart (2010)	American/Various landscapes and climate

This study	Observation	Pemnan-Montheith equation	Whole-ecosystems	Cai et al. (2007)	Chinese/Various landscapes and climate
		Assimilation method and temporal upscaling	agricultural ecosystem (Corn)	Crow et al. (2008)	East of American/Plain/Temperate continental climate
	Model	Micro-lysimeter, Sap flow, Ventilated chamber	Forest, Orchard, Cropland, shrub- grass and Fired patch		Southwest China/karst landscape/humid subtropical monsoon
		PML, RS-PT, Hargreave models	Whole-ecosystems		

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751 **Table 2.** Baseline information for the five land cover types

Types	Vegetation species	ET measurement	Data	Experimental spacing (day)	Growth stage
			spacing (min)		
Forest	<i>Quercus fabri Hance/Albizia</i>	TDP	5	Continuous	Mar-Nov
	<i>julibrissin Durazz./Toona</i>				
	<i>sinensis/Platycarya strobilacea</i>				
	<i>Sieb.et Zucc./Kalopanax</i>				
	<i>septemlobus (Thunb.)</i>				
	<i>Koidz./Populus adenopodaMaxim.</i>				

Orchard	Grass and soil	Ventilated-chamber	5	10-15	
	<i>Toona sinensis</i> / <i>Pyrus, i, f./Catalpa bungei</i> C. A. Mey.	TDP	5	Continuous	Mar-Nov
	Bare soil	Ventilated-chamber	5	10-15	NA
Cropland	Maize	Ventilated-chamber	5	10-15	Mar-Jun
	Oilseed rape	chamber	5		Dec-Mar
Shrub-grass	<i>Coriaria nepalensis</i>				
	<i>Wall./Pyracantha fortuneana</i>	TDP	5	Continuous	
	(<i>Maxim.</i>) Li				Mar-Nov
Burned patch	Grass	Ventilated-chamber	5	10-15	
	<i>Populus adenopoda</i> Maxim.	TDP	5	Continuous	
	Grass and soil	Ventilated-chamber	5	10-15	Mar-Nov

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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.

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79 9 **Fig.4** Spatial-temporal distribution of daily *ET* for HOUZHAI Basin.

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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 SANCHAH River 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.