

Article

Hydroclimatic Gradients Shape Differential Responses of Vegetation Photosynthesis in Croplands and Typical Natural Vegetation to Atmospheric Evaporative Demand and Soil Moisture

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Abstract

Vegetation photosynthesis is jointly regulated by precipitation supply, atmospheric water demand, and vertically stratified soil moisture, but their relative roles across vegetation types and hydroclimatic backgrounds remain unclear. Using monthly satellite solar-induced chlorophyll fluorescence (SIF), ERA5-Land hydroclimatic variables, and vegetation-type data across China from 2000 to 2024, this study combined monthly anomaly analysis, lagged partial correlation, and XGBoost–SHAP to quantify moisture-response patterns in cropland, forest, grassland, and shrubland along an arid–humid gradient. Vegetation SIF increased overall from 2000 to 2024, with a clear northwest–southeast gradient and higher multiyear mean SIF in forests and shrublands than in croplands and grasslands. XGBoost–SHAP results showed that vapor pressure deficit (VPD) was the largest single contributor to SIF anomalies at the national scale, accounting for 31.8% of total moisture-factor contribution, followed by precipitation, shallow soil moisture, and middle- plus deep-layer soil moisture. The VPD contribution differed among vegetation types, reaching 43.3% in grassland, 32.5% in cropland, 30.4% in shrubland, and 27.5% in forest. Lagged responses also varied with soil depth and hydroclimatic background. Precipitation and shallow soil moisture mainly produced concurrent or 1-month lagged responses, whereas middle- and deep-layer soil moisture generated 2–3-month delayed effects in some arid and semi-arid cropland and woody vegetation. Across the arid–humid gradient, dominant moisture constraints shifted from deeper soil-water regulation in arid regions toward VPD control in transitional zones and precipitation or shallow-soil-moisture control in humid ecosystems. These findings demonstrate that vegetation SIF anomalies are shaped by coupled atmospheric demand, precipitation input, and soil-water storage, with vegetation traits and hydroclimatic background jointly determining the dominant moisture-response pathway.



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Keywords: solar-induced chlorophyll fluorescence; lagged response; XGBoost–SHAP; vapor pressure deficit; stratified soil moisture

1. Introduction

Vegetation photosynthesis constitutes a fundamental physiological process that sustains terrestrial carbon sink functioning, maintains ecosystem primary productivity, and mediates land–atmosphere carbon and water exchanges, serving as a cornerstone of global carbon cycling and terrestrial ecosystem stability. Under ongoing global warming, altered precipitation patterns and increasing atmospheric evaporative demand have intensified atmospheric drought stress and soil moisture imbalance, making them two key constraints on vegetation photosynthetic processes and terrestrial water-stress responses [1]. Spanning broad and continuous hydroclimatic gradients, China features diverse dominant vegetation types, including croplands, forests, grasslands, and shrublands. These vegetation communities exhibit substantial disparities in canopy structure, phenological rhythm, vertical root distribution, and water-use strategies, which may lead to divergent water-stress tolerance and photosynthetic response regimes across ecosystems. However, how vegetation photosynthetic responses to moisture anomalies vary with vegetation type and regional hydroclimatic background remain poorly quantified and mechanistically unclear. Clarifying these differences is therefore essential to understanding terrestrial carbon–water coupling and ecosystem water-limitation mechanisms under climate change.

Solar-induced chlorophyll fluorescence (SIF) represents a weak fluorescence signal emitted by chlorophyll molecules during photosynthesis, which tightly tracks reflecting photosynthetic electron transport and canopy-level photosynthetic activity. Distinct from traditional vegetation indices that primarily capture canopy greenness or structural traits, SIF provides a more direct proxy for photosynthetic processes, serving as a critical remote sensing indicator for monitoring vegetation functional dynamics and their responses to moisture dynamics [2,3]. Accumulating evidence has demonstrated that satellite-derived SIF is strongly associated with ecosystem gross primary productivity (GPP) and variations in ecosystem photosynthesis, validating its reliability for monitoring vegetation photosynthetic activity at regional scales and over long time series [4,5]. Recent advancements in long-term, high-precision normalized SIF products, integrated with multi-source meteorological data and stratified soil moisture datasets, have established a solid data and methodological foundation for systematically disentangling the functional heterogeneity of vegetation photosynthetic dynamics and their divergent water response patterns across diverse hydroclimatic gradients [6].

Vegetation photosynthesis is not governed by a single water-related factor but is jointly constrained by the coupled interactions of atmospheric water demand, precipitation supply, and profile-soil water storage. Vapor pressure deficit (VPD) is a key indicator of atmospheric drought intensity and potential evaporative demand and can directly suppress vegetation photosynthetic efficiency by modulating stomatal kinetics and exacerbating canopy water loss through transpiration [1,7]. As the primary external water input to terrestrial ecosystems, precipitation sustains soil water replenishment and underpins regional hydrological balance. In contrast, vertically stratified soil moisture directly maintains root-zone water availability and largely regulates long-term ecosystem water-stress and land–atmosphere hydrological feedbacks [8]. Notably, soil moisture exhibits pronounced vertical stratification in its temporal dynamics. Shallow soil moisture responds rapidly to precipitation pulses and surface evaporation, featuring intense short-term fluctuations. By contrast, middle-layer and deep-layer soil moisture display pronounced lagged variability

and higher storage stability, preserving persistent signals of long-term moisture surplus or deficit. Therefore, integrating multi-depth soil moisture information enables a more comprehensive, profile-scale characterization of plant-available water status and improves the mechanistic assessment of moisture-induced photosynthetic anomalies [9,10]. Furthermore, soil texture and type-dependent water-retention properties modulate the persistence of soil water deficits, whereas vegetation adaptation strategies and seasonal canopy development reshape the sensitivity of SIF to moisture stress. Given the substantial spatial heterogeneity in field capacity and plant-available water capacity across soil types, this study adopts relative soil moisture anomalies (departures from local climatological baselines) rather than absolute deviations from field capacity. This standardized correction eliminates spatial soil property biases and provides a consistent benchmark for cross-comparisons of SIF moisture responses across vegetation types and hydroclimatic zones.

Existing studies have shown that vegetation sensitivity and response patterns to drought vary markedly along hydroclimatic gradients [11,12], with soil moisture stress exerting an increasingly severe constraint on regional vegetation productivity in recent decades [13]. As a robust remote sensing proxy for vegetation photosynthetic functioning, SIF can effectively capture dynamic photosynthetic responses in response to meteorological drought [14,15]. Meanwhile, vegetation water stress typically exhibits pronounced lagged responses and cumulative effects, which substantially influence the temporal dynamics of vegetation photosynthesis [16,17]. Although there are growing insights into vegetation photosynthetic responses to drought, critical research gaps remain. Most prior studies have focused on individual moisture drivers (e.g., VPD, precipitation, or surface soil moisture) but lack systematic comparisons and quantitative attribution across multiple moisture dimensions, including atmospheric drought, precipitation, and vertically stratified soil moisture. In particular, the hierarchical regulatory role of profile-soil moisture dynamics has long been underappreciated. Integrating vegetation functional heterogeneity and hydrological landscape conditions, therefore, offers a promising avenue to disentangle the spatial variability of photosynthetic moisture responses, which represents a key scientific issue that warrants in-depth systematic investigation.

Based on these considerations, this study integrates monthly satellite SIF products, ERA5-Land meteorological data, and vertically stratified soil moisture datasets covering China for the period 2000 to 2024. We first partitioned the study domain by dominant vegetation classes and nationwide hydroclimatic zones, then deployed a multi-method framework incorporating time-series trend diagnostics, lagged partial correlation, and interpretable XGBoost–SHAP machine learning. Centered on three core analytical dimensions—spatiotemporal SIF dynamics, lagged photosynthetic responses to moisture drivers, and divergent factor contributions across multi-source water variables—we systematically disentangled heterogeneous SIF responses of major vegetation types to atmospheric drought and layered soil moisture under contrasting hydroclimatic regimes. Three pivotal scientific questions are explicitly addressed herein: (1) Whether long-term SIF spatiotemporal trends (2000–2024) exhibit substantial disparities across China’s hydroclimatic zones and vegetation functional types; (2) How synchronous and lagged SIF sensitivities to VPD, precipitation, and vertically stratified soil moisture diverge among the four vegetation types within distinct hydroclimatic contexts; (3) Whether the relative contributions of atmospheric drought, precipitation supply, and multi-layer soil moisture profiles to SIF variability shift as a function of climatic background and vegetation category.

2. Materials and Methods

2.1. Study Area

China spans extensive territory coverage with striking spatial heterogeneity in hydrothermal conditions (Figure 1a). A continuous hydroclimatic gradient stretches from the humid monsoon region in the southeast to the arid inland basins in the northwest, accompanied by substantial spatial variations in atmospheric aridity and background soil moisture regimes. This unique geographical setting provides an ideal natural laboratory for exploring vegetation photosynthetic responses to diverse moisture environments. This study focuses on four nationally representative vegetation types, namely cropland, forest, grassland, and shrubland, as the core study objects (Figure 1b). Cropland represents an artificial vegetation type regulated by human cultivation, irrigation, and management, whereas forest, grassland, and shrubland represent the dominant natural vegetation types across regions. Collectively, these four vegetation types represent well the major terrestrial photosynthetic systems in China and can effectively reflect their divergent water-stress response characteristics.

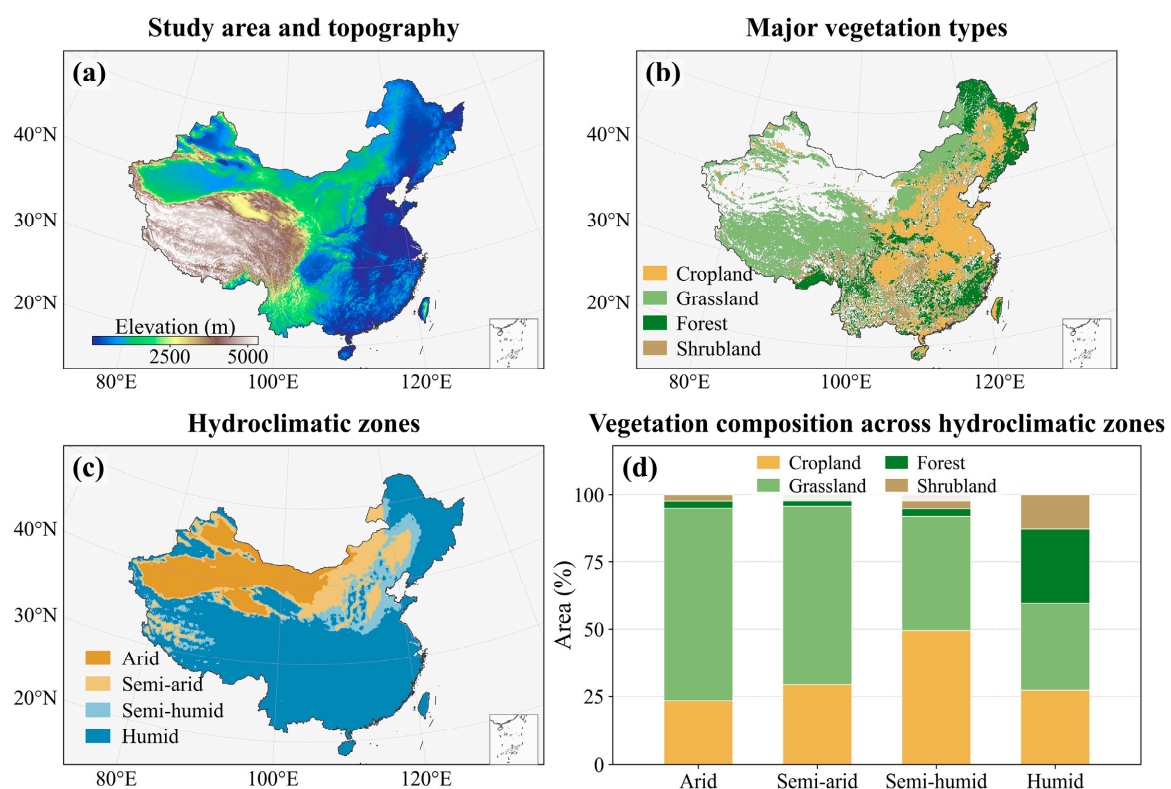


Figure 1. Study area, vegetation types, and hydroclimatic zones. (a) Location and topography of the study area. (b) Spatial distribution of cropland, grassland, forest, and shrubland. (c) Hydroclimatic zones, classified based on the aridity index. (d) Area proportions of vegetation types within each hydroclimatic zone. Hydroclimatic zones were classified using the aridity index (AI), defined as the ratio of precipitation to potential evapotranspiration. The arid, semi-arid, semi-humid, and humid zones correspond to $AI < 0.20$, $0.20 \leq AI < 0.50$, $0.50 \leq AI < 0.65$, and $AI \geq 0.65$, respectively.

To systematically disentangle how hydroclimatic backgrounds shape vegetation moisture response patterns, the entire study area was classified into four climatic zones (arid, semi-arid, semi-humid, and humid) based on the multiyear mean aridity index (Figure 1c). By spatially overlaying the vegetation distribution and hydroclimatic zoning datasets, we established integrated vegetation–hydroclimatic analytical units. This framework enables comparative analysis of SIF anomaly responses to moisture anomalies across different

vegetation types within identical hydroclimatic contexts and further characterizes the continuous shifts in vegetation photosynthetic moisture response patterns of the same vegetation type along the hydroclimatic gradient (Figure 1d).

2.2. Data

This study integrated monthly satellite SIF, ERA5-Land hydroclimatic variables, vegetation type data, and long-term aridity index data to construct a dataset for analyzing SIF moisture responses in cropland and typical natural vegetation across China from 2000 to 2024 (Table 1). All datasets used in this study are publicly available, and their data sources and access information are summarized in Table 1. SIF was used to characterize canopy photosynthesis; precipitation, VPD, and vertically stratified soil moisture were used to describe water input, atmospheric drought, and soil moisture conditions at different depths, respectively; and vegetation types and hydroclimatic zones were used for grouped comparisons.

Table 1. Overview of the research data sources.

Variable	Period	Spatial Resolution	Temporal Resolution	Source	Purpose
SIF	2000–2024	0.05°	Monthly	GOSIF (https://globalcogy.unh.edu/data/GOSIF.html , accessed on 10 February 2026)	Response variable
Precipitation, air temperature, dew-point temperature	2000–2024	0.1°	Monthly	ERA5-Land (https://cds.climate.copernicus.eu/ , accessed on 10 February 2026)	Hydroclimatic variables and VPD calculation
Soil moisture (0–289 cm)	2000–2024	0.1°	Monthly	ERA5-Land (https://cds.climate.copernicus.eu/ , accessed on 10 February 2026)	Vertically stratified soil moisture status
Vegetation type data (cropland/ grassland/ forest/shrubland)	Static	1 km	Static	Resource and Environment Science and Data Center, Chinese Academy of Sciences (https://www.resdc.cn/ , accessed on 10 February 2026)	Vegetation type classification
Aridity index	Static	0.05°	Static	National Earth System Science Data Center, China (https://www.geodata.cn/ , accessed on 10 February 2026)	Hydroclimatic zoning

2.2.1. Solar-Induced Chlorophyll Fluorescence Data

The monthly, spatially continuous Global OCO-2 solar-induced chlorophyll fluorescence product (GOSIF) from 2000 to 2024 was used to characterize vegetation photosynthetic dynamics. This product was developed from OCO-2 satellite SIF observations by integrating MODIS remote sensing variables and meteorological reanalysis datasets, enabling long-term, high-accuracy, and spatially continuous monitoring of global SIF dynamics. It is therefore suitable for investigating large-scale spatiotemporal changes in vegetation photosynthesis and their environmental responses [6]. Following the official scaling standard of the product, the raw GOSIF data were converted using the prescribed

scale factor to obtain SIF values with explicit physical meaning, expressed in $\text{W m}^{-2} \mu\text{m}^{-1} \text{sr}^{-1}$. To minimize interference from non-vegetated surfaces, we used the vegetation-type dataset as a land-cover mask. Only pixels classified as cropland, grassland, forest, or shrubland were retained. Water bodies, permanent snow and ice, bare land, built-up land, and other non-target land-cover classes were set to NoData, and the same mask was applied to the SIF and hydroclimatic datasets.

2.2.2. Soil Moisture Data

Soil moisture data were obtained from the monthly ERA5-Land reanalysis product [18]. ERA5-Land provides volumetric soil water content ($\text{m}^3 \text{m}^{-3}$) for four soil layers, corresponding to 0–7 cm, 7–28 cm, 28–100 cm, and 100–289 cm, respectively. In this study, soil moisture was grouped into shallow, middle, and deep layers to describe moisture conditions in the near-surface, middle, and deeper soil layers, respectively. Shallow soil moisture (SM_shallow) was calculated by weighting the 0–7 cm and 7–28 cm layers according to layer thickness, as follows:

$$\text{SM_shallow} = (7 \times \text{SM}_{0-7} + 21 \times \text{SM}_{7-28}) / 28 \quad (1)$$

Middle-layer soil moisture (SM_mid) corresponded to the 28–100 cm soil layer, whereas deep-layer soil moisture (SM_deep) corresponded to the 100–289 cm soil layer.

2.2.3. Precipitation, Temperature, and VPD Data

Monthly precipitation, air temperature, and dew-point temperature data were obtained from ERA5-Land [18]. Precipitation was used to represent external water input. Vapor pressure deficit (VPD) was calculated from monthly mean air temperature and monthly mean dew-point temperature and was used to characterize atmospheric dryness and atmospheric evaporative demand. The formula is as follows:

$$e_s(T) = 0.6108 \times \exp\left(\frac{17.27T}{T + 237.3}\right) \quad (2)$$

$$e_a(T_d) = 0.6108 \times \exp\left(\frac{17.27T_d}{T_d + 237.3}\right) \quad (3)$$

$$\text{VPD} = e_s(T) - e_a(T_d) \quad (4)$$

where T is monthly mean air temperature used to calculate VPD, T_d is monthly mean dew-point temperature, and $e_s(T)$ and $e_a(T_d)$ denote saturated vapor pressure and actual vapor pressure, respectively. In the equations, air temperature and dew-point temperature are expressed in $^{\circ}\text{C}$, and VPD is expressed in kPa.

2.2.4. Vegetation Type and Hydroclimatic Zoning Data

Vegetation type data were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences. Based on this product, four vegetation types, namely cropland, grassland, forest, and shrubland, were extracted. Cropland represents artificial vegetation regulated by human agricultural activities, whereas forest, grassland, and shrubland represent typical natural vegetation across regions, together forming two contrasting vegetation groups in this study.

Hydroclimatic zones were classified using the aridity index (AI), defined as the ratio of multiyear mean annual precipitation to multiyear mean annual potential evapotranspiration:

$$\text{AI} = \frac{P}{\text{PET}} \quad (5)$$

where P denotes multiyear mean annual precipitation, obtained from ERA5-Land. PET denotes multiyear mean annual potential evapotranspiration, obtained from the National Earth System Science Data Center, China. Because higher AI values indicate wetter moisture conditions, the study area was classified into four hydroclimatic zones using commonly adopted aridity index thresholds [19]: arid zone ($AI < 0.20$), semi-arid zone ($0.20 \leq AI < 0.50$), semi-humid zone ($0.50 \leq AI < 0.65$), and humid zone ($AI \geq 0.65$). The hydroclimatic classification was used to assess whether SIF responses to atmospheric drought and soil moisture varied with background water availability. In the stratified analysis, cropland, grassland, forest, and shrubland were overlaid with the four hydroclimatic zones to analyze differences in SIF responses among vegetation types under different background moisture conditions.

2.3. Methods

2.3.1. Time-Series Trend Analysis

Pixel-scale trends in SIF were estimated using the Theil–Sen method, and their statistical significance was assessed using the Mann–Kendall test [20,21]:

$$\beta = \text{median}\left(\frac{x_j - x_i}{j - i}\right), j > i \quad (6)$$

where β represents the trend in SIF, and x_i and x_j denote the SIF values at the i -th and j -th time points, respectively. When $\beta > 0$, SIF shows an increasing trend; when $\beta < 0$, SIF shows a decreasing trend.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (7)$$

$$\text{sgn}(x_j - x_i) = \begin{cases} 1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases} \quad (8)$$

Trend significance was determined based on the standardized statistic Z . When $|Z| > 1.96$, the trend was considered statistically significant at the 0.05 significance level. In this study, the Theil–Sen trend results were combined with the Mann–Kendall test results to identify regions with significantly increasing SIF, significantly decreasing SIF, and non-significant changes.

2.3.2. Response Analysis to Multiple Moisture Factors

Because SIF, precipitation, VPD, and soil moisture all exhibit pronounced seasonal cycles, direct analysis of raw monthly values may confound SIF–moisture relationships with shared seasonal variability. Therefore, monthly anomaly series were used, and two methods, lagged partial correlation and XGBoost–SHAP, were applied to analyze SIF responses to multiple moisture factors, with a focus on anomalies relative to normal seasonal conditions. For a given variable X , the anomaly was calculated as follows:

$$X'_{i,m,y} = X_{i,m,y} - \overline{X_{i,m}} \quad (9)$$

where $X'_{i,m,y}$ denotes the anomaly value of pixel (i) in year (y) and month (m), $X_{i,m,y}$ is the corresponding monthly value, and $\overline{X_{i,m}}$ represents the multiyear mean for the same month at that pixel. The SIF anomaly represents the deviation from the normal seasonal level for the same month. Multiple moisture factors, including precipitation anomaly (P), VPD anomaly, shallow soil moisture anomaly (SM_shallow), middle-layer soil moisture anomaly (SM_mid), and deep-layer soil moisture anomaly (SM_deep), represent deviations

of the corresponding environmental conditions from their multiyear mean states for the same month.

Lagged partial correlation analysis was used to examine the responses of SIF anomalies to multiple moisture factors at lag times of 0–3 months [22]. Because precipitation, VPD, and soil moisture are physically interdependent, the partial-correlation results should be interpreted as conditional statistical associations rather than strict causal effects. The 0–3-month lag window was selected to capture immediate atmospheric effects, short-term precipitation and shallow soil moisture responses, and medium-term memory effects of middle- and deep-layer soil moisture, while maintaining sufficient monthly samples and limiting excessive autocorrelation from longer lags. For each target moisture variable, the partial correlation between the current-month SIF anomaly and the anomaly of that variable at the concurrent month and at lags of 1–3 months was calculated, while controlling for the other moisture factors at the same lag time.

Let Y_t denote the current-month SIF anomaly as the response variable, $X_{k,t-l}$ denote the target environmental variable lagged by l months, and $Z_{k,t-l}$ denote the set of control variables at the same lag, where ($l = 0, 1, 2, 3$). Partial correlation coefficients were calculated using the residual-correlation method:

$$r_{Y_t X_{k,t-l} \cdot Z_{k,t-l}} = \text{corr}(e_{Y_t}, e_{X_{k,t-l}}) \quad (10)$$

where $r_{Y_t X_{k,t-l} \cdot Z_{k,t-l}}$ denotes the partial correlation coefficient between the SIF anomaly and the anomaly of the target variable after controlling for the remaining moisture factors. e_{Y_t} and $e_{X_{k,t-l}}$ are the residuals obtained by regressing the response variable and the target variable against the control variables, respectively. Lag times of 1, 2, and 3 months represent the relationships between moisture-factor anomalies in the previous 1, 2, and 3 months and the current-month SIF anomaly, respectively.

To jointly account for the spatial extent and strength of the correlations, a lag-selection index was constructed as follows:

$$\text{Score}_{k,l} = A_{\text{sig},k,l} \times |\bar{r}|_{\text{sig},k,l} \quad (11)$$

where $A_{\text{sig},k,l}$ denotes the area proportion of pixels showing significant correlations for variable k at lag l , and $|\bar{r}|_{\text{sig},k,l}$ denotes the mean absolute partial correlation coefficient across significant pixels. For each variable, the lag month with the highest score among lag times of 0–3 months was selected as the optimal lag month.

On this basis, the dominant moisture factor for SIF anomalies was further identified at the pixel scale. The candidate factors included precipitation anomaly (P), VPD anomaly, shallow soil moisture anomaly (SM_shallow), middle-layer soil moisture anomaly (SM_mid), and deep-layer soil moisture anomaly (SM_deep). For each pixel, significant partial-correlation results corresponding to the optimal lag of each moisture factor were extracted ($p < 0.05$). The factor with the largest absolute partial correlation coefficient was identified as the dominant moisture factor for that pixel, and its optimal lag, relationship direction, and partial-correlation strength were recorded.

2.3.3. XGBoost–SHAP Analysis

To identify the nonlinear contribution structure of different moisture factors to SIF anomalies, an XGBoost regression model was constructed, and the SHAP method was used to quantify the relative contributions of variables [23,24]. The model used monthly SIF anomalies as the response variable and air temperature anomalies as the thermal background variable. Precipitation anomaly (P), VPD anomaly, shallow soil moisture anomaly (SM_shallow), middle-layer soil moisture anomaly (SM_mid), and deep-layer soil

moisture anomaly (SM_deep) at the concurrent month and at lags of 1–3 months were used as moisture explanatory variables. Models were built separately at the national scale, the vegetation-type scale, and the combined vegetation type $\times$ hydroclimatic zone scale. The sampling unit for the XGBoost model was a pixel-month observation, and each sample included the SIF anomaly and the corresponding concurrent and lagged hydroclimatic explanatory variables. All monthly observations from 2000 to 2024 were pooled to construct the full sample set, rather than building separate subsets for individual months. The dataset was then divided into training and testing subsets at a ratio of 70:30. To reduce the risk of overestimating model performance, the split was applied to the full pooled dataset while maintaining the overall distribution of samples across years, months, vegetation types, and hydroclimatic zones. The same sampling and splitting strategy were applied to the national, vegetation-type, and vegetation type $\times$ hydroclimatic zone models. The candidate ranges and selected values of the main XGBoost hyperparameters are provided in Table S1. Model performance was evaluated using RMSE and R^2 , and the performance metrics of all XGBoost models are reported in Table S2. Because spatially adjacent pixels and temporally adjacent months may not be fully independent in the pooled pixel-month samples, these performance metrics were used primarily as diagnostic indicators for model fitting and SHAP-based attribution, rather than as strict evidence of fully independent spatial prediction:

$$y_i = \sum_{k=1}^K f(x_i), f_k \in F \quad (12)$$

where y_i is the predicted value for sample i , x_i is the set of explanatory variables, f_k is the k -th regression tree, K is the number of trees, and F is the function space composed of all regression trees.

The SHAP method was used to interpret the contributions of different variables to model predictions. For sample i , the model output can be decomposed as follows:

$$f(x_i) = E[f(x)] + \sum_{j=1}^p \phi_{ij} \quad (13)$$

where $f(x_i)$ is the model prediction for sample i , $E[f(x)]$ is the mean model prediction, ϕ_{ij} is the SHAP value of variable j for the prediction of sample i , and p is the number of explanatory variables. A positive SHAP value indicates that the variable increases SIF relative to the mean model state, whereas a negative SHAP value indicates that the variable decreases SIF relative to the mean model state. The mean absolute SHAP value was used to quantify the overall contribution of each variable to the model output.

3. Results

3.1. Spatiotemporal Patterns of SIF Across Vegetation Types and Hydroclimatic Backgrounds

Monthly SIF climatology exhibited distinct seasonal variability at both the national scale and among the four vegetation types (Figure 2a). SIF remained relatively low throughout winter and early spring, increased rapidly during the growing season, and peaked in summer. The magnitude of such intra-annual seasonal fluctuations differed among vegetation types. Forest and shrubland maintained relatively high SIF levels during the peak growing season, while cropland exhibited a sharp summer SIF rise that corresponded to their annual maximum. By contrast, grassland showed both lower SIF levels and a weaker seasonal amplitude. Regarding peak phenology, national-scale SIF, together with forest and shrubland SIF, mainly peaked in July, whereas the cropland peak was slightly delayed to August. These results indicate that vegetation types diverge considerably in

both multiyear mean photosynthetic intensity and intra-annual phenological and seasonal photosynthetic dynamics.

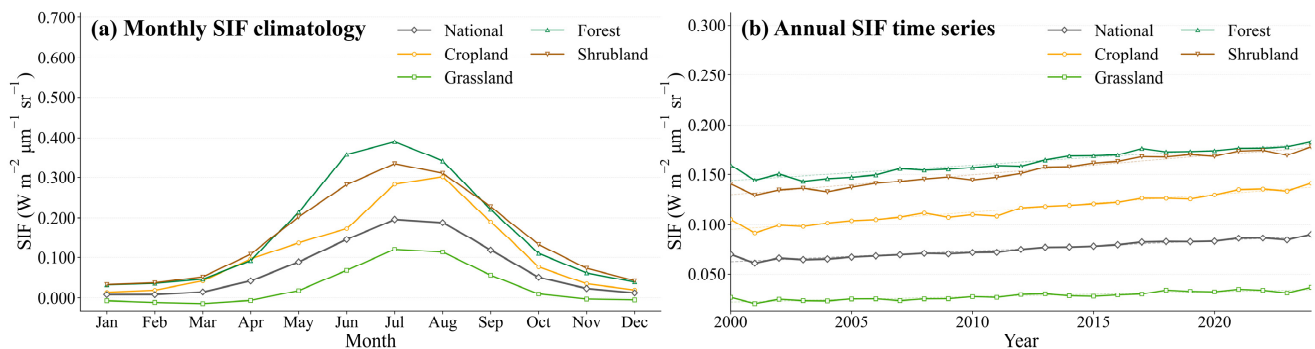


Figure 2. Climatology (a) and interannual variation (b) of SIF at the national scale and across major vegetation types from 2000 to 2024.

The interannual analysis showed a widespread increase in national-scale SIF across all four vegetation types from 2000 to 2024 (Figure 2b). Forest and shrubland exhibited the highest multiyear mean SIF values, followed by cropland, while grasslands showed the lowest baseline SIF levels. The magnitude of long-term SIF trends also differed substantially among vegetation functional types. Cropland, forest, and shrubland had pronounced increasing SIF trends, whereas grassland displayed a milder upward trend, accompanied by lower baseline magnitudes and weaker temporal variability. Collectively, these indicate that the SIF of terrestrial vegetation in China has generally strengthened over the past 25 years, with distinct inter-type disparities in both SIF baseline levels and long-term growth rates driven by inherent vegetation traits.

The spatial pattern of multiyear mean SIF showed a clear southeast–northwest gradient, with consistently high values in southeastern regions and low values in the northwest (Figure 3a). High-SIF areas were mainly concentrated in the humid and semi-humid zones, whereas low-SIF regions were primarily distributed across the arid and semi-arid regions. Vegetation-type statistics comparisons further confirmed that forest had the highest multi-year mean SIF, followed by shrubland and cropland, while grassland maintained the lowest photosynthetic baseline (Figure 3b). Such pronounced spatial differentiation is jointly shaped by the inherent photosynthetic capacity of different vegetation types and the spatial heterogeneity in regional water availability. This pattern underscores the necessity of accounting for vegetation-specific photosynthetic baselines when attributing SIF variability to moisture perturbations.

From 2000 to 2024, the areas with significant SIF increasing trends were mainly concentrated in eastern and southern China, mainly covering the semi-humid to humid hydro-climatic zones (Figure 3c). In contrast, arid and semi-arid regions of northwestern China exhibited weaker and mostly non-significant SIF enhancements. Vegetation type statistics analysis showed consistent positive interannual SIF trends for all four vegetation categories, with distinct disparities in trend magnitudes (Figure 3d). Forest and shrubland showed the highest rates of SIF increase, whereas cropland maintained a stable upward trend and grassland exhibited the weakest increase. These observations reveal that SIF enhancement constitutes a national-scale characteristic of vegetation photosynthetic dynamics in China, while its growth intensity is strongly vegetation-dependent.

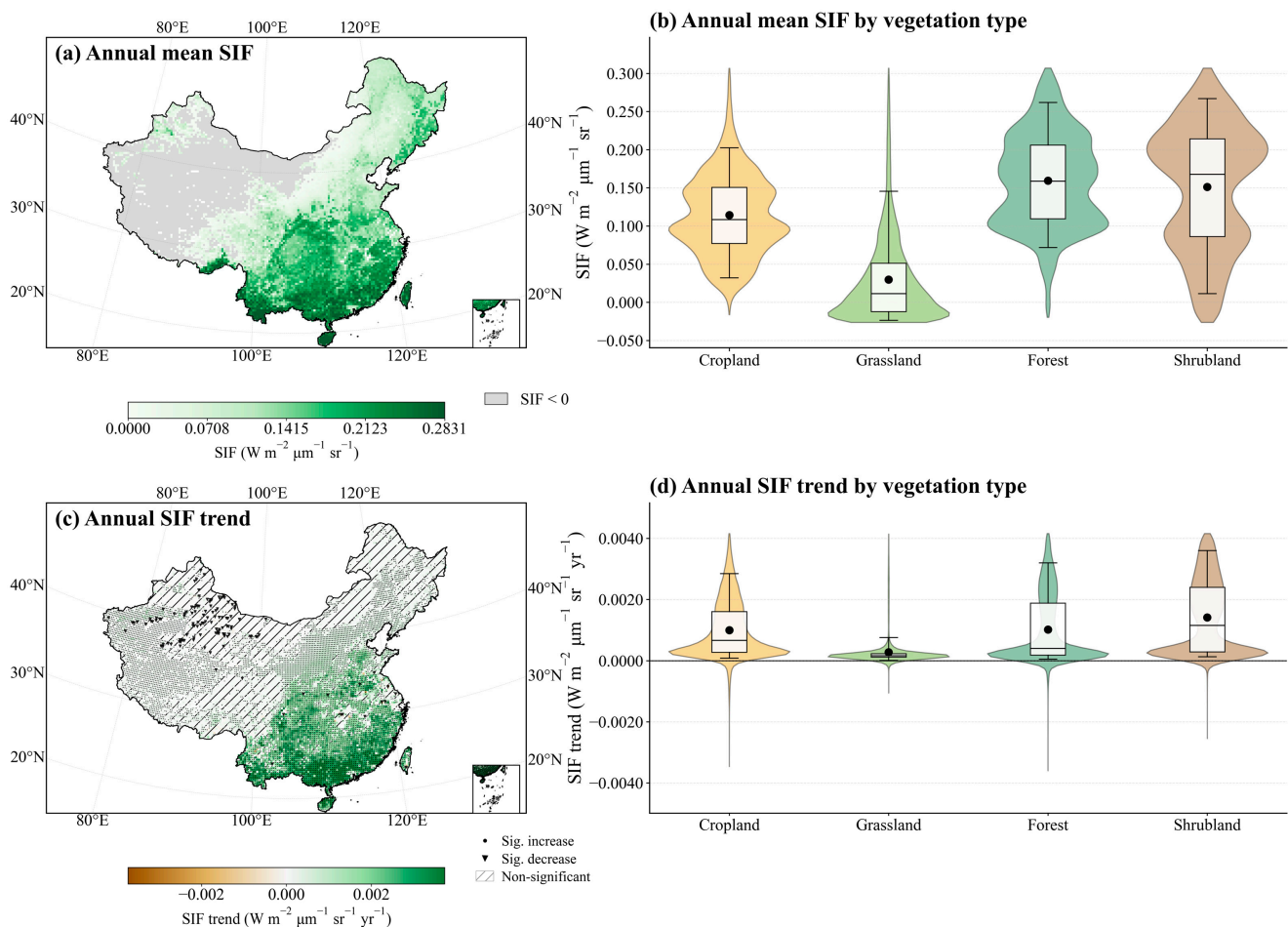


Figure 3. Spatial patterns of annual mean SIF and its trend from 2000 to 2024.

Zonal statistics highlighted the coupled control of hydroclimatic background and vegetation type on SIF spatiotemporal dynamics. For multiyear mean SIF values, all vegetation types exhibited a consistent increasing trend along the arid-to-humid hydroclimatic gradient (Figure 4a), suggesting that background water availability serves as a fundamental environmental driver modulating regional vegetation photosynthetic capacity. Interannual SIF trends followed a similar hydroclimatic gradient, with wetter zones exhibiting more pronounced long-term SIF enhancements (Figure 4b). However, substantial inter-vegetation variability in trend magnitude was observed across climatic gradients. Specifically, forest and shrubland in humid zones maintained high SIF baselines, while shrubland and cropland showed pronounced SIF growth rates. By contrast, grassland consistently exhibited the lowest multiyear mean SIF and the weakest temporal trends across all four hydroclimatic zones. Collectively, these findings indicate that the spatial patterns and long-term dynamics of vegetation SIF over the past 25 years cannot be solely attributed to hydroclimatic conditions; vegetation-specific inherent properties also substantially shape divergent photosynthetic performances across ecosystems.

3.2. Lagged Responses of SIF Anomalies to Multiple Moisture Drivers

Lagged partial correlation analysis was used to quantify the temporal linkages between diverse moisture variables and monthly SIF anomalies, by comparing optimal response lags spanning 0–3 months for atmospheric drought, precipitation, and vertically stratified soil moisture (Figure 5). At the national scale, SIF anomalies exhibited stronger correlations with same-month or 1-month lagged moisture anomalies; precipitation and shallow soil moisture displayed consistent 1-month lagged signals, a pattern replicated across all

vegetation functional types. Croplands, grasslands, forests, and shrublands uniformly showed dominant 1-month lagged SIF responses to precipitation and topsoil moisture, demonstrating that photosynthetic anomalies are tightly coupled with recent water inputs and near-surface soil water status.

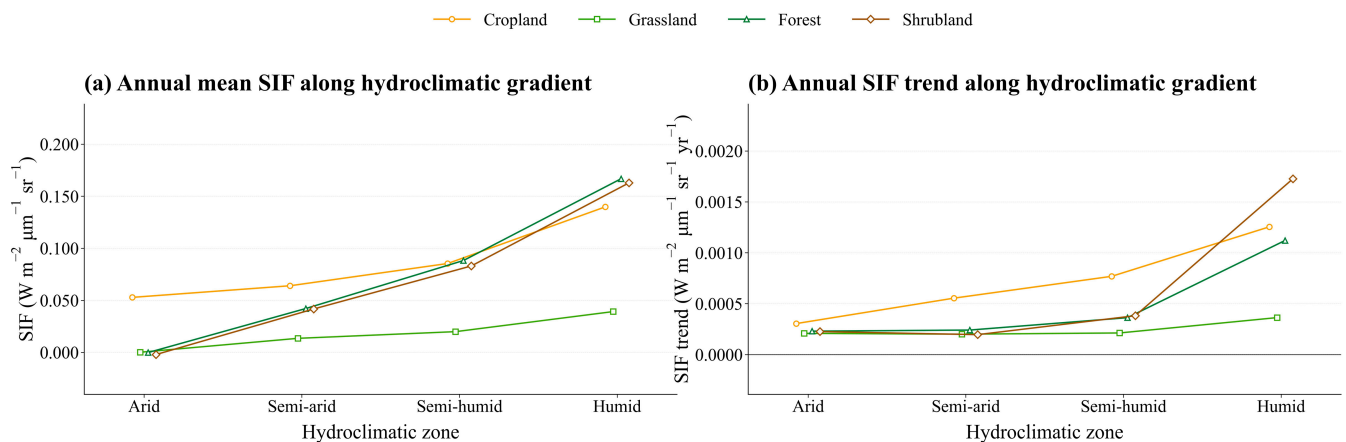


Figure 4. Differences in annual mean SIF and its rate of change among vegetation types and hydroclimatic zones.

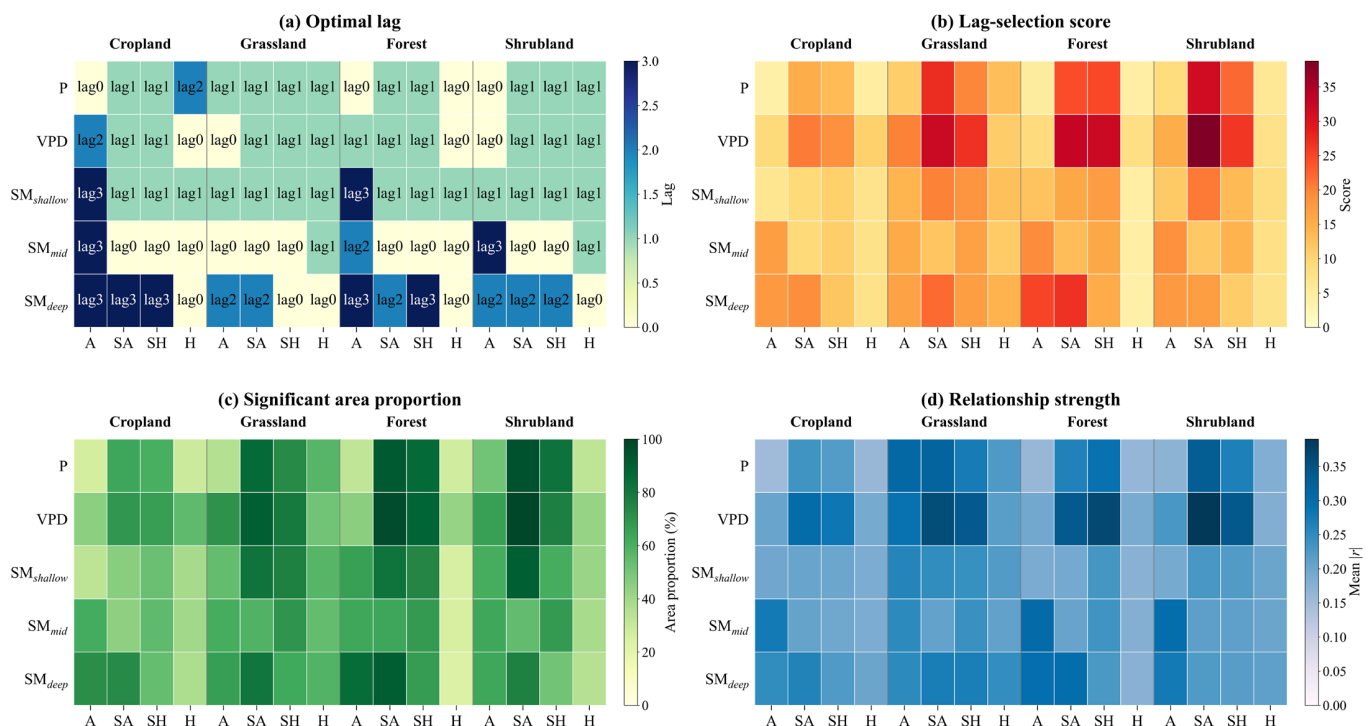


Figure 5. Temporal responses of SIF anomalies to moisture factors across vegetation–hydroclimatic combinations. (a) Optimal response time, including concurrent response and 1–3-month lagged responses. (b) Lag-selection score. (c) Proportion of pixels with significant partial correlations. (d) Mean absolute partial correlation in significant pixels. A, SA, SH, and H denote arid, semi-arid, semi-humid, and humid zones, respectively.

Distinct lag structures were further detected across vegetation types within identical hydroclimatic zones. In the arid zone, cropland SIF anomalies responded to both mid-layer and deep soil moisture with a 3-month lag; forest SIF presented consistent 3-month lags for shallow and deep soil moisture, while shrubland SIF variations were governed by a 3-month lag response to mid-layer soil moisture. In contrast, grassland SIF anomalies

correlated primarily with concurrent, or 1-month lagged moisture signals, with only deep soil moisture triggering a 2-month delayed response. These outcomes reveal that prolonged 3-month lagged signals in arid zones are restricted to mid and deep soil moisture for particular vegetation categories, rather than representing a universal ecosystem response.

Within the semi-arid and semi-humid zones, SIF anomalies of all four vegetation types shared consistent 1-month lagged responses to VPD, reflecting uniform temporal sensitivity to atmospheric dryness. However, vegetation-specific disparities persisted in lagged responses to deep soil moisture. In the semi-arid zone, cropland SIF anomalies exhibited a 3-month lag to deep soil moisture, whereas grasslands, forests, and shrublands showed 2-month lags. For the semi-humid zone, cropland and forest SIF anomalies retained a 3-month lagged response to deep-layer soil moisture, shrubland showed a 2-month lag, and grassland SIF co-varied synchronously with deep soil moisture. Collectively, these suggest that while VPD-driven lagged responses remain stable across vegetation types under semi-arid and semi-humid climates, delayed photosynthetic reactions to deep soil moisture are strongly contingent on vegetation functional traits.

In the humid zone, SIF anomalies were predominantly synchronized with or lagged by one month behind all moisture variables. Humid cropland SIF co-varied concurrently with VPD, mid-layer and deep soil moisture; forest SIF tracked all moisture drivers synchronously except shallow soil moisture, which induced a 1-month lagged signal. Grasslands and shrublands in humid zones also displayed mostly synchronous or 1-month lagged correlations with moisture factors. Relative to arid, semi-arid, and semi-humid counterparts, humid zones featured drastically diminished 2–3-month lag signals, confirming that photosynthetic fluctuations under wet background conditions are closely tied to contemporary and short-term water supply.

Across the full hydroclimatic gradient, the lag durations of SIF responses to mid and deep soil moisture progressively shortened as regional background wetness increased. For croplands and forests, deep-soil-moisture lags contracted from three months in arid/semi-arid zones to synchronous coupling in humid zones. Grassland SIF anomalies generally maintained synchronous or 1-month lagged responses to most moisture factors, with extended lags only emerging for deep soil moisture within arid and semi-arid regions. Shrubland response to mid-layer soil moisture shifted from a 3-month lag in the arid zone to a 1-month lag in the humid zone, while deep-soil-moisture lags declined from two months (arid/semi-arid) to synchronous covariation under humid climates. Overall, prolonged 2–3-month lags exclusively arose from SIF responses to mid and deep soil moisture and were constrained to specific vegetation–climate combinations. By contrast, SIF responses to precipitation, VPD, and shallow-layer soil moisture were universally dominated by synchronous or 1-month-lagged effects.

Comparisons of the fractional area of significant correlations and mean correlation magnitudes further indicated that lag length alone cannot fully quantify response sensitivity. Semi-arid and semi-humid zones exhibited extensive significant spatial coverage for VPD, precipitation, and deep soil moisture; by contrast, humid zones saw a general reduction in significant pixel fractions for all moisture variables. Even for a single moisture driver, absolute correlation magnitudes $|r|$ varied widely across vegetation–hydroclimatic combinations. Overall, the lagged responses of SIF anomalies to moisture factors exhibited triple dimensional differentiation among moisture factors, vegetation types, and hydroclimatic backgrounds. Extended 2–3-month lags mainly capture delayed photosynthetic reactions to subsurface soil moisture under specific climatic and vegetation conditions, rather than constituting an ubiquitous water-response regime.

3.3. Differentiation of Dominant Moisture Factors Across Vegetation Types Under Different Hydroclimatic Backgrounds

After determining the optimal lag window for each moisture factor, we further pinpointed the primary moisture driver governing SIF anomalies at the pixel scale based on the magnitude of partial correlation coefficients, thereby mapping the spatial dominance patterns of individual moisture predictors (Figure 6). Nationwide statistics revealed that VPD constituted the most widespread dominant driver, explaining 42% of the total area. Precipitation and deep-layer soil moisture ranked second, each accounting for nearly 18%, whereas shallow and middle-layer soil moisture occupied far smaller dominant fractions. Vegetation-specific statistics breakdowns showed that VPD ranked as the leading moisture constraint for SIF anomalies in all four vegetation types, yet it was the dominant-factor structure. For croplands, VPD dominated 48% of pixels, with deep soil moisture contributing an additional 24%. Grasslands displayed balanced multi-factor regulation: VPD accounted for 35%, while precipitation and deep-layer soil moisture each contributed 23% and 24%, respectively. Forests were primarily constrained by VPD (40%), with precipitation and deep soil moisture occupying substantially smaller dominant areas. In shrublands, VPD only dominated 26% of the landscape, whereas precipitation and multi-layer soil moisture collectively accounted for comparable fractional coverage. Collectively, VPD exerted pan-regional control over terrestrial SIF anomalies variability nationwide, yet the magnitude of its dominance varied substantially among vegetation communities.

Within the arid zone, the dominant moisture sources of SIF fluctuations exhibited strong heterogeneity among the four vegetation types. Cropland photosynthetic anomalies were jointly governed by mid-layer (33.4%) and deep-layer soil moisture (32.4%). Grasslands were predominantly limited by VPD, which dominated 32.7% of the area. Forests relied heavily on deep soil moisture (38.6%), while shrubland SIF dynamics were controlled chiefly by mid-layer soil moisture (43.9%). These observations demonstrate that vegetation photosynthetic variability in arid landscapes is not universally constrained by atmospheric drought; instead, vegetation functional traits drive distinct vertical rooting dependencies on stratified soil water reservoirs.

Semi-arid and semi-humid zones were characterized by pervasive VPD dominance over SIF anomalies, although with vegetation-specific disparities in driver composition. In the semi-arid zone, VPD acted as the primary limiting factor for all four vegetation types. Shrublands featured the largest VPD-dominated fraction (75.5%), followed by forests (60.5%) and grasslands (56.4%), while croplands held a relatively lower proportion (46.7%). Mid and deep soil moisture still represented substantial secondary regulators for croplands (36.4%) and forests (33.1%), respectively. The semi-humid zone retained a VPD-centered regulatory framework: forests exhibited the highest VPD-dominated coverage (74.3%), grasslands and shrublands both reached approximately 60%, and croplands stood at 52.5%. Nevertheless, mid and deep soil moisture remained prominent secondary drivers for croplands and grasslands. These results illustrate that semi-arid and semi-humid climates substantially expand the spatial footprint of VPD limitation on photosynthesis, while the intensity of VPD control and the relative importance of secondary soil moisture predictors remain contingent on vegetation type.

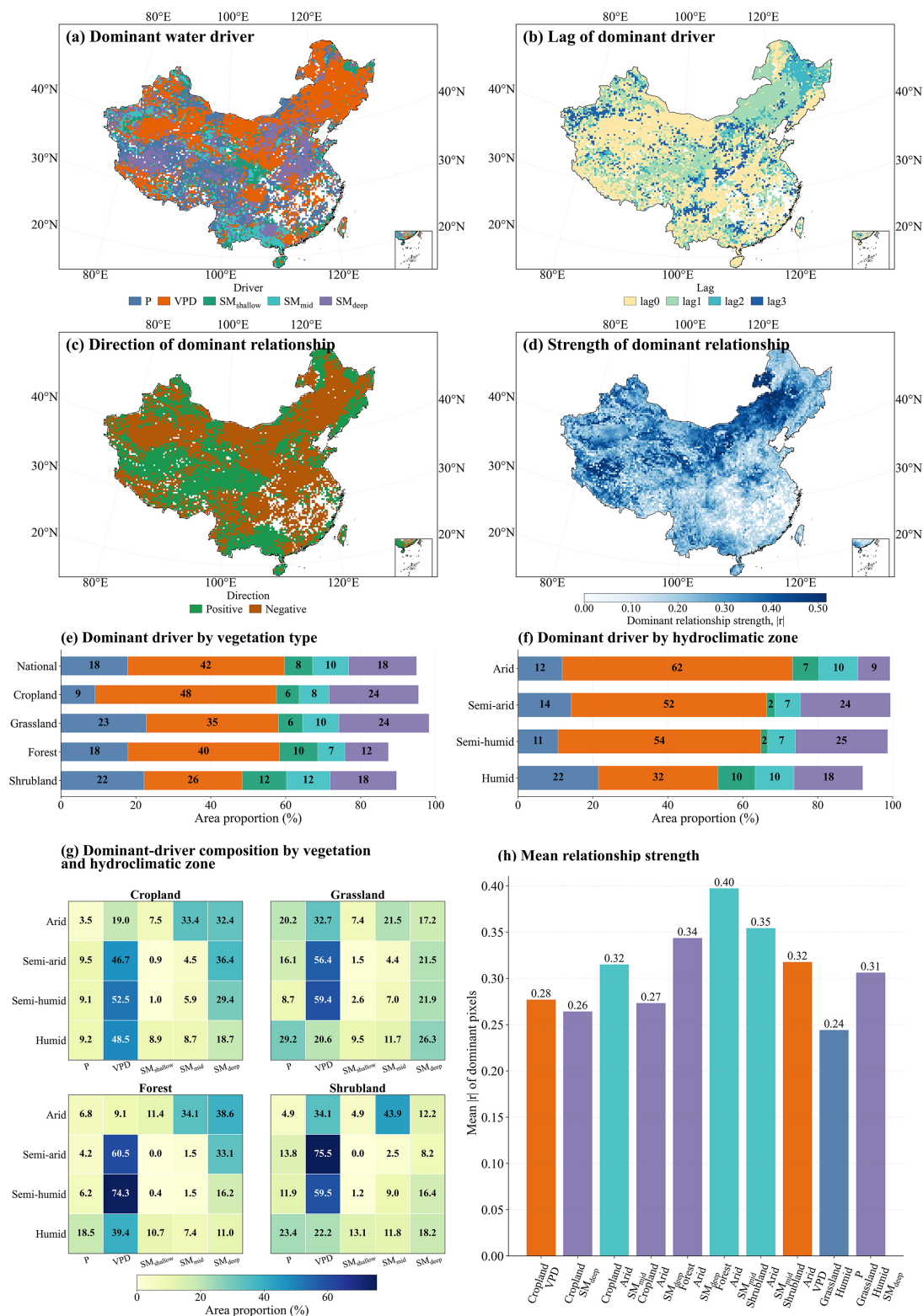


Figure 6. Dominant moisture factors and response characteristics of vegetation SIF anomalies in China. (a) Spatial distribution of the dominant moisture factor. (b) Response time of the dominant moisture factor. (c) Direction of the dominant relationship. (d) Strength of the dominant relationship. (e) Dominant factor composition by vegetation type. (f) Dominant factor composition by hydroclimatic zone. (g) Dominant factor composition across vegetation–hydroclimatic groups. (h) Relationship strength in selected vegetation–hydroclimatic groups. Note: Panels (e,f) use the same color scheme as panel (a) to denote P, VPD, SM_{shallow}, SM_{mid}, and SM_{deep}.

The humid zone again exhibited pronounced vegetation divergence in the dominant drivers of SIF anomalies. Croplands and forests remained primarily dominated by VPD, accounting for 48.5% and 39.4% of their respective spatial extents. In contrast, grassland and shrubland shifted their respective spatial extents. Humid grassland displayed nearly balanced regulation by precipitation (29.2%) and deep soil moisture (26.3%). For humid shrubland, precipitation, VPD, and deep soil moisture exerted comparable regulatory effects, contributing 23.4%, 22.2%, and 18.2% of dominant pixels separately. Such patterns indicate that humid conditions disperse the dominance of individual moisture variables, and inter-vegetation differences in photosynthetic sensitivity manifest through redistributed regulatory weights across atmospheric, surface, and subsurface water pools.

Across the full arid-to-humid hydroclimatic gradient, each vegetation type underwent systematic shifts in the primary moisture driver shaping SIF variability. Croplands shifted from mid/deep soil moisture limitation in the arid zone to VPD dominance across semi-arid, semi-humid, and humid zones, although deep soil moisture retained substantial secondary regulatory power in semi-arid and semi-humid cropland ecosystems. Grasslands were constrained primarily by VPD from the arid to semi-humid climates, before shifting to precipitation limitation under humid conditions. Forests shifted from deep soil moisture dominance in the arid zone to consistent VPD dominance in the wetter hydroclimatic zones. Shrublands evolved from mid-layer soil moisture limitation in arid regions to VPD dominance in semi-arid and semi-humid zones, with precipitation gaining slightly greater regulatory weight under humid backgrounds. Overall, regional hydroclimatic conditions reorganize the hierarchical regulatory structure of moisture drivers for vegetation photosynthetic activity by modulating the relative importance of atmospheric evaporative demand, precipitation water supply, and vertically stratified soil moisture reservoirs.

3.4. Contributions of Moisture Drivers and Lag Effects Across Vegetation–Hydroclimatic Regimes

After identifying the optimal lag for each moisture variable, pixel-wise partial correlations only mapped the spatial dominant driver of SIF anomalies yet failed to quantify the independent relative contribution of each moisture variable under multi-factor co-regulation. Thus, we adopted the XGBoost–SHAP interpretable machine learning framework to disentangle the relative contributions of VPD, precipitation, and vertically stratified soil moisture, and further partitioned soil moisture contributions by synchronous and 1–3 month lagged signals (Figures 7 and 8).

Nationwide and vegetation-averaged results revealed VPD as the top contributor to SIF variability (Figure 7a). At the national scale, VPD explained 31.8% of SIF anomalies, exceeding precipitation (24.9%), topsoil soil moisture (19.0%), and the combined contribution of mid and deep soil moisture (24.3%). Among the four vegetation types, VPD exerted the strongest control over grasslands (43.3%), followed by cropland (32.5%), shrubland (30.4%), and forest (27.5%). This confirms VPD as a universal key regulator of photosynthetic fluctuations, despite substantial inter-vegetation disparities in its explanatory power. Stratified soil moisture contributions also diverged by vegetation: shallow soil moisture mattered most for croplands and forests; mid and deep soil moisture contributed equally to shrublands; for grasslands, all soil layers exerted weaker effects than VPD and precipitation, implying grassland photosynthesis is primarily governed by atmospheric aridity and rainfall.

Within identical hydroclimatic background, vegetation types displayed clear differences in total moisture factor contributions, dominant soil depth layers, and lagged signal sources (Figures 7b and 8). Figure 7b illustrates aggregate factor contributions, while Figure 8 quantifies how shallow, mid, and deep soil moisture effects partition across syn-

chronous and 1–3 month lagged time windows, pinpointing the critical lag periods for subsurface water regulation.

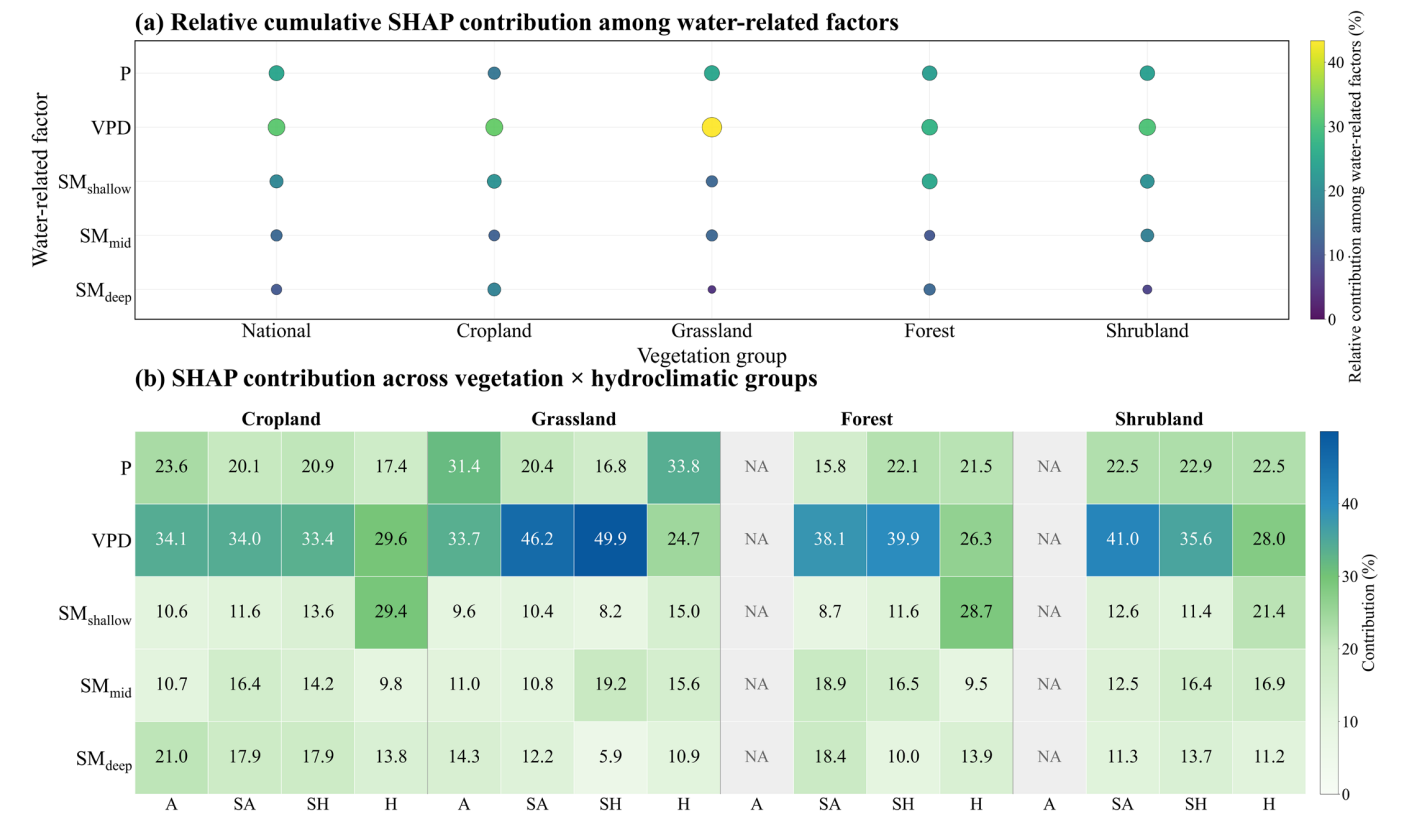


Figure 7. Contributions of moisture factors under different vegetation–hydroclimatic backgrounds. (a) SHAP contributions of moisture factors at the national and vegetation-type levels. (b) SHAP contributions of moisture factors across vegetation–hydroclimatic groups. A, SA, SH, and H denote arid, semi-arid, semi-humid, and humid zones, respectively.

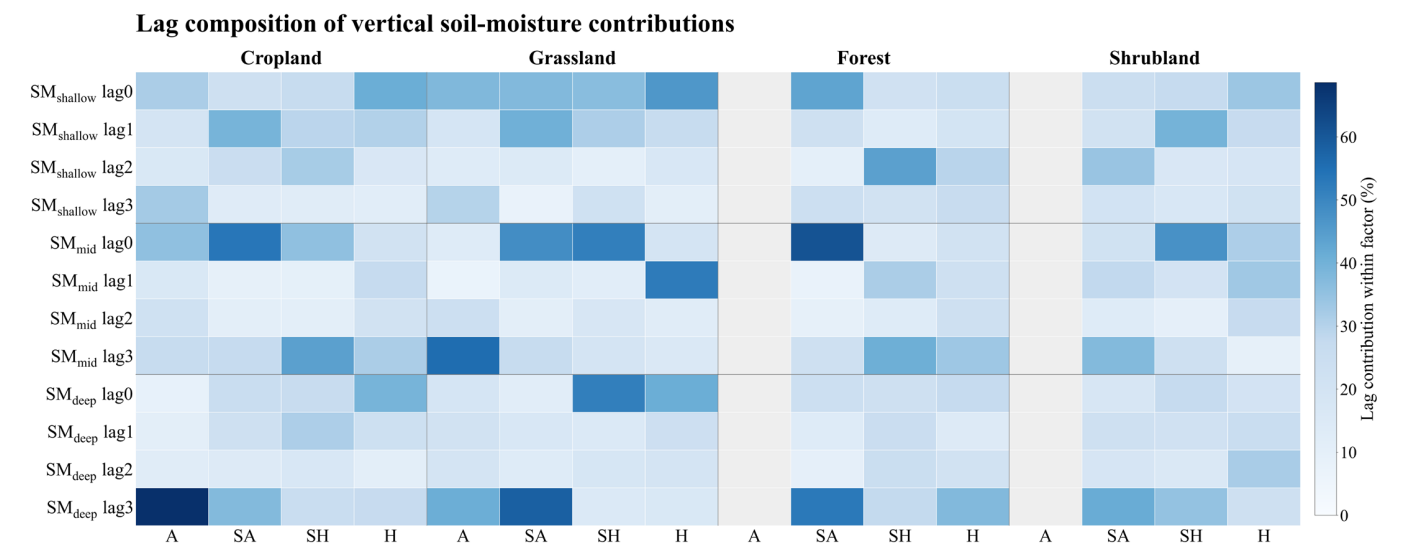


Figure 8. Lagged contributions of moisture factors across vegetation–hydroclimatic combinations.

Arid zone: Vegetation exhibited highly divergent moisture contribution profiles. VPD led SIF variability for croplands and grasslands, yet secondary water constraints differed sharply. Grasslands relied heavily on precipitation (31.4%), whereas croplands were sen-

sitive to deep soil moisture (21.0%) with a dominant 3-month lag signal. Semi-arid zone: VPD dominated all four vegetation types but with variable explanatory magnitudes; grasslands (46.2%) and shrublands (41.0%) showed stronger VPD control than forests (38.1%) and croplands (34.0%). The primary soil moisture layer also differed: forests responded most to mid-layer soil moisture, while croplands depended on 3-month lagged deep soil moisture. Semi-humid zone: VPD remained the leading driver overall, with the largest share for grasslands (49.9%), followed by forests, shrublands, and croplands. Cropland SIF anomalies were mainly controlled by 1-month lagged deep soil moisture. Grasslands, forests, and shrublands were regulated by mid-layer soil moisture, whose effect on forests stemmed largely from 3-month lagged signals. Humid zone: Vegetation divergence in moisture contribution structures reached its maximum with clear driver shifts. For cropland, there was nearly balanced control by VPD (29.6%) and shallow soil moisture (29.4%). For grasslands, precipitation became the primary driver (33.8%) via a 1-month lag. For forests, shallow soil moisture dominated (28.7%), mainly through 2-month lag signals. For shrubland, VPD remained the top factor (28.0%), yet precipitation (22.5%) and shallow soil moisture (21.4%) gained comparable weights, forming a balanced multi-water-source regulatory framework. Collectively, inherent vegetation functional traits determine the primary limiting moisture variable, critical soil depth layers, and dominant lag windows of photosynthetic variability under fixed hydroclimatic backgrounds, generating ecosystem-specific water response strategies.

Along the arid–humid hydroclimatic gradient, each vegetation type followed distinct transition trajectories in moisture contribution structures. For croplands, VPD consistently ranked first across all zones, yet the combined contribution of three soil layers always surpassed VPD, highlighting persistent subsurface water regulation. The dominant soil layer shifted from deep soil moisture (arid, semi-arid, semi-humid) to shallow soil moisture (humid), with lag signals evolving from 3-month deep soil moisture lags (arid/semi-arid) to 1-month deep soil moisture lags (semi-humid). In grasslands, VPD dominated from arid to semi-humid zones, before precipitation (1-month lag) became the leading driver under humid conditions. For forest, VPD prevailed in semi-arid and semi-humid zones, whereas shallow soil moisture with a 2-month lag governed SIF variability in humid regions. In shrubland, VPD maintained the highest contribution in semi-arid, semi-humid, and humid zones. As climate became wetter, explanatory gaps between VPD, precipitation, and shallow soil moisture narrowed, yielding a more evenly distributed moisture regulatory structure.

In summary, hydroclimatic regimes and vegetation functional types jointly shape the relative contribution of moisture variables to SIF anomalies. Hydroclimatic gradients reshape the weights of atmospheric evaporative demand, rainfall supply, and layered soil moisture, while vegetation traits further differentiate the dominant soil layers and their lagged response windows. No universal moisture response regime exists across vegetation–climate combinations; instead, atmospheric water demand, precipitation, and vertically stratified soil moisture collectively form heterogeneous contribution patterns.

4. Discussion

4.1. VPD Constraints on SIF Anomalies and Environmental Boundary Conditions

VPD was identified as a key nationwide driver of SIF anomalies, demonstrating that atmospheric drought serves as a core constraint on terrestrial photosynthetic variability across China. Elevated VPD intensifies canopy–atmosphere vapor gradients and increases transpiration loss, triggering stomatal closure, restricting intercellular CO₂ supply, and ultimately suppressing photosynthetic carbon assimilation [1,25,26]. Leaf-level canopy-scale studies have confirmed that VPD modulates stomatal dynamics, transpiration, and

water-use efficiency to directly regulate photosynthetic performance [27]. Given that SIF reliably tracks canopy photosynthetic electron transport and functional activity [2,3], the pervasive VPD dominance in our results reflects widespread physiological limitations of atmospheric drought on vegetation photosynthesis.

VPD exerted the most consistent and robust control over SIF anomalies in semi-arid and semi-humid transitional climates across grasslands, forests, and shrublands. These transitional zones feature coexisting moderate soil water availability and strong atmospheric evaporative demand, where atmospheric aridity fluctuates prior to or concurrently with soil water deficits, thereby regulating photosynthetic dynamics via stomatal and transpiration adjustments. Consistent with previous flux observations, high VPD and soil water deficit exert non-equivalent stress effects on ecosystem productivity, with their relative importance modulated by climate and vegetation type [28]. Semi-arid field experiments further support that post-precipitation VPD elevation substantially reduces ecosystem productivity and water-use efficiency [29], aligning well with our finding of prevailing VPD limitation in hydroclimatic transition zones.

Notably, VPD dominance exhibits distinct environmental and vegetation-specific boundaries rather than representing a universal regulatory pattern. In humid grasslands and forests, precipitation and shallow soil moisture replaced VPD as the primary drivers of SIF variability, while arid croplands, forests, and shrublands relied heavily on mid- and deep-layer soil moisture. These divergent responses highlight that photosynthetic variability is governed by the dynamic balance between atmospheric evaporative demand and soil water supply. VPD dominates under conditions with stable soil water availability but fluctuating atmospheric aridity. In contrast, frequent precipitation recharge in humid regions and stable deep soil water storage in arid regions strengthen soil water regulation and offset VPD limitation. Moreover, soil moisture deficits amplify VPD-induced photosynthetic suppression, whereas sufficient soil water buffers atmospheric drought stress [30,31]. This further suggests that VPD constraints on photosynthetic SIF variability must be interpreted within a coupled supply–hydrological framework.

4.2. Joint Regulation of SIF-Anomaly Moisture-Response by Hydroclimatic Gradients and Functional Traits

Our results demonstrate that regional hydroclimatic backgrounds and inherent vegetation traits co-determine the spatial patterns, dominant drivers, and lagged characteristics of photosynthetic moisture responses. Within identical hydroclimatic zones, vegetation types differed substantially in moisture contribution structures, while the same vegetation type exhibited systematic driver transitions along the arid–humid gradient, confirming climate-dependent vegetation drought response heterogeneity [11,12].

Arid zones exhibited the most pronounced vegetation differentiation in moisture response strategies. Arid shallow soil moisture is highly unstable due to episodic precipitation and intensive evaporation, only supporting short-term photosynthetic fluctuations. Accordingly, arid grasslands with shallow root systems and simple canopy structures showed immediate, short-lag SIF responses to VPD and precipitation pulses, reflecting high sensitivity to transient moisture variability [16,29]. In contrast, arid croplands, forests, and shrublands depend on stable mid- and deep-layer soil water reservoirs, generating prolonged 2–3 month lagged SIF responses. Deep root systems, hydraulic redistribution, and subsurface water utilization enable woody vegetation and croplands to buffer drought stress and access persistent soil water resources [32–34], explaining their divergent lagged responses relative to shallow-rooted grasslands.

Semi-arid and semi-humid transition zones were characterized by VPD-dominated photosynthetic regulation, with soil moisture acting as a secondary modifier. These transitional regions feature strong evaporative demand and relatively adequate soil water

supply, forming a critical zone where atmospheric water demand predominates over soil water limitation. Despite widespread VPD dominance, vegetation-specific traits induced heterogeneous responses: grasslands were most sensitive to VPD fluctuations, whereas croplands and forests maintained stable reliance on mid- and deep-layer soil moisture. This aligns with flux evidence that forest photosynthesis is co-regulated by dynamic VPD and soil moisture balance [35].

The humid zone experienced comprehensive restructuring of vegetation moisture response patterns, with precipitation and shallow soil moisture partially replacing VPD as core drivers. Frequent rainfall and rapid shallow soil water recharge rapidly modulate root-zone moisture conditions and photosynthetic variability. Humid grassland SIF variations were primarily controlled by 1-month lagged precipitation, while forest SIF anomalies were dominated by 2-month lagged shallow soil moisture. Humid croplands exhibited balanced sensitivity to VPD and shallow soil moisture, reflecting combined constraints of atmospheric drought and recent water supply. Overall, humid vegetation photosynthesis is less limited by atmospheric aridity and more governed by short-term precipitation and surface soil water dynamics [10].

In general, hydroclimatic gradients do not simply amplify or weaken moisture stress but fundamentally reshape vegetation water-use strategies [36]. This leads to systematic response transitions: arid vegetation relies on stable subsurface soil moisture, transitional ecosystems are dominated by atmospheric VPD stress, and humid vegetation is primarily regulated by frequent precipitation and shallow soil moisture fluctuations.

4.3. Layer-Specific Regulation and Temporal Memory Effects of Stratified Soil Moisture

This study revealed distinct depth-dependent regulatory mechanisms and temporal memory effects of vertically stratified soil moisture on vegetation photosynthesis, advancing the mechanistic understanding of multi-layer soil water regulation of terrestrial carbon dynamics. Shallow soil moisture is highly sensitive to precipitation and evaporation, exhibiting rapid temporal fluctuations and short response windows. Correspondingly, SIF anomalies displayed synchronous or 1-month lagged responses to shallow soil moisture, dominating short-term photosynthetic variability. In contrast, mid- and deep-layer soil moisture features higher storage stability and persistent hydrological signals, generating prominent 2–3-month temporal memory effects, particularly in arid and semi-arid water-limited ecosystems.

Soil layer dependence of SIF variability was strongly vegetation specific. Arid and semi-arid croplands primarily depended on deep-layer soil moisture with long lagged responses, as unstable surface soil water fails to sustain continuous crop photosynthesis. In humid regions, sufficient precipitation stabilizes shallow root-zone moisture, making shallow soil moisture the dominant driver of cropland SIF dynamics. Additionally, agricultural irrigation and field management further reshape cropland vertical moisture utilization, differentiating its response patterns from natural vegetation [37,38].

Forests and shrublands with complex root and canopy systems exhibit flexible moisture utilization strategies. Under dry conditions, woody vegetation relies on mid- and deep-layer soil water via hydraulic redistribution and deep-root water uptake to alleviate drought stress [33,34]. Under humid conditions, frequent surface water recharge prioritizes shallow soil moisture regulation, consistent with observed shifts in forest moisture drivers [35,39]. By comparison, shallow-rooted grasslands lack access to stable deep soil water reservoirs, with SIF variations predominantly responding to short-term precipitation and atmospheric moisture changes and showing negligible temporal memory from deep soil moisture. These divergent patterns demonstrate that deep soil moisture regulation is

not a universal arid-zone feature but emerges from the coupling of vegetation root traits, water-use strategies, and regional hydrological conditions.

In summary, shallow soil moisture primarily regulate short-term fluctuations in SIF anomalies, whereas mid- and deep-layer soil moisture mediate medium- to long-term drought legacy effects. Vertically stratified soil moisture collectively forms a multi-timescale regulatory system that explains the spatiotemporal heterogeneity of SIF-anomaly moisture responses.

4.4. Implications and Uncertainties

The vegetation-specific and gradient-dependent moisture response patterns identified in this study provide practical insights for ecological drought monitoring and vegetation water-stress assessment. Single moisture indicators are insufficient to characterize photosynthetic water limitation, as dominant stress factors vary drastically across vegetation types and climatic backgrounds [28,40,41]. Arid cropland drought monitoring requires prioritizing deep soil moisture reserves and their lagged legacy effects; grassland assessment should integrate both VPD-driven atmospheric stress and short-term precipitation pulses; forest and shrubland monitoring needs to distinguish the relative contributions of atmospheric drought and stratified soil moisture under different hydroclimatic contexts.

For agroecosystems, exclusive reliance on precipitation or surface drought indicators underestimates crop sensitivity to deep soil water deficits. Incorporating deep-layer soil moisture and its lagged effects can substantially improve crop water-stress evaluation accuracy. For natural ecosystems, our gradient-based response framework supports ecological vulnerability assessment and targeted vegetation restoration across hydroclimatic transition zones.

Several limitations and uncertainties remain in this study. First, ERA5-Land fixed soil layers cannot fully match vegetation-specific root distribution and actual root water uptake depth, limiting the precision of root-zone moisture quantification. Second, this study did not distinguish between irrigated and rainfed croplands, ignoring the modulating effects of crop types and anthropogenic management on moisture responses. Irrigation can decouple cropland photosynthetic activity from natural precipitation and soil moisture variability by supplementing root-zone water supply, while crop type, planting date, and management intensity can alter phenological development, canopy structure, rooting depth, and water-use strategy [42,43]. Therefore, the cropland-related moisture responses identified here should be interpreted as integrated signals of both hydroclimatic variability and agricultural management effects. Third, the analysis relies on remote sensing and reanalysis datasets without site-level experimental and flux validation. Future studies should integrate in situ flux observations, field-measured stratified soil moisture, irrigation zoning data, and crop inventory information to refine the physiological mechanism interpretation and improve multi-scale vegetation water-stress assessment models.

5. Conclusions

Using 2000–2024 SIF, ERA5-Land data and XGBoost–SHAP models, we quantified the lagged photosynthetic responses to VPD, precipitation, and stratified soil moisture across four vegetation types along China’s arid–humid gradient. The key findings are as follows: (1) Regarding the first question on long-term SIF spatiotemporal patterns, national vegetation photosynthetic activity increased steadily from 2000 to 2024. Spatial heterogeneity, co-determined by vegetation traits and hydroclimatic background, produced a clear northwest–southeast SIF gradient, with forests and shrublands showing higher photosynthetic baselines than croplands and grasslands. (2) Regarding the second question on concurrent and lagged moisture responses, SIF anomalies showed distinct

depth-dependent response times. Precipitation and shallow soil moisture mainly drove synchronous or 1-month-lagged responses, whereas middle- and deep-layer soil moisture generated 2–3-month delayed effects for cropland and woody vegetation in dry zones, indicating the role of soil-water storage memory in buffering drought stress. (3) Regarding the third question on relative moisture-factor contributions, dominant moisture constraints shifted systematically along the arid–humid gradient. VPD dominated SIF anomalies at the national scale and in semi-arid to semi-humid zones, while arid vegetation depended more strongly on subsurface soil moisture, and humid grasslands and forests were mainly associated with precipitation and shallow soil moisture, respectively. These patterns indicate that vegetation rooting traits and vertical water access jointly regulate carbon–water coupling.

We established a multi-timescale, depth-resolved framework showing photosynthetic variability arises from coupled atmospheric, rainfall and subsurface water controls, and not from single moisture factors. This work improves the mechanistic knowledge of vegetation drought sensitivity and guides drought monitoring and carbon cycle modeling.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agronomy16141392/s1>, Table S1. Candidate ranges and selected hyperparameters for the XGBoost models. Table S2. Performance metrics of XGBoost models across vegetation types and vegetation-hydroclimatic combinations.

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