

Sub-pixel TROPOMI SIF enables process-based estimation of soybean carbon–water coupling across China

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ABSTRACT

Accurately characterizing regional differences and relative environmental contributions to crop carbon assimilation, water consumption, and water-use efficiency (WUE) is essential for improving our understanding of crop carbon–water processes. We developed a process-based crop carbon–water framework constrained by solar-induced chlorophyll fluorescence (SIF). In this framework, crop-distribution information was used to separate the soybean SIF signal to reduce mixed-pixel effects. The retrieved soybean SIF was then used to estimate net photosynthesis, and canopy conductance (G_c) was incorporated as a key input into a Penman–Monteith scheme to estimate transpiration (T), from which WUE is derived. For soybean across China during 2019–2025, the framework-derived multi-year growing-season mean estimates of gross primary production (GPP), G_c , T , and WUE were $1151.8 \text{ gC m}^{-2} \text{ season}^{-1}$, 0.00725 m s^{-1} , $699.7 \text{ mm season}^{-1}$, and $1.672 \text{ gC kg}^{-1} \text{ H}_2\text{O}$, respectively. Pixel-wise analysis revealed substantial spatial heterogeneity in the strength of interannual T –WUE co-variation among soybean-growing regions. Within the present modelling framework, partial-correlation and dominance analyses further showed that atmospheric dryness had a greater relative explanatory contribution to model-estimated WUE variability than soil water supply in more than 89% of soybean areas. Overall, the proposed SIF-based framework provides consistent large-scale estimates of T and WUE, highlights the comparatively greater explanatory contribution of atmospheric dryness to soybean WUE variability, and provides a regional diagnostic basis for identifying soybean areas where such atmospheric dryness may deserve closer attention in irrigation and water-productivity assessment.

1. Introduction

Soybean is a major global oilseed and protein crop, and it plays a key role in both food and feed supply systems (Hartman et al., 2011; Mei et al., 2024). China's soybean demand has continued to increase over the last decade, and China's consumption has remained above 30% of the global total (Mei et al., 2024). However, according to USDA FAS (2026), China contributes only ~5% of global soybean production (e.g., 20.9 Mt / 425.7 Mt in 2025), and domestic production still cannot meet the rapidly growing demand, leaving the country highly dependent on imports (Wang et al., 2023). In 2024, China's soybean sown area was 10.33 million ha (National Bureau of Statistics of China, 2025).

Soybean-producing regions in China span multiple agro-ecological zones, including Northeast China, the Huang–Huai–Hai Plain, and southern China, and the climatic constraints and water limitation mechanisms differ across regions. Moreover, soybean production is water-demanding, with a global average water footprint of $\sim 2145 \text{ m}^3 \text{ t}^{-1}$ (Mekonnen and Hoekstra, 2011). Therefore, studies need to estimate soybean carbon gain and water use more clearly at the national scale. Such characterization can provide more direct evidence for production zoning, irrigation management, and risk identification in soybean regions (Wang and Shi, 2024).

Solar-induced chlorophyll fluorescence (SIF) provides new opportunities for addressing these issues (Sun et al., 2023a). SIF is emitted

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during the energy partitioning of photosynthesis. SIF contains physical information related to canopy structure and chlorophyll content, and it also contains physiological information related to the fraction of absorbed photosynthetically active radiation and fluorescence yield (Porcar-Castell et al., 2021; Yang et al., 2021). Satellite SIF observations have become an important remote sensing signal for monitoring ecosystem function and agricultural productivity (Sun et al., 2023b). At present, many SIF-based gross primary production (GPP) estimates still rely on correlations/regression models. Such approaches provide limited support for process interpretation and may lose accuracy when applied to heterogeneous regions. Gu et al. (2019) first developed a theoretical framework for directly estimating GPP from SIF, namely the mechanistic light response (MLR) model. Subsequent leaf-level experiments across multiple species showed its good performance in estimating photosynthetic CO₂ rate (Han et al., 2022). Liu et al. (2024); (2022) further improved the estimation of key parameters and variables in the MLR model at the canopy scale. Their studies demonstrated that regional GPP can be directly estimated using SIF, reflectance, and meteorological data without relying on eddy-covariance observations as training inputs.

SIF constraints have also been extended to vegetation water loss processes, leading to the development of various methods for estimating transpiration (T) or evapotranspiration (Shan et al., 2021; Zhang et al., 2024). Existing SIF-based T models can generally be grouped into two categories. The first uses statistical relationships between SIF and transpiration, treating SIF as an integrated proxy for the factors regulating water loss (Alemohammad et al., 2017; Pagán et al., 2019). For example, Lu et al. (2018) used flux-tower measurements over a temperate forest canopy and reconstructed broadband SIF to develop a SIF-based transpiration model, highlighting the advantages of multi-band SIF. Maes et al. (2020) combined satellite SIF with the SCOPE model to examine empirical SIF–transpiration relationships and reported stable regression performance across different SIF products. The second category establishes empirical or semi-mechanistic relationships between SIF and canopy conductance (G_c), which are then coupled with the Penman–Monteith (PM) equation to estimate latent heat flux. Shan et al. (2019); (2021) incorporated SIF into a PM framework to infer conductance and estimate transpiration, showing that SIF can capture canopy conductance and transpiration at daily and seasonal scales. Zhou et al. (2022) further integrated SIF with meteorological variables, Fick's law, and optimal stomatal conductance theory to develop a process-based model for evapotranspiration. At the global scale, Yang et al. (2024) estimated transpiration from satellite SIF and emphasized the dominant role of atmospheric drought in regulating vegetation water loss.

Here, we develop a process-based remote sensing framework to assess soybean carbon–water processes across China. The framework integrates high-resolution soybean distribution information with vegetation structural information to extract crop-specific sub-pixel SIF signals, which are subsequently used to estimate GPP through the mechanistic light response (MLR) model. The resulting photosynthetic estimates are then coupled with the unified stomatal optimization (USO) model and the Penman–Monteith (PM) equation to derive G_c and T . GPP and T are then combined to calculate soybean water use efficiency (WUE). Specifically, this study makes three main contributions. First, methodologically, we adapt and apply an existing sub-pixel SIF extraction approach to soybean and integrate it with a carbon–water estimation sequence linking satellite SIF to GPP, G_c , T , and WUE. Second, empirically, we provide national-scale estimates of soybean carbon–water processes across four major agro-ecological zones in China during 2019–2025, revealing regional differences and interannual variability in carbon gain, water use, and water-use efficiency. Third, diagnostically, we compare the relative explanatory contributions of atmospheric dryness, represented by VPD, and soil water content (SWC) to model-estimated soybean WUE across agro-ecological regions within the proposed modelling framework. Together, these contributions provide a

process-based framework for diagnosing regional soybean carbon–water dynamics and their environmental constraints across China.

2. Model description

Given the kilometre-scale footprint of TROPOMI SIF observations and the resulting mixed cropland pixels after gridding to 0.05°, our framework first extracts soybean sub-pixel SIF emission within mixed pixels. It integrates meteorological drivers (e.g., air temperature) and sequentially couples a photosynthesis mechanism model, an optimal stomatal conductance model, and the PM formulation to estimate daily soybean GPP, G_c , T , and WUE. The model structure is shown in Fig. 1. Definitions of symbols and units used in this study are outlined in Appendix A.

2.1. Extracting sub-pixel SIF for soybean

Current satellite-based SIF observations (i.e., SIF_{TOC}) typically have kilometer-scale resolutions, often mixing SIF signals from multiple crops or natural vegetation. Accurate crop yield estimation thus requires extracting crop-specific sub-pixel SIF signals. SIF_{TOC} in the near-infrared spectral region can be expressed as (Dechant et al., 2022):

$$\text{SIF}_{\text{TOC}} = \text{NIRv} \cdot \text{PAR} \cdot \Phi_F \quad (1)$$

where NIRv is the near-infrared reflectance of vegetation, PAR is the flux of photosynthetically active radiation, and Φ_F is fluorescence yield.

To represent sub-footprint heterogeneity, we discretize each 0.05° gridded SIF_{TOC} cell into 500 m sub-pixels using MODIS-derived NIRv . Following Wang et al. (2025), within each 500 m sub-pixel, PAR is assumed to have negligible spatial variation and fluorescence yield Φ_F is assumed approximately constant. Although Φ_F can differ among vegetation types, this assumption generally holds at large scales due to mixed vegetation conditions. In monoculture regions, Φ_F is inherently uniform at any given time.

So, for a given 0.05° gridded SIF_{TOC} cell encompassing multiple NIRv sub-pixels (e.g., 500 m × 500 m), we have:

$$\text{SIF}_{\text{TOC}, i} = \text{SIF}_{\text{TOC}} \times \frac{\text{NIRv}_i}{\text{NIRv}_{\text{avg}}} \quad (2a)$$

$$\text{NIRv}_{\text{avg}} = \frac{1}{m} \sum_{i=1}^m \text{NIRv}_i \quad (2b)$$

where $\text{SIF}_{\text{TOC}, i}$ is the SIF value for sub-pixel i , NIRv_i is the NIRv value for sub-pixel i , NIRv_{avg} is the average NIRv_i value, and m represents the total number of NIRv sub-pixels within each SIF grid cell. Note that the spatial

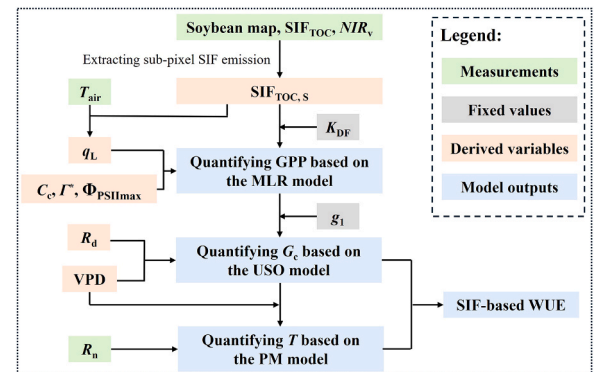


Fig. 1. Overview of the SIF-based framework for estimating soybean carbon–water processes. The MLR model is the mechanistic light response model; the USO model is the unified stomatal optimal model; the PM model is the Penman–Monteith model.

resolution of $SIF_{TOC, i}$ is the same as that of $NIRv_i$, both being 500 m.

The current land cover data (which should include agricultural land distribution) typically has a resolution of 30 m or finer. This means that each $NIRv$ sub-pixel can be further subdivided into different land cover types. Based on Eq. 1, we also have (Kira and Sun, 2020):

$$SIF_{TOC, i} = \sum_{j=1}^n (f_{ij} \cdot NIRv_{ij} \cdot PAR_{ij} \cdot \Phi_{ij}^F) \quad (3)$$

where n is the number of vegetation types within the sub-pixel i , f_{ij} is the fractional area covered by vegetation type j in sub-pixel i , $NIRv_{ij}$ is the $NIRv$ value corresponding to vegetation type j in sub-pixel i (to be estimated below), PAR_{ij} denotes the PAR of vegetation type j in sub-pixel i , and Φ represents the fluorescence yield for vegetation type j within sub-pixel i .

The workflow of the SIF separation procedure is schematically illustrated below Fig. 2:

If we assume that Φ is approximately constant across all vegetation types within each sub-pixel i , the $SIF_{TOC, ij}$ for a specific vegetation type j in sub-pixel i can be considered proportional to its corresponding $NIRv_{ij}$. Additionally, PAR is assumed to exhibit negligible spatial variation within each sub-pixel. Thus, we have:

$$SIF_{TOC, ij} = \frac{f_{ij} \cdot NIRv_{ij}}{\sum_{j=1}^n (f_{ij} \cdot NIRv_{ij})} \cdot SIF_{TOC, i} \quad (4)$$

To estimate $NIRv_{ij}$, we use least squares regression to solve the following minimization problem:

$$\min \sum_{i=1}^m \left(NIRv_i - \sum_{j=1}^n f_{ij} \cdot NIRv_{ij} \right)^2, NIRv_{ij} \geq 0 \quad (5)$$

After obtaining $SIF_{TOC, ij}$, the contributions from soybean ($SIF_{TOC, s}$) to SIF_{TOC} can be estimated as:

$$SIF_{TOC, s} = \frac{1}{m} \sum_{i=1}^m \frac{SIF_{TOC, ij}}{f_{ij}}, j \in \text{soybean} \quad (6)$$

2.2. The mechanistic relationship between SIF and GPP

The development of the MLR model enables the use of SIF for crop photosynthesis estimation by mechanistically linking SIF emissions to

GPP. In this study, the soybean-specific SIF contribution ($SIF_{TOC, s}$) was used as input to estimate soybean GPP. Specifically, this model enables direct estimation of GPP based on:

$$GPP = \frac{C_c - \Gamma^*}{4C_c + 8\Gamma^*} \times q_L \times \frac{\Phi_{PSII\max} \times (1 + K_{DF})}{1 - \Phi_{PSII\max}} \times \sum_{\lambda=640}^{850} \left(\pi \frac{SIF_{TOC, s}(\lambda) \times f_{PSII}(\lambda)}{f_{esc, P-C}} \times \frac{\eta_{PSII, \lambda'}}{\eta_{PSII, \lambda}} \times \frac{\lambda'}{h \times c \times N_A} \right) \quad (7)$$

where C_c (μbar) is intercellular CO_2 concentration; Γ^* (μbar) is the chloroplastic CO_2 compensation point; q_L is the fraction of open PSII reaction centers; $\Phi_{PSII\max}$ is the maximum photochemical yield of dark-acclimated leaves, (typically 0.80, van der Tol et al., 2014); K_{DF} is defined as the ratio of the rate coefficients for inherent thermal dissipation and fluorescence (typically 9.0, Liu et al., 2022); λ (nm) is wavelength; λ' spans the full SIF spectrum from 640 to 850 nm; $SIF_{TOC, s}(\lambda)$ ($\text{mW m}^{-2} \text{nm}^{-1} \text{sr}^{-1}$) is the retrieved soybean-specific TOC SIF at a given wavelength λ nm; $f_{PSII}(\lambda)$ is the fraction of PSII fluorescence at wavelength λ ; $f_{esc, P-C}$ is the probability of SIF photons escaping from PSII within leaves to the canopy surface, estimated from the PAR absorption efficiency (f_{APAR}) and $NIRv$ (Zeng et al., 2019); $\eta_{\lambda', PSII}$ and $\eta_{\lambda, PSII}$ are the emission spectra for full-spectrum and specific-band PSII fluorescence (Pedrós et al., 2010, 2008; van der Tol et al., 2009); h is the Planck constant ($6.63 \times 10^{-34} \text{J s}$); c is the speed of light ($3 \times 10^8 \text{m s}^{-1}$); and N_A is Avogadro's constant ($6.02 \times 10^{23} \text{mol}^{-1}$). More details on estimating parameters C_c , Γ^* are provided in Supplementary Text S1. At the canopy scale, q_L can be estimated from SIF by using a hyperbolic function (Liu et al., 2024):

$$q_L = \frac{m}{\delta \times \sum_{\lambda=640}^{850} \left(\pi \frac{SIF_{TOC, s}(\lambda) \times f_{PSII}(\lambda)}{f_{esc, P-C}} \times \frac{\eta_{PSII, \lambda'}}{\eta_{PSII, \lambda}} \times \frac{\lambda'}{h \times c \times N_A} \right)^{1/m} + m} \quad (8)$$

where δ is a constant, set at $1 \mu\text{mol}^{-1} \text{m}^2 \text{s}$; m , reflecting the influence of temperature on q_L , is estimated as follows:

$$m = m_{\text{opt}} \times \frac{H_d \times \exp\left(\frac{H_d \times (T_{\text{leaf}} - T_{\text{opt}})}{T_{\text{leaf}} \times R \times T_{\text{opt}}}\right)}{H_d - H_a \times \left(1 - \exp\left(\frac{H_d \times (T_{\text{leaf}} - T_{\text{opt}})}{T_{\text{leaf}} \times R \times T_{\text{opt}}}\right)\right)} \quad (9)$$

where T_{leaf} is leaf surface temperature (K); T_{opt} (K) represents the

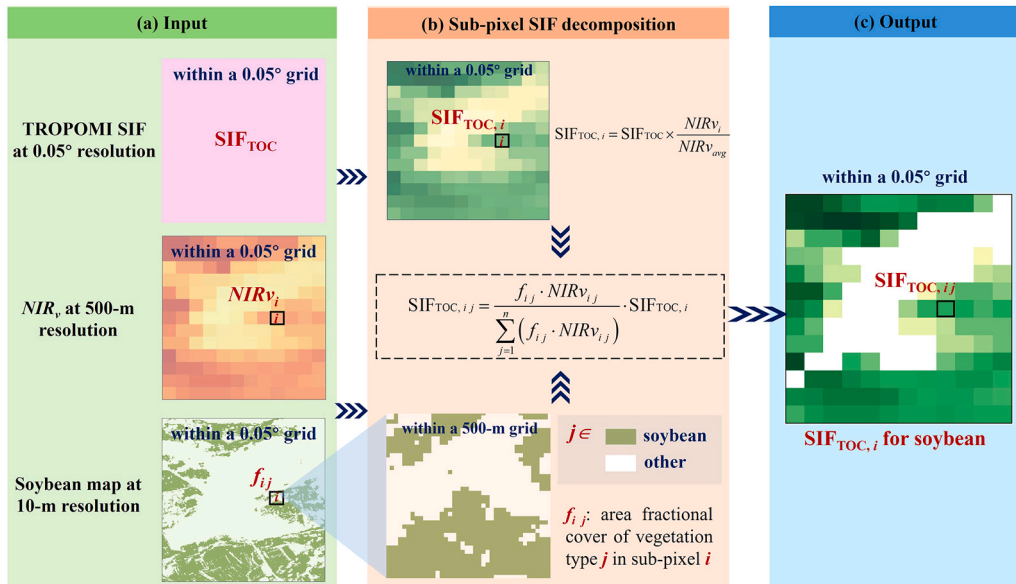


Fig. 2. Schematic workflow of the sub-pixel SIF extraction procedure.

optimal T_{Leaf} ; m_{opt} is the value of m at T_{opt} ; H_d (kJ mol^{-1}) stands for the decrease rate of the peaked function above T_{opt} ; H_a (kJ mol^{-1}) indicates the increase rate of the peaked function below T_{opt} ; and R is the universal gas constant ($8.314 \text{ J mol}^{-1} \text{ K}^{-1}$). It should be noted that Eq. (8) & (9) can be applied at both the leaf scale and the canopy scale. For canopy scale applications, one should use air temperature (T_{air} , $^{\circ}\text{C}$) instead of T_{Leaf} . This substitution is advised because of the challenges in precisely estimating T_{Leaf} distribution across the canopy. Detailed information on these four parameters (m_{opt} , H_d , H_a , and T_{opt}) for soybean is 1.63, 212.66 kJ mol^{-1} , 12.26 kJ mol^{-1} and 308.16 K, respectively. The photosynthesis-related q_L parameters need to be determined via leaf experiments (Liu et al., 2024), with details provided in Guo et al. (2025).

2.3. Estimation of G_c

In this study, the optimal and empirical approaches (Medlyn et al., 2011) was used to calculate soybean G_c :

$$G_c = g_0 + 1.6 \times \left(1 + \frac{g_1}{\sqrt{\text{VPD}}}\right) \times \frac{A_{\text{net}}}{C_a} \quad (10)$$

where g_0 is the residual conductance ($\approx 0.01 \text{ mol m}^{-2} \text{ s}^{-1}$); g_1 ($\text{kPa}^{0.5}$) represents the stomatal slope parameter, which is proportional to the marginal water cost of assimilation and the CO_2 compensation point, and varies among PFTs; VPD (kPa) is the atmospheric water vapour pressure deficit; C_a (μbar) is the ambient air CO_2 partial pressure; A_{net} is the soybean net photosynthetic rate ($\mu\text{mol m}^{-2} \text{ s}^{-1}$) provided by the MLR model using SIF_{TOC}, s as an input:

$$A_{\text{net}} = \text{GPP} - R_d \quad (11)$$

where R_d is the daytime leaf dark respiration ($\mu\text{mol m}^{-2} \text{ s}^{-1}$) and computed as the function of maximum carboxylation rate (V_{cmax} , $\mu\text{mol m}^{-2} \text{ s}^{-1}$): $R_d = 0.015 \times V_{\text{cmax}}$. More details on estimating parameters V_{cmax} is provided in Supplementary Text S2.

2.4. Estimation of T

The estimated soybean G_c was subsequently incorporated into the PM equation to estimate soybean T ($\text{g m}^{-2} \text{ s}^{-1}$):

$$T = \frac{\Delta \times (R_n - G) + \rho \times C_p \times \text{VPD} \times g_a}{\Delta + (1 + g_a/G_c) \times \gamma} \times \frac{1}{\lambda_v} \quad (12)$$

where Δ is the slope of saturated water vapour pressure with T_{air} , assumed to be $0.155 \text{ kPa } ^{\circ}\text{C}^{-1}$; R_n is the net radiation (W m^{-2}); G is the soil heat flux (W m^{-2}); ρ is the density of dry air ($\approx 1.2 \text{ kg m}^{-3}$); C_p is the specific heat capacity of air ($\approx 1013 \text{ J kg}^{-1} \text{ } ^{\circ}\text{C}^{-1}$); g_a is the aerodynamic resistance for heat and water vapour (m s^{-1}), and was estimated from air temperature (Supplementary Text S3) (Thornton, 1998); γ is the psychrometric constant ($\approx 0.067 \text{ kPa } ^{\circ}\text{C}^{-1}$); λ_v is the latent heat of vaporization ($\approx 2450 \text{ kJ kg}^{-1}$); G_c (m s^{-1}) is assumed to be equal to the surface conductance for the retrieved soybean canopy component during the growing season.

2.5. Calculation of WUE

Carbon assimilation associated with a given physiological water loss, WUE, is defined as the ratio of GPP to T in units of $\text{g C/kg H}_2\text{O}$. An explicit expression for soybean WUE is given as (Huang et al., 2015):

$$\text{WUE} = \frac{\text{GPP}}{T} \quad (13)$$

2.6. Sensitivity and uncertainty analysis

A variance-based Sobol global sensitivity analysis (GSA) was used to assess how uncertainty in model inputs and parameters affects the SIF-

driven carbon–water estimates. The analysis was conducted separately for sub-pixel SIF retrieval, MLR-based GPP estimation, Medlyn-based G_c estimation, and Penman–Monteith T estimation, with soybean-specific SIF, GPP, G_c , and T as their respective outputs. The coupled framework was also evaluated using WUE as its output. Each output was calculated for an individual sampled input combination, without spatial or seasonal aggregation. Input ranges were based on published literature, $\pm 20\%$ variations around default values, model simulations, and observation-based data (Table S1). All sampled inputs were assumed to follow independent uniform distributions within these ranges.

Inputs were sampled using scrambled Sobol sequences, with a base sample size of $N = 2^m$. We selected $m = 12$, giving $N = 4096$. Two sets of input combinations were generated from a joint Sobol sampling design. Additional combinations were constructed by replacing one input at a time in the first set with its corresponding value from the second set, while keeping the remaining inputs unchanged. For an analysis with p input factors, this required $N(p + 2)$ model evaluations. The SIF, GPP, G_c , T , and coupled WUE analyses included 3, 6, 4, 5, and 15 input factors, respectively. First-order and total-order Sobol indices were calculated using Saltelli-type and Jansen estimators, respectively. Output variance was estimated from the combined outputs of the two base sample sets. Total-order indices measure the influence of each input, including its interactions with other inputs. For presentation, negative total-order estimates were set to zero, and each resulting index was divided by the sum of the indices within the same analysis. These normalized values indicate relative sensitivity rather than separate, non-overlapping shares of output variance.

For the individual component analyses, intermediate input ranges were determined from preliminary simulations using 2^{15} samples per relevant component. Soybean-specific SIF and G_c were sampled uniformly between the 1st and 99th percentiles of their simulated values. The lower A_{net} bound was calculated by subtracting the maximum R_d from the 1st percentile of simulated GPP, and the upper bound by subtracting the minimum R_d from the 99th percentile, with both bounds constrained to be non-negative. In the coupled analysis, outputs from one component were passed to the next rather than sampled again. The same VPD value was used in both G_c and T calculations. However, q_L , C_i , and Γ^* were sampled independently as effective model inputs rather than recalculated from temperature or VPD.

An additional 2^{16} scrambled Sobol samples were used to assess uncertainty propagation through the coupled framework under the same input distributions. The output distributions were summarized using the mean, standard deviation, coefficient of variation, median, and 2.5th–97.5th percentiles. These percentile intervals describe the spread of model outputs under the specified input distributions and model assumptions; they do not represent confidence intervals for the national estimates.

2.7. Quantifying the relative contributions of VPD and SWC to soybean WUE

To investigate the independent relationships of atmospheric dryness and soil water availability with soybean WUE, partial correlation analysis and dominance analysis were conducted using daily growing-season observations from 2019 to 2025. Only pixels with soybean fraction ≥ 0.01 were retained for the analysis. Partial correlation analysis was performed at the pixel level. Specifically, the partial correlation between WUE and VPD was calculated while controlling for SWC, whereas the partial correlation between WUE and SWC was calculated while controlling for VPD.

Furthermore, dominance analysis was performed to quantify the relative contribution of VPD and SWC to variations in soybean WUE. For each pixel, variations in soybean WUE were modeled as a function of VPD and SWC using multiple linear regression, expressed as $\text{WUE} = \beta_0 + \beta_1 \text{VPD} + \beta_2 \text{SWC} + \varepsilon$, where β_0 is the intercept, β_1 and β_2 are the regression coefficients for VPD and SWC, respectively, and ε represents

the residual error. The relative importance of VPD and SWC was determined by decomposing the explained variance (R^2) of regression models containing different combinations of predictors. The dominance contribution of VPD was calculated as:

$$\text{VPD}_{\text{dominance}} = \frac{0.5[R^2(\text{VPD}) + R^2(\text{VPD}, \text{SWC}) - R^2(\text{SWC})]}{R^2(\text{VPD}, \text{SWC})} \times 100\% \quad (14)$$

where $R^2(\text{VPD})$, $R^2(\text{SWC})$, and $R^2(\text{VPD}, \text{SWC})$ represent the explained variance of models including VPD alone, SWC alone, and both VPD and SWC, respectively. The relative contribution of SWC was calculated as $100\% - \text{VPD}_{\text{dominance}}$. A higher dominance percentage indicates a greater relative share of the regression-explained variation in model-estimated soybean WUE within the present modelling framework.

3. Data and preprocessing

3.1. Study area

We focused on the major soybean-producing regions in China as the study area. The study area includes 14 major soybean-producing provincial-level administrative units (including Chongqing Municipality, Fig. 3). Soybean-planted areas were identified using a 10 m crop-distribution product, which was used to construct soybean masks (and fractions) for subsequent analyses (Mei et al., 2024). To capture regional differences in geographic environment and cropping systems, we followed Mei et al. (2024) and classified soybean-planted areas into four

agro-ecological zones (AEZs). Zone I (NE) includes Heilongjiang, Jilin, and eastern Inner Mongolia. Zone II (HH) includes Shandong, Henan, Shanxi, and Shaanxi. Zone III (MLY) includes Jiangsu, Anhui, and Hubei. Zone IV (SW) includes eastern Sichuan, Guizhou, Yunnan, and Chongqing. In particular, Zones I and II constitute the core soybean-producing regions in China and together account for more than 70% of the national soybean planting area. We mainly analyzed data during the soybean growing season. Following Mei et al. (2024), we applied zone-specific growing-season windows, with Zones I–IV defined as April–September, May–October, June–October, and August–November, respectively.

3.2. Inputs for the SIF-based model

3.2.1. Satellite data

We used SIF observations from TROPOMI (v2.1 L2B) on Sentinel-5 Precursor (Köhler et al., 2018). TROPOMI provides near-daily global coverage with a swath width of 2600 km and spatial resolution of $7 \times 3.5 \text{ km}^2$ at nadir. Our analysis utilized daily averaged TROPOMI L2B SIF data (743–758 nm) from January 2019 to December 2025. The fraction of absorbed photosynthetically active radiation (f_{APAR}) data were derived from MODIS MCD15A3H v006 at a 4-day interval and 500 m resolution (Myneni et al., 2015). NIR_v was derived from the MODIS MCD43A4 Nadir BRDF-Adjusted Reflectance (NBAR) product using the red (620–670 nm) and near-infrared (841–876 nm) bands. This product provides daily 500 m reflectance data. In this study, NIR_v was used for two purposes: (1) to estimate the $f_{\text{esc_P-C}}$ after aggregation to

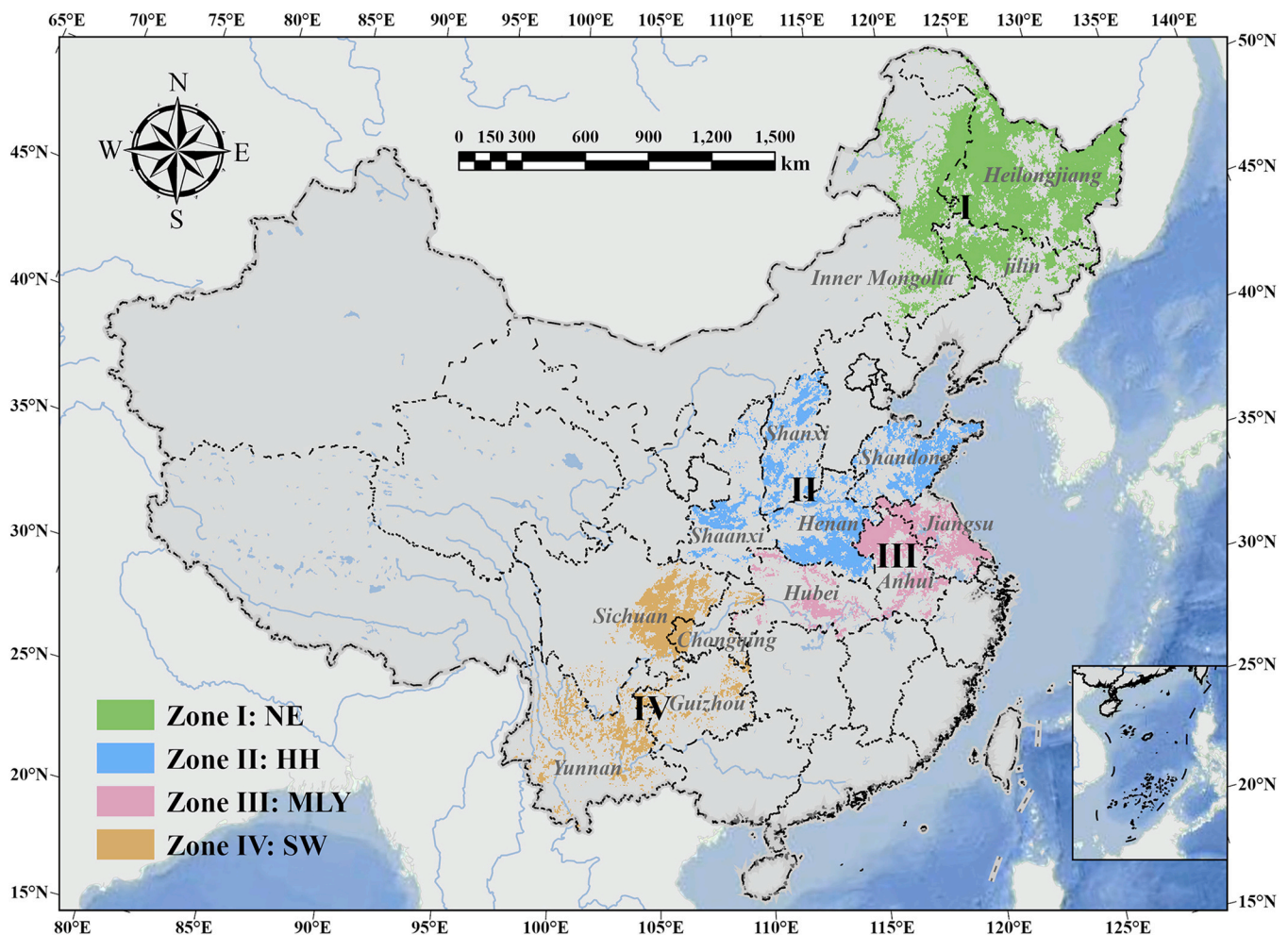


Fig. 3. Spatial distribution of major soybean-producing regions and four agro-ecological zones (AEZs) in China.

0.05°, and (2) to support sub-pixel SIF separation at its native 500 m resolution.

3.2.2. Meteorological datasets

The required meteorological inputs are T_{air} , dew point temperature (T_d , °C) and R_n . VPD, used for estimating the C_c and T , was calculated from T_{air} and T_d following Wu et al. (2019). The hourly T_{air} , T_d and R_n data were obtained from the fifth-generation European Centre for Medium-Range Weather Forecasts reanalysis dataset (ERA5-Land) (Muñoz-Sabater et al., 2021), providing hourly surface variables at ~9 km resolution from 1950 to the present.

3.2.3. Soil data

Hourly volumetric SWC data were obtained from ERA5-Land. Soil moisture in ERA5-Land is available at four soil layers (0–7, 7–28, 28–100, and 100–289 cm). In this study, daytime SWC was calculated using the depth-weighted average of the upper three soil layers (0–100 cm) to represent root-zone soil water availability.

3.2.4. Pre-processing of input data

Temporal processing. We used daytime-mean TROPOMI SIF as the fluorescence input. For meteorological drivers, we aggregated hourly T_{air} , T_d , R_n , and SWC into daytime averages to match the SIF data used in this study. The 4-day composite f_{APAR} product was linearly interpolated to daily estimates, and was subsequently smoothed the f_{APAR} time series

using a Savitzky–Golay filter. The daily NIRv product was used directly without additional temporal processing. The soybean land-cover map (soybean fraction) was assumed to remain unchanged throughout the study period.

Spatial processing. The daytime-mean TROPOMI SIF was gridded to a spatial resolution of 0.05° using the GriddingMachine tool (Wang et al., 2022). Variable-specific strategies were then applied to other inputs: datasets originally coarser than 0.05° T_{air} , T_d , R_n , and SWC were bilinearly interpolated to 0.05°, whereas products finer than 0.05° (f_{APAR} and NIRv) were aggregated to 0.05° by area-weighted averaging. Notably, the spatial aggregation of NIRv to 0.05° was performed only for $f_{\text{esc-P-C}}$ estimation. For sub-pixel SIF separation, the original daily 500 m NIRv product was retained at its native resolution.

4. Results

4.1. Multi-year mean spatial patterns of soybean growing-season carbon–water processes across China

The multi-year (2019–2025) growing-season means of GPP, G_c , T , and WUE derived using the SIF-driven carbon–water framework exhibited pronounced spatial heterogeneity across China's soybean-growing areas (Fig. 4). For presentation at the growing-season scale, GPP and T were temporally aggregated and reported as $\text{gC m}^{-2} \text{ season}^{-1}$ and mm season^{-1} , respectively. At the national scale, the estimated

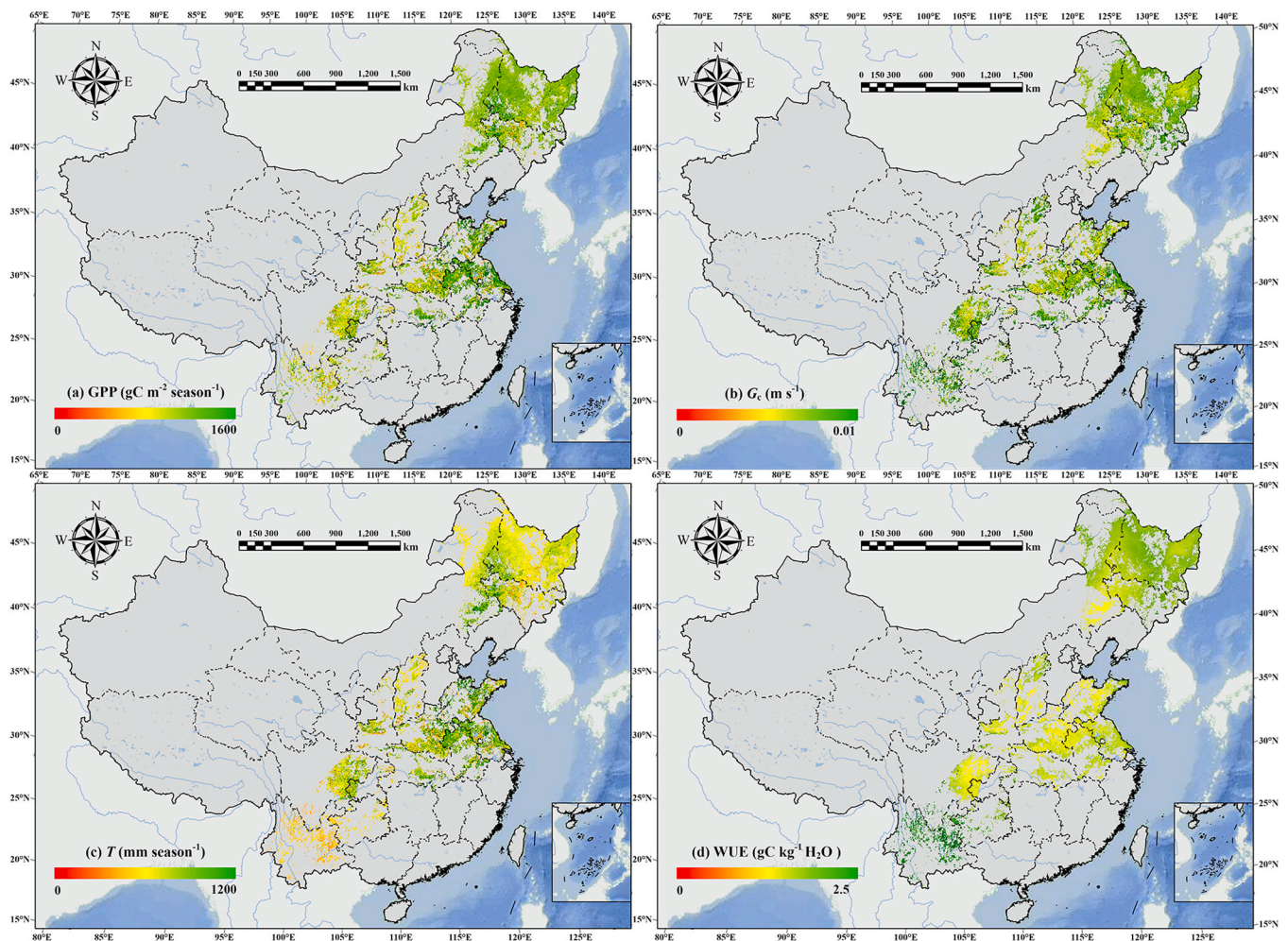


Fig. 4. Spatial distribution of multi-year mean soybean growing-season gross primary productivity (a: GPP, $\text{gC m}^{-2} \text{ season}^{-1}$), canopy conductance for water vapour (b: G_c , m s^{-1}), transpiration (c: T , mm season^{-1}), and water use efficiency (d: WUE, $\text{gC kg}^{-1} \text{ H}_2\text{O}$) estimated by the proposed model across China over the period 2019–2025. Only pixels with soybean fraction ≥ 0.01 were retained.

growing-season mean GPP, G_c , T , and WUE were $1151.8 \text{ gC m}^{-2} \text{ season}^{-1}$, 0.00725 m s^{-1} , $699.7 \text{ mm season}^{-1}$, and $1.672 \text{ gC kg}^{-1} \text{ H}_2\text{O}$, respectively. Across approximately 80% of soybean pixels, the estimated values ranged from 969.8 to $1321.4 \text{ gC m}^{-2} \text{ season}^{-1}$ for GPP (Fig. 4a), from 0.00612 to 0.00844 m s^{-1} for G_c (Fig. 4b), from 568.3 to $875.0 \text{ mm season}^{-1}$ for T (Fig. 4c), and from 1.415 to $1.841 \text{ gC kg}^{-1} \text{ H}_2\text{O}$ for WUE (Fig. 4d). Spatially, the Northeast China Plain and the major soybean belts extending from the Huang–Huai–Hai Plain to the Middle–Lower Yangtze region generally show higher GPP and stronger G_c , accompanied by greater T . In contrast, the southwestern mountainous regions and areas with scattered soybean distribution are characterized by lower GPP, G_c , and T . By comparison, WUE, as an integrated efficiency metric relating carbon gain to water loss, does not vary monotonically with either GPP or T . Higher WUE is observed in Northeast China and parts of the Huang–Huai–Hai soybean region, whereas lower WUE occurs in localized high-transpiration hotspots in the Middle–Lower Yangtze region and in scattered soybean-growing areas in the Southwest. These spatial contrasts largely reflect local decoupling between carbon gain and water loss: in some regions, photosynthetic assimilation is relatively high, but transpiration increases even more strongly, so carbon gain per unit water consumed does not increase proportionally, resulting in lower WUE (Fig. 4d).

Subregional comparisons further show clear differences in carbon–water coupling (Fig. 4). The Middle–Lower Yangtze (MLY) zone has the

strongest carbon assimilation and water consumption, with the highest GPP ($1298.1 \text{ gC m}^{-2} \text{ season}^{-1}$) and the highest T ($889.6 \text{ mm season}^{-1}$), resulting in relatively lower WUE ($1.483 \text{ gC kg}^{-1} \text{ H}_2\text{O}$). This pattern suggests that enhanced seasonal carbon gain is achieved at the expense of greater water use. In the Northeast China (NE), GPP ($1163.3 \text{ gC m}^{-2} \text{ season}^{-1}$) is close to the national mean, but WUE is the highest ($1.712 \text{ gC kg}^{-1} \text{ H}_2\text{O}$) with comparatively lower T ($684.5 \text{ mm season}^{-1}$), indicating more carbon gain per unit water loss under lower transpirational demand. By contrast, the Huang–Huai–Hai (HH) zone shows lower GPP ($1044.5 \text{ gC m}^{-2} \text{ season}^{-1}$) and the lowest WUE ($1.458 \text{ gC kg}^{-1} \text{ H}_2\text{O}$), together with a larger interannual standard deviation of WUE ($0.448 \text{ gC kg}^{-1} \text{ H}_2\text{O}$), suggesting that carbon–water processes are more sensitive to environmental conditions and management heterogeneity. The Southwest (SW) shows an overall low-intensity regime, with both GPP ($982.5 \text{ gC m}^{-2} \text{ season}^{-1}$) and T ($629.4 \text{ mm season}^{-1}$) being relatively low, while WUE ($1.667 \text{ gC kg}^{-1} \text{ H}_2\text{O}$) remains close to the national mean. This pattern indicates that the region is mainly constrained by the overall magnitude of assimilation and transpiration, rather than by systematically low carbon gain per unit water loss.

The global sensitivity analysis revealed clear differences in the dominant uncertainty sources among the individual components of the carbon–water estimation framework (Figs. S1–S5). Crop-specific sub-pixel SIF retrieval was primarily sensitive to SIF_{TOC} , followed by NIRv , whereas the contribution of soybean fractional area (f_{ij}) was relatively

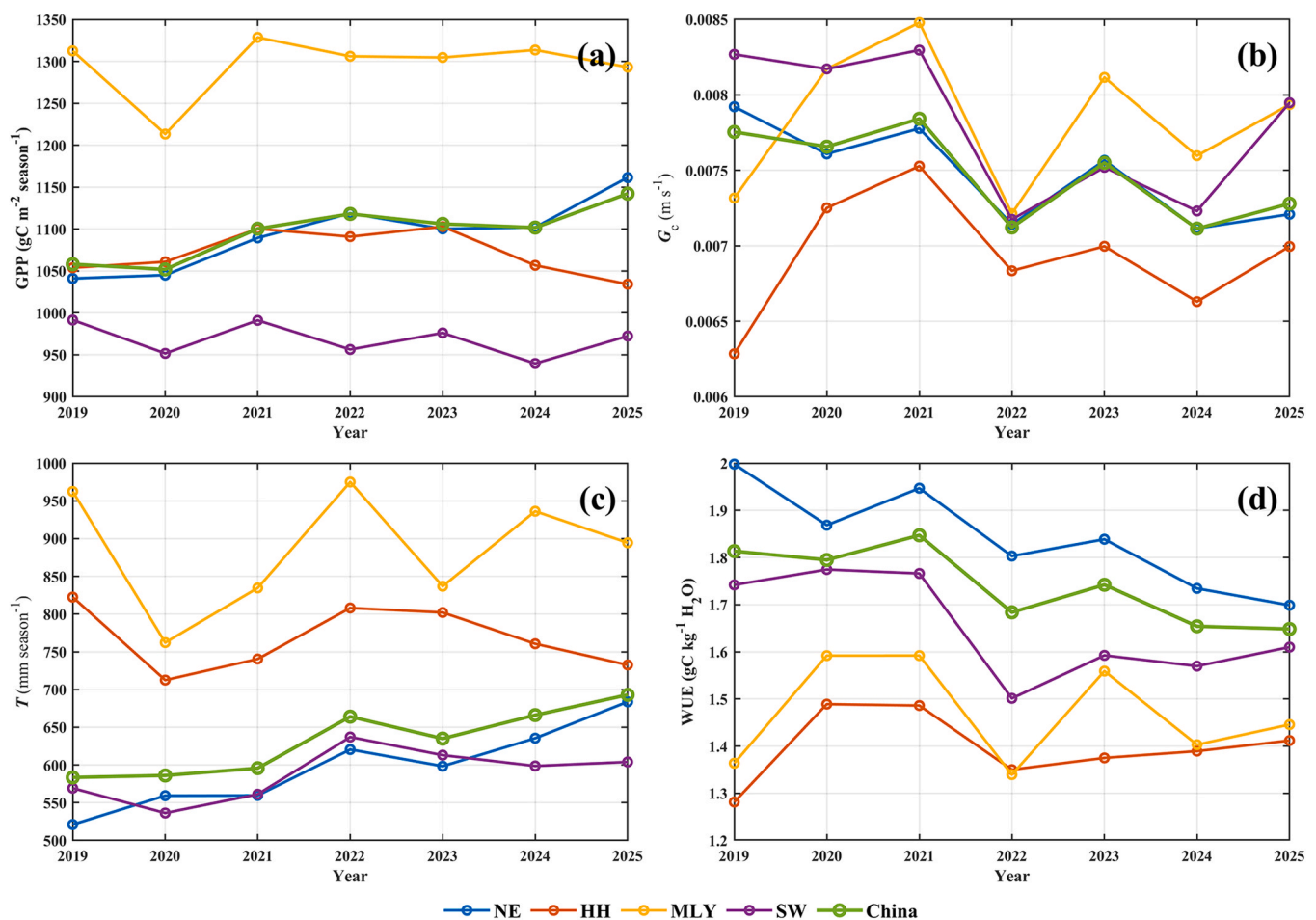


Fig. 5. Interannual variations (2019–2025) in the soybean-area-weighted growing-season means of gross primary productivity (a: GPP, $\text{gC m}^{-2} \text{ season}^{-1}$), canopy conductance for water vapour (b: G_c , m s^{-1}), transpiration (c: T , mm season^{-1}), and water use efficiency (d: WUE, $\text{gC kg}^{-1} \text{ H}_2\text{O}$) across China's soybean-growing areas and four agro-ecological zones (AEZs). Only pixels with soybean fraction ≥ 0.01 were retained, and soybean fraction was used as the spatial weight when calculating national and regional means. The four zones are: the Northeast single-cropping region (NE, Zone I; Heilongjiang, Jilin, and eastern Inner Mongolia), the Huang–Huai–Hai double-cropping region (HH, Zone II; Shanxi, Shaanxi, Henan, and Shandong), the Middle–Lower Yangtze River double-cropping region (MLY, Zone III; Jiangsu, Anhui, and Hubei), and the Southwest double-cropping region (SW, Zone IV; Chongqing, Sichuan, Guizhou, and Yunnan).

small. GPP estimation was most sensitive to soybean-specific SIF (SIF_{TOC}, S), f_{esc_P-C} , and q_L , while C_i , $\Phi_{PSII_{max}}$, and I^* showed comparatively lower contributions. For canopy conductance, A_{net} and VPD were the dominant factors, followed by g_i , whereas the contribution of g_o was negligible. Transpiration was primarily sensitive to VPD and R_n , with secondary contributions from g_a and G_c . When uncertainties were propagated through the complete framework to WUE, f_{esc_P-C} , VPD, R_n , SIF_{TOC}, and q_L emerged as the leading contributors.

4.2. Interannual variability and stability of soybean growing-season carbon–water processes

Based on the framework proposed in this study, the growing-season GPP, G_c , T , and WUE across China and the four soybean AEZs exhibited pronounced interannual variability and clear regional contrasts during 2019–2025 (Fig. 5). Given the relatively short seven-year study period, the temporal changes described here are interpreted as short-term interannual tendencies rather than long-term trends. These tendencies were quantified using ordinary least-squares regression of soybean-area-weighted annual means against year, and their robustness was further assessed using 95% confidence intervals (CIs) and leave-one-year-out sensitivity analysis (Fig. S6; Table S2).

At the national scale, GPP and T showed statistically significant positive interannual tendencies during 2019–2025, with slopes of 13.34

$gC\ m^{-2}\ season^{-1}\ yr^{-1}$ (95% CI: 4.65–22.04, $p = 0.011$) and 19.67 $mm\ season^{-1}\ yr^{-1}$ (95% CI: 10.59–28.75, $p = 0.003$), respectively. In contrast, WUE showed a significant negative tendency (slope = $-0.033\ gC\ kg^{-1}\ H_2O\ yr^{-1}$, 95% CI: -0.056 to -0.010 , $p = 0.014$), indicating that the increase in seasonal water use outpaced the corresponding increase in carbon gain. The interannual tendency in G_c was not statistically significant ($p = 0.066$), suggesting comparatively weaker temporal change in canopy conductance than in carbon assimilation and transpiration.

The leave-one-year-out analysis further showed that the directions of the national GPP, T , and WUE tendencies were retained in all seven refits. Statistical significance was retained in 5/7 refits for GPP, 7/7 for T , and 6/7 for WUE, indicating that the overall directions of these tendencies were not determined by any single year, although the significance of GPP and WUE remained somewhat sensitive to the limited record length (Fig. S6; Table S2).

Beyond the national-scale tendencies, subregional comparisons revealed that the magnitude and direction of interannual variability differed substantially among soybean AEZs (Fig. 5). In terms of carbon assimilation, the Middle–Lower Yangtze (MLY) zone consistently exhibits the highest growing-season GPP and the largest year-to-year fluctuations (Fig. 5a), whereas the Southwest (SW) remains lowest throughout the period. Changes in canopy conductance are broadly coherent across regions, with a pronounced decline around 2022

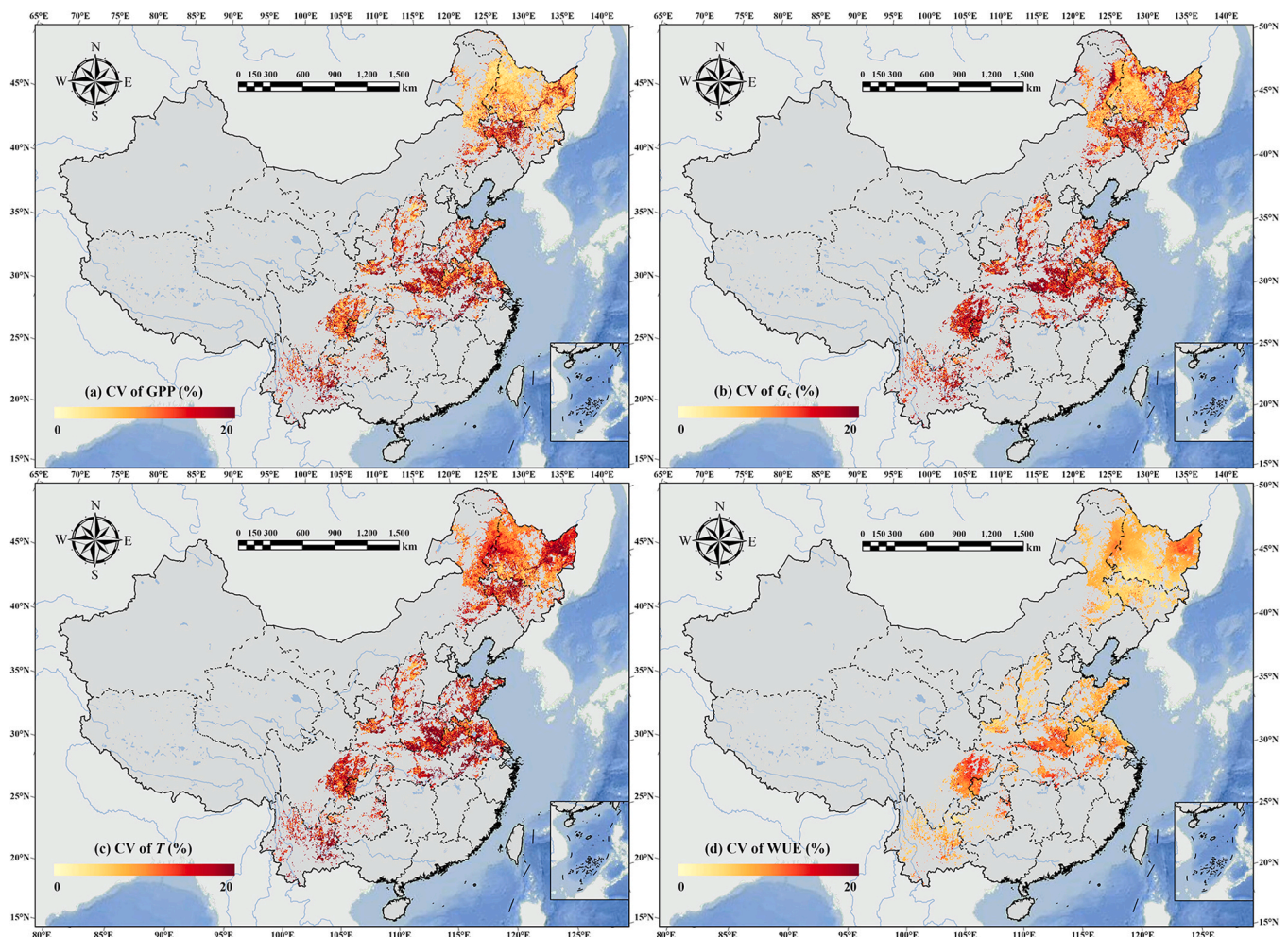


Fig. 6. Coefficients of variation (CV, %) of growing-season gross primary productivity (a: GPP), canopy conductance for water vapour (b: G_c), transpiration (c: T), and water use efficiency (d: WUE) across China and four agro-ecological zones (NE, HH, MLY, and SW) during 2019–2025. CV was calculated at the pixel level from the annual growing-season values during 2019–2025. Only pixels with soybean fraction ≥ 0.01 and at least five valid years were retained. For regional summary statistics, soybean fraction was used as the spatial weight.

followed by partial recovery (Fig. 5b), indicating broadly coherent interannual variability in canopy conductance across regions. Transpiration shows the strongest regional contrast: MLY maintains the highest transpiration while NE stays comparatively low (Fig. 5c). Consequently, WUE is systematically higher in NE and lower in MLY (Fig. 5d), reflecting higher carbon gain per unit water loss in NE under a lower-transpiration regime, whereas MLY achieves higher carbon gain at the expense of greater water use.

To further evaluate the interannual stability of soybean growing-season carbon–water processes, we calculated the coefficient of variation (CV; $CV = \text{standard deviation}/\text{mean} \times 100\%$) for each metric at the pixel level over 2019–2025 and mapped their spatial distributions (Fig. 6). Higher CV values indicate stronger interannual variability and thus lower stability. Overall, all four metrics exhibit clear spatial clustering in CV, although the locations of high-variability hotspots differ among processes (Fig. 6). For carbon fluxes and stomatal regulation, high-CV areas are more concentrated and spatially extensive. High-variability areas for GPP and G_c are mainly located in the core soybean region of Northeast China and in stripe- or patch-like areas within the soybean belt extending from the Huang–Huai–Hai Plain to the Middle–Lower Yangtze region (Fig. 6a–b), indicating substantial interannual instability in carbon assimilation and stomatal openness even within major production zones. Transpiration shows the highest overall CV and the most pronounced spatial pattern. In addition to the Northeast core region, contiguous high-CV areas are especially evident across

the Huang–Huai–Hai and Middle–Lower Yangtze regions (Fig. 6c), suggesting that soybean water consumption is more sensitive to interannual hydroclimatic variability and fluctuates more strongly from year to year. By contrast, WUE has generally lower CV values and a more fragmented spatial pattern, with high variability limited to localized hotspots (Fig. 6d). This indicates that efficiency is more stable overall, but can still show marked interannual fluctuations where changes in carbon gain and water loss are not synchronized.

Regional statistics further support these spatial features. At the national scale, WUE shows the smallest interannual variability ($CV = 8.0\%$), lower than GPP (9.4%), G_c (11.0%), and T (14.3%) (Fig. S7), implying that the integrated efficiency of carbon gain per unit water use is more strongly buffered across years than flux-based processes. Across AEZs, the Northeast (NE) consistently exhibits relatively low CV for all four metrics (GPP: 7.2% , T : 12.7% , G_c : 9.4% , WUE: 7.6%), consistent with its more continuous, generally low-to-moderate CV pattern in space. By contrast, the HH, MLY, and SW zones show stronger overall variability, with higher variability in T and GPP in the HH and MLY zones (HH: GPP 17.3% , T 19.7% ; MLY: GPP 16.1% , T 19.5%), while the SW zone displays particularly strong instability in G_c and WUE (G_c 17.3% , WUE 10.0%). Collectively, these results indicate that interannual instability is most strongly manifested through enhanced variability in transpiration water use, whereas WUE is relatively stable but still exhibits localized hotspots of efficiency variability (Fig. 6; Fig. S7).

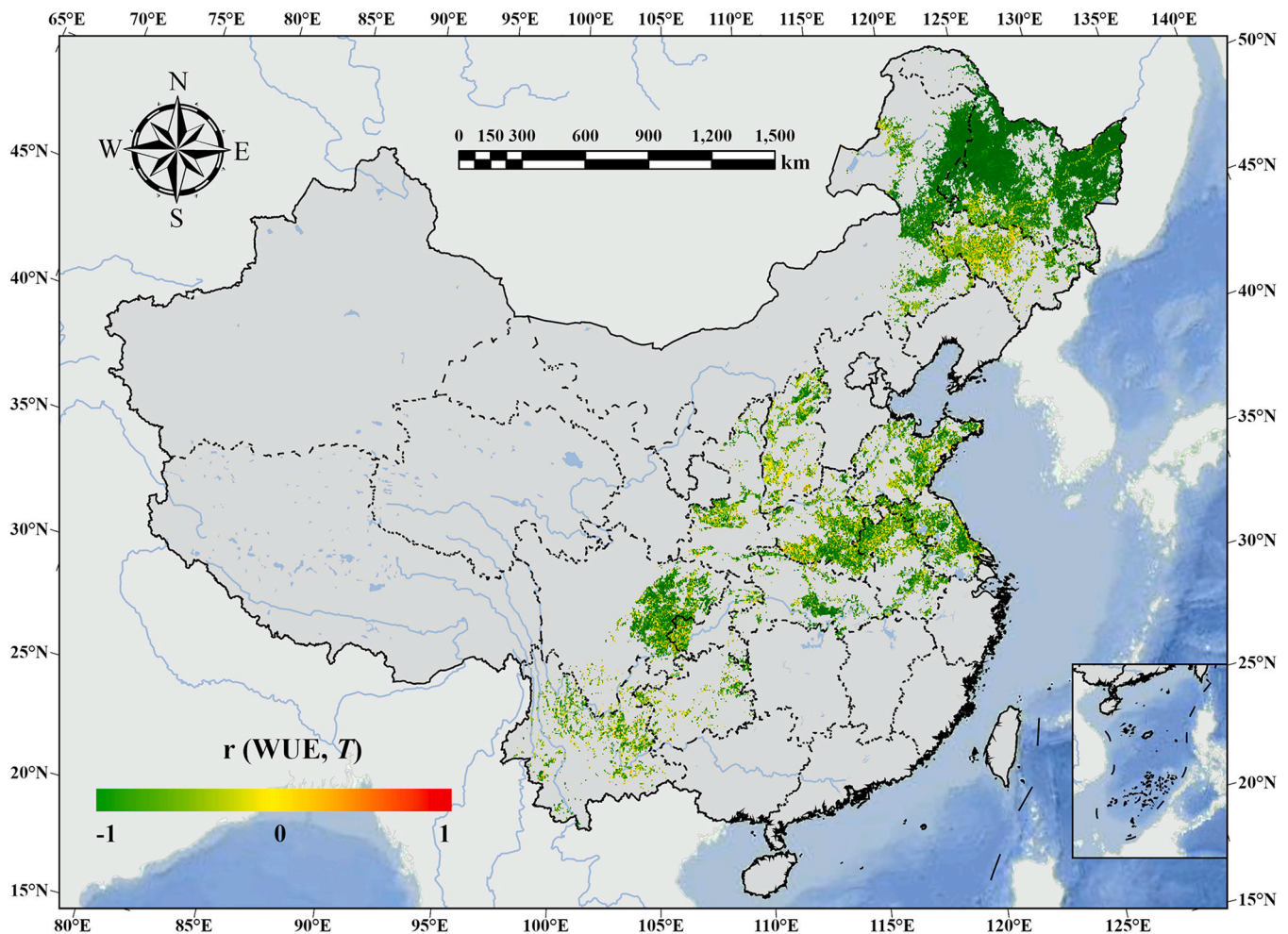


Fig. 7. Pixel-wise Pearson correlation (r) between transpiration (T) and water-use efficiency (WUE) across soybean-growing areas during 2019–2025. Colors denote the magnitude and sign of r : green indicates negative correlations (WUE tends to decrease as T increases), red indicates positive correlations (WUE tends to increase with T), and darker colors represent stronger associations (larger $|r|$). Correlations were computed at the pixel level, and soybean-area weighting was applied in the summary statistics (pixels with soybean fraction ≥ 0.01 were retained).

4.3. Spatial heterogeneity in transpiration–water-use efficiency co-variation

The preceding analyses of the multi-year mean and interannual variability of T and WUE during the growing season characterize the overall intensity and stability of water-related processes, but they do not reveal how closely interannual changes in T are associated with changes in WUE across different regions. Therefore, we calculated the pixel-wise Pearson correlation coefficient (r) between T and WUE during 2019–2025 to characterize the spatial heterogeneity in their temporal co-variation (Fig. 7). Because WUE is defined as GPP/T , T is mathematically embedded in WUE; therefore, the correlation is used here primarily as a descriptive measure of the strength and spatial variation of their interannual co-variation, rather than as independent evidence of a physiological relationship. Larger $|r|$ denotes a stronger temporal association.

Clear spatial differences in the strength of T –WUE co-variation were observed across China (Fig. 7). At the national scale, the area-weighted mean correlation was -0.796 , with 94.5% of pixels exhibiting $|r| \geq 0.3$ and 88.9% exhibiting $|r| \geq 0.5$ (Fig. 7), indicating that interannual changes in T and WUE were closely associated over most soybean-growing areas. However, the strength of this association varied substantially among regions. The NE zone showed the strongest co-variation (area-weighted mean $r = -0.854$ and 94.2% with $|r| \geq 0.5$), whereas the HH zone showed a markedly weaker association (area-weighted mean $r = -0.537$ and 63.1% with $|r| \geq 0.5$). MLY and SW exhibited intermediate levels of co-variation (area-weighted mean $r = -0.627$ and -0.587 , respectively) (Fig. 7). These results highlight substantial regional heterogeneity in the degree to which interannual changes in transpiration correspond to changes in water-use efficiency.

Given the inherent mathematical dependence between T and WUE, we further examined whether the observed regional pattern contained information beyond the denominator effect alone. To this end, we directly analyzed the scaling relationship between GPP and T , without using WUE in the calculation. For each pixel, the relationship was expressed as $\ln(GPP) = \alpha + \beta \times \ln(T)$, where β represents the GPP– T scaling elasticity (Fig. S8). At the national scale, the soybean-area-weighted mean β was 0.473, and 75.7% of soybean area had a 95% confidence interval for β entirely below 1. Mean β values were also below 1 across all four AEZs, although the strength and statistical support of this pattern varied regionally. This sub-proportional scaling indicates that interannual changes in GPP were generally smaller than the corresponding changes in T over much of the soybean-growing area. Therefore, while the negative T –WUE co-variation is partly constrained by the mathematical definition of WUE, the regional differences observed in Fig. 7 are not attributable to the denominator effect alone and are also consistent with asynchronous interannual variation in carbon gain and transpiration.

4.4. Relative contributions of atmospheric dryness and soil water on WUE: partial correlations and dominance analysis

The coupling patterns above indicate an overall trade-off between T and WUE; however, this relationship may be jointly regulated by VPD and SWC. To further characterize the statistical associations of VPD and SWC with model-estimated WUE within the present modelling framework, we computed pixel-wise partial correlation coefficients using daily growing-season samples (2019–2025). Specifically, $r_{\text{partial}}(\text{WUE}, \text{VPD}|\text{SWC})$ quantifies the association between WUE and VPD after removing the linear effect of SWC, whereas $r_{\text{partial}}(\text{WUE}, \text{SWC}|\text{VPD})$ quantifies the association between WUE and SWC after removing the linear effect of VPD. In addition, we assessed the relative importance of VPD versus SWC for explaining WUE variability using dominance analysis (Fig. 8).

The $r_{\text{partial}}(\text{WUE}, \text{VPD}|\text{SWC})$ exhibits a spatially consistent and strongly negative pattern across soybean-growing regions in China

(Fig. 8a). The national area-weighted mean partial correlation is -0.672 ± 0.116 , and 100% of the included pixels show negative values. The association is generally strong, with 99.4% of pixels having $|r_{\text{partial}}(\text{WUE}, \text{VPD}|\text{SWC})| \geq 0.3$ and 89.8% having $|r_{\text{partial}}(\text{WUE}, \text{VPD}|\text{SWC})| \geq 0.5$. Spatially, the more pronounced negative partial correlations are concentrated in the Northeast China soybean belt and extend across major soybean areas in North China and the Middle–Lower Yangtze region, with additional strong negative patches in parts of Southwest China (Fig. 8a). All four AEZs (NE, HH, MLY, and SW) display robust negative partial correlations (weighted means of -0.659 , -0.712 , -0.722 , and -0.732 , respectively). Notably, the fraction of strong correlations ($|r_{\text{partial}}(\text{WUE}, \text{VPD}|\text{SWC})| \geq 0.5$) is close to unity in HH and MLY (99.4% and 99.7%, respectively) (Fig. 8a).

In contrast, $r_{\text{partial}}(\text{WUE}, \text{SWC}|\text{VPD})$ shows a much weaker and more spatially fragmented pattern (Fig. 8b). The national area-weighted mean partial correlation is only -0.027 ± 0.066 , with 68.6% of pixels being negative and 31.4% positive, indicating mixed signs and an overall weak linear association between SWC and WUE after controlling for VPD. Accordingly, the fraction of pixels exhibiting moderate-to-strong associations is negligible: only 0.071% have $|r_{\text{partial}}(\text{WUE}, \text{SWC}|\text{VPD})| \geq 0.3$ and 0.009% have $|r_{\text{partial}}(\text{WUE}, \text{SWC}|\text{VPD})| \geq 0.5$. Spatially, noticeable (but localized) signals mainly appear as scattered patches, with relatively more negative values occurring in parts of Southwest China, whereas weak-to-mixed signs are widespread across North China and the Northeast (Fig. 8b). Across AEZs, the negative partial correlation is slightly more pronounced in SW (mean -0.074), followed by MLY (-0.052), while NE is weakest (-0.021); however, the fraction of strong correlations remains below 0.5% in all zones (Fig. 8b).

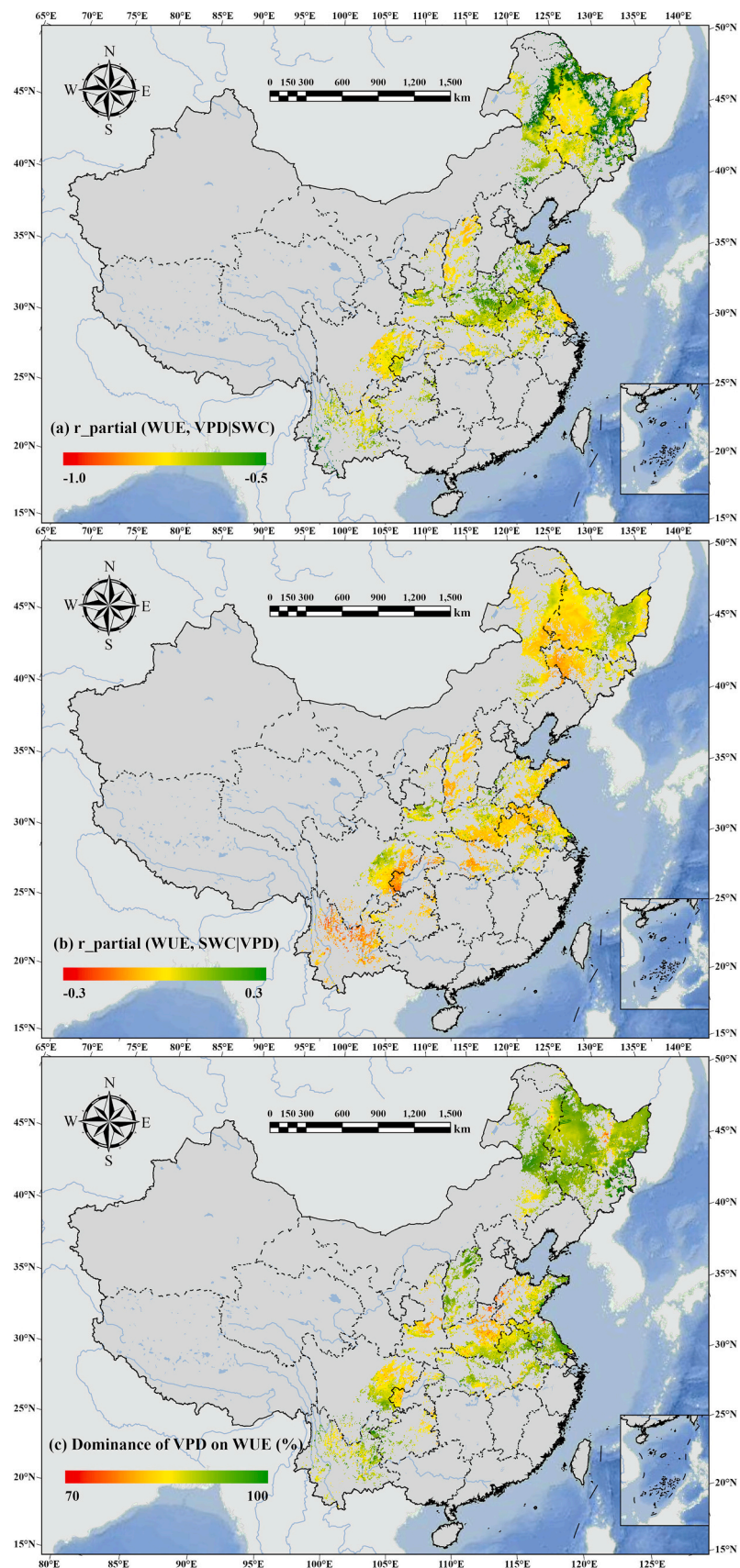
Within the present modelling framework, dominance analysis indicates a substantially greater relative explanatory contribution of VPD than SWC to the regression-explained variation in model-estimated WUE at the national scale (Fig. 8c). The national area-weighted mean VPD dominance is 89.80% (median 90.45%), and 99.91% of pixels have dominance $\geq 70\%$; 56.72% exceed 90%. Spatially, high dominance values are widespread across the main soybean regions, with particularly extensive areas of dominance $\geq 90\%$ in the Northeast, while comparatively lower dominance (though still mostly $>70\%$) is more frequent in Southwest China (Fig. 8c). Marked regional differences are evident: NE shows the highest VPD dominance (mean 90.51%, with 64.81% of pixels $\geq 90\%$), whereas SW is lowest (mean 86.37%, with 15.23% of pixels $\geq 90\%$). HH and MLY are intermediate, with $\geq 90\%$ fractions of 30.996% and 32.466%, respectively (Fig. 8c).

5. Discussion

5.1. Spatial co-variation of carbon gain and transpiration and its implications for efficiency

The spatial patterns indicate that carbon gain and water consumption are largely co-located across China's soybean regions: pixels with higher growing-season GPP and stronger canopy conductance (G_c) generally exhibit higher transpiration (T), concentrated in the Northeast China Plain and the major soybean belt spanning the Huang–Huai–Hai Plain to the Middle–Lower Yangtze region (Fig. 4a–c). This is consistent with the core understanding in crop water productivity research: crop production (or carbon gain) is closely coupled to water depletion, and improving water productivity is less about using less water per se than about generating more effective output per unit water consumed (Molden et al., 2010; Passioura, 2006; Zwart and Bastiaanssen, 2004). In contrast, WUE exhibits a more heterogeneous pattern and does not vary monotonically with either GPP or T (Fig. 4d). This suggests that comparable seasonal carbon gain can be achieved via different water-use pathways: in several high-transpiration hotspots, T increases more than carbon assimilation, resulting in lower carbon gain per unit water consumed (reduced WUE), even when GPP remains high (Fig. 4d).

These patterns indicate that high GPP and high T do not necessarily



(caption on next page)

Fig. 8. Partial correlations of model-estimated WUE with VPD (controlling for SWC) and SWC (controlling for VPD), and the relative explanatory contribution of VPD quantified by dominance analysis within the present modelling framework. Analyses were conducted at the pixel scale using daily soybean growing-season samples during 2019–2025. SWC was derived from ERA5-Land as the depth-weighted mean soil moisture of the upper three soil layers (0–100 cm). Dominance analysis decomposed the explained variance (R^2) of regression models containing VPD and SWC; the dominance percentage represents the relative contribution of VPD to the total explained variation in WUE, with higher values indicating a greater relative explanatory contribution of VPD. Only pixels with soybean fraction ≥ 0.01 were retained, and soybean fraction was used as the spatial weight for national and regional summary statistics.

lead to high WUE. When productivity gains are achieved mainly through increased water consumption, without commensurate improvements in carbon gain per unit water use, overall water productivity may decline (Molden et al., 2010; Passioura, 2006). Comparisons among AEZs further support this interpretation. The Middle–Lower Yangtze zone shows high GPP together with the highest T but relatively lower WUE, reflecting a more water-demanding pathway to sustain high carbon gain. In contrast, Northeast China maintains higher WUE under a lower transpiration background, indicating greater carbon return per unit water consumed (Fig. 4). The Huang–Huai–Hai zone exhibits the lowest WUE and larger spatial variability, suggesting that efficiency outcomes are more sensitive to heterogeneity in water supply and management. These results suggest that regional differences in carbon gain and water use may provide useful information for future evaluation of farmland management strategies (Khorchani et al., 2024; Molden et al., 2010; Pereira et al., 2002).

5.2. Implications of interannual variability and stability for water management

Based on Fig. 5, growing-season GPP and T increased significantly from 2019 to 2025 at the national scale, whereas WUE declined significantly. Meanwhile, at the pixel scale, T exhibits higher interannual variability (CV) than WUE, forming more continuous high-variability patches across the Northeast core production region and the Huang–Huai–Hai to Middle–Lower Yangtze soybean belt (Fig. 6). This pattern suggests that interannual fluctuations in soybean water consumption intensity (represented by T) may be more sensitive to interannual climate variability and changes in atmospheric evaporative demand, while the declining WUE may indicate that carbon gains per unit water use have not increased accordingly. The classical crop water requirement framework highlights that evaporative demand is jointly controlled by radiation, air temperature, wind speed, and humidity, thereby amplifying seasonal water demand and irrigation pressure in high-demand years (Allen et al., 1998). At broader scales, atmospheric dryness (with VPD as a key component) has also been shown to strongly regulate interannual variability of terrestrial carbon uptake and is associated with suppressed vegetation growth (He et al., 2022; Novick et al., 2016; Yuan et al., 2019).

The more extensive high-CV patches in HH and MLY suggest that transpiration may be more prone to interannual variability in these major production zones, suggesting that these regions may warrant further field-based evaluation of irrigation scheduling and in-field soil-water conservation strategies. Deficit irrigation and stage-specific water regulation can improve returns per unit water used when water is limiting (Feres and Soriano, 2007). Moreover, water productivity studies emphasize that improving output per unit water is not merely about reducing water use, but rather about enhancing the conversion efficiency between productive outputs and water consumption and identifying attainable ranges of regional water productivity (Molden et al., 2010; Zwart and Bastiaanssen, 2004). Therefore, the observed pattern—more volatile water use but relatively buffered yet weakening efficiency—suggests that soybean management may need to jointly consider water-use stability and improved returns per unit water consumed.

5.3. Transpiration–efficiency relationships and regional heterogeneity

Based on the pixel-wise correlation analysis in Fig. 7, T –WUE is predominantly negative across China and all AEZs, indicating that, in most soybean-growing areas, higher seasonal transpiration water use tends to be accompanied by lower carbon return per unit water consumed. Although this negative co-variation is partly constrained by the ratio structure of WUE, the independent GPP– T scaling analysis (Fig. S8) showed predominantly sub-proportional carbon gain relative to transpiration, suggesting that the pattern also reflects asynchronous variation in carbon gain and water loss rather than the denominator effect alone. This interpretation is consistent with the theory summarized by Buckley (2017), which emphasizes that carbon gain and water loss are jointly regulated by stomata but their responses to environmental forcing are not necessarily synchronous: when increases in transpiration are driven primarily by elevated atmospheric evaporative demand or by passive stomatal responses to environmental fluctuations, water loss can rise more rapidly than assimilation gains, such that efficiency declines and the coupling becomes negative (Condon et al., 2004; Sinclair, 1984). This implies that increasing water use alone does not necessarily improve water productivity. Instead, it is important to separate water use that contributes effectively to carbon assimilation and yield formation from water losses that do not, and to assess irrigation and agronomic inputs based on their marginal carbon (or yield) return per unit water consumed (Feres and Soriano, 2007; Zwart and Bastiaanssen, 2004).

Notably, the weaker negative correlations and stronger spatial heterogeneity in the HH zone suggest that the T –WUE relationship is more likely to vary across locations—and may even show localized co-variation—under the combined influences of intensive management interventions (e.g., irrigation method, scheduling thresholds, and in-field water conservation) and interannual climate variability. This is consistent with field evidence that different irrigation scheduling approaches can simultaneously alter transpiration, stomatal behavior, yield, and irrigation water productivity: scheduling triggered by soil water potential or plant status can often maintain or improve productive returns while controlling water use, although trade-offs commonly exist between yield stabilization and water-saving efficiency (França et al., 2024). Therefore, the widespread negative coupling revealed in Fig. 7 may serve as a regional diagnostic signal of areas where increasing water use is accompanied by declining efficiency. Such information could help identify regions that warrant further field-based evaluation of irrigation and soil-water management strategies (Feres and Soriano, 2007; Wood, 2020).

5.4. Relative contributions of atmospheric dryness versus soil water on WUE

Within the present modelling framework, the results in Fig. 8 show that model-estimated WUE has a spatially coherent and strongly negative partial correlation with VPD after controlling for SWC, whereas its partial correlation with SWC after controlling for VPD is generally weak. Dominance analysis further indicates a greater relative explanatory contribution of VPD than SWC to the regression-explained variation in model-estimated WUE. This finding is consistent with the growing eco-crop scale evidence that atmospheric dryness is becoming an increasingly important constraint on carbon–water processes: rising VPD can systematically alter the proportionality between carbon

assimilation and water loss by regulating stomatal conductance and transpiration demand, thereby shaping interannual variability and long-term trends in carbon sinks and WUE from regional to global scales (He et al., 2022; Li, 2023; Novick et al., 2016; Yang et al., 2024). Mechanistically, although stomata tend to close under high VPD, the greater atmospheric water-vapour pressure deficit can increase the driving force for transpiration, while carbon assimilation may also be constrained, potentially reducing WUE. This interpretation is consistent with observations that increasing VPD has contributed to the saturation or slowdown of global ecosystem WUE increases (Li, 2023) and with synthesis studies documenting widespread impacts of rising VPD across vegetation, including managed ecosystems (Grossiord, 2020).

Meanwhile, the partial-correlation signal of SWC is generally weak and spatially fragmented, which does not imply that soil water is unimportant; rather, it likely reflects the stronger threshold behavior, nonlinearity, and spatiotemporal heterogeneity of soil-water effects. In humid regions or under irrigation supplementation, the SWC signal may be muted; however, in drier environments or at critical growth stages, SWC can still jointly constrain the attainable upper limit of WUE with VPD by limiting leaf water potential, root water uptake, and stomatal opening (Fang, 2022; Katul et al., 2010; Lin, 2015; Song et al., 2020; Wolf et al., 2016). Within the present modelling framework, the ranking in Fig. 8c identifies VPD as a stronger statistical explanatory variable than SWC for model-estimated soybean WUE. This diagnostic result does not establish the relative causal importance of atmospheric and soil-water constraints or provide direct evidence for specific irrigation interventions. Areas with a lower relative explanatory contribution of VPD may be priorities for further investigation of local soil-water and topographic conditions using independent observations at finer spatial scales (Fang and Leung, 2022).

5.5. Uncertainties

Uncertainties remain in this study. First, when the MLR framework is applied at regional scale, some key physiological processes and parameters are inevitably treated as fixed—for example, assuming constant $\Phi_{PSII\max}$ and K_{DF} . Under years with high evaporative demand or strong stress, these parameters and process responses may deviate from the calibration conditions, introducing uncertainty into the model's quantitative estimates (Liu et al., 2024; Wang et al., 2025). Second, the parameters used to estimate q_L are primarily derived from experiments on soybean cultivars sampled in Yangling, whereas soybean production across China involves substantial cultivar and management diversity. In addition, stress conditions (e.g., drought and heat) can alter photochemical regulation and energy partitioning. Therefore, extrapolating q_L directly to large scales may cause regional biases and, in turn, affect spatial comparisons of WUE and the quantitative inference of the relative roles of VPD versus SWC. Uncertainty may also arise from assumptions in the sub-pixel SIF retrieval, including negligible within-sub-pixel PAR variation and approximately constant fluorescence yield. In addition, because VPD is explicitly involved in the estimation of G_c and T , its subsequent use in explaining WUE variability may introduce structural dependence within the modelling framework. Finally, soybean distribution was relatively stable over the available comparison period, but this assessment did not cover every year of the 2019–2025 study period. The use of a fixed soybean distribution mask may introduce additional uncertainty into crop-specific SIF extraction and subsequent carbon-water process estimation if substantial interannual changes in soybean planting patterns occur. Future studies integrating annually updated high-spatial-resolution crop distribution products could further reduce this uncertainty and improve the reliability of long-term crop-specific remote sensing assessments.

Another limitation concerns independent validation of the framework-derived estimates. The present framework is specifically designed to retrieve soybean-specific carbon–water signals from mixed satellite pixels. Conventional gridded GPP or transpiration products

generally represent the integrated signal of the entire mixed pixel rather than the soybean component alone. Therefore, direct comparison with such products would involve a mismatch in spatial representativeness and would not constitute a like-for-like validation of the soybean-specific estimates. Suitable independent observations that are spatially and temporally matched to the soybean-specific G_c , T , and WUE estimates were not available for the present national-scale analysis. Accordingly, the sensitivity analysis, uncertainty-propagation assessment, and soybean-mask stability analysis conducted here should be regarded as evaluations of model behaviour and major uncertainty sources rather than as substitutes for independent observational validation. Future studies should further evaluate these framework-derived estimates using spatially and temporally matched crop-specific field or flux observations.

6. Conclusions

In this study, we developed a process-based, SIF-enabled crop carbon–water framework to quantify soybean growing-season carbon assimilation, water consumption, and WUE across China during 2019–2025. The framework uses satellite SIF to estimate net photosynthesis and uses G_c as a key input within a Penman–Monteith scheme to estimate T , from which WUE is derived. At the national scale, the multi-year growing-season means of GPP, G_c , T , and WUE were 1151.8 gC m⁻² season⁻¹, 0.00725 m s⁻¹, 699.7 mm season⁻¹, and 1.672 gC kg⁻¹ H₂O, respectively. Partial-correlation and dominance analyses further indicate that VPD has a greater relative explanatory contribution to WUE variability than SWC, within the present modelling framework, with this pattern occurring across more than 89% of soybean pixels nationwide. The key advantages of the proposed framework are that it (1) integrates crop-distribution information to partition SIF at the crop scale, thereby reducing mixed-pixel effects, and (2) introduces physiologically grounded constraints by linking SIF to net photosynthesis for determining G_c , enabling consistent large-scale estimates of T and WUE. Overall, the proposed framework provides a process-based approach for interpreting regional soybean carbon–water patterns. Nevertheless, the resulting estimates remain subject to uncertainties associated with sub-pixel SIF partitioning, physiological parameterization, soybean-mask stability, and conductance-based transpiration modelling.

CRedit authorship contribution statement

Jingjing Yang: Writing – original draft, Methodology, Data curation, Conceptualization. **Zhunqiao Liu:** Writing – review & editing, Methodology, Investigation, Funding acquisition. **Wenyan Xiao:** Data curation. **Yu Tian:** Data curation. **Huanjie Cai:** Resources. **Qiang Yu:** Data curation, Resources. **Xiaoliang Lu:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Definitions of symbols and units used

Symbols	Definition	Unit
A_{net}	Net photosynthetic rate	$\mu\text{mol m}^{-2} \text{ s}^{-1}$
c	Speed of light	m s^{-1}
C_a	Ambient CO ₂ partial pressure	μbar
C_c	Chloroplastic CO ₂ partial pressure	μbar
C_p	Specific heat capacity of air	$\text{J kg}^{-1} \text{ }^{\circ}\text{C}^{-1}$
$f_{\text{esc,P-C}}$	The fraction of SIF photons escaping from the PSII reaction centers to TOC.	\
f_{PSII}	The relative contribution of PSII fluorescence to total fluorescence	\
G	Soil heat flux	W m^{-2}
g_1	Fitting parameter related to the plant's water use strategy	$\text{kPa}^{0.5}$
g_a	Aerodynamic resistance for heat and water vapor	m s^{-1}
G_c	Canopy conductance	m s^{-1}
g_o	Residual conductance	$\text{mol m}^{-2} \text{ s}^{-1}$
GPP	Gross primary production	$\mu\text{mol m}^{-2} \text{ s}^{-1}$
h	Planck constant	J s
H_a	The rate at which the peak function increases below T_{opt}	kJ mol^{-1}
H_d	The rate at which the peak function decreases above T_{opt}	kJ mol^{-1}
K_{DF}	The ratio of K_D to K_F	\
m	The fitted parameter for estimating $q_{\text{L,SIF}}$	\
m_{opt}	The value of m at T_{opt}	\
N_A	Avogadro's constant	mol^{-1}
NIRv	Near-infrared reflectance of vegetation	\
q_L	The fraction of open Photosystem II reaction centers	\
R	The molar gas constant	$\text{m}^3 \text{ Pa mol}^{-1} \text{ K}^{-1}$
R_d	Daytime leaf dark respiration	$\mu\text{mol m}^{-2} \text{ s}^{-1}$
R_n	Net radiation	W m^{-2}
SIF _{TOC}	Top-of-canopy (TOC) SIF observations	$\text{mW m}^{-2} \text{ nm}^{-1} \text{ sr}^{-1}$
T	Transpiration	$\text{g m}^{-2} \text{ s}^{-1}$
T_{air}	Air temperature	$^{\circ}\text{C}$
T_d	Dew point temperature	$^{\circ}\text{C}$
T_{Leaf}	Leaf surface temperature	K
T_{opt}	The optimal T_{Leaf}	K
V_{cmax}	Maximum carboxylation rate	$\mu\text{mol m}^{-2} \text{ s}^{-1}$
VPD	Atmospheric water vapour pressure deficit	kPa
WUE	Water use efficiency	$\text{g C/kg H}_2\text{O}$
λ	Wavelength	nm
λ'	Full SIF spectrum from 640 to 850 nm	nm
Φ_{PSIImax}	The maximum photochemical quantum yield of PSII under unstressed conditions	\
$\eta_{\lambda, \text{PSII}}$	Emission spectra for full-spectrum	\
$\eta_{\lambda, \text{PSII}}$	Specific-band PSII fluorescence	\
Δ	Slope of saturated water vapour pressure with air temperature	$\text{kPa } ^{\circ}\text{C}^{-1}$
ρ	Density of dry air	kg m^{-3}
γ	Psychometric constant	$\text{kPa } ^{\circ}\text{C}^{-1}$
λ_v	Latent heat of vaporization	kJ kg^{-1}
Γ^*	Chloroplastic compensation point of CO ₂	μbar

Appendix B. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.agwat.2026.110891](https://doi.org/10.1016/j.agwat.2026.110891).

Data Availability

Data will be made available on request.

References

Alemohammad, S.H., Fang, B., Konings, A.G., Aires, F., Green, J.K., Kolassa, J., Miralles, D., Prigent, C., Gentine, P., 2017. Water, Energy, and Carbon with Artificial Neural Networks (WECANN): A statistically-based estimate of global surface turbulent fluxes and gross primary productivity using solar-induced fluorescence. *Biogeosciences* 14, 4101–4124.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration—Guidelines for computing crop water requirements (FAO Irrigation and Drainage Paper No. 56). FAO, Rome.

Buckley, T.N., 2017. Modeling stomatal conductance. *Plant. Physiol.* 174, 572–582.

Condon, A.G., Richards, R.A., Rebetzke, G.J., Farquhar, G.D., 2004. Breeding for high water-use efficiency. *J. Exp. Bot.* 55, 2447–2460.

Dechant, B., Ryu, Y., Badgley, G., Köhler, P., Rascher, U., Migliavacca, M., Zhang, Y., Tagliabue, G., Guan, K., Rossini, M., Goulas, Y., Zeng, Y., Frankenber, C., Berry, J. A., 2022. NIRVP: A robust structural proxy for sun-induced chlorophyll fluorescence and photosynthesis across scales. *Remote. Sens. Environ.* 268, 112763.

Fang, Y., Leung, L.R., 2022. Relative controls of vapor pressure deficit and soil water stress on canopy conductance in global simulations by an Earth system model. *Earth's. Future* 10, e2022EF002810.

Fereres, E., Soriano, M.A., 2007. Deficit irrigation for reducing agricultural water use. *J. Exp. Bot.* 58, 147–159.

França, A.C.F., Coelho, R.D., Gundim, A.S., Costa, J.O., Quiloango-Chimarro, C.A., 2024. Effects of different irrigation scheduling methods on physiology, yield, and irrigation water productivity of soybean varieties. *Agric. Water Manag.* 293, 108709.

Grossiord, C., Buckley, T.N., Cernusak, L.A., Novick, K.A., Poulter, B., Siegwolf, R.T.W., Sperry, J.S., McDowell, N.G., 2020. Plant responses to rising vapor pressure deficit. *New. Phytol.* 226, 1550–1566.

Gu, L., Han, J., Wood, J.D., Chang, C.Y.Y., Sun, Y., 2019. Sun-induced Chl fluorescence and its importance for biophysical modeling of photosynthesis based on light reactions. *New. Phytol.* 223, 1179–1191.

Guo, C., Liu, Z., Lu, X., 2025. Application of Simultaneous Active and Passive Fluorescence Observations: Extending a Fluorescence-Based qL Estimation Model. *Sensors* 25, 1700.

- Han, J., Chang, C.Y.Y., Gu, L., Zhang, Y., Meeker, E., Magney, T.S., Walker, A., Wen, J., Kira, O., McNaull, S., Sun, Y., 2022. The physiological basis for estimating photosynthesis from Chla fluorescence. *New Phytol.* 234, 1206–1219.
- Hartman, G.L., West, E.D., Herman, T.K., 2011. Crops that feed the World 2. Soybean—worldwide production, use, and constraints caused by pathogens and pests. *Food Secur.* 3, 5–17.
- He, B., Chen, C., Lin, S., Yuan, W., Chen, H.W., Chen, D., Zhang, Y., Guo, L., Zhao, X., Liu, X., Piao, S., Zhong, Z., Wang, R., Tang, R., 2022. Worldwide impacts of atmospheric vapor pressure deficit on the interannual variability of terrestrial carbon sinks. *Natl. Sci. Rev.* 9 nwab150.
- Huang, M., Piao, S., Sun, Y., Ciais, P., Cheng, L., Mao, J., Poulter, B., Shi, X., Zeng, Z., Wang, Y., 2015. Change in terrestrial ecosystem water-use efficiency over the last three decades. *Glob. Chang. Biol.* 21, 2366–2378.
- Katul, G., Manzoni, S., Palmroth, S., Oren, R., 2010. A stomatal optimization theory to describe the effects of atmospheric CO₂ on leaf photosynthesis and transpiration. *Ann. Bot.* 105, 431–442.
- Khorchani, M., Awada, T., Schmer, M., Jin, V., Birru, G., Dangal, S.R.S., Suyker, A., Freidenreich, A., 2024. Long-term croplands water productivity in response to management and climate in the Western US Corn Belt. *Agric. Water Manag.* 291, 108640.
- Kira, O., Sun, Y., 2020. Extraction of sub-pixel C3/C4 emissions of solar-induced chlorophyll fluorescence (SIF) using artificial neural network. *I ISPRS J. Photogramm. Remote. Sens.* 161, 135–146.
- Köhler, P., Frankenberg, C., Magney, T.S., Guanter, L., Joiner, J., Landgraf, J., 2018. Global retrievals of solar-induced chlorophyll fluorescence with TROPOMI: First results and intersensor comparison to OCO-2. *Geophys. Res. Lett.* 45, 10456–10463.
- Li, F., Xiao, J., Chen, J., Ballantyne, A., Jin, K., Li, B., Abrah, M., John, R., 2023. Global water use efficiency saturation due to increased vapor pressure deficit. *Science* 381, 672–677.
- Lin, Y.-S., Medlyn, B.E., Duursma, R.A., Prentice, I.C., Wang, H., Baig, S., Eamus, D., Resco de Dios, V., Mitchell, P., Ellsworth, D.S., Op de Beeck, M., Wallin, G., Uddling, J., Tarvainen, L., Linderson, M.-L., Cernusak, L.A., Nippert, J.B., Ocheltree, T.W., Tissue, D.T., Martin-StPaul, N.K., Rogers, A., Warren, J.M., De Angelis, P., Hikosaka, K., Han, Q., Onoda, Y., Gimeno, T.E., Barton, C.V.M., Bennie, J., Bonal, D., Bosc, A., Löw, M., Macinins-Ng, C., Rey, A., Rowland, L., Setterfield, S.A., Tausz-Pösch, S., Zaragoza-Castells, J., Broadmeadow, M.S.J., Drake, J.E., Freeman, M., Ghanoun, O., Hutley, L.B., Kelly, J.W., Kikuzawa, K., Kolari, P., Koyama, K., Limousin, J.-M., Meir, P., Lola da Costa, A.C., Mikkelsen, T. N., Salinas, N., Sun, W., Wingate, L., 2015. Optimal stomatal behaviour around the world. *Nat. Clim. Chang.* 5, 459–464.
- Liu, Z., Guo, C., Yu, Q., Zhu, P., Peng, X., Dong, M., Cai, H., Lu, X., 2024. A SIF-based approach for quantifying canopy photosynthesis by simulating the fraction of open PSII reaction centers (qL). *Remote. Sens. Environ.* 305, 114111.
- Liu, Z., Zhao, F., Liu, X., Yu, Q., Wang, Y., Peng, X., Cai, H., Lu, X., 2022. Direct estimation of photosynthetic CO₂ assimilation from solar-induced chlorophyll fluorescence (SIF). *Remote. Sens. Environ.* 271, 112893.
- Lu, X., Liu, Z., An, S., Miralles, D.G., Maes, W.H., Tang, J., 2018. Potential of solar-induced chlorophyll fluorescence to estimate transpiration in a temperate forest. *Agric. For. Meteorol.* 252, 75–87.
- Maes, W.H., Pagán, B.R., Martens, B., Gentine, P., Guanter, L., Steppe, K., Verhoest, N., Dorigo, W., Li, X., Xiao, J., Miralles, D.G., 2020. Sun-induced fluorescence closely linked to ecosystem transpiration as evidenced by satellite data and radiative transfer models. *Remote. Sens. Environ.* 249, 112030.
- Medlyn, B.E., Duursma, R.A., Eamus, D., Ellsworth, D.S., Prentice, I.C., Barton, C.V.M., Crous, K.Y., De Angelis, P., Freeman, M., Wingate, L., 2011. Reconciling the optimal and empirical approaches to modelling stomatal conductance. *Glob. Chang. Biol.* 17, 2134–2144.
- Mei, Q., Zhang, Z., Han, J., Song, J., Dong, J., Wu, H., Xu, J., Tao, F., 2024. ChinaSoyArea10m: a dataset of soybean-planting areas with a spatial resolution of 10 m across China from 2017 to 2021. *Earth Syst. Sci. Data* 16, 3213–3231.
- Mekonnen, M.M., Hoekstra, A.Y., 2011. The green, blue and grey water footprint of crops and derived crop products. *Hydrol. Earth Syst. Sci.* 15, 1577–1600.
- Molden, D., Oweis, T., Steduto, P., Bindraban, P., Hanjra, M.A., Kijne, J., 2010. Improving agricultural water productivity: Between optimism and caution. *Agric. Water Manag.* 97, 528–535.
- Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D.G., Piles, M., Rodríguez-Fernández, N.J., Zsoter, E., Buontempo, C., Thépaut, J.-N., 2021. ERA5-Land: a state-of-the-art global reanalysis dataset for land applications. *Earth Syst. Sci. Data* 13, 4349–4383.
- Myneni, R., Knyazikhin, Y., Park, T., 2015. MCD15A3H MODIS/Terra+Aqua Leaf Area Index/FPAR 4-Day L4 Global 500 m SIN Grid V006. NASA EOSDIS Land. Process. DAAC.
- National Bureau of Statistics of China, 2025. Statistical Communiqué of the People's Republic of China on the 2024 National Economic and Social Development. National Bureau of Statistics of China, Beijing.
- Novick, K.A., Ficklin, D.L., Stoy, P.C., Williams, C.A., Bohrer, G., Oishi, A.C., Papuga, S. A., Blanken, P.D., Noormets, A., Sulman, B.N., Scott, R.L., Wang, L., Phillips, R.P., 2016. The increasing importance of atmospheric demand for ecosystem water and carbon fluxes. *Nat. Clim. Chang.* 6, 1023–1027.
- Pagán, B.R., Maes, W.H., Gentine, P., Martens, B., Miralles, D.G., 2019. Exploring the Potential of Satellite Solar-Induced Fluorescence to Constrain Global Transpiration Estimates. *Remote. Sens.* 11, 413.
- Passioura, J., 2006. Increasing crop productivity when water is scarce—from breeding to field management. *Agric. Water Manag.* 80, 176–196.
- Pedrés, R., Goulas, Y., Jacquemoud, S., Louis, J., Moya, I., 2010. FluorMODleaf: A new leaf fluorescence emission model based on the PROSPECT model. *Remote. Sens. Environ.* 114, 155–167.
- Pedrés, R., Moya, I., Goulas, Y., Jacquemoud, S., 2008. Chlorophyll fluorescence emission spectrum inside a leaf. *Photochem. & Photobiol. Sci.* 7, 498–502.
- Pereira, L.S., Oweis, T., Zairi, A., 2002. Irrigation management under water scarcity. *Agric. Water Manag.* 57, 175–206.
- Porcar-Castell, A., Malenovsky, Z., Magney, T., Van Wittenberghe, S., Fernandez-Marin, B., Maignan, F., Zhang, Y., Maseyk, K., Atherton, J., Albert, L.P., Robson, T. M., Zhao, F., Garcia-Plazaola, J.-I., Ensminger, I., Rajewicz, P.A., Grebe, S., Tikkanen, M., Kellner, J.R., Ihalainen, J.A., Rascher, U., Logan, B., 2021. Beyond APAR and NPQ: Factors coupling and decoupling SIF and GPP across scales. 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS. IEEE, pp. 1925–1927.
- Shan, N., Ju, W., Migliavacca, M., Martini, D., Guanter, L., Chen, J.M., Goulas, Y., Zhang, Y., 2019. Modeling canopy conductance and transpiration from solar-induced chlorophyll fluorescence. *Agric. For. Meteorol.* 268, 189–201.
- Shan, N., Zhang, Y., Chen, J.M., Ju, W., Migliavacca, M., Peñuelas, J., Yang, X., Zhang, Z., Nelson, J.A., Goulas, Y., 2021. A model for estimating transpiration from remotely sensed solar-induced chlorophyll fluorescence. *Remote. Sens. Environ.* 252, 112134.
- Sinclair, T.R., 1984. Leaf area development in field-grown soybeans. *Agron. J.* 76, 141–146.
- Song, X., Lyu, S., Wen, X., 2020. Limitation of soil moisture on the response of transpiration to vapor pressure deficit in a subtropical coniferous plantation subjected to seasonal drought. *J. Hydrol.* 591, 125301.
- Sun, H., Lu, M., Yang, Y., Chen, J., Wang, J., Yan, D., Xue, J., Zhang, W., 2023a. Revisiting the role of transpiration in the variation of ecosystem water use efficiency in China. *Agric. For. Meteorol.* 332, 109344.
- Sun, Y., Wen, J., Gu, L., Joiner, J., Chang, C.Y., Van Der Tol, C., Porcar-Castell, A., Magney, T., Wang, L., Hu, L., Rascher, U., Zarco-Tejada, P., Barrett, C.B., Lai, J., Han, J., Luo, Z., 2023. From remotely-sensed solar-induced chlorophyll fluorescence to ecosystem structure, function, and service: Part II—Harnessing data. *Glob. Chang. Biol.* 29, 2893–2925.
- Thornton, P.E., 1998. Regional ecosystem simulation: Combining surface- and satellite-based observations to study linkages between terrestrial energy and mass budgets. PhD dissertation. University of Montana, Missoula, MT, USA.
- USDA Foreign Agricultural Service (USDA FAS), 2026. Oilseeds: World Markets and Trade. U.S. Department of Agriculture, Washington, DC.
- Van Der Tol, C., Berry, J.A., Campbell, P.K., Rascher, U., 2014. Models of fluorescence and photosynthesis for interpreting measurements of solar-induced chlorophyll fluorescence. *J. Geophys. Res. Biogeophys.* 119, 2312–2327.
- Van Der Tol, C., Verhoef, W., Timmermans, J., Verhoef, A., Su, Z., 2009. An integrated model of soil-canopy spectral radiances, photosynthesis, fluorescence, temperature and energy balance. *Biogeosciences* 6, 3109–3129.
- Wang, M., Shi, W., 2024. The annual dynamic dataset of high-resolution crop water use in China from 1991 to 2019. *Sci. Data* 11, 1373.
- Wang, Y., Köhler, P., Braghieri, R.K., Longo, M., Doughty, R., Bloom, A.A., Frankenberg, C., 2022. GriddingMachine, a database and software for Earth system modeling at global and regional scales. *Sci. Data* 9, 258.
- Wang, Y., Ling, X., Ma, C., Zhang, W., Huang, J., Peng, S., Deng, N., 2023. Can China get out of soy dilemma? A yield gap analysis of soybean in China. *Agron. Sustain. Dev.* 43, 47.
- Wang, Y., Yu, Q., Liu, Z., Ren, W., Lu, X., 2025. A practical SIF-based crop model for predicting crop yields by quantifying the fraction of open PSII reaction centers (qL). *Remote. Sens. Environ.* 320, 114658.
- Wolf, A., Anderegg, W.R.L., Pacala, S.W., 2016. Optimal stomatal behavior with competition for water and risk of hydraulic impairment. *Proc. Natl. Acad. Sci. U. S. A.* 113, E7222–E7230.
- Wood, C.W., Krutz, L.J., Henry, W.B., Irby, T., Orlowski, J.M., Bryant, C.J., Atwill, R.L., Spencer, G.D., Mills, B.E., 2020. Developing sensor-based irrigation scheduling that maximizes soybean grain yield, irrigation water use efficiency, and returns above irrigation costs. *Crop. Forage Turfgrass Manag.* 6, e20029.
- Wu, X., Li, X., Chen, Y., Bai, Y., Tong, Y., Wang, P., Liu, H., Wang, M., Shi, F., Zhang, C., Huang, Y., Ma, Y., Hu, X., Shi, C., 2019. Atmospheric water demand dominates daily variations in water use efficiency in alpine meadows, northeastern Tibetan Plateau. *J. Geophys. Res. Biogeosci.* 124, 2174–2185.
- Yang, J., Liu, Z., Yu, Q., Lu, X., 2024. Estimation of global transpiration from remotely sensed solar-induced chlorophyll fluorescence. *Remote. Sens. Environ.* 303, 113998.
- Yang, P., Van Der Tol, C., Campbell, P.K.E., Middleton, E.M., 2021. Unraveling the physical and physiological basis for the solar-induced chlorophyll fluorescence and photosynthesis relationship using continuous leaf and canopy measurements of a corn crop. *Biogeosciences* 18, 441–465.
- Yuan, W., Zheng, Y., Piao, S., Ciais, P., Lombardozzi, D., Wang, Y., Ryu, Y., Chen, G., Dong, W., Hu, Z., Jain, A.K., Jiang, C., Kato, E., Li, S., Lienert, S., Liu, S., Nabel, J.E. M.S., Qin, Z., Quine, T., Sitch, S., Smith, W.K., Wang, F., Wu, C., Xiao, Z., Yang, S., 2019. Increased atmospheric vapor pressure deficit reduces global vegetation growth. *Sci. Adv.* 5 eaax1396.
- Zeng, Y., Badgley, G., Dechant, B., Ryu, Y., Chen, M., Berry, J.A., 2019. A practical approach for estimating the escape ratio of near-infrared solar-induced chlorophyll fluorescence. *Remote. Sens. Environ.* 232, 111209.

- Zhang, Q., Liu, X., Zhou, K., Zhou, Y., Gentile, P., Pan, M., Katul, G.G., 2024. Solar-induced chlorophyll fluorescence sheds light on global evapotranspiration. *Remote. Sens. Environ.* 305, 114061.
- Zhou, K., Zhang, Q., Xiong, L., Gentile, P., 2022. Estimating evapotranspiration using remotely sensed solar-induced fluorescence measurements. *Agric. For. Meteorol.* 314, 108800.
- Zwart, S.J., Bastiaanssen, W.G.M., 2004. Review of measured crop water productivity values for irrigated wheat, rice, cotton and maize. *Agric. Water Manag.* 69, 115–133.