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Research Article

Keywords: Citrus orchard, Evapotranspiration simulation, Penman-Monteith model, Sensitivity analysis

Posted Date: June 24th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9905865/v1>

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Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at Irrigation Science on September 16th, 2026. See the published version at <https://doi.org/10.1007/s00271-026-01176-4>.

Performance comparison of the Penman-Monteith-based evapotranspiration
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Abstract: Accurate estimation of evapotranspiration (ET) is critical for precise irrigation management and sustainable water use in agriculture. This study evaluated five Penman-Monteith based models, including Penman-Monteith (P-M), Shuttleworth-Wallace (S-W), Two-Patch (T-P), Topography and Vegetation-based surface energy partitioning algorithm (TVET), and Hybrid-Dual Source (H-D) models, in simulating half-hourly, daily, and growth-stage-specific ET in a young citrus orchard using four-year eddy covariance data. Results showed that model performance varied significantly across temporal scales. At the half-hourly scale, the H-D model performed best ($R^2 = 0.84$, $RMSE = 0.038 \text{ mm} \cdot 0.5\text{h}^{-1}$), while the S-W model exhibited systematic overestimation during noon hours. On a daily scale, the patch-based T-P model and its derivatives (TVET, H-D) consistently outperformed the single-source and layered models (P-M and S-W), with the H-D model again showing the highest accuracy ($R^2 = 0.91$, $RMSE = 0.47 \text{ mm} \cdot \text{d}^{-1}$). Model performance also varied across different growth stages. The H-D model excelled during both the flowering and fruiting period, and fruit ripening period (R^2 of 0.82-0.85, $RMSE$ of 0.15-0.45 $\text{mm} \cdot \text{d}^{-1}$), whereas the T-P model performed best during the fruit expansion period, with R^2 of 0.88 and $RMSE$ of 0.40 $\text{mm} \cdot \text{d}^{-1}$. Among resistance parameters, simulated ET was most sensitive to canopy resistance (r_c) in P-M model or leaf stomatal resistance (r_s^c) in other models, a 20% decrease in r_c or r_s^c led to a 3.71%-7.41% increase in ET. Simulated ET was most responsive to soil water content (SWC) among environmental inputs, a 20% increase in SWC resulted in a 10.43%-32.27% change in simulated ET. ET simulated by the S-W model was most sensitive to leaf area index (LAI) among the models, with a decrease of 11.38% when LAI decreased by 20%. This study identifies optimal ET models for citrus orchards and clarifies the structural and parametric drivers of model performance, offering a mechanistic basis for model selection and improvement in subtropical orchard ecosystems, which is beneficial to citrus precision irrigation and regional water

43 resource management.

44 **Key words:** Citrus orchard; Evapotranspiration simulation; Penman-Monteith model; Sensitivity

45 analysis

46

47 1. Introduction

48 Accurate estimation of crop evapotranspiration (ET) is essential for optimizing irrigation strategies,
49 improving water use efficiency, and ensuring food security in water-sensitive agricultural systems
50 (Gong et al., 2021; Gu et al., 2020). As a key component of the water and energy cycle, ET directly
51 influences soil moisture dynamics, crop growth, biomass accumulation, and yield formation (Jiang et
52 al., 2019; Lian et al., 2018). However, quantifying ET remains challenging due to the complex
53 interactions among meteorological, soil, and vegetation factors governing the process (Fisher et al.,
54 2007; Liu, 2022).

55 Methods for estimating ET include hydrological approaches, such as the water balance, water flux
56 (Bernier, 2020; Ji et al., 2025); micrometeorological techniques like the aerodynamic, eddy covariance
57 (EC), Bowen ratio energy balance (BREB) methods (Peddinti and Kisekka, 2025; Yan et al., 2025);
58 and plant physiological methods, including tracer, sap flow, and porometer techniques, etc. (Ghiat et
59 al., 2021; Peng et al., 2021). Remote sensing inversion is also employed for large-scale ecosystem ET
60 estimation (Derardja et al., 2024; Zhang et al., 2025; Jin et al., 2024). While these techniques can
61 provide reliable measurements, their high cost and operational complexity often limit widespread
62 application, necessitating robust models for broader estimation (Callejas-Rodelas et al., 2024; Peddinti
63 and Kisekka, 2025; Yan et al., 2025). The Penman-Monteith (P-M) model, which integrates energy
64 balance and aerodynamic principles, has been widely applied due to its physical soundness and reliable
65 performance across well-vegetated ecosystems (Allen et al., 1998). However, the classical single-
66 source P-M framework exhibits limitations in sparsely vegetated or heterogeneous landscapes (Cui et
67 al., 2023; Allen et al., 2005). Its core assumption of a uniform “big-leaf” canopy prevents the separation
68 of soil evaporation (E) from plant transpiration (T), leading to potential inaccuracies in water flux

69 partitioning (Shuttleworth & Wallace, 1985). Furthermore, the P-M model simplifies pore and
70 boundary layer resistance into a bulk canopy resistance term, which can be a major source of error as
71 it aggregates complex stomatal responses to multiple environmental drivers (Liu et al., 2020; Xu et al.,
72 2017).

73 To address these limitations, improved schemes have been proposed, including dual-source or multi-
74 source models that distinguish E from T, enhancing ET simulation over partially vegetated surfaces
75 (McColl, 2020). The Shuttleworth-Wallace (S-W) model, a seminal two-layer approach, assumes fully
76 vegetation cover and distributes energy vertically between the canopy and the soil layers while
77 accounting for their interactions (Shuttleworth & Wallace, 1985). Although physically comprehensive,
78 its complex structure and high parameter requirement often hinder practical application (Nyolei et al.,
79 2021; Gao et al., 2023). In contrast, the Two-Patch (T-P) model represents the surface as a parallel
80 combination of vegetation and bare soil patches under low or patchy cover, calculating total ET as an
81 area-weighted sum (Lhomme and Chehbouni, 1999). This simplification enhances practicality but may
82 overlook inter-component feedback (Lu et al., 2014). Recent research has focused on synthesizing
83 these paradigms. The Topography and Vegetation-based surface energy partitioning algorithm (TVET)
84 model combines the resistance network of the S-W model with the patch-aggregation scheme of the
85 T-P model (Guan and Wilson, 2009). Building on this, the Hybrid-Dual Source (H-D) model employs
86 a more integrated solution, employing a layered scheme for energy distribution while utilizing a patch
87 method for flux aggregation, and incorporating atmospheric stability corrections to refine aerodynamic
88 resistance estimates (Lu et al., 2014).

89 As numerous ET models have been proposed, comparative studies on agroecosystem ET
90 simulation have attracted considerable attention, given the diverse crop types and planting

characteristics. For example, Wang et al. (2024) investigated the S-W model's performance in a sparsely vegetated semi-arid farmland and found that improved soil moisture representation significantly enhanced ET estimation accuracy. Gao et al. (2023) compared an improved S-W model, the Priestley-Taylor (P-T) model, and the dual-crop coefficient (DK) model for ET simulation in dryland spring maize on China's Loess Plateau, and recommended the improved P-T as optimal. Shao et al. (2022) applied the P-M, S-W, and P-T models to estimate tomato transpiration in solar greenhouses in the North China Plain, and found the P-T model performed better. Nyolei et al. (2021) evaluated several P-M-based models in sparse vegetation systems and found that the PM-based S-W dual-source interactive model showed higher performance. Despite these advancements, comparative studies often focus on daily or longer timescales, overlooking sub-daily biophysical processes crucial for understanding model behavior and plant physiological responses (Nyolei et al., 2021). Moreover, a quantitative sensitivity analysis systematically deconstructing each model's reliance on specific resistance parameters and environmental forcings is needed. Such analysis moves beyond identifying "which model performs best to explain why, offering insights for model refinement and selection under data-scarce conditions.

Citrus orchards in hilly Southwest China, covering over 400,000 hectares, hold high economic value and play a crucial role in rural development. The region experiences a subtropical humid monsoon climate with abundant but uneven annual rainfall, making precise irrigation essential for water conservation and fruit quality. The complex topography and specific canopy structure of citrus orchards create a spatially heterogeneous environment that tests the assumptions of different ET models. This study has two objectives: (1) to rigorously evaluate model performance across half-hourly, daily, and growth-stage-specific scales, identifying optimal models for different temporal and

phenological contexts; and (2) to quantitatively assess the sensitivity of each model's ET output to key resistance parameters, environmental variables, and vegetation characteristics. By integrating multi-scale validation with a mechanistic sensitivity analysis, this research aims to provide a practical guideline for model selection in citrus orchards and to deepen understanding of the structural strengths and weaknesses of P-M based models, ultimately supporting more precise water management in subtropical orchard ecosystems.

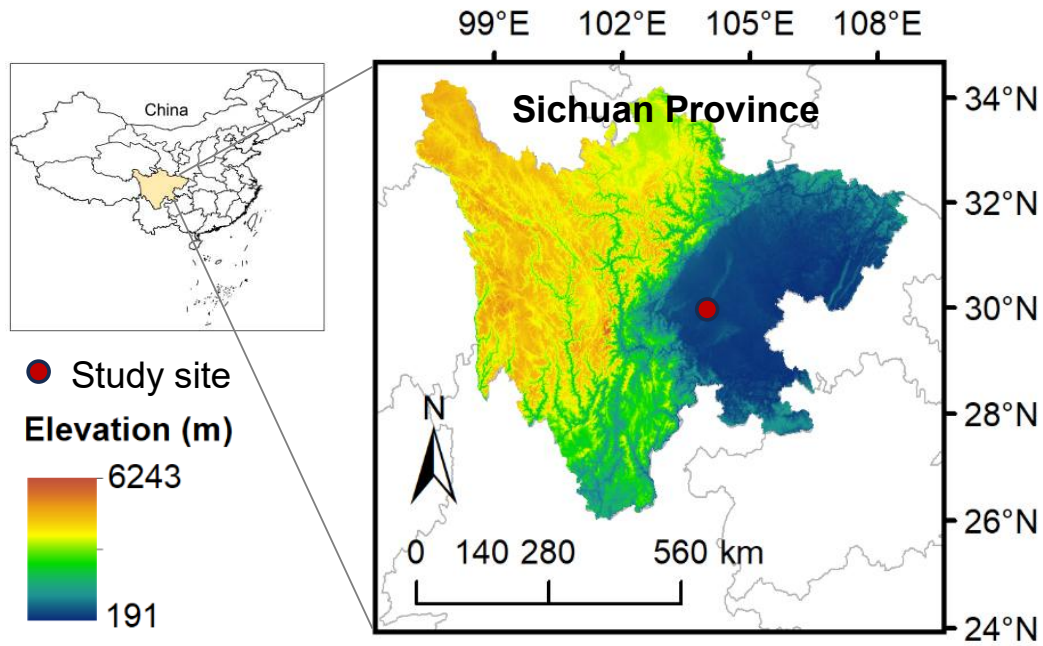
2. Materials and Methods

2.1 Study area

The long-term field experiment was conducted from April 2020 to November 2023 at the Citrus Farm (103.45°E, 30.34°N) of Jitao Agricultural Investment and Development Company in Qionglai City, Sichuan Province. The region has a subtropical humid monsoon climate with an average annual temperature of 17.5 °C, relative humidity of 88%, and annual rainfall of 1117.3 mm. The soil is classified as loam, with a field water capacity of 35% (θ_f), wilting point of 15% (θ_w), saturation point of 38% (θ_s), and bulk density of 1.15 g·cm⁻³ in the 0-60 cm layer. Soil nutrient analysis showed total nitrogen content of 1.49 g·kg⁻¹, alkaline nitrogen content of 64.66 mg·kg⁻¹, available phosphorus content of 2.25 mg·kg⁻¹, and available potassium content of 74.84 mg·kg⁻¹.

The orchard was planted with sugar orange (*Citrus Tachibana* Hort. ex Tanaka). Canopy height of the trees was 2.0-2.3 m, with a diameter at breast height of 10-13 cm. Planting and row spacing were 3.0 and 4.0 m, respectively, giving a planting density of approximately 900 plants per hectare. Citrus trees were watered via a drip irrigation system, with emitters spaced 0.3 m apart and a flow rate of 2 L·h⁻¹. Irrigation was triggered when soil water content (SWC) dropped below 70% θ_f , whereas it stopped when SWC exceeded 85% θ_f . The citrus phenological cycle from April to mid-November can

135 be roughly divided into four growth stages: the flowering and fruiting period (Phase I, April 1-30), the
 136 young fruit period (Phase II, May 1-June 15), the fruit swelling period (Phase III, June 16-September
 137 15), and the fruit ripening period (Phase IV, September 16-November 15). Trees in the experimental
 138 area were healthy and growing uniformly.



139 ..
 140 **Fig.1.** The overview of the study area.

141 **2.2 Field observations and data processing**

142 **2.2.1 EC measurements and data processing**

143 Latent heat (LE , $W \cdot m^{-2}$) and sensible heat (H , $W \cdot m^{-2}$) fluxes were continuously measured using an
 144 eddy covariance (EC) system installed at the orchard center. The EC system consisted of a three-
 145 dimensional sonic anemometer (CSAT3, Campbell Scientific Inc, USA) and an open-path CO_2/H_2O
 146 gas analyzer (EC150, Campbell Scientific Inc, USA) mounted 5.0 m above ground. Citrus is grown
 147 within 500 m in all directions from the flux tower. LE and H were calculated as:

$$148 \quad LE = \lambda \rho_a \overline{w'q'} \quad (1)$$

$$H = C_p \rho_a \overline{w'T'} \quad (2)$$

Where λ is the latent heat of vaporization, $\text{J}\cdot\text{kg}^{-1}$; ρ_a is the air density, $\text{kg}\cdot\text{m}^{-3}$; C_p is specific heat at constant pressure, $\text{J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$; $\overline{w'T'}$ and $\overline{w'q'}$ are the average covariances between vertical velocity component w' ($\text{m}\cdot\text{s}^{-1}$) and potential temperature T' (K) and specific humidity q' ($\text{kg}\cdot\text{kg}^{-1}$), respectively, averaged over 30 min.

The raw 10 Hz data were processed using the EddyPro software (LI-COR Biosciences, USA) following standard protocols, including double-coordinate rotation, low- and high-frequency corrections, and WPL density corrections for the open-path system (Falge et al., 2001). Half-hourly flux values were calculated and stored by a datalogger (CR3000, Campbell Scientific Inc, USA). Rigorous quality control was applied based on EddyPro flags, and low-quality data were discarded (Jiang et al., 2022b). Gaps shorter than 2 hours were filled via linear interpolation method, longer gaps (>2 hours) were filled using the mean diurnal variation method (Reichstein et al., 2005).

2.2.2 Measurement of environmental variables

Meteorological variables and SWC were measured by sensors integrated into the EC system. Data include rainfall (P) (RG13 H2NN, Vaisala, Finland), air temperature (T_a) and relative humidity (RH) (HMP155, Vaisala, Finland) at 4 m height, four components of radiation (NR01, Hukseflux, Netherlands) above the canopy, and wind speed (u) and direction at 4 m height. Wind speed at 2 m height was calculated from the 4 m measurement using $u_2=4.87 u_z/\ln(67.8Z-5.42)$, where u_z is the measured wind speed at the reference height of Z .

SWC at depths of 0-100 cm (10 cm intervals) was monitored using soil water content sensors (ET100, Insentek, China), calibrated via the gravimetric sampling-drying method. Soil heat flux (G) was measured using heat flux plates (HFP01, Hukseflux, Netherlands) installed at 2 cm and 6 cm

171 depths. Sensors were placed in both inter-row and under-canopy areas; average SWC and G values
 172 from these positions were used for analysis.

173 2.2.3 Determination of leaf area index

174 Canopy leaf area index (LAI_c , $m^2 \cdot m^{-2}$) was measured every 1-2 weeks during the growing season
 175 (2020-2023) using a Plant Canopy Analyzer (LAI-2000, LI-COR Inc, USA). Total leaf area index
 176 (LAI_t , $m^2 \cdot m^{-2}$) was obtained from MODIS 15A2H (<https://modis.ornl.gov/data.html>) at 500 m spatial
 177 and 8 d temporal resolution. Original LAI_t data were smoothed and corrected using TIMESAT software
 178 to remove cloud-induced outliers, with missing data filled by linear interpolation. Finally, 8 d LAI_t
 179 data was interpolated to daily values by a spline interpolation method.

180 2.3 ET calculation models

181 This study evaluated five ET models rooted in the P-M framework but differing in their
 182 conceptualization of the land surface. A summary of their core structures, resistance networks, and key
 183 characteristics is provided in Table 1. The following subsections describe each model category.

184 **Table 1.** Summary of the key characteristics of the five Penman-Monteith-based evapotranspiration
 185 models evaluated in this study.

Model	Conceptual Scheme	Source Separation	Key Features	Primary Resistances Considered
Penman-Monteith (P-M)	Single-Source (Big Leaf)	No	Industry standard; simple but limited in sparse vegetation.	r_c , r_a
Shuttleworth-Wallace (S-W)	Dual-Source (Layer)	Yes, interactive	High physical realism; complex parameterization.	r_s^c , r_a^a , r_a^s , r_a^c , r_s^s
Two-Patch (T-P)	Dual-Source (Patch)	Yes, non-interactive	Simple structure; ignores soil-vegetation interactions.	r_s^c , r_a^a , r_a^s , r_a^c , r_s^s
Topography and Vegetation-based surface energy partitioning algorithm (TVET)	Dual-Source (Layer+Patch)	Yes	Combines S-W resistance with T-P aggregation.	r_s^c , r_a^a , r_a^s , r_a^c

Hybrid-Dual Source (H-D)	Dual-Source (Layer+Patch)	Yes	Includes atmospheric stability corrections; most complex.	$r_s^c, r_a^a, r_a^s, r_a^c, r_s^s$
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2.3.1 Penman-Monteith model

The P-M model is a single-source model commonly used for estimating terrestrial ecosystem ET. It combines energy balance and mass transfer principles without separating E and T. The model is described as (Monteith, 1973):

$$\lambda ET = \frac{\Delta(R_n - G) + \rho_a C_p VPD / r_a}{\Delta + \gamma(1 + r_c / r_a)} \quad (3)$$

Where Δ is the slope of the vapor pressure temperature curve, $\text{kPa} \cdot ^\circ\text{C}^{-1}$. R_n is the net radiation, $\text{W} \cdot \text{m}^{-2}$. G is the soil heat flux, $\text{W} \cdot \text{m}^{-2}$. C_p is the specific heat of air at constant pressure, $\text{J} \cdot \text{kg}^{-1} \cdot ^\circ\text{C}$. VPD is the vapor pressure deficit, kPa . γ is the hygroscopic constant, $\text{kPa} \cdot ^\circ\text{C}^{-1}$. r_c is the canopy resistance, $\text{s} \cdot \text{m}^{-1}$. r_a is the aerodynamic resistance, $\text{s} \cdot \text{m}^{-1}$, calculated as follows:

$$r_a = \frac{\ln[(z_m - d)/z_{om}] \ln[(z_h - d)/z_{oh}]}{k^2 u_2} \quad (4)$$

Where k is the von Karman constant (0.41). d is zero plane displacement height, m . z_m and z_h are the measurement heights for wind and humidity, m . u_2 is the wind speed at 2 m height, $\text{m} \cdot \text{s}^{-1}$. z_{om} is the roughness length of momentum transfer, m . z_{oh} is the roughness length of heat and steam transfer, m . Generally, d , z_{om} and z_{oh} are expressed as functions of average plant height (h) (Campbell and Norman, 1998).

A primary uncertainty is the parameterization of r_c , estimated here using a Jarvis model that accounts for the multiplicative effects of photosynthetically active radiation (PAR), T_a , VPD, and SWC. The Jarvis model is described as follows (Jarvis, 1989):

$$r_c = \frac{r_{c-\min}}{2LAI_t f(PAR) f(T_a) f(VPD) f(\theta)} \quad (5)$$

Where r_{c-min} is the minimum canopy resistance when plant leaves were not stressed by environmental factors, $s \cdot m^{-1}$. LAI_t is the total leaf area index, $m^2 \cdot m^{-2}$. $f(PAR)$, $f(T_a)$, $f(VPD)$ and $f(\theta)$ represent the constraints of PAR, T_a , VPD, and SWC on canopy resistance, respectively, which can be determined by the following:

$$f(PAR) = \frac{PAR(1000 + a_1)}{1000(PAR + a_2)} \quad (6)$$

$$f(T_a) = \left(\frac{T_a - T_{min}}{T_{opt} - T_{min}} \right) \left(\frac{T_{max} - T_a}{T_{max} - T_{opt}} \right)^{(T_{max} - T_{opt}) / (T_{opt} - T_{min})} \quad (7)$$

$$f(VPD) = 1 - a_3 \times VPD \quad (8)$$

$$f(\theta) = \begin{cases} 0 & \theta_z \leq \theta_w \\ \frac{\theta_z - \theta_w}{\theta_f - \theta_w} & \theta_w < \theta_z < \theta_f \\ 1 & \theta_z \geq \theta_f \end{cases} \quad (9)$$

Where T_{min} 、 T_{max} and T_{opt} are the lowest, highest and optimal temperatures for citrus leaves photosynthesis, which were set as 0 °C, 40 °C and 25 °C, respectively (Yuan et al., 2007). a_1 、 a_2 and a_3 were parameters calibrated using the least square fitting method based on observed ET data.

2.3.2 Shuttleworth-Wallace model

The S-W model is a representative of the layered two-source model and serves as the foundation for several other layered formulations (Lu et al., 2014). Although physically comprehensive, it requires numerous input parameters. The general formulation is as follows (Shuttleworth and Wallace, 1985):

$$\lambda ET = \lambda T + \lambda E = C_c PM_c + C_s PM_c \quad (10)$$

$$PM_c = \frac{\Delta A + (\rho_a C_p VPD - \Delta r_a^c A_s) / (r_a^a + r_a^c)}{\Delta + \gamma [1 + r_s^c / (r_a^a + r_a^c)]} \quad (11)$$

$$PM_s = \frac{\Delta A + (\rho_a C_p VPD - \Delta r_a^s A_c) / (r_a^a + r_a^s)}{\Delta + \gamma [1 + r_s^s / (r_a^a + r_a^s)]} \quad (12)$$

$$C_c = \frac{1}{1 + [R_c R_a / (R_s (R_c + R_a))]} \quad (13)$$

$$C_s = \frac{1}{1 + [R_s R_a / (R_c (R_s + R_a))]} \quad (14)$$

$$R_c = (\Delta + \gamma) r_a^c + \gamma r_s^c \quad (15)$$

$$R_s = (\Delta + \gamma) r_a^s + \gamma r_s^s \quad (16)$$

$$R_a = (\Delta + \gamma) r_a^a \quad (17)$$

Where λT and λE are the latent heat fluxes from canopy and soil, respectively, $W \cdot m^{-2}$. PM_c and PM_s are the P-M type equations for full-cover transpiration and bare soil evaporation, respectively. C_c and C_s are the combined coefficients of canopy and soil resistance, respectively. r_a^c is the boundary layer resistance of crop leaves, $s \cdot m^{-1}$. r_a^a is the aerodynamic resistance from the canopy height to the reference height, $s \cdot m^{-1}$. r_s^c is the leaf stomatal resistance, $s \cdot m^{-1}$. r_a^s is the aerodynamic resistance from the soil surface to the canopy height, $s \cdot m^{-1}$. r_s^s is the soil surface resistance, $s \cdot m^{-1}$. A 、 A_s and A_c are the total available energy, soil surface available energy and canopy available energy, respectively, which are expressed as follows:

$$A = R_n - G \quad (18)$$

$$A_s = R_n \exp(-KLAI) - G \quad (19)$$

$$A_c = A - A_s \quad (20)$$

Where K is the extinction coefficient of radiation attenuation (0.70).

The S-W model assumes r_a^a and r_a^s vary linearly with LAI_t :

$$r_a^a = \begin{cases} 0.25 \times LAI_t \times r_a^a(\alpha) + 0.25 \times (4 - LAI_t) \times r_a^a(0), & 0 < LAI_t < 4 \\ r_a^a(\alpha), & LAI_t > 4 \end{cases} \quad (21)$$

$$r_a^s = \begin{cases} 0.25 \times LAI_t \times r_a^s(\alpha) + 0.25 \times (4 - LAI_t) \times r_a^s(0), & 0 < LAI_t < 4 \\ r_a^s(\alpha), & LAI_t > 4 \end{cases} \quad (22)$$

243 Where $r_a^a(0)$ and $r_a^s(0)$ are the aerodynamic resistance for bare soil. $r_a^a(\alpha)$ and $r_a^s(\alpha)$ are the
 244 aerodynamic resistance for fully vegetated. $r_a^a(\alpha)$ can be calculated by Eq (4). $r_a^s(\alpha)$ is calculated
 245 using the following formula:

$$246 \quad r_a^s(\alpha) = \frac{\ln \frac{z-d}{z_{om}}}{k^2 u_2} \frac{h}{n(h-d)} \left\{ \exp(n) - \exp \left[n \left(1 - \frac{d+z_{om}}{h} \right) \right] \right\} \quad (23)$$

247 Where n is the attenuation coefficient of turbulent diffusion (2.5) (Shuttleworth and Wallace, 1985).

248 For bare soil, $r_a^a(0)$ and $r_a^s(0)$ are respectively expressed as:

$$249 \quad r_a^a(0) = \frac{\ln \frac{z_m}{z_{om}} \ln \frac{z_h}{z_{oh}}}{k^2 u_2} - r_a^s(0) \quad (24)$$

$$250 \quad r_a^s(0) = \frac{\ln \frac{h}{z_{om}} \ln \frac{h}{z_{oh}}}{k^2 u_2} \quad (25)$$

251 Where z'_{om} and z'_{oh} are the roughness lengths for momentum and heat over bare soil, respectively
 252 ($z'_{om} = 0.01$; $z'_{oh} = 0.01$). r_a^c is calculated as follows (Choudhury and Monteith, 2010):

$$253 \quad r_a^c = \frac{n}{0.02} \sqrt{\frac{l_w}{u_h}} \frac{1}{1 - e^{-\frac{n}{2}}} \quad (26)$$

$$254 \quad u_h = \frac{\ln[(h-d)/z_{om}]}{\ln[(z_m-d)/z_{om}]} u_2 \quad (27)$$

255 Where l_w is the characteristic width of leaves (0.05 m) (Zhou and Ye, 2010). u_h is the wind speed at the
 256 top of the citrus canopy.

257 r_s^s is determined by the empirical formula (Lin and Sun, 1983):

$$258 \quad r_s^s = 3.5 \left(\frac{\theta_s}{\theta_1} \right)^{2.3} + 33.5 \quad (28)$$

259 Where θ_1 is soil water content of the surface layer (10 cm depth).

260 The stomatal resistance, r_s^c can also be calculated by Eq (5), where the minimum stomatal

261 resistance $r_{s-\min}^c$ is substituted for $r_{c-\min}$.

262 2.3.3 Two-Patch model

263 The T-P model assumes soil and vegetation are directly exposed to solar radiation, and that water
264 vapor transport between the two sources are independent of each other. ET in T-P model is obtained
265 by numerically weighting ET of the same "sub-blocks" based on the vegetation coverage (F_c) (Lhomme
266 and Chehbouni, 1999). The model is expressed as follows:

$$267 \quad \lambda ET = F_c \times \lambda T + (1 - F_c) \times \lambda E \quad (29)$$

$$268 \quad \lambda T = \frac{\Delta A + \rho_a C_p VPD / (r_a^a + r_a^c)}{\Delta + \gamma [1 + r_s^c / (r_a^a + r_a^c)]} \quad (30)$$

$$269 \quad \lambda E = \frac{\Delta A + \rho_a C_p VPD / (r_a^a + r_a^s)}{\Delta + \gamma [1 + r_s^s / (r_a^a + r_a^s)]} \quad (31)$$

270 In the T-P model, T is assumed to only occur in the completely vegetated area and E only occurs in the
271 bare soil area, so r_a^a in Eq. (30) is represented by Eq. (4). In Eq. (31), r_a^a and r_a^s are represented by
272 Eq. (24) and Eq. (25), respectively. For vegetation patches, LAI_c replaces LAI_t and $r_{s-\min}^c$ replaces
273 $r_{c-\min}$ in Eq. (5) for calculating r_s^c .

274 2.3.4 TVET Model

275 The TVET model represents a hybrid ET estimation approach. It combines the resistance network
276 of the S-W model, and the patch-aggregation scheme of the T-P model (Guan and Wilson, 2009), which
277 is calculated as follows:

$$278 \quad \lambda ET = \lambda E + \lambda T \quad (32)$$

$$279 \quad \lambda E = \frac{\Delta A_s + (1 - F_c) \rho_a C_p VPD / (r_a^a + r_a^s)}{\Delta + \gamma} \quad (33)$$

$$280 \quad \lambda T = \frac{\Delta A_c + F_c \rho_a C_p VPD / (r_a^a + r_a^c)}{\Delta + \gamma [1 + r_s^c / (r_a^a + r_a^c)]} \quad (34)$$

281 Where r_a^a and r_a^s are determined by Eq. (21) and Eq. (22), respectively, and r_s^c is the same as the T-
 282 P model.

283 2.3.5 Hybrid-Dual Source model

284 The H-D model employs a layered scheme for energy distribution between soil and vegetation but
 285 uses a patch method for flux aggregation. A key advancement in this model is the incorporation of
 286 atmospheric stability correction factors for the aerodynamic resistances, enhancing its physical realism
 287 under non-neutral conditions. The model is described as follows (Lu et al., 2014):

$$288 \quad \lambda ET = F_c \times \lambda T + (1 - F_c) \times \lambda E \quad (35)$$

$$289 \quad \lambda T = \frac{\Delta A_c + F_c \rho_a C_p VPD / (r_a^a + r_a^c)}{\Delta + \gamma [1 + r_s^c / (r_a^a + r_a^c)]} \quad (36)$$

$$290 \quad \lambda E = \frac{h_u \Delta A_s + (1 - F_c) \rho_a C_p [h_u e_{sat}(z) - e_z] / (r_a^a + r_a^s)}{\Delta h_u + \gamma [1 + r_s^s / (r_a^a + r_a^s)]} \quad (37)$$

$$291 \quad h_u = \exp\left(\frac{gh_s}{Rt_s}\right) \quad (38)$$

292 Where $e_{sat}(z)$ is the saturated vapor pressure at the reference height, e_z is the actual vapor pressure at
 293 the reference height. h_u is the relative saturation of water vapor in the air above the soil surface. R is
 294 the gas constant of water vapor, $461.5 \text{ J} \cdot \text{kg}^{-1} \cdot \text{K}^{-1}$. t_s is the soil surface temperature, K. g is the
 295 gravitational acceleration, $9.8 \text{ m} \cdot \text{s}^{-2}$. h_s is the soil water potential at the surface, m. h_s is calculated by
 296 the Van Genuchten model (Genuchten, 1980; Ghorbani et al., 2025):

$$297 \quad h_s = -\frac{1}{\alpha} \left[\left(\frac{\theta_s - \theta_w}{\theta - \theta_w} \right)^{\frac{1}{m}} - 1 \right]^{\frac{1}{\beta}} \quad (39)$$

$$298 \quad m = 1 - \frac{1}{\beta} \quad (40)$$

299 Where α is an empirical scale parameter, cm^{-1} , β is the curve shape factor, and m is an empirical shape

factor related to β , which are determined by soil type. The recommended $\alpha = 0.015 \text{ cm}^{-1}$ and $\beta = 1.5$ for the specific soil properties in this study.

Aerodynamic resistances r_a^a and r_a^s follow the S-W model. To account for atmospheric stability effects on aerodynamic resistance, atmospheric stability correction factors were added into the momentum and heat terms (Lu et al., 2014):

$$r_a^a(\alpha) = \frac{\ln\left(\frac{z_m - d}{z_{om}} + \varphi_M\right) + \ln\left(\frac{z_h - d}{z_{oh}} + \varphi_H\right)}{k^2 u_2} \quad (41)$$

$$r_a^s(\alpha) = \frac{\ln\frac{z_m - d}{z_{om}} + \varphi_M}{k^2 u_2} \frac{h}{n(h - d)} \left\{ \exp(n) - \exp\left[n\left(1 - \frac{d + z_{om}}{h}\right)\right] \right\} \quad (42)$$

$$r_a^a(0) = \frac{\left(\ln\frac{z_m}{z'_{om}} + \varphi_M\right)\left(\ln\frac{z_h}{z'_{oh}} + \varphi_H\right)}{k^2 u_2} - r_a^s(0) \quad (43)$$

$$r_a^s(0) = \frac{(\ln\frac{h}{z'_{om}} + \varphi_M)(\ln\frac{h}{z'_{oh}} + \varphi_H)}{k^2 u_2} \quad (44)$$

Where φ_M and φ_H are the atmospheric stability correction factors for momentum and heat, respectively, as described by Brutsaert (1982).

2.4 Model performance evaluation and sensitivity analysis

The performance of the five ET models was assessed against the EC-measured ET. The root mean square error (RMSE) and mean absolute error (MAE) were used to evaluate the accuracy of the simulated values, and the coefficient of determination (R^2) and consistency index (d_1) were used to evaluate the agreement between the observed and simulated values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (O_i - X_i)^2}{n}} \quad (45)$$

$$MAE = \frac{\sum_{i=1}^n |O_i - X_i|}{n} \quad (46)$$

$$d_1 = 1 - \frac{\sum_{i=1}^n |O_i - X_i|}{\sum_{i=1}^n (|O_i - \bar{O}| + |X_i - \bar{O}|)} \quad (47)$$

$$R^2 = \left[\frac{\sum_{i=1}^n (O_i - \bar{O})(X_i - \bar{X})}{\sqrt{\sum_{i=1}^n ((O_i - \bar{O})^2 \sum_{i=1}^n (X_i - \bar{X})^2)}} \right]^2 \quad (48)$$

Where O_i is the observed value. X_i is the simulated value. $\bar{O}$ is the mean observed value. $\bar{X}$ is the mean simulated value. n is the number of data sets.

A global sensitivity analysis was conducted to quantify the influence of key input variables on the simulated ET. The variables included resistance parameters (e.g., r_c , r_s^c), environmental factors (R_n , T_a , VPD, U_2 , SWC, PAR), and the vegetation variable. For each variable, its value was systematically perturbed by $\pm 10\%$ and $\pm 20\%$ from its baseline. The sensitivity was then expressed as the relative change in the simulated ET output compared to the original value.

3. Results

3.1 Seasonal variations of biophysical variables in citrus orchard

The seasonal variations of key biophysical variables during the citrus growing seasons (2020-2023) are depicted in Fig. 2. LAI_t and LAI_c exhibited a consistent single-peak seasonal pattern across all years, with a pronounced increase beginning in the flowering and fruiting stage, and reaching their maximum during the fruit expansion stage. The average LAI_t was 1.49, 1.42, 1.43, 1.56 $m^2 \cdot m^{-2}$ for four years, respectively, while the average LAI_c was 2.94, 2.93, 2.95, 3.03 $m^2 \cdot m^{-2}$ for four years, respectively. T_a , PAR, VPD, and R_n showed distinct seasonal patterns that increased during the early and middle seasons, peaking in July-August before declining. The average T_a , PAR, VPD, and R_n were 21.74 °C, 73.32 $W \cdot m^{-2}$, 0.66 kPa, 86.31 $W \cdot m^{-2}$, respectively. The u_2 showed no strong seasonal pattern, maintaining an average of 1.15 $m \cdot s^{-1}$ throughout the growing seasons. The cumulative P during the citrus growing season were 1316.83, 917.25, 634.20 and 764.65 mm in 2020-2023, respectively. The corresponding SWC averaged at 25.76%, 26.37%, 25.88%, and 23.99%.

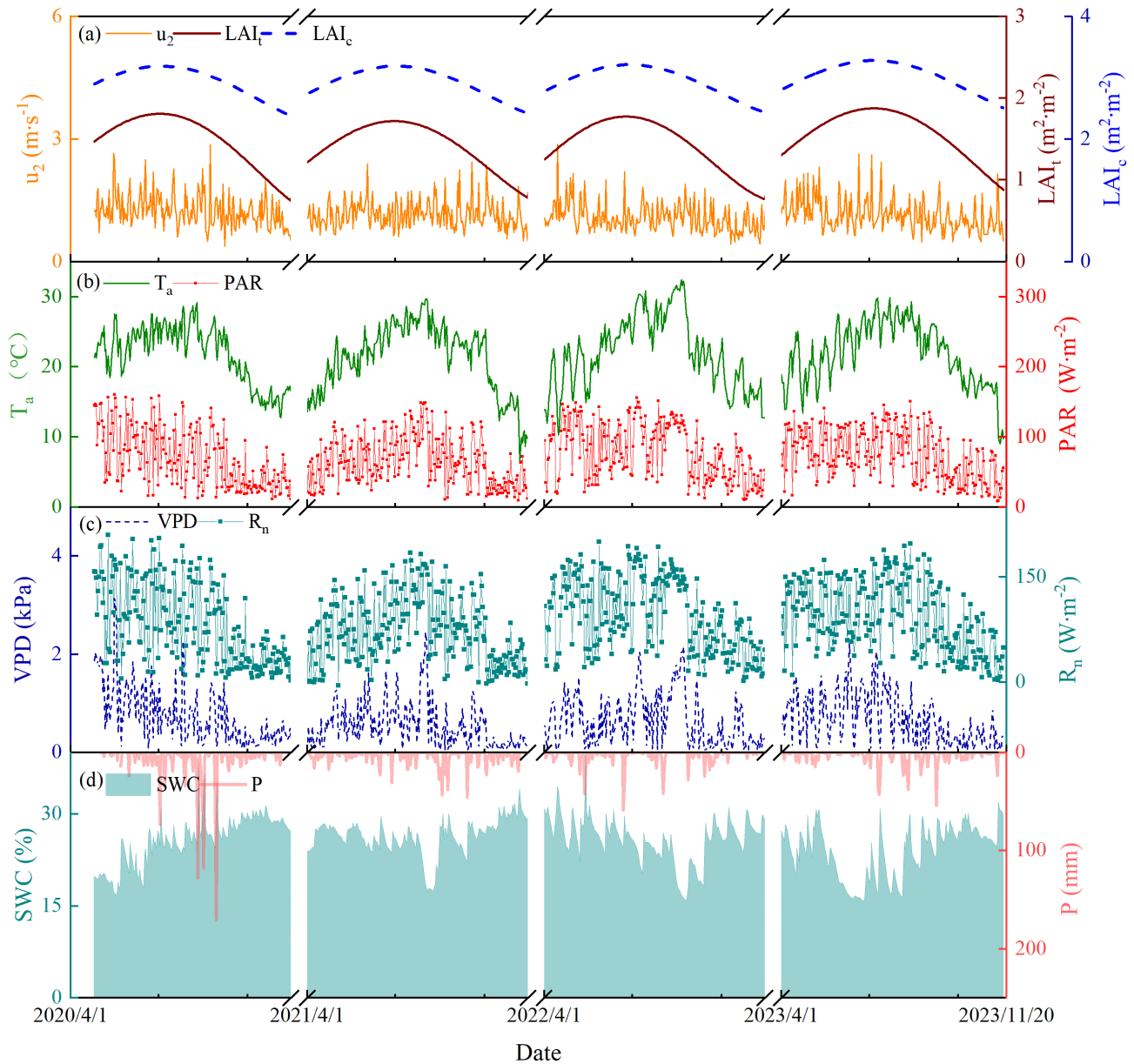
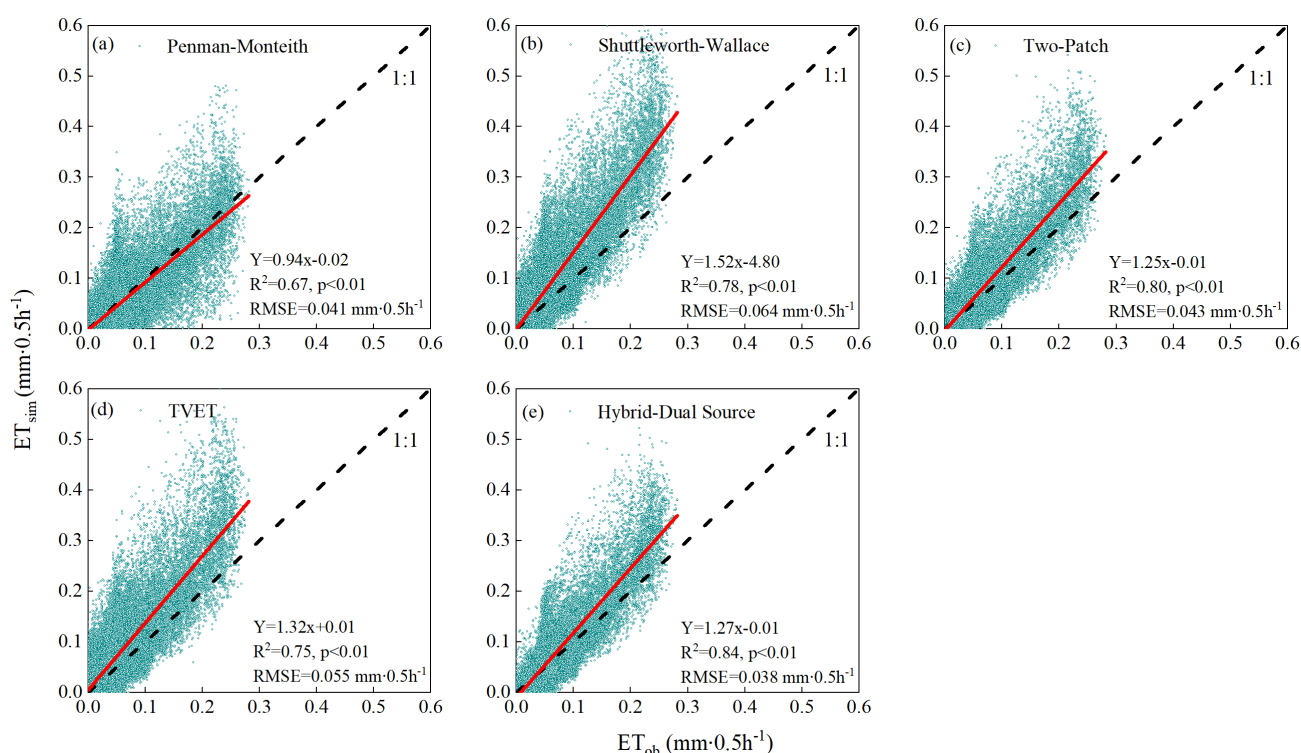


Fig.2. Seasonal variations of (a) leaf area index (LAI_t , LAI_c), wind speed at 2 m (u_2), (b) air temperature (T_a), photosynthetically active radiation (PAR), (c) vapor pressure deficit (VPD), net radiation (R_n), (d) 0-60 cm soil moisture content (SWC) and precipitation (P) during the citrus growing season of 2020-2023.

3.2 Comparison of the half-hourly scale ET simulated by different PM-based models

At the half-hourly scale, all models generally captured the dynamics of observed ET (ET_{ob}), but the estimated accuracy varied across the different models (Fig. 3). The P-M and S-W model showed the weakest performances, with R^2 of 0.67 and 0.78, RMSE of 0.041 and 0.064 mm $0.5h^{-1}$, respectively, primarily due to a systematic overestimation of the noon-time peak ET (Fig. 4). Moreover, the P-M

350 model mainly overestimates ET during the first three growth periods, while the overestimation
 351 phenomenon of the S-W model covers the entire growing season. The performance of the T-P and
 352 TVET models is more reliable, with higher R^2 of 0.80 and 0.75, RMSE of 0.043 and 0.055 $\text{mm} \cdot 0.5\text{h}^{-1}$.
 353 The H-D model was most accurate in ET estimation, yielded the highest R^2 (0.84) and the lowest
 354 RMSE ($0.038 \text{ mm} \cdot 0.5\text{h}^{-1}$), and best reproduced the diurnal cycle, including the noon peak.



355
 356 **Fig.3.** Relationship between the half-hourly simulated evapotranspiration (ET_{sim}) by (a) Penman-
 357 Monteith (P-M), (b) Shuttleworth-Wallace (S-W), (c) Two-Patch (T-P), (d) Topography- and
 358 vegetation-based surface energy partitioning algorithm (TVET), and (e) Hybrid-Dual Source (H-D)
 359 models and observed ET (ET_{ob}).
 360

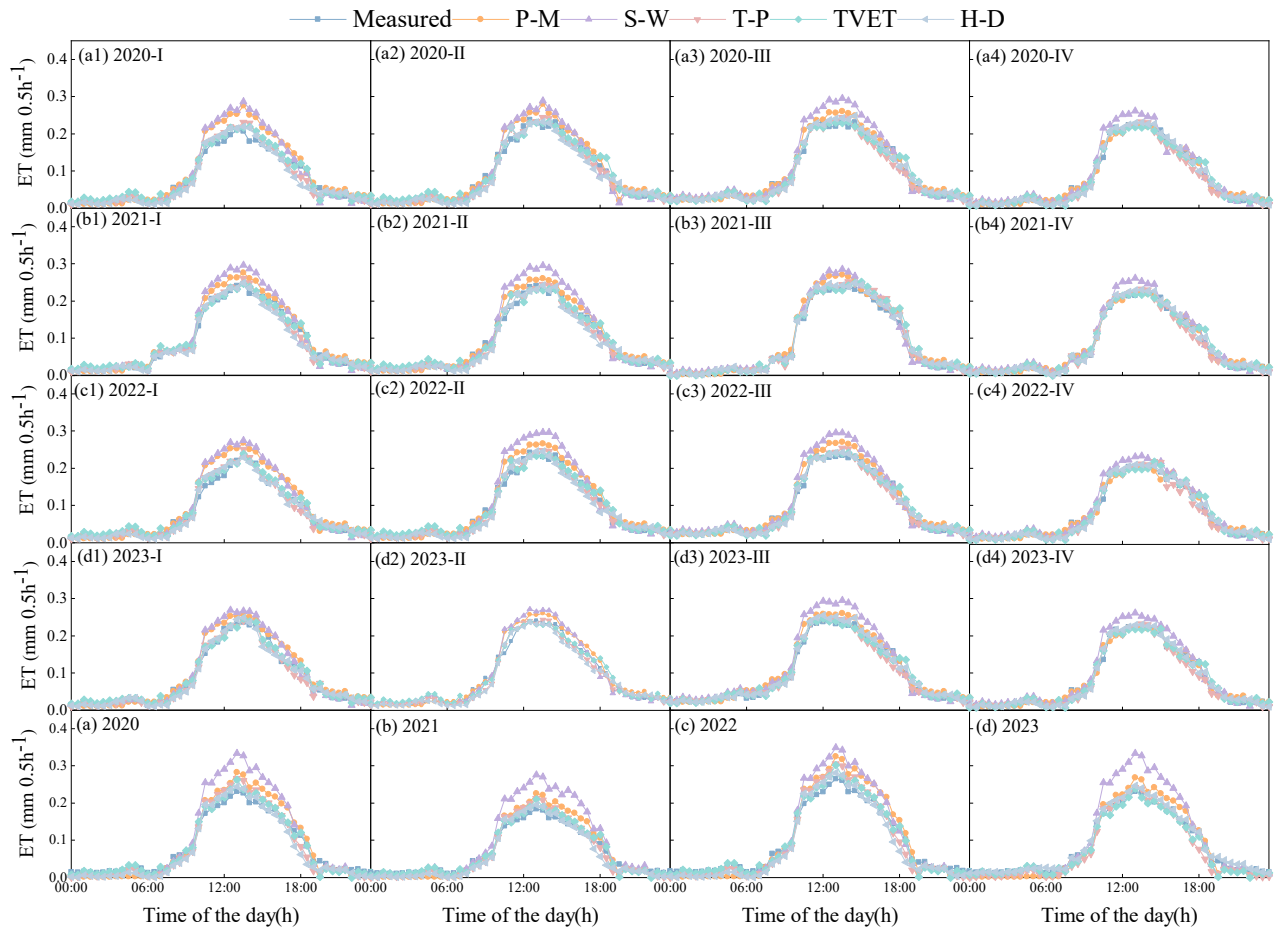


Fig.4. Diurnal variations of evapotranspiration (ET) simulated by Penman-Monteith (P-M) model, Shuttleworth-Wallace (S-W) model, Two-Patch (T-P) model, Topography- and vegetation-based surface energy partitioning algorithm (TVET) model, Hybrid-Dual Source (H-D) model, and the measured ET during the citrus growing season of 2020-2023 (a-b), and the intraday variations of ET during different reproductive periods of 2020-2023.

3.3 Comparison of the daily-scale ET simulated by different PM-based models

The comparison between the daily ET simulated by P-M, S-W, T-P, TVET, and H-D models and the ET_{ob} during the citrus growing season is shown in Fig 5, and the statistical evaluation metrics are shown in Table 2. The R^2 , RMSE, MAE and d_1 values of the 5 models ranged from 0.60 to 0.92, 0.55 to 1.43 $mm \cdot d^{-1}$, 0.41 to 1.10 $mm \cdot d^{-1}$, and 0.61 to 0.87 between 2020 and 2023, respectively.

On a daily basis, the performance hierarchy became more pronounced, with the slope of 0.48-0.81, RMSE of 0.47-1.35 $mm \cdot d^{-1}$, and R^2 of 0.74-0.90 (Fig. 5). Among the five models, the P-M and S-W models consistently overestimated ET_{ob} by 16.14% and 21.20% on average, respectively. The P-M model showed the lowest R^2 (0.74) and highest RMSE (1.35 $mm \cdot d^{-1}$). For the S-W model, R^2 was 0.84, RMSE was 1.06 $mm \cdot d^{-1}$. The dual-source and hybrid models (T-P, TVET, and H-D) showed markedly superior performance, with R^2 ranging from 0.86 to 0.90 and RMSE below 0.67 $mm \cdot d^{-1}$. It's worthwhile that the H-D model slightly underestimated the ET of 1.63% on average, with a maximum deviation of less than 5% across the four growing seasons. Consistent with the results of half-hourly, H-D model outperformed the other models in daily ET simulations, with a mean R^2 of 0.90, RMSE of 0.47 $mm \cdot d^{-1}$, MAE of 0.80 $mm \cdot d^{-1}$, and d_1 of 0.84 during the growing seasons.

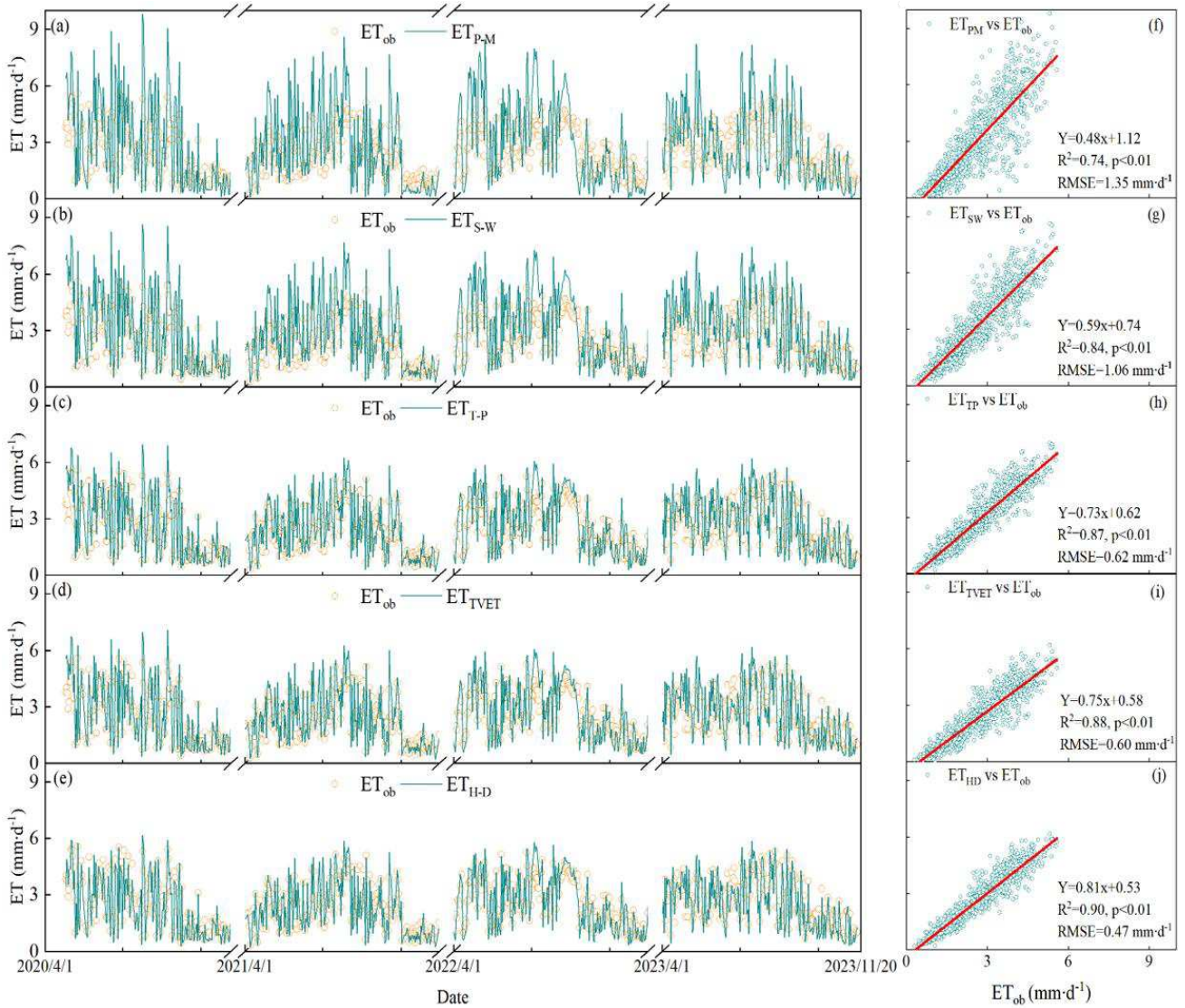


Fig.5. Seasonal variations and comparisons between observed evapotranspiration (ET_{ob}) and simulation values by Penman-Monteith (ET_{P-M}), Shuttleworth-Wallace (ET_{S-W}), Two-Patch (ET_{T-P}), Topography- and vegetation-based surface energy partitioning algorithm (ET_{TVET}), and Hybrid-Dual Source (ET_{H-D}) models.

Table 2. Statistical parameters of daily evapotranspiration (ET) simulated by different PM-type models during the citrus growing season of 2020-2023.

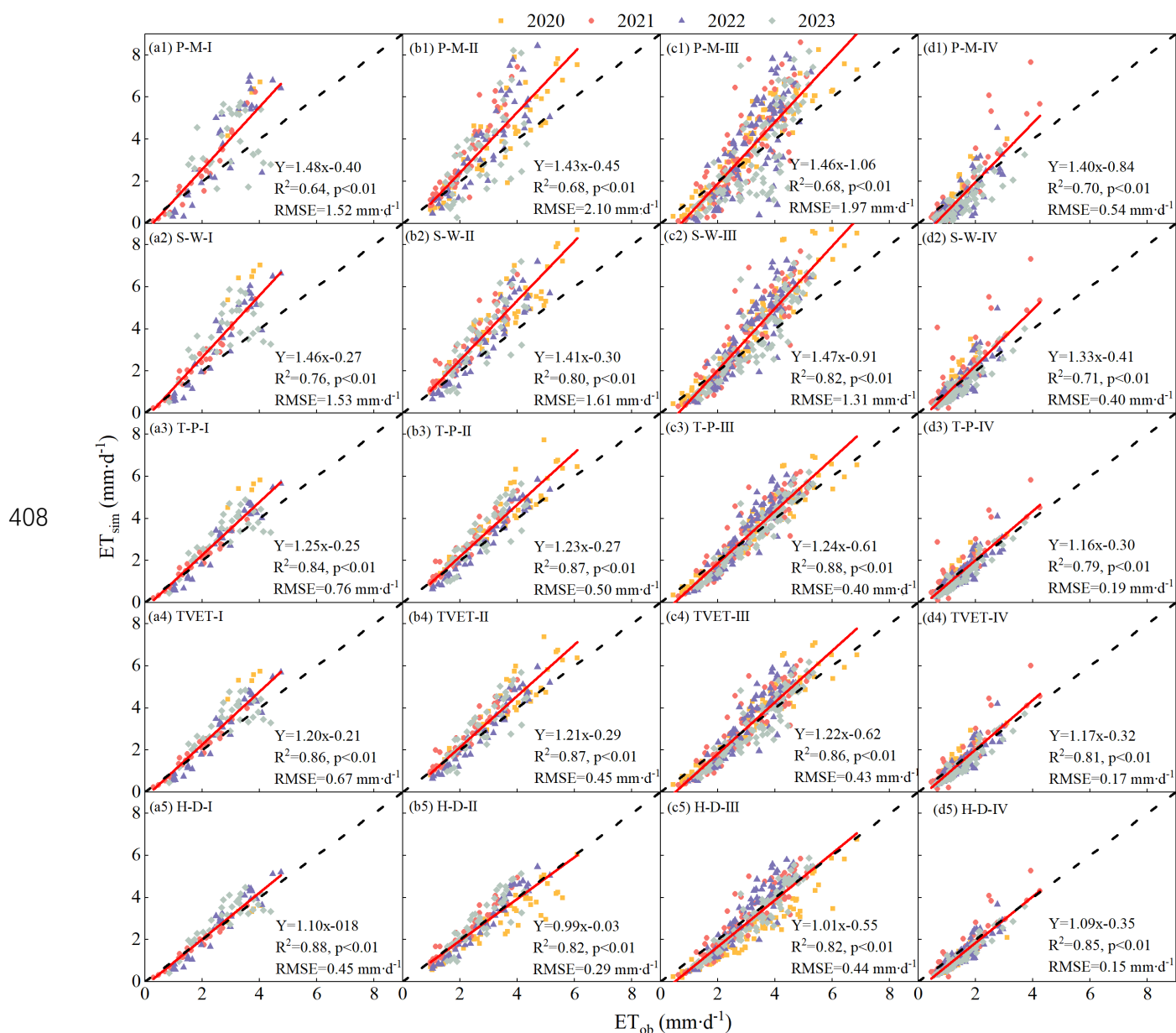
Model	Year	R^2	RMSE ($mm \cdot d^{-1}$)	MAE ($mm \cdot d^{-1}$)	d_i	Equation of regression
Penman-Monteith (P-M)	2020	0.87	1.29	0.89	0.74	$ET_{P-M}=0.58ET_{observed}+0.77$
	2021	0.80	1.28	0.92	0.65	$ET_{P-M}=0.50ET_{observed}+0.92$
	2022	0.74	1.42	1.10	0.62	$ET_{P-M}=0.45ET_{observed}+1.27$
	2023	0.60	1.32	1.03	0.61	$ET_{P-M}=0.45ET_{observed}+1.42$
Shuttleworth-Wallace (S-W)	2020	0.85	1.43	0.89	0.74	$ET_{S-W}=0.58ET_{observed}+0.66$
	2021	0.82	1.06	0.75	0.69	$ET_{S-W}=0.58ET_{observed}+0.63$
	2022	0.86	1.07	0.81	0.70	$ET_{S-W}=0.56ET_{observed}+0.87$

	2023	0.77	1.00	0.76	0.69	$ET_{S-W}=0.58ET_{observed}+0.91$
Two-Patch (T-P)	2020	0.90	0.67	0.45	0.85	$ET_{T-P}=0.77ET_{observed}+0.41$
	2021	0.87	0.60	0.42	0.81	$ET_{T-P}=0.73ET_{observed}+0.47$
	2022	0.90	0.62	0.49	0.80	$ET_{T-P}=0.69ET_{observed}+0.71$
	2023	0.85	0.59	0.47	0.79	$ET_{T-P}=0.72ET_{observed}+0.66$
Topography and Vegetation-based surface energy partitioning algorithm (TVET)	2020	0.90	0.65	0.44	0.85	$ET_{TVET}=0.78ET_{observed}+0.41$
	2021	0.87	0.60	0.42	0.81	$ET_{TVET}=0.73ET_{observed}+0.86$
	2022	0.90	0.62	0.48	0.80	$ET_{TVET}=0.70ET_{observed}+0.72$
	2023	0.84	0.58	0.49	0.78	$ET_{TVET}=0.73ET_{observed}+0.72$
Hybrid-Dual Source (H-D)	2020	0.90	0.64	0.43	0.87	$ET_{H-D}=0.78ET_{observed}+0.34$
	2021	0.88	0.58	0.41	0.83	$ET_{H-D}=0.74ET_{observed}+0.44$
	2022	0.92	0.61	0.48	0.83	$ET_{H-D}=0.71ET_{observed}+0.40$
	2023	0.87	0.55	0.46	0.82	$ET_{H-D}=0.74ET_{observed}+0.61$

389

390 The performance of the different PM-type models at different growth stages of citrus is shown in
391 Fig. 6 and Table 3. The evaluation revealed that model performance was phenology-dependent rather
392 than static. During the flowering and fruiting (Fig. 5, a1-a5), all the PM-type models overestimated
393 the ET, with the S-W model showing the largest bias (+35.94%). The H-D model was the most accurate,
394 with a minimal overestimation of 3.16%, and superior statistical indicators (R^2 of 0.88, RMSE of 0.45
395 $\text{mm}\cdot\text{d}^{-1}$, MAE of 0.36 $\text{mm}\cdot\text{d}^{-1}$, and d_1 of 0.82). During the young fruit period (Fig 6, b1-b5), the P-M
396 and S-W models continued to show significant overestimation and high error, with RMSE of 2.10
397 $\text{mm}\cdot\text{d}^{-1}$ and 1.61 $\text{mm}\cdot\text{d}^{-1}$, respectively. The T-P and TVET models performed well, with R^2 of 0.87
398 and 0.87, RMSE of 0.50 $\text{mm}\cdot\text{d}^{-1}$ and 0.45 $\text{mm}\cdot\text{d}^{-1}$, respectively. The H-D model consistently provided
399 the most reliable estimates during these key growth periods, with R^2 of 0.82, an RMSE of 0.29 $\text{mm}\cdot\text{d}^{-1}$.
400 During the fruit swelling period (Fig 6, c1-c5), the T-P, TVET, and H-D models are all better than the
401 P-M model and the S-W model. Among them, the T-P model performs the best, with R^2 of 0.88 and
402 RMSE of 0.40 $\text{mm}\cdot\text{d}^{-1}$, and the TVET model follows. While the P-M model and the S-W model have

403 similar performance to that at the young fruit period, with RMSE of $1.97 \text{ mm} \cdot \text{d}^{-1}$ and $1.31 \text{ mm} \cdot \text{d}^{-1}$,
 404 respectively. During the fruit ripening period (Fig 5, d1-d5), the P-M, S-W, T-P, TVET and H-D models
 405 all performed well, with R^2 of 0.70-0.85, MAE of 0.31 - $0.56 \text{ mm} \cdot \text{d}^{-1}$, RMSE of 0.15 - $0.54 \text{ mm} \cdot \text{d}^{-1}$, and
 406 d_1 of 0.62-0.75. Notably, the H-D model achieved an exceptional R^2 of 0.85 and the lowest RMSE of
 407 $0.15 \text{ mm} \cdot \text{d}^{-1}$ at this stage.



409 **Fig.6.** Relationship between evapotranspiration simulated by different P-M-based models (ET_{sim})
 410 with observed ET (ET_{ob}) at different growth stages during the citrus growing season of 2020-2023.
 411 (a1-d1) Penman-Monteith (P-M), (a2-d2) Shuttleworth-Wallace (S-W), (a3-d3) Two-Patch (T-P),
 412 (a4-d4) Topography- and vegetation-based surface energy partitioning algorithm (TVET), and (a5-

413 d5) Hybrid-Dual Source (H-D) models.

414

415 **Table 3.** Statistical parameters of daily evapotranspiration (ET) simulated by different PM-type models
 416 at different citrus growth stages during 2020-2023.

Model	Stage	R ²	RMSE (mm·d ⁻¹)	MAE (mm·d ⁻¹)	d ₁
Penman-Monteith (P-M)	Flowering and fruiting period (I)	0.64	1.52	1.19	0.53
	Young fruiting period (II)	0.68	2.10	1.07	0.60
	Fruit swelling period (III)	0.68	1.97	1.11	0.61
	Fruit ripening period(IV)	0.70	0.54	0.56	0.62
Shuttleworth-Wallace (S-W)	Flowering and fruiting period (I)	0.76	1.53	1.17	0.54
	Young fruiting period (II)	0.80	1.61	0.96	0.62
	Fruit swelling period (III)	0.82	1.31	0.86	0.68
	Fruit ripening period(IV)	0.71	0.40	0.41	0.70
Two-Patch (T-P)	Flowering and fruiting period (I)	0.84	0.76	0.59	0.73
	Young fruiting period (II)	0.87	0.50	0.52	0.77
	Fruit swelling period (III)	0.88	0.40	0.49	0.80
	Fruit ripening period(IV)	0.79	0.19	0.31	0.75
Topography and Vegetation-based surface energy partitioning algorithm (TVET)	Flowering and fruiting period (I)	0.84	0.76	0.59	0.72
	Young fruiting period (II)	0.87	0.45	0.48	0.78
	Fruit swelling period (III)	0.86	0.43	0.51	0.79
	Fruit ripening period(IV)	0.81	0.17	0.30	0.75
Hybrid-Dual Source (H-D)	Flowering and fruiting period (I)	0.88	0.45	0.36	0.82
	Young fruiting period (II)	0.82	0.29	0.40	0.80
	Fruit swelling period (III)	0.82	0.44	0.53	0.77
	Fruit ripening period(IV)	0.85	0.15	0.31	0.75

417 3.4 Sensitivity analysis of different PM-type models to input variables

418 Across all models, ET was most sensitive to r_c in P-M or r_s^c in other models (Fig 7). Specifically,
 419 ET increased by 6.18%, 5.70%, 7.41%, 4.88% and 3.71%, respectively, when r_c or r_s^c decreased of
 420 20% in the P-M, S-W, T-P, TVET, and H-D models. Aerodynamic resistances (r_a^s , r_a^a , r_a in P-M) and
 421 soil resistance (r_s^s) had comparatively minor influences on ET, with changes of $\pm 20\%$ resulting in ET
 422 variations generally below 3%.

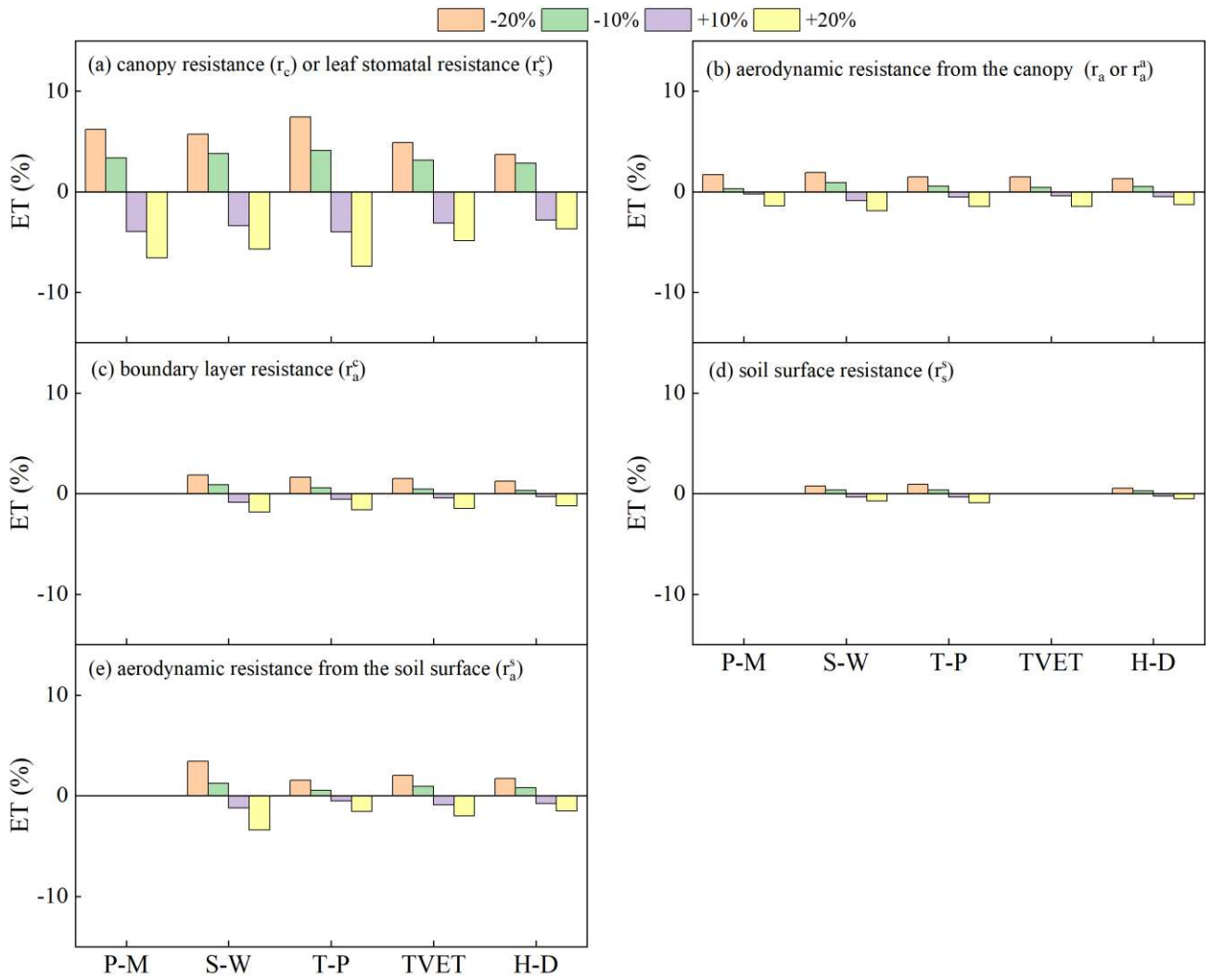


Fig.7. Sensitivity of different P-M-based evapotranspiration (ET) models to resistance variable inputs (r_c or r_s^c , r_a or r_a^a , r_a^c , r_a^s , r_s^s)

Environmental factors also affected ET simulation through the resistance parameters. r_c or r_s^c was estimated based on the Jarvis model, expressing the response of surface resistance to various environmental factors in the form of the product of the minimum resistance multiplied by the independent constraint function. Therefore, changes in the involved environmental factors (PAR, VPD, T_a and SWC) also affect the estimation of ET. r_a , r_a^a and r_a^c were affected not only by crop growth characteristics, but also by the input environmental variable u_2 , while SWC mainly influenced r_s^s . Among these environmental factors, SWC acted as the most sensitive one affecting ET simulation in all models, followed by R_n and T_a (Fig 8). When SWC increased by 20%, the simulated ET in P-M, S-

W, T-P, TVET, and H-D models increased by 22.95%, 24.18%, 32.27%, 11.49% and 10.43% ,
 respectively. In contrast, ET was less sensitive to PAR, VPD and u_2 in those models. Specifically, when
 PAR and VPD decreased 20%, the ET decreased by 7%-10%. u_2 changes of 20% or 10%, the change
 in ET was less than 7%. Additionally, the influence of LAI_t on ET simulation was highly model-
 specific. It was most pronounced in the S-W model, where a 20% decrease in LAI_t reduced ET by
 11.38%. When LAI_t increased by 20%, ET increased by 7.16% in the P-M model. In contrast, the T-P,
 TVET, and H-D models, which rely on vegetation coverage F_c , exhibited lower sensitivity to LAI_c
 variations. When the LAI_c changes of 20% or 10%, the changes of the simulated ET by those models
 were all below 7%.

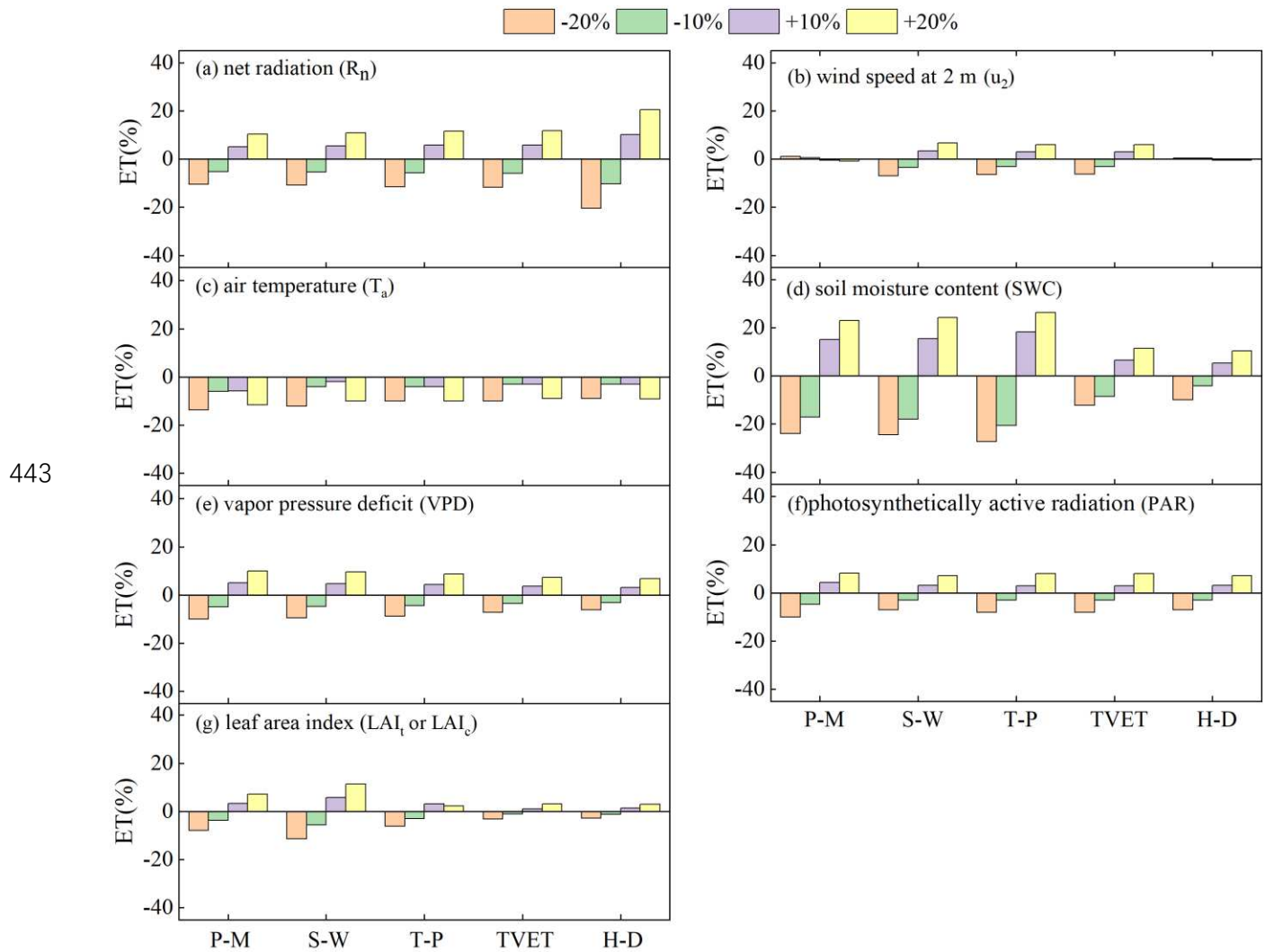


Fig.8. Sensitivities of the different P-M-based evapotranspiration (ET) models to the environmental factors (R_n , T_a , VPD, u_2 , SWC, PAR) and vegetation variable (LAI_t in the P-M and S-W model; LAI_c in the T-P, TVET, H-D model)

4. Discussion

4.1 Model Performance: unveiling structural strengths and weaknesses

This study provides a systematic, multi-scale evaluation of the PM-based ET model family in an orchard ecosystem, moving beyond performance ranking to uncover structural reasons behind model behavior. The P-M model is commonly used to simulate ET (Allen et al., 1998) and is considered reliable when the soil surface is fully covered by vegetation canopy (Liu et al., 2020; Palmer et al., 2020). In this citrus orchard, the P-M model had a lower ET simulation performance for the entire growing season and different growth stages than other models. The persistent overestimation by the single-source P-M model, especially during the flowering and fruiting, young fruit period with low cover, aligns with findings in other sparse canopies (Li et al., 2020). Gao et al. (2023) also indicated that a major cause of P-M overestimation is its inability to partition E and T when the soil surface is wet and exposed.

The superior performance of the dual-source and hybrid models underscores the critical importance of explicitly representing soil-vegetation interactions in a sparse orchard ecosystem. However, their performance is not uniform. The S-W model physically describes the ET process under sparse vegetation (Shuttleworth et al., 1990) and generally performs better than the P-M model, but its structure is much more complex. However, the S-W model's notable overestimation was found in our study. Li et al. (2020) also found the S-W model overestimated ET by more than 35% at the early stage of summer maize growth. An overestimation phenomenon in the S-W model was also reported by Shao et al. (2022) in solar greenhouses, attributing it to the model's complex resistance network. Li et al.

467 (2020) also indicated that although the S-W model clearly distinguishes between the vegetation canopy
468 and the soil surface as two sources, the overestimated ET lies in the determination of each resistance
469 parameter, especially for r_s^c simulation. Furthermore, some studies proved that the overestimation of
470 ET by the S-W model at the early stage of crop is mainly due to the error caused by the Jarvis model,
471 which is amplified under high atmospheric demand (Irmak and Mutiibwa, 2010; Wu et al., 2024).

472 In contrast, the patch-based T-P model and its derivatives (TVET, H-D) showed greater robustness
473 across the citrus growing season and different stages, indicating that patch-based approaches better
474 describe ET in incompletely covered orchards than layered or single-source models. The T-P model
475 divides the underlying surface into "vegetation patches" and "soil patches", and the ET of the entire
476 underlying is calculated as the area-weighted sum of the ET from the two patches (Lhomme et al., 1999;
477 Lu et al., 2014; Gao et al., 2023). However, the T-P model assumes that the ET from two patches occurs
478 independently, ignoring the interaction between the two patches. Especially when vegetation is
479 relatively sparse, such as during the flowering and fruiting, the performance of the T-P model is slightly
480 inferior to that of the TVET and H-D models. However, during the fruit swelling period and fruit
481 ripening period, the performance of the T-P model is generally superior. The TVET model also
482 aggregates ET as a weighted sum but distinguishes between inter-canopy and under-canopy soil
483 evaporation (Guan and Wilson., 2009). The H-D model builds on the TVET model, and simultaneously
484 uses two important vegetation parameters to describe the vegetation coverage (Lu et al., 2014).
485 Compared to the TVET model, the H-D model not only considers the influence of environmental
486 factors on ET, but also includes the key factor of soil moisture status. In addition, its incorporation of
487 atmospheric stability corrections for aerodynamic resistances is a key differentiator, likely providing a
488 more physically realistic simulation of turbulent transfer, especially under the stable/unstable

conditions common in heterogeneous landscapes, which explains its exceptional accuracy at the half-hourly scale (Lu et al., 2014).

The strong performance of the H-D model across most stages confirms its general reliability. However, the fact that the simpler T-P model performed best during the fruit swelling period (Phase III, Table 3) is insightful. This suggests that when the canopy is dense, and soil evaporation is suppressed, the additional complexity of resistance network (like S-W) or stability corrections (like H-D) may introduce greater potential errors and yield diminishing returns. This finding provides practical guidance for model selection under varying seasonal conditions and canopy structures, a nuance often overlooked in single-stage model evaluations.

4.2 The sensitivity of the P-M type model to the resistance and environmental variables

The output ET is most sensitive to r_c or r_s^c , highlighting them as the primary regulating factor and the largest uncertainty source in ET estimates. r_c or r_s^c is influenced by both environmental and biophysical factors, including R_n , T_a , VPD, SWC, and LAI (Irmak and Mutiibwa, 2010; Liu et al., 2020). As a key resistance term directly controlling the diffusion of water vapor from the interior of leaves to the atmosphere (Wu et al., 2024), this reinforces that the accurate characterization of plant physiological responses to environmental stressors is the linchpin of reliable ET simulation (Irmak and Mutiibwa, 2010; Wu et al., 2024; Xu et al., 2017).

Among various environmental factors, ET had the highest response to SWC, which had a positive effect on ET, underscoring the critical role of soil moisture in this subtropical system prone to seasonal drought. The increase of SWC would reduce the resistance of both from the soil land surface (r_s^s) and the plants' leaves (r_s^c) to the atmosphere. Seneviratne et al. (2010) showed that SWC is the main factor in the ET process in arid and semiarid areas, and there were also lots of studies to improve or adjust

the soil content constraint function to enhance the ET simulation (Zhang et al., 2025; Lai et al., 2025; Liu et al., 2025; Ying et al., 2022). In addition, the exceptionally high sensitivity of the T-P model to SWC (a 32% change in ET for a 20% SWC change) suggests that its non-interactive patch scheme may amplify the direct soil evaporation component.

The sensitivity of the models to environmental variables collectively underscores that R_n is the predominant driver of the ET process. All models exhibited a strong, consistent positive response to an increase in R_n . This reaffirms the fundamental role of R_n as the primary energy source for ET, directly driving the energy balance equation at the core of all model structures (Liu et al., 2020). The influence of PAR and T_a was predominantly reflected in transpiration terms of the ET models. An increase in PAR directly reduces the r_s^c via the corresponding stress function in the Jarvis model, thereby promoting T and ET. However, although rising T_a increases the atmospheric evaporative demand, both our analysis and the results of Cui et al. (2023) showed a slight decrease in simulated ET with increasing T_a . The underlying mechanism is the strong, negative physiological regulation that T_a exerts on r_s^c through the non-linear temperature stress function (Eq. 7). The reduction in T caused by stomatal closure (increased r_s^c) in response to elevated T_a outweighs the potential increase in E from enhanced environmental evaporative power, resulting in a net decrease in total ET. This highlights the critical role of plant physiological feedback to environmental factors in ET simulation.

4.3 Mechanistic insights into model sensitivity to vegetation factor

Our sensitivity analysis revealed pronounced differences in how the models responded to changes in LAI, a divergence primarily rooted in their distinct physical structures and the specific parameterization pathways for LAI. ET was most sensitive to LAI_t in the S-W model, and less sensitive to LAI_c in T-P, TVET and H-D models. LAI is a key factor for simulating the canopy resistance and

533 the surface resistance. The high sensitivity in the P-M and S-W model is due to LAI_t 's direct role in
534 calculating resistances and partitioning energy (Cui et al., 2023; Li et al., 2013). The S-W model
535 exhibited the highest sensitivity to LAI_t , a direct consequence of its complex multi-layer architecture.
536 In the S-W model, LAI_t is simultaneously and directly used to calculate several key resistances: it
537 determines the r_s^c via the Jarvis model and linearly weights both the aerodynamic resistance above
538 the canopy (r_a^a) and the resistance between the canopy and soil (r_a^s). This multi-pathway, tightly
539 coupled parameterization means that a perturbation in LAI is amplified and propagated throughout the
540 model's resistance network, leading to significant fluctuations in simulated ET and its components (Cui
541 et al., 2023; Liu et al., 2020).

542 In contrast, the T-P and TVET models demonstrated a different sensitivity pattern, characteristic
543 of parallel (patch) approaches. In these models, LAI_c primarily influences fluxes by determining
544 the vegetation F_c . An increase in LAI_c raises F_c , thereby directly increasing the weighting of plant T in
545 total ET while simultaneously reducing the weighting of soil E. Consequently, a change in LAI_c in T-
546 P and TVET models primarily induces a trade-off between T and E, resulting in a smaller net effect on
547 total ET (Cui et al., 2023; Gao et al., 2023). It is noteworthy that in the T-P model, LAI_c is used for
548 upscaling stomatal resistance to the canopy level, which buffers the model's response to LAI_c variation
549 since F_c changes synchronously with LAI_c . This observation is consistent with Cui et al. (2023), who
550 noted that the net impact of LAI_c on total ET in patch models is attenuated by the opposing responses
551 of T and E. The H-D model in our study showed comparatively lower sensitivity to LAI_c , underscoring
552 the advantage of its integrated structure. The H-D model employs a layered scheme for energy
553 distribution but utilizes a patch method for flux aggregation. This design likely reduces over-reliance
554 on the single LAI parameter (Lu et al., 2014). More importantly, Cui et al. (2023), in their innovative

Two patch-Two layer model, demonstrated that further disaggregating the canopy into sunlit and shaded leaves and calculating their respective LAI and resistances provides a more physiologically realistic representation. When total LAI changes, the LAI of sunlit and shaded leaves changes asymmetrically, which leads to different change rates in their respective sunlit and shaded canopy resistances. This suggests that moving beyond a bulk LAI to account for within-canopy heterogeneity is a promising direction for reducing model uncertainty related to LAI estimation and enhancing simulation robustness.

5. Conclusion

This study presents a comprehensive evaluation of five PM-based ET models in a subtropical citrus orchard, integrating multi-temporal validation with a mechanistic sensitivity analysis. The H-D model demonstrated superior overall performance, achieving the best accuracy at both the half-hourly ($R^2 = 0.84$, $RMSE = 0.038 \text{ mm} \cdot 0.5\text{h}^{-1}$) and daily ($R^2 = 0.91$, $RMSE = 0.47 \text{ mm} \cdot \text{d}^{-1}$) scales. Its robust structure, which incorporates atmospheric stability corrections and dual-source energy partitioning, makes it highly suitable for a heterogeneous orchard. Although the strong performance of the H-D model across most stages, the simpler T-P model performed best during the fruit swelling period, suggesting that patch-based approaches may be sufficient under dense canopy conditions. The sensitivity analysis highlighted that canopy resistance and soil moisture are the dominant controls on ET simulations across all models, underscoring the need for accurate parameterization of plant physiological and soil hydraulic processes. Furthermore, the influence of vegetation parameters (especially LAI) on ET was most pronounced in the S-W model and P-M model. These findings provide not only practical guidance for model selection in precision irrigation management, but also deeper insights into the structural limitations and strengths of the P-M based model family.

Acknowledgment:

This work was also financially funded by the National Key Research and Development Program of China (2023YFD1901203), National Natural Science Foundation of China (52309055, 52579041, 52279041), Sichuan Province Science and Technology Program (2026NSFSCZY0051, 2026YFHZ0113, 2024ZHCG0101, 2024YFHZ0200, 2024YFHZ0217), Technological Innovation and R&D Project of Chengdu Eastern New Area (2024-DBXQ-KJYF008-LH), and the Training Program of the Innovation Guidance and Scientific and Technological Enterprise of Yunnan Province (202304BT090019).

References

- Allen, R.G., Pruitt, W.O., Wright, J.L., Howell, T. A., Ventura, F., Snyder, R., Itenfisu, D., Steduto, P., Berengena, J., Yrisarry, J.B., Smith, M., Pereira, L.S., Raes, D., Perrier, A., Alves, I., Walter, I., Elliott, R. A recommendation on standardized surface resistance for hourly calculation of reference ET_o by the FAO56 Penman-Monteith method. *Agricultural Water Management*, 2006, 81(1-2): 1-22. <https://doi.org/10.1016/j.agwat.2005.03.007>.
- Bernier, T.P. The Use of Water Vapor Isotopes to Determine Evapotranspiration Source Contributions in the Natural Environment. *Water*, 2020, 12(11): 3023. <https://doi.org/10.3390/w12113203>.
- Brutsaert, W. *Evaporation into the atmosphere: theory, history and applications*. Springer Science & Business Media, 2013.
- Callejas-Rodelas, J.Á., Knohl, A., Van Ramshorst, J., Mammarella, R., Markwitz, C. Comparison between lower-cost and conventional eddy covariance setups for CO_2 and evapotranspiration measurements above monocropping and agroforestry systems. *Agricultural and Forest Meteorology*, 2024, 354: 110086. <https://doi.org/10.1016/j.agrformet.2024.110086>.
- Campbell, G.S. Norman J.M. *An Introduction to Environmental Biophysics*; Springer: New York, NY, USA, 1998.

599 Choudhury, B., Monteith, J. A four-layer model for the heat budget of homogeneous land surfaces. Quarterly Journal
600 of the Royal Meteorological Society, 2010, 114(480): 373-398. <https://doi.org/10.1002/qj.49711448006>.

601 Cui, N., He, Z., Jiang, S., Wang, M.J., Yu, X.Y., Zhao, L., Qiu, R.J., Gong, D.Z., Wang, Y.S., Feng, Y. Inter-comparison
602 of the Penman-Monteith type model in modeling the evapotranspiration and its components in an orchard
603 plantation of Southwest China. Agricultural Water Management, 2023, 289: 0378-
604 3774. <https://doi.org/10.1016/j.agwat.2023.108541>.

605 Derardja, B., Khadra, R., Abdelmoneim, A.A.A., El-Shirbeny, M.A., Valsamidis, T., De Pasquale, V., Deflorio, A.M.,
606 Volden, E. Advancements in Remote Sensing for Evapotranspiration Estimation: A Comprehensive Review of
607 Temperature-Based Models. Remote Sensing, 2024, 16(11): 1927. <https://doi.org/10.3390/rs16111927>.

608 Falge, E., Baldocchi, D., Olson, R., Anthoni, P., Aubinet, M., Bernhofer, C., Burba, G., Ceulemans, R., Clement, R.,
609 Dolman, H., Granier, A., Gross, P., Grünwald, T., Hollinger, D., Jensen, N., Katul, G., Keronen, P., Kowalski, A.,
610 Lai, C.T., Law, B.E., Meyers, T., Moncrieff, J., Moors, E., Munger, J.W., Pilegaard, K., Rannik, U., Rebmann, C.,
611 Suyker, A., Tenhunen, J., Tu, K., Verma, S., Vesala, T., Wilson, K., Wofsy, S. Gap filling strategies for defensible
612 annual sums of net ecosystem exchange. Agricultural and Forest Meteorology 2001, 107: 43–69.
613 [https://doi.org/10.1016/S0168-1923\(00\)00225-2](https://doi.org/10.1016/S0168-1923(00)00225-2).

614 Fisher, J.B., Tu, K.P., Baldocchi, D.D. Global estimates of the land-atmosphere water flux based on monthly AVHRR
615 and ISLSCP-II data, validated at 16 FLUXNET sites. Remote Sensing of Environment, 2008, 112(3): 901-
616 919. <https://doi.org/10.1016/j.rse.2007.06.025>.

617 Gao, X., Mei, X., Zhang, J., Cai, J., Gu, F.X., Hao, W.P., Gong, D.Z. Comparison of three modified models in
618 evapotranspiration and its components over a rainfed spring maize cropland on the Loess Plateau, China.
619 Agricultural and Forest Meteorology, 2023, 330: 109322. <https://doi.org/10.1016/j.agrformet.2023.109322>.

620 Genuchten, M.T.V. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. Soil science

society of America journal, 1980, 44(5): 892-898.<https://doi.org/10.2136/sssaj1980.03615995004400050002x>.

Ghiat, I., Mackey, H.R., Al-Ansari, T. A Review of evapotranspiration measurement models, techniques and methods for open and closed agricultural field applications. *Water*, 2021,13(18): 2523. <https://doi.org/10.3390/w13182523>.

Ghorbani, A., Babaeian, E., Sadeghi, M., Durner, W., Jones, S.B, Martinus, T., Genuchten, V. An improved Van Genuchten soil water characteristic model to account for surface adsorptive forces. *Journal of Hydrology*, 2025: 133692. <https://doi.org/10.1016/j.jhydrol.2025.133692>.

Gong, X., Qiu, R., Zhang, B., Wang, S.S., Ge, J.K., Gao, S.K., Yang, Z.Q. Energy budget for tomato plants grown in a greenhouse in northern China. *Agricultural Water Management*, 2021, 255: 107039.<https://doi.org/10.1016/j.agwat.2021.107039>.

Guan, H., Wilson, J.L. A hybrid dual-source model for potential evaporation and transpiration partitioning. *Journal of Hydrology*, 2009, 377(3-4): 405-416.<https://doi.org/10.1016/j.jhydrol.2009.08.037>.

Gu, Z., Zhu, T., Jiao, X., Xu, J.Z., Qi, Z.M. Neural network soil moisture model for irrigation scheduling. *Computers and Electronics in Agriculture*, 2020, 180: 105801.<https://doi.org/10.1016/j.compag.2020.105801>.

Han, Y., Calabrese, S., Du, H., Yin, J. Evaluating biases in Penman and Penman–Monteith evapotranspiration rates at different timescales. *Journal of Hydrology*, 2024, 638: 131534.<https://doi.org/10.1016/j.jhydrol.2024.131534>.

Irmak, S., Mutiibwa, R. On the dynamics of canopy resistance: Generalized linear estimation and relationships with primary micrometeorological variables. *Water Resources Research*, 2010, 46(8): 863-863.<https://doi.org/10.1029/2009wr008484>

Jarvis N J. A simple empirical model of root water uptake. *Journal of Hydrology*, 1989, 107(1-4):57-72.[https://doi.org/10.1016/0022-1694\(89\)90050-4](https://doi.org/10.1016/0022-1694(89)90050-4)

Jiang, S., Liang, C., Cui, N., Zhao, L., Du, T.S., Hu, X.T., Feng, Y., Guan, J., Feng, Y. Impacts of climatic variables on reference evapotranspiration during growing season in Southwest China. *Agricultural Water Management*, 2019,

216: 365-378..<https://doi.org/10.1016/j.agwat.2019.02.014>.

Jin, L., Chen, S., Yang, H., Zhang, C.C. Evaluation and drivers of four evapotranspiration products in the Yellow River Basin. *Remote Sensing*, 2024, 16(11): 1829.<https://doi.org/10.3390/rs16111829>.

Ji, L., Senay, G.B., Friedrichs, M.K., Kagone, S. Estimating agricultural irrigation water consumption for the High Plains aquifer region with integrated energy-and water-balance evapotranspiration modeling approaches. *Agricultural Water Management*, 2025, 309: 109308. <https://doi.org/10.1016/j.agwat.2025.109308>.

Lai, Y., Zhang, L., Cheng, L., Wang, X., Liu, P. Dynamic soil water stress function improves evapotranspiration estimation in areas with significant vegetation variability. *Journal of Hydrology*, 2025: 133585.<https://doi.org/10.1016/j.jhydrol.2025.133585>.

Lhomme, J.P., Monteny, B., Amadou, M. Estimating sensible heat flux from radiometric temperature over sparse millet. *Agricultural and Forest Meteorology*, 1994, 68(1-2): 77-91.[https://doi.org/10.1016/0168-1923\(94\)90070-1](https://doi.org/10.1016/0168-1923(94)90070-1).

Lhomme, J., Chehbouni, A. Comments on dual-source vegetation-atmosphere transfer models. *Agricultural and Forest Meteorology*, 1999, 94(3-4): 269-273.[https://doi.org/10.1016/S0168-1923\(98\)00109-9](https://doi.org/10.1016/S0168-1923(98)00109-9).

Lin, J., Sun, S. A Study of Moisture and Heat Transport in Soil and the Effect of Surface Resistance to Evaporation. *Journal of Hydraulic Engineering*, 1983, (07): 1-8. <https://doi:10.13243/j.cnki.slxb.1983.07.001>.(in Chinese).

Li, S., Kang, S., Zhang, L., Ortega-Farias, S., Li, F.S., Du, T.S., Tong, L., Wang, S.F., Ingman, M., Guo, W.H. Measuring and modeling maize evapotranspiration under plastic film-mulching condition. *Journal of Hydrology*, 2013, 503: 153-168.<https://doi.org/10.1016/j.jhydrol.2013.07.033>.

Lian, X., Piao, S., Hunting, F.C., Li, Y., Zeng, Z.Z., Wang, X.H., Ciais, P., McVicar, T.R., Peng, S.S., Ottlé, C., Yang, H., Yang, Y.T., Zhang, Y.Q., Wang, T. Partitioning global land evapotranspiration using CMIP5 models constrained by observations. *Nature Climate Change*, 2018, 8(7): 640-646. <https://doi.org/10.1038/s41558-018-0207-9>.

Liu, X., Xu, J., Wang, W., Lv, Y.P., Li, Y.W. Modeling rice evapotranspiration under water-saving irrigation condition:

665 Improved canopy-resistance-based. Journal of Hydrology, 2020, 590:
666 125435.<https://doi.org/10.1016/j.jhydrol.2020.125435>.

667 Liu, Z. Estimating land evapotranspiration from potential evapotranspiration constrained by soil water at daily scale.
668 Science of the total environment, 2022, 834: 155327.<https://doi.org/10.1016/j.scitotenv.2022.155327>.

669 Liu, X., Zhou, K., Zhang, Q. Using solar-induced chlorophyll fluorescence to estimate forest evapotranspiration.
670 Journal of Hydrology, 2025: 133595.<https://doi.org/10.1016/j.jhydrol.2025.133595>.

671 Lu, H., Liu, T., Yang, Y., Yao, D.D. A hybrid dual-source model of estimating evapotranspiration over different
672 ecosystems and implications for satellite-based approaches. Remote Sensing, 2014, 6(9): 8359-
673 8386.<https://doi.org/10.3390/rs6098359>.

674 McColl, K.A. Practical and theoretical benefits of an alternative to the Penman-Monteith evapotranspiration equation.
675 Water Resources Research, 2020, 56(6): e2020wr027106.<https://doi.org/10.1029/2020wr027106>.

676 Monteith, J.L. Principles of Environmental Physics. New York: American Elsevier:1973, 241.

677 Nyolei, D., Diels, J., Mbilinyi, B., Mbungu, W., Griensven, A.V. Evapotranspiration simulation from a sparsely
678 vegetated agricultural field in a semi-arid agro-ecosystem using Penman-Monteith models. Agricultural and Forest
679 Meteorology, 2021, 303, 108370.<https://doi.org/10.1016/j.agrformet.2021.108370>

680 Peng, X., Hu, X., Chen, D., Zhou, Z., Guo, Y., Deng, X., Zhang, X., Yu, T. Prediction of Grape Sap Flow in a
681 Greenhouse Based on Random Forest and Partial Least Squares Models. Water, 2021, 13(21):3078.
682 <https://doi.org/10.3390/w13213078>.

683 Peddinti, S.R., Kisekka, I. Evaluation of the LI-710 evapotranspiration sensor in comparison to full eddy covariance
684 for monitoring energy fluxes in perennial and annual crops. Agricultural Water Management, 2025, 313:
685 109501.<https://doi.org/10.1016/j.agwat.2025.109501>.

686 Reichstein, M., Falge, E., Baldocchi, D., Papale, D., Aubinet, M., Berbigier, P., Valentini, R. On the separation of net

ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm. *Global Change Biology*, 2005, 11: 1424-1439. <https://doi.org/10.1111/j.1365-2486.2005.001002.x>

Seneviratne, S.I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., Teuling, A.J. Investigating soil moisture–climate interactions in a changing climate: A review. *Earth-Science Reviews*, 2010, 99(3-4): 125-161. <https://doi.org/10.1016/j.earscirev.2010.02.004>.

Shuttleworth, W., Wallace, J. Evaporation from sparse crops-an energy combination theory. *Quarterly Journal of the Royal Meteorological Society*, 1985, 111(469): 839-855. <https://doi.org/10.1002/qj.49711146910>.

Shuttleworth, W., Gurney, R. The theoretical relationship between foliage temperature and canopy resistance in sparse crops. *Quarterly Journal of the Royal Meteorological Society*, 1990, 116(492): 497-519. <https://doi.org/10.1002/qj.49711649213>

Shao, M., Liu, H., Yang, L. Estimating tomato transpiration cultivated in a sunken solar greenhouse with the Penman-monteith, Shuttleworth-Wallace and Priestley-Taylor models in the North China Plain. *Agronomy*, 2022, 12(10): 2382. <https://doi.org/10.3390/agronomy12102382>.

Wang, X., Wei, Q., Wang, W., Wang, S., Huo, Z., Qu, Y., Lei, H. Estimating and partitioning evapotranspiration in a film mulched cropland with shallow groundwater by the improved dual source model. *Journal of Hydrology*, 2024, 637:131375. <https://doi.org/10.1016/j.jhydrol.2024.131375>.

Wu, Y., Li, Q., Zhong, X., Liu, X. Evaluating the accuracy of nine canopy resistance models in estimating winter wheat evapotranspiration using the Penman–Monteith equation. *Frontiers in Plant Science*, 2024, 15: 1470409. <https://doi.org/10.3389/fpls.2024.1470409>.

Xu, J., Liu, X., Yang, S., Qi, Z., Wang, Y. Modeling rice evapotranspiration under water-saving irrigation by calibrating canopy resistance model parameters in the Penman-Monteith equation. *Agricultural Water Management*, 2017, 182: 55-66. <https://doi.org/10.1016/j.agwat.2016.12.010>.

709 Yan, W., He, L., Jiang, J., Chen, X., Luo, Y., Xiong, Y. Evaluation of Bowen Ratio Method for Evapotranspiration in
710 Humid Forests Using Flux Tower Data. *Ecohydrology*, 2025, 18(5): e70083. <https://doi.org/10.1002/eco.70083>.

711 Yinglan, A., Wang, G., Hu, P., Wang, L., Xue, B., Shrestha, S. Modification and upscaling of S–W model based on
712 vertical distributions of soil moisture and vegetation root biomass. *Environmental Research*, 2022, 208:
713 112765. <https://doi.org/10.1016/j.envres.2022.112765>.

714 Yuan, W.P., Liu, S.G., Zhou, G.S., Zhou, G.Y., Tieszen, L.L., Baldocchi, D., Bernhofer, C., Gholz, H., Goldstein,
715 A.H., Goulden, M.L., Hollinger, D.Y., Hu, Y., Lawn, B.E., Stoy, P.C., Vesala, T., Wofsy, S.C., 2007. Deriving a
716 light use efficiency model from eddy covariance flux data for predicting daily gross primary production across
717 biomes. *Agric. Forest Meteorol.* 143 (3-4), 189–207.

718 Zhou, K., Ye, Y. *Journal of Chinese Fruit Trees. Citrus Rolls*. China Forestry Publishing House, 2010.

719 Zhang, Q., Kong, J., Wang, L., Zhong, Y. Estimating evapotranspiration using an improved two-source energy
720 balance model coupled with soil moisture in arid and semi-arid regions. *Journal of Hydrology*, 2025, 659:
721 133283. <https://doi.org/10.1016/j.jhydrol.2025.133283>.

