

Observed declining strength of vegetation-atmosphere coupling

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ABSTRACT

Land-atmosphere coupling (LAC) directly influences the occurrence of extreme climate events. Traditionally, the studies of LAC strength have primarily used soil moisture as a proxy for land conditions. However, recent research has highlighted the significant role of vegetation-atmosphere coupling (VC) in the evolution of extreme climate events through its regulation of the water and energy cycles. Despite this progress, the global patterns and driving mechanisms of VC remain unclear. In this study, the index with a clear physical meaning, ω , defined as the relationship between the canopy conductance (g_c) and aerodynamic conductance (g_a), was introduced to represent VC values. Long-term (1981–2018) global annual VC values were derived using two high-quality reanalysis datasets (ERA5 and MERRA2) based on two different g_c models. Both g_c models exhibited similar spatial distributions that the highest VC values in Arid regions, the lowest in Humid regions, and intermediate values in Transition zones. Results showed 38.84–61.98 % of global land with decreasing VC trend. An attribution analysis using a nonlinear machine learning approach revealed that leaf area index (LAI) and wind speed dominated the VC changes across different climate zones. An increase in LAI reduced VC strength, whereas enhanced wind speed increased VC values. LAI was the dominant factor influencing VC through transpiration regulation (i.e., g_c) over Transition and Arid regions, while wind speed controlled VC variations via g_a over Humid regions. Our study analyzed the spatiotemporal changes in VC values and their driving mechanisms across global land areas. These findings contribute to a deeper understanding of vegetation-climate feedback and its role in amplifying extreme climate events.

1. Introduction

Changes in soil moisture regulate surface water and energy partitioning by influencing evapotranspiration (Seneviratne et al., 2010), which in turn affects local cloud formation and atmospheric boundary layer, ultimately modulating large-scale circulations in downwind regions (Taylor et al., 2011, 2012; Hsu et al., 2017). Soil moisture induced land-atmosphere coupling (LAC), a measure of the strength of water and energy exchanges between land surface and atmosphere (Seneviratne

et al., 2010), is typically stronger in transitional and water-limited environments compared to energy-limited areas (Dirmeyer et al., 2013). However, recent studies suggest that LAC hotspots are shifting towards non-transitional regimes due to increasing net radiation, declining soil moisture, and rising CO₂ levels (Denissen et al., 2022; Hsu and Dirmeyer, 2023). Such intensification of LAC has the potential to amplify compound hydroclimatic extremes, such as heatwaves and droughts (Zhou et al., 2019; Miralles et al., 2019; Berg et al., 2016). Vegetation has been hypothesized to play a further important control in LAC dynamics (Li

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et al., 2024; Zscheischler et al., 2015; Williams et al., 2015); however empirical evidence is still lacking at large scales. Understanding the underlying mechanisms controlling LAC dynamics is, therefore, a crucial prerequisite for improving disaster risk management and enhancing ecosystem resilience to climate extremes.

LAC has been typically assessed using regression method, physics-based statistical method, process-based Earth system models (Dirmeyer et al., 2011; Miralles et al., 2014; Schwingshackl et al., 2017; Koster et al., 2006). For instance, Dirmeyer et al. (2011) estimated LAC by combining the linear slope of evaporative fraction (EF) and the standard deviation of soil moisture. Miralles et al. (2014) introduced a metric to examine the coupling between soil moisture and air temperature by quantifying the effects of soil moisture changes on energy balance. In other studies, LAC was quantified as the coupling strength between soil moisture and variables such as air temperature and evapotranspiration, based on process-based model simulations from the Global Land–Atmosphere Coupling Experiment (Koster et al., 2006). In these studies, soil moisture has been regarded as a unique proxy for land conditions, ignoring the control of vegetation on energy–water partition. Vegetation plays a crucial role in influencing temperature and moisture conditions through water and energy exchanges between land and atmosphere. For instance, an increase in vegetation cover generally reduces surface albedo ultimately enhancing solar energy absorption (Wang et al., 2023; Tian et al., 2014). At the same time, greater vegetation density promotes evapotranspiration (latent heat flux) while reducing sensible heat flux (Forzieri et al., 2020; Chen et al., 2023). The relative net warming or cooling effect on land surface temperature results from the combination of such opposite radiative terms and turbulent fluxes, further modulated by local environmental conditions (Forzieri et al., 2020).

VC represents the bidirectional exchange of energy, water, and carbon between vegetation and atmosphere. Through stomatal regulation, vegetation controls transpiration and photosynthesis, which not only respond to atmospheric drivers such as radiation and vapor pressure deficit but also feedback to the atmosphere by altering humidity, temperature, energy partitioning and boundary-layer dynamics (De Kauwe et al., 2017; Miralles et al., 2025). Some studies have attempted to quantify the strength of VC from different perspectives. A vegetation–atmosphere coupling index has been recently proposed to account for the relationship between air temperature and vegetation photosynthetic activity and explore the role of vegetation affecting LAC in the evolution of compound heatwaves and droughts (Zscheischler et al., 2015). This method is useful for identifying whether a region is in an energy-limited or water-limited regime; however, it is less effective at detecting the strength of VC. A decoupling metric Ω was early proposed to estimate the coupling degree between vegetation and atmosphere (Jarvis and McNaughton, 1986). It was defined as the ratio of canopy conductance (g_c) to aerodynamic conductance (g_a), scaled by the moisture holding capacity of the atmosphere. Zhang et al. (2022) and De Kauwe et al. (2017) have already used the metric to estimate the strength of VC at site scale with FLUXNET sites' observations. The physical meaning of the metric represents the ability of vegetation to exchange carbon and water with the atmosphere through the regulation of its stomatal status.

The metric Ω serves as a useful indicator for quantifying the strength of VC. However, the long-term changes in VC and their underlying mechanisms remain complex to be analyzed at large scales. One challenge is that when estimating g_c with empirical models, such as Ball–Berry–Leuning model (BBL), several parameters need to be calibrated for different plant functional types, however the few and sparse distribution of observation sites limits the applicability of the metric at large areas. This is why Zhang et al. (2022) and De Kauwe et al. (2017) employed the inverted Penman–Monteith equation, using latent heat flux as an input, to estimate surface conductance. However, the derived surface conductance inherently combines the effects of both vegetation and bare soil, thereby compromising the physical interpretability of the

metric. To overcome these limitations, Wang et al. (2017) and Stocker et al. (2020) proposed a new approach (P model) to retrieve g_c based on eco-evolutionary optimality, thus capturing the response of optimal stomatal behavior to environmental variables (Tan et al., 2021).

Despite the relevant insights gathered from these studies, a proper quantification of the role of VC and its driving mechanisms at the global level is still lacking, impeding a comprehensive understanding of the effects of vegetation on LAC and on the evolution of extreme events. To address this research gap, we used the ω metric (the reciprocal of the metric Ω) to express the vegetation–atmosphere coupling by exploiting two different physical models (P model, BBL model) to estimate g_c and two state-of-the-art meteorological datasets (ERA5 and MERRA2) as input forcing. A Random Forest model was implemented to attribute VC annual trends to LAI and climatic factors' annual trends.

2. Methodology

2.1. Land surface products

Multiple datasets were exploited in this study to estimate VC values and elucidate the underlying mechanisms. Monthly atmospheric variables were acquired from the reanalysis products ERA5 and MERRA2 and include: 2-meter air temperature and dewpoint temperature, near surface pressure, wind speed, solar radiation downward, precipitation, soil moisture, latent and sensible heat (Gelaro et al., 2017; Hersbach et al., 2020). Air temperature and dewpoint temperature were used to estimate VPD according to the formulation proposed by Allen et al. (1998). Furthermore, the 10-m wind speed retrieved from ERA5 was adjusted to the 2-meter level to be consistent with MERRA2 estimates (Allen et al., 1998). The 1-meter soil moisture retrieved from ERA5 and rootzone soil moisture from MERRA2 was used as water constrain to estimate GPP values based on the P model and the BBL model (additional methodological details in the following section). It should be noted that MERRA2 does not provide soil moisture values at the same depths of ERA5, its rootzone soil moisture is selected. ERA5 covers the period 1940–present with a 0.25-degree spatial resolution, while MERRA2 covers the period 1980–present with a 0.625×0.5 -degree spatial resolution.

The two models (P model, BBL model) exploited in this study to estimate g_c require LAI data as input. To this aim, we used LAI retrievals from the high-quality long-term Global Land Surface Satellite (GLASS) product (Liang et al., 2021). GLASS LAI has a spatial resolution of 0.05-degree and it covers the period 1981–2018. The P model and the BBL model produce GPP estimates as intermediate variable. To validate their performance, independent GPP retrievals were acquired from data-driven upscaling of FLUXNET sites' observations for the period 2001–2020 and used as benchmark in this study (Nelson et al., 2024).

In addition to the data mentioned above, several necessary ancillary datasets were also required for the estimation of VC. Global monthly mean CO_2 values were obtained from National Oceanic and Atmospheric Administration Earth System Research Laboratory for the period 1980–to-present. CO_2 data was used as input to estimate g_c in the P and BBL models. C3 and C4 vegetation percentages were derived from the International Satellite Land Surface Climatology Project Initiative (ISLSCP) II (Still et al., 2009) as a static map at 1-degree spatial resolution and used as input for the P model. Global land cover types were retrieved from ISLSCP II MODIS (Collection 4) International Geosphere-Biosphere Program for the period 2000–2001 at 0.5-degree spatial resolution to calculate g_c within the BBL model (Friedl et al., 2010). Vegetation height data was obtained at 1-km spatial resolution from spaceborne LIDAR acquisitions (Simard et al., 2011) which was used to calculate aerodynamical conductance.

2.2. Data preprocessing

All datasets described in the previous section were resampled to the

common 0.5-degree spatial resolution through bicubic interpolation method and the 1981–2018 was selected as reference period considering the temporal overlapping of the available data. Land pixels with multi-year average LAI lower than 0.1 were excluded from our analyses (Lian et al., 2018). The growing season was defined based on monthly climatological temperature greater than 0 °C using ERA5 as reference. Such growing season definition has been compared with other methods based on vegetation index, and is widely used in the related studies (Li et al., 2023a; Feng et al., 2021). All monthly gridded values of time-varying meteorological variables, LAI, CO₂, and transpiration were aggregated to the growing season level (Feng et al., 2021).

Global land excluding Greenland and Antarctica was classified in three main climate zones: Arid region (aridity index < 0.2), Transition region (0.2 ≤ aridity index ≤ 0.65), Humid region (aridity index > 0.65). The aridity index was defined in this work as the ratio between precipitation and potential evapotranspiration. Here, we used the aridity index during 1970–2000 provided by Zomer et al. (2022) to define these three climate zones. Arid, Transition and Humid regions accounted for 16.30 %, 35.56 %, 48.14 % of global land, respectively Fig. 1.

2.3. Vegetation-atmosphere coupling

The vegetation-atmosphere coupling (VC) was represented through the metric ω (Ek et al., 2016; Zhang et al., 2022), a dimensionless variable ranging between 0 and 1 indicating low and high coupling between vegetation and atmosphere, respectively. Its analytical formulation is as follows:

$$\omega = \left[\left(\frac{m + \gamma}{\gamma} \right) \frac{g_c}{g_a} + 1 \right]^{-1} \quad (1)$$

where m is the derivative of the saturation vapor pressure function with respect to air temperature (Pa/°C) and γ represents the psychrometric constant (Pa/°C). Both parameters were obtained from Allen et al. (1998). The aerodynamical conductance (g_a) and the canopy conductance (g_c) are two additional essential parameters whose retrievals required a series of additional modelling steps detailed below.

Ek et al. (2016) provided a clear physical interpretation of the metric ω , indicating that it quantifies the sensitivity of the transpiration-related evaporative fraction to variations in soil moisture. As the evaporative fraction is defined as the ratio of latent heat flux to available energy (i.e. net radiation minus soil heat flux), it links surface energy partitioning to hydrological conditions and serves as a key indicator in studies of land–atmosphere coupling (Seneviratne et al., 2010). Due to its significance, several studies have employed the evaporative fraction to develop a metric for quantifying LAC (Dirmeyer et al., 2011; Hsu and Dirmeyer, 2023). The metric ω uses transpiration-related evaporative fraction, actually reflecting the physiological capacity of vegetation to regulate carbon–water exchange with the atmosphere through stomatal control. Thus, it is regarded as the metric of representing the strength of VC.

The reciprocal of the metric ω (i.e., Ω) is often used to estimate the

strength of VC at the site scale, as discussed in the Introduction section. Here, we compared these two metrics using the P model forced by ERA5 as an example (Fig. S1). In terms of the long-term global land average, the two metrics yielded results that are reciprocals of each other.

2.3.1. The calculation of g_a

g_a is estimated based on an empirical relationship documented in literature (Leuning et al., 2008; Zhang et al., 2019) as follows:

$$g_a = \frac{k^2 u_z}{\ln[(z_m - d)/z_{om}] \ln[(z_m - d)/z_{ov}]} \quad (2)$$

where z_m is the height at which wind speed and humidity are measured, d is the zero-plane displacement height, z_{om} and z_{ov} are the roughness lengths that govern the transfer of momentum and water vapor, respectively, k is the von Kármán constant (0.41), and u_z is the wind speed measured at the height z_m . Besides, d , z_{om} , and z_{ov} are estimated as $d = \frac{2}{3}h$, $z_{om} = 0.123h$ and $z_{ov} = 0.1z_{om}$, where h is the canopy height (Allen et al., 1998). Here, the reference height for wind speed and dew point temperature was 2-meter, thus, z_m was set to 2-meter. The canopy height h was derived from the global gridded dataset mentioned above. However, the canopy height over areas with very sparse vegetation was set to zero in the gridded dataset. To ensure that Eq. (2) was valid, the canopy height for very sparse vegetation was set to 0.1 m (Vargas et al., 2023).

2.3.2. The calculation of g_c based on P model

The P model expresses g_c for C3 and C4 vegetation which differ in their photosynthetic pathways. Traditional vegetation types (e.g. evergreen coniferous forest, evergreen broadleaf forest) belong to C3 or C4 types. It is expressed as follows (Wang et al., 2017):

$$g_c = 1.6 \frac{A_n}{c_a(1 - \chi)} \quad (3)$$

where A_n is the carbon assimilation rate ($\mu\text{mol}/(\text{m}^2 \text{ s})$), c_a represents ambient CO₂ partial pressure (Pa), χ is the ratio of c_i to c_a , with c_i the internal CO₂ partial pressure of leaf (Pa) and c_a ambient CO₂ partial pressure (Pa). For C4 vegetation, χ was set to a constant value (0.45) in agreement with reported estimates in literature (Farquhar et al., 1989). The g_c for C3 and C4 ($g_{c_{c3}}$, $g_{c_{c4}}$) were estimated with Eq. (3). To upscale g_c from leaf to ecosystem scale, A_n was replaced by GPP (Liu et al., 2022). GPP, c_i , and c_a were obtained following methodology presented in Stocker et al. (2020) and Tan et al. (2023). Soil moisture was used as water constraint when estimating GPP. To this aim, rootzone soil moisture was used from MERRA2, whereas one-meter soil moisture was from ERA5. The ultimate estimate of g_c accounting for the mixture of differences between C3 and C4 vegetation at the pixel scale was derived as follows:

$$g_c = g_{c_{c3}} \times \text{percent}_{c3} + g_{c_{c4}} \times \text{percent}_{c4} \quad (4)$$

where percent_{c3} and percent_{c4} reflected the fraction of C3 and C4 vege-

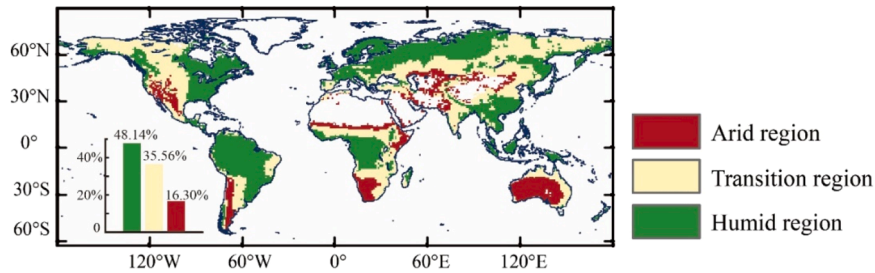


Fig. 1. Spatial distribution of three main climate zones (Arid, Transition, Humid region) over global land (LAI > 0.1) excluding Greenland and Antarctica. Arid region, Transition region, and Humid region are defined with aridity index < 0.2, 0.2 ≤ aridity index ≤ 0.65, aridity index > 0.65, respectively. Regions with multi-year average LAI < 0.1 were marked in white and not considered in subsequent analysis.

tation.

2.3.3. The calculation of g_c based on BBL model

g_c is derived by exploiting the BBL model (Leuning, 1995) as follows:

$$g_c = 1.6 \times \left(\frac{k \times A_n}{(C_s - \Gamma) \times (1 + VPD_s/VPD_0)} + g_0 \right) \quad (5)$$

where A_n is the carbon assimilation rate ($\mu\text{mol}/(\text{m}^2 \text{ s})$), C_s indicates CO_2 concentration of leaf-surface (ppm), Γ represents CO_2 concentration's compensation point (ppm), VPD_s is leaf-surface Humidity deficit values (kPa), VPD_0 (kPa) reflects the stomata sensitivity of VPD changes and set to 0.35 kPa (Leuning, 1995), k and g_0 are calibration parameters for different land cover types. Here, m and g_0 values were defined according to Liu et al. (2022). The upscaling from leaf to ecosystem scale was produced by replacing g_0 , C_s , A_n , VPD_0 by $g_0 \times \text{LAI}$, atmospheric CO_2 concentration, GPP, VPD, respectively (Liu et al., 2022; Li et al. 2023b). GPP was obtained using the standard Farquhar model following Wang et al. (2017). Similarly to the P model, the estimation of GPP used soil moisture values as water constraint.

2.4. Attribution analysis

We used a random forest model (Breiman, 2001) to attribute the VC annual trend to annual trends in LAI and climatic variables such as air temperature (tas), soil moisture (mrso), solar radiation (rsds), VPD, wind speed, surface pressure (sp) and CO_2 . The trends were calculated with Theil-Sen's slope method (Wilcox, 2010). Furthermore, to better discriminate emerging mechanisms across the globe, we focused on three main climatic zones – namely arid, Transition and Humid regions. A random forest model was implemented for each climate zone. For each model run, we randomly split VC trends and predictor variables' trends

into two parts: keeping 75 % of pixels for training and the remaining 25 % for validation. The hyperparameters (leaf node count and regression tree size) of the RF model were determined based on Bayesian optimization (Breiman, 2001). Model performance was estimated in terms of coefficient of determination (R^2) and Root Mean Square Error (RMSE). To increase comparability across the RF runs, each variable's importance score was divided by the sum of the importance scores of all variables (i.e. percentages) (Dong et al., 2023).

3. Results

3.1. The spatiotemporal change characteristics of VC values over global land

Fig. 2 illustrates clear spatial gradients in the long-term average of VC, with markedly higher values observed in Arid regions and substantially lower values in Humid zones. This spatial pattern is robust across different forcing datasets (ERA5, MERRA2) and canopy conductance (g_c) models (P model, BBL model), particularly for the MERRA2-P and MERRA2-BBL combinations. The response of VC values to the aridity index is clearly illustrated in Fig. 2 (e). Denser vegetation types (i.e., ENF, EBF, DNF, DBF forests) display lower VC values, whereas sparser vegetation types such as GRA and SAV exhibit higher VC values (Fig. 2 f).

Notably, the P model consistently yields slightly lower VC estimates, particularly in Transition and Arid regions, compared to the BBL. Specifically, VC values derived from the P model range from 0 to 0.3 in Humid regions and from 0.4 to 0.8 in Arid and Transition zones. In contrast, the BBL model produces higher VC values—often between 0.7 and 1.0—in Arid regions such as the western United States, South Africa, western Asia, and Australia. This discrepancy primarily arises because

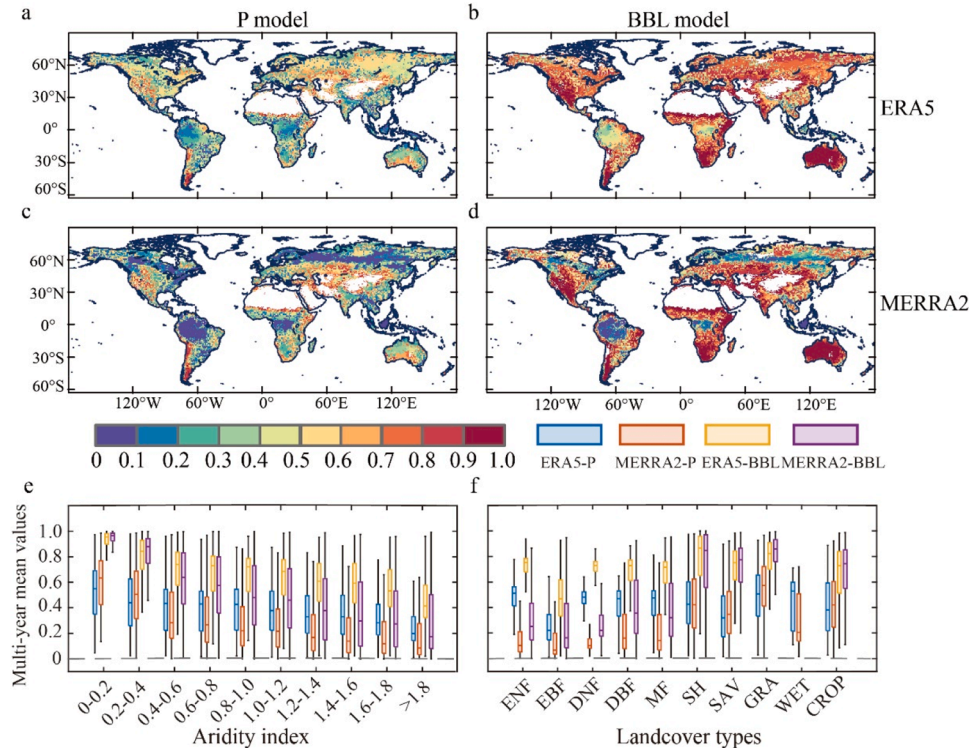


Fig. 2. Spatial distribution of the long-term average of VC during 1981–2018 estimated by the P model (ERA5-P, MERRA2-P) and BBL model (ERA5-BBL, MERRA2-BBL). Panels (a, b) show results driven by ERA5 reanalysis, while panels (c, d) correspond to MERRA2-driven simulations. Panel (e, f) displays boxplots of VC values across different aridity index bins and landcover types for each product. Landcover types include Evergreen Needleleaf Forest (ENF), Evergreen Broadleaf Forest (EBF), Deciduous Needleleaf Forest (DNF), Deciduous Broadleaf Forest (DBF), Mixed Forest (MF), Shrublands (SH), Savanna (SAV), Grassland (GRA), Wetland (WET), and Cropland (CROP). Besides, closed shrublands and open shrublands are combined into a single 'Shrublands' category, while woody savannas and savannas are merged into a unified 'Savannas' class.

the P model's estimation of GPP is evidently higher than that of the BBL model (see Fig. S2), which inflates g_c estimates via Eq. (3) and consequently lowers VC values according to Eq. (1). Regarding the influence of reanalysis forcing datasets, ERA5 and MERRA2 generally yield consistent VC estimates, except in regions with dense vegetation, where MERRA2 tends to produce lower VC values over Amazon and Congo rainforest, boreal forest relative to ERA5. These findings underscore the sensitivity of VC estimation to model structure and regional forcing data, emphasizing the need for careful model selection and validation in land-atmosphere coupling studies.

The annual trends of VC over global land from 1981 to 2018 are analysed using each configuration of models and reanalysis datasets (Fig. 3). For the P model, spatial patterns of VC trends are relatively consistent between ERA5 and MERRA2. Increasing VC trends are observed in western and eastern North America, most of South America, central and southern Africa, eastern Europe, northern Asia, and eastern-central Australia. Conversely, decreasing trends appear in northern and southern North America, southern Africa, India, China, and central-western Asia. The largest positive trends, ranging from 1 to 4×10^{-3} per year, occur in western Russia and northern China, while the greatest negative trends, between -4 and -1×10^{-3} per year, are found in western India, China, and central Asia. The BBL model reveals predominantly significant decreases in VC trends across most global land areas, notably in central North America, eastern Europe, southern Africa, India, and China, with magnitude exceeding 4×10^{-3} per year in some regions. Overall, the spatial distribution of global VC trends seems primarily influenced by the choice of the model used to retrieve g_c rather than the driving reanalysis dataset. For instance, the BBL model indicates widespread decreasing VC trends globally, when compared to P model.

3.2. Forcing dataset's agreement in VC trends

Fig. 4 illustrates that spatial distribution of forcing dataset's agreement in VC annual trends between ERA5-forced and MERRA2-forced simulations with P model (a) and BBL model (b). For each model, if both ERA5 and MERRA2 show an increasing (or decreasing) trend at a given pixel, that pixel is classified as increasing (or decreasing). In P model-driven results (Fig. 4 a), 32.27 % of the global land area exhibits

consistent increasing VC trends between ERA5 and MERRA2. These regions include western North America, South America, central Africa, western Russia, eastern Asia, and eastern Australia. In addition, approximately 3.70 % of the global land area exhibits a significant increasing trend, primarily distributed across central Africa. Conversely, 38.84 % of global land shows unanimous decreasing VC trends, notably in middle North America, eastern Europe, central Asia, eastern China, and India. 9.92 % of global land is significantly decreasing. By contrast, under BBL model, the fraction of land with consistent increasing VC trends decreases substantially to 14.12 %, while the proportion exhibiting consistent decreasing trends raises to 61.98 %. This shift is primarily attributed to a reversal from positive to negative VC trends in regions such as South America Europe, central-southern Africa, China, and Australia. Besides, 24.22 % of global land significantly decreases, especially in India, China, Africa, and Australia. These results highlight that the agreement between ERA5 and MERRA2 forcing dataset on VC trend direction is sensitive to the choice of conductance models.

3.3. Attribution of VC changes

To get insights on the drivers of VC annual trend during 1981–2018, a random forest model was developed. We used LAI and climatic variables' annual trends to predict VC annual trends across three climate zones. In the subsection above, the annual trends of VC were mainly determined by the models used to estimate g_c , rather than by the forcing data. Fig. 5 shows the results of the P and BBL models, which represent the averages of the attribution results from ERA5-P and MERRA2-P, and from ERA5-BBL and MERRA2-BBL, respectively. Fig. 5 a–f presents the importance scores (%) of independent variables' trends for VC trends estimated by P model and BBL model. LAI and wind speed emerge as the dominant drivers of VC changes across Humid, Transition, and Arid zones. In the Humid region, wind speed is the primary factor for both models, contributing approximately 40 %, followed by LAI with over 20 %, while other variables contribute less than or close to 10 %. In the Arid region, LAI become the leading factor, evidently exceeding wind speed. In the Transition region, LAI and wind speed have the comparable contributions. The choice of forcing dataset (ERA5 or MERRA2) have only a minor impact on the attribution results of VC trends (Fig. S3).

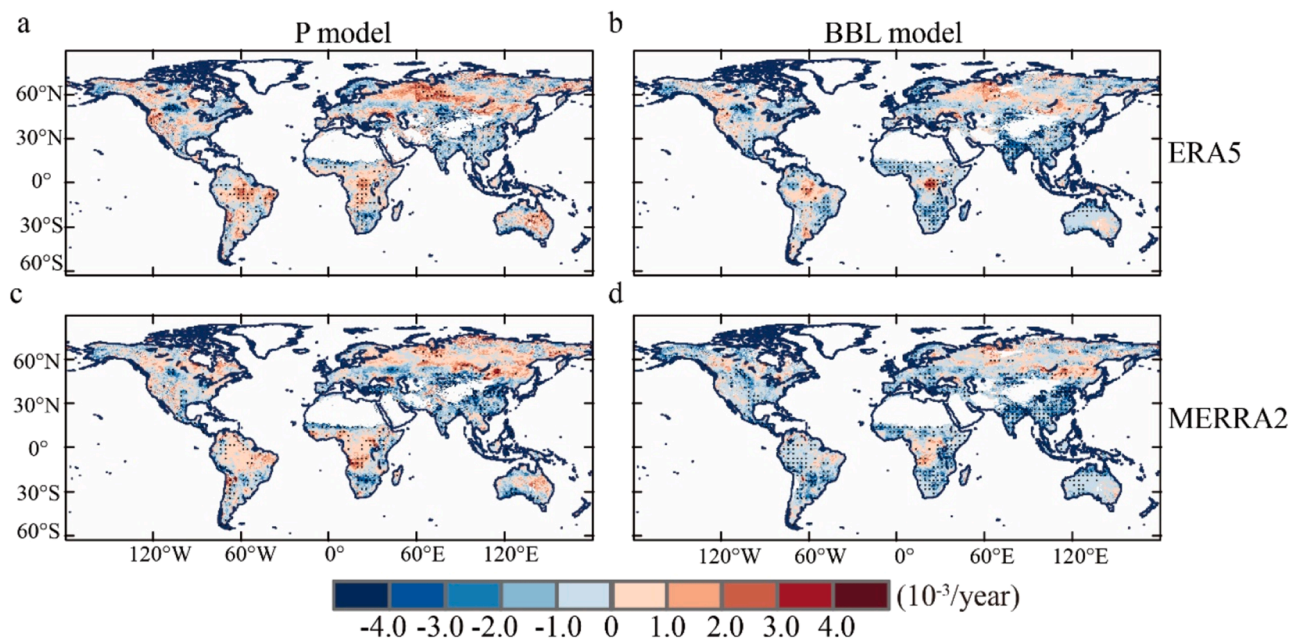


Fig. 3. Spatial distribution of annual trends in VC from 1981 to 2018 estimated by the P model (ERA5-P, MERRA2-P) and BBL model (ERA5-BBL, MERRA2-BBL). Panels (a, b) show trends driven by ERA5, while panels (c, d) show trends driven by MERRA2. Dotted pixels indicate trends statistically significant at the 5 % level based on the Mann-Kendall test.

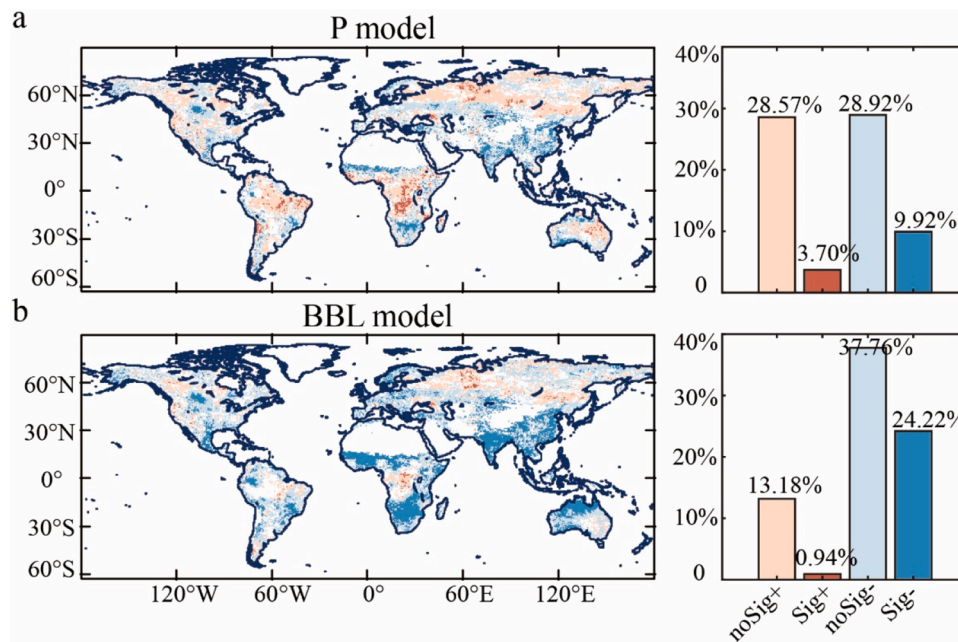


Fig. 4. Spatial distribution of forcing dataset's agreement in VC annual between ERA5-forced and MERRA2-forced simulations with P model (a) and BBL model (b). Red and blue pixels represent agreement between ERA5 and MERRA2 for positive and negative VC trends, respectively. Light red (noSig+) and light blue (noSig-) pixels fail to reach statistical significance at the 5 % level, while dark red (Sig+) and dark blue (Sig-) pixels are statistically significant at the 5 % level. The global land fractions exhibiting increasing or decreasing VC trends were calculated as area-weighted averages, accounting for the spatial extent of each pixel.

Marginal effect analyses (Fig. 5 g–h) reveal contrasting roles of LAI and wind speed on VC. As the LAI trends transition from negative to positive, VC shows a continuous decrease across all climate zones and conductance models, with the strongest decline observed in the Arid region. These results indicate vegetation greening (Zhu et al., 2016) is making VC values decrease. Conversely, VC trends increase sharply with rising wind speed before levelling off past a threshold. Increases in air temperature and VPD generally enhance VC values, while higher soil moisture tends to suppress them. The effects of solar radiation and surface pressure are relatively subtle (Fig. S4).

4. Discussions

4.1. Uncertainties of estimating VC values with ω

In this study, we employed the metric ω to estimate vegetation–atmosphere coupling (VC) values, representing the first global-scale analysis of VC change characteristics. Despite the ω metric is derived through rigorous physical deduction, its estimation critically depends on accurate modelling of g_c , which remains a significant challenge due to the complex response of stomatal behaviour under gradually increasing warming conditions. Li et al. (2023b) previously applied both the P model and the BBL model to estimate g_c , subsequently deriving global land transpiration by incorporating these g_c estimates into the Penman–Monteith (PM) equation. Their comparisons between modelled transpiration and observations demonstrated that both models perform relatively well in estimating g_c .

Relying on these promising results, we further evaluated the ability of the P and BBL models to estimate gross primary productivity (GPP), a key input for g_c calculation, using a new data-driven GPP product based on FLUXNET site observations. Fig. S2 compared global monthly GPP estimates from the P and BBL models (forced by ERA5 and MERRA2) with the FLUXGPP dataset at the pixel scale during 2001–2018. The P model showed good agreement with FLUXGPP, with coefficients of determination (R^2) of 0.75 and 0.71 and root mean square errors (RMSE) of 44.09 and 48.56 g C month⁻¹ for ERA5 and MERRA2, respectively, with ERA5-P performing slightly better. The BBL model exhibited

similar patterns, with ERA5-BBL outperforming MERRA2-BBL ($R^2 = 0.79$, RMSE = 22.96 g C month⁻¹ vs. $R^2 = 0.65$, RMSE = 32.99 g C month⁻¹). Overall, these results confirm the robust performance of the P and BBL models in estimating g_c .

To examine the contributions of the two main components (g_c and g_a) to VC values estimated with ω , we plotted the boxplots of long-term average (1981–2018) g_a (Fig. S5a), g_c (Fig. S5b) across different land-cover types, following Zhang et al. (2022). From the Fig. S5b, we found that forest types, such as ENF, EBF, DNF, and DBF, exhibit higher g_c due to their higher GPP, whereas cropland and grassland types, with lower GPP, show lower g_c . Because forests with sufficient water supply generally maintain active stomatal opening, which facilitates water–carbon–energy exchanges with the atmosphere (Flo et al., 2022). From Fig. S5a, different land-cover types exhibit comparable g_a in ERA5-P and ERA5-BBL, whereas forest types show smaller g_a in MERRA2-P and MERRA2-BBL compared with cropland and grassland types. However, observations from FLUXNET sites indicate that forest types have higher g_a than cropland and grassland types (Zhang et al., 2022). The discrepancy in g_a between the estimates in this study and site observations from FLUXNET may lead to lower vegetation–atmosphere coupling for forest types when quantified using the metric ω . The estimation of g_a is primarily controlled by wind speed (Villalobos et al., 2024). Therefore, we further plotted boxplots of wind speed across different land-cover types (Fig. S5c). By comparing Fig. S5a and S5c, we found that wind speed largely determines the variation of g_a among different land-cover types. These results indicate that the uncertainty in g_a estimation in this study mainly arises from uncertainties in wind speed. In the future, more accurate simulations of wind speed using advanced assimilation and artificial intelligence techniques could improve the estimation of g_a and the precision of vegetation–atmosphere coupling strength quantified by the metric ω (Ivanova et al., 2025; Liu and Yang, 2025).

In this study, we used one empirical method, BBL model, and one optimal approach, P model, to estimate g_c at the global land scale. In both methods, vegetation photosynthesis serves as an important input parameter. Actually, vegetation photosynthesis can become decoupled from leaf stomatal conductance under extreme climate conditions (Diao

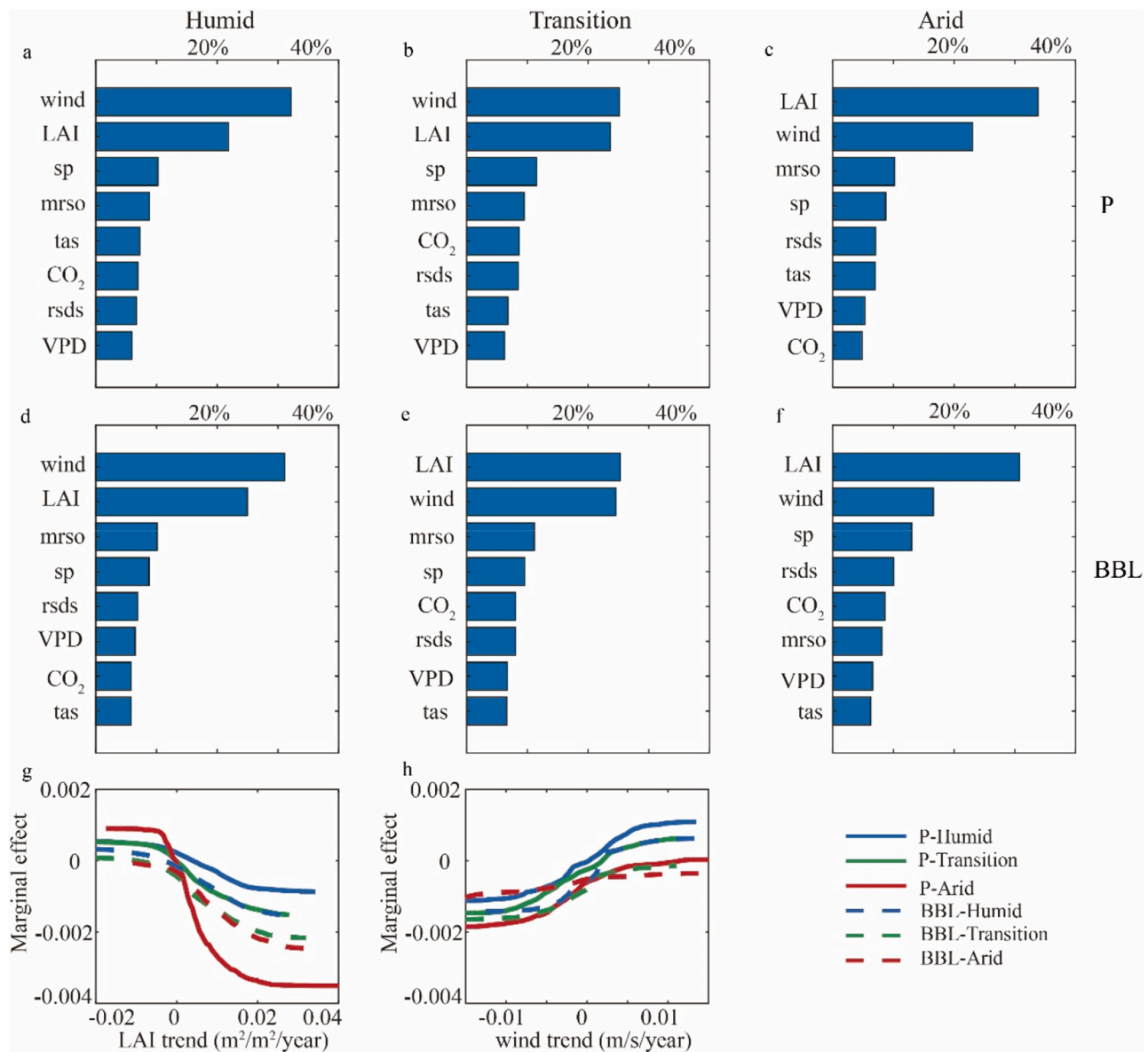


Fig. 5. Relative importance scores (%) of LAI and climatic variables' annual trends for predicting VC annual trends during 1981–2018. Panels (a–c) and (d–f) show results for P model and BBL model, respectively, across Humid, Transition, and Arid climate zones. Panels (g) and (h) depict the marginal effects of annual trends of LAI and wind speed on VC annual trends. The P and BBL models represent the average of the attribution results from ERA5-P and MERRA2-P, and from ERA5-BBL and MERRA2-BBL, respectively.

et al., 2024; Marchin et al., 2023; De Kauwe et al., 2019). For example, under extreme heat conditions, vegetation photosynthesis is strongly inhibited, while transpiration increases to effectively cool leaves below air temperature (Marchin et al., 2023). This provides new insights into how to improve stomatal conductance modelling under extreme climate conditions and to further investigate the characteristics of vegetation-atmosphere coupling under such conditions.

The present contribution is a first step trying to characterize vegetation-atmosphere coupling at the global scale using a comprehensive metric such as ω . This task presents inherent complexity due to the different vegetation physiological response to the factors involved, further exacerbated to the changes in climate and the feedbacks from vegetation adaptation response (Liu et al., 2024).

4.2. Evaluation of attribution method uncertainty

We analyzed VC annual trends using the ω metric as a function of an

ensemble of LAI and climatic variables. Quantifying the contribution of each independent variable trends to VC trends is challenging due to the complex, nonlinear relationships involved. To address this, we employed a random forest regression approach, which accounts for nonlinear relationships between independent variables and response variable. Potential collinearity among the independent variables is also well managed by this method.

Fig. S6 presents the validation performance of the random forest models for the period 1981–2018 across Humid, Transition, and Arid climate zones estimated by ERA5-P, ERA5-BBL, MERRA2-P, MERRA2-BBL. The models demonstrated strong predictive capacity, with coefficients of determination (R^2) ranging from 0.56 to 0.71 and root mean square errors (RMSE) between 5.71 and 11.8×10^{-4} .

These results corroborate the choices in our modelling approach. Firstly, they confirm the robustness of the random forest approach in capturing the nonlinear dependencies between VC and its driving variables, supporting its use for attribution analysis in this study. Secondly,

the models' performances support the selection made on the predictive variables in explaining the response variable, since they explain between 56 % to 71 % of the variance in VC.

4.3. VC results comparison

We found that the estimation of VC using the ω metric yields VC values that are the highest in the Transition and Arid regions, where water availability limits vegetation activity, and lowest in the energy-limited Humid region (Fig. 2). This pattern reflects the fundamental ecological principle that vegetation in water-limited environments regulates g_c to adapt to environmental stresses. For instance, if limited water availability is sensed by the vegetation, i.e. in case of declining soil moisture, a cascade of physiological responses aimed to spare water loss are implemented (stomata closure, reduced g_c and thus transpiration). These mechanisms are all modulated by the vegetation, thereby strengthening vegetation control over land–atmosphere coupling, reflected in higher VC values. In contrast, in energy-limited or Humid regions, where the atmospheric water demand remains low or the water supply from the soil is enough to balance the losses, vegetation has no physiological reason to close stomata and slow down the assimilation processes. Therefore, the stomata of vegetation are usually more active, the effect of vegetation on LAC gradually diminishes, resulting in the lower VC values (Miralles et al., 2025; Denissen et al., 2022; Dirmeyer et al., 2011). This spatial pattern aligns well with previous studies using alternative metrics (Denissen et al., 2022; Dirmeyer et al., 2011) and is robust across different forcing datasets and g_c estimation models.

The attribution analyses based on random forest models (Fig. 5) confirms these hypotheses. Our results identify LAI and wind speed as the primary drivers of VC changes. In addition, LAI influences g_c and thus energy partitioning through transpiration regulation (Yang et al., 2023; Lu et al., 2021), while wind speed enhances atmospheric turbulence, facilitating matter and energy exchange between vegetation and the atmosphere. Higher wind speeds increase aerodynamic conductance (g_a), especially in densely vegetated areas (Villalobos et al., 2024; Angelini et al., 2011). Indeed, LAI contributes more than wind speed in Arid regions, whereas wind speed dominates in the Humid region, indicating a relatively weaker vegetation control on VC in energy-limited zones and a stronger influence of atmospheric turbulence (Yang et al., 2023; Villalobos et al., 2024).

Marginal effect analyses (Fig. 5 g–h) further confirm LAI and wind speed as dominant factors, where both appear to exert a saturation-like effect. Increasing LAI expands the transpiring surface area, which—under conditions of sufficient soil moisture—enables vegetation to sustain higher photosynthetic activity through enhanced transpiration without experiencing water stress. However, beyond a critical LAI threshold, soil moisture availability may become insufficient to meet the elevated transpiration demand associated with further LAI increases. This limitation induces stomatal closure, causing vegetation to transition from a passive reliance on soil moisture to an active regulation of water loss via stomatal conductance. Consequently, the plant prioritizes water conservation over carbon assimilation, resulting in a plateau in the LAI-VC relationship, where VC stabilizes rather than continuing to decline. Conversely, wind speed could enhance turbulence, facilitate the exchange of matter and energy between the atmosphere and vegetation. It should be noted that the higher the wind speed, the greater the turbulence intensity, which in turn increases the atmospheric aerodynamic conductance (g_a), particularly in areas with dense vegetation (Villalobos et al., 2024; Angelini et al., 2011).

Increases in soil moisture slightly reduces VC, consistent with the notion that enhanced water availability reduces vegetation's regulatory capacity. This aligns with the lower VC values observed in Humid regions (Denissen et al., 2022). Additionally, increases in air temperature and VPD lead to higher VC values by enhancing atmospheric water demand and canopy transpiration (Li et al., 2023a; Zhou et al., 2019).

5. Conclusions

In this study, we analysed the temporal and spatial variations of VC values using the metric ω and quantified the contributions of LAI and climatic variables' annual trends to VC annual trends using a non-linear random forest model. The key conclusions are as follows:

- (1). Spatial distribution of VC values: two g_c models show similar spatial patterns in multi-year averages that the highest VC values are observed in Arid regions, the lowest VC values are in Humid regions, and Transition regions exhibit intermediate values.
- (2). Model agreement of VC trends: across all models, 38.84 %–61.98 % of global land shows decreasing VC trend, particularly in regions such as northern and southern North America, parts of central and southern Africa, Europe, central Asia, India, China, and the mid-west of Australia.
- (3). Key drivers of VC changes: LAI and wind speed are the primary drivers of VC trends across Humid, Transition, and Arid regions. Increasing LAI would reduce VC values, while increasing wind speed increase VC values.

CRediT authorship contribution statement

Shijie Li: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Guojie Wang:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Shanlei Sun:** Writing – review & editing. **Zefeng Chen:** Writing – review & editing. **Matteo Mura:** Writing – review & editing. **Jiao Lu:** Writing – review & editing. **Qi Liu:** Writing – review & editing. **Ji Li:** Writing – review & editing. **Daniel Fiifi Tawia Hagan:** Writing – review & editing, Conceptualization. **Almudena García-García:** Writing – review & editing. **Jian Peng:** Writing – review & editing, Supervision.

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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Supplementary materials

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Data availability

Data will be made available on request.

References

- Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop Evapotranspiration: Guidelines for Computing Crop Requirements. FAO Irrigation and Drainage, Roma, Italia, FAO, p. 56. Paper.

- Angelini, I.M., Garstang, M., Davis, R.E., et al., 2011. On the coupling between vegetation and the atmosphere. *Theor. Appl. Climatol.* 105, 243–261. <https://doi.org/10.1007/s00704-010-0377-5>.
- Berg, A., Findell, K., Lintner, B., et al., 2016. Land-atmosphere feedbacks amplify aridity increase over land under global warming. *Nat. Clim. Chang.* 6, 869–874.
- Breiman, L., 2001. Random forests. *Mach. Learn.* 45, 5–32.
- Chen, Z., Wang, W., Cescatti, A., Forzieri, G., 2023. Climate-driven vegetation greening further reduces water availability in drylands. *Glob. Change Biol.* 29 (6), 1628–1647. <https://doi.org/10.1111/gcb.16561>.
- De Kauwe, M.G., Medlyn, B.E., Pitman, A.J., Williams, C.A., 2017. Ideas and perspectives: how coupled is the vegetation to the boundary layer? *Biogeosciences* 14, 4435–4453.
- De Kauwe, M.G., Medlyn, B.E., Pitman, A.J., Drake, J.E., Ukkola, A., Griebel, A., Pendall, E., Prober, S., Roderick, M., 2019. Examining the evidence for decoupling between photosynthesis and transpiration during heat extremes. *Biogeosciences* 16, 903–916.
- Denissen, J.M.C., Teuling, A.J., Pitman, A.J., et al., 2022. Widespread shift from ecosystem energy to water limitation with climate change. *Nat. Clim. Change* 12, 677–684.
- Diao, H., Cernusak, L.A., Saurer, M., Gessler, A., Siegwolf, R.T.W., Lehmann, M.M., 2024. Uncoupling of stomatal conductance and photosynthesis at high temperatures: mechanistic insights from online stable isotope techniques. *New Phytologist* 241 (6), 2366–2378.
- Dirmeyer, P.A., 2011. The terrestrial segment of soil moisture–climate coupling. *Geophys. Res. Lett.* 38, L16702. <https://doi.org/10.1029/2011GL04826>.
- Dirmeyer, P.A., Jin, Y., Singh, B., Yan, X., 2013. Trends in land–atmosphere interactions from CMIP5 simulations. *J. Hydrometeorol.* 14, 829–849.
- Dong, C., Fan, L., Fensholt, R., Frappart, F., Ciais, P., Xiao, X., Wigneron, J.P., 2023. Asymmetric response of primary productivity to precipitation anomalies in Southwest China. *Agric. For. Meteorol.* 331, 109350.
- Ek, M., et al., 2016. On the nature of local land-atmosphere coupling strength for vegetated surfaces. Monograph. https://github.com/pdirmeyer/1-a-cheat-sheets/blob/main/Ek_little-omega.pdf.
- Farquhar, G.D., Ehleringer, J.R., Hubick, K.T., 1989. Carbon isotope discrimination and photosynthesis. *Annu. Rev. Plant Biol.* 40, 503–537.
- Feng, X., Fu, B., Zhang, Y., Pan, N., Zeng, Z., Tian, H., et al., 2021. Recent leveling off of vegetation greenness and primary production reveals the increasing soil water limitations on the greening. *Earth Sci. Bull.* 66 (14), 1462–1471.
- Flo, V., Martínez-Vilalta, J., Granda, V., Mencuccini, M., Poyatos, R., 2022. Vapour pressure deficit is the main driver of tree canopy conductance across biomes. *Agric. For. Meteorol.* 322, 109029.
- Forzieri, G., et al., 2020. Increased control of vegetation on global terrestrial energy fluxes. *Nat. Clim. Change* 10, 356–362.
- Friedl, M.A., Strahler, A.H., Hodges, J., et al., 2010. ISLSCP II MODIS (Collection 4) IGBP Land Cover, 2000–2001. In: Hall, F.G., et al. (Eds.), ISLSCP Initiative II Collection. Data set. Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, TN, USA. Available online from: <https://doi.org/10.3334/ORNLDAAAC/968>.
- Gelaro, R., et al., 2017. The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). *J. Clim.* 30, 5419–5454.
- Hersbach, H., et al., 2020. The ERA5 global reanalysis. *Q. J. R. Meteorol. Soc.* 146, 1999–2049.
- Hsu, H., Dirmeyer, P.A., 2023. Soil moisture–evaporation coupling shifts into new gears under increasing CO₂. *Nat. Commun.* 14, 1162.
- Hsu, H., Lo, M.-H., Guillod, B.P., Miralles, D.G., Kumar, S., 2017. Relation between precipitation location and antecedent/subsequent soil moisture spatial patterns: precipitation–soil moisture coupling. *J. Geophys. Res. Atmos.* 122, 6319–6328.
- Ivanova, T., Porchetta, S., Buckingham, S., Glabeke, G., van Beeck, J., Munter, W., 2025. Improving wind and power predictions via four-dimensional data assimilation in the WRF model: case study of storms in February 2022 at Belgian offshore wind farms. *Wind Energ. Sci.* 10, 245–268.
- Jarvis, P., McNaughton, K., 1986. Stomatal control of transpiration: scaling up from leaf to region. *Adv. Ecol. Res.* 15, 1–49.
- Koster, R.D., et al., 2006. GLACE: the Global Land–Atmosphere coupling Experiment. Part I: Overview. *J. Hydrometeorol.* 7, 590–610.
- Leuning, R., 1995. A critical appraisal of a combined stomatal-photosynthesis model for C₃ plants. *Plant Cell Environ.* 18 (4), 339–355.
- Leuning, R., Zhang, Y.Q., Rajaud, A., Cleugh, H., Tu, K., 2008. A simple surface conductance model to estimate regional evaporation using MODIS leaf area index and the Penman-Monteith equation. *Water Resour. Res.* 44, W10419.
- Li, J., Zhang, Y., Bevacqua, E., et al., 2024. Future increase in compound soil drought-heat extremes exacerbated by vegetation greening. *Nat. Commun.* 15, 10875. <https://doi.org/10.1038/s41467-024-55175-0>.
- Li, S.J., Wang, G.J., Zhu, C.X., et al., 2023a. Vegetation growth due to CO₂ fertilization is threatened by increasing vapor pressure deficit. *J. Hydrol.* 619 (3), 129292.
- Li, S., Wang, G., Zhu, C., et al., 2023b. Spatial patterns and recent temporal trends in global transpiration modelled using eco-evolutionary optimality. *Agric. For. Meteorol.* 342, 109702.
- Lian, X., Piao, S., Huntingford, C., et al., 2018. Partitioning global land evapotranspiration using CMIP5 models constrained by observations. *Nat. Clim. Change* 8, 640–646.
- Liang, S., et al., 2021. The global land surface satellite (GLASS) product suite. *Bull. Am. Meteorol. Soc.* 102 (2), E323–E337.
- Liu, H., Yang, R., 2025. Artificial intelligence for wind speed forecasting: a review on multi-scale decomposition and intelligent fusion strategies. *Adv. Wind Eng.* 100055.
- Liu, J., Ryu, Y., Luo, X., et al., 2024. Evidence for widespread thermal acclimation of canopy photosynthesis. *Nat. Plants* 10, 1919–1927. <https://doi.org/10.1038/s41477-024-01846-1>.
- Liu, Y., Zhang, Y., Shan, N., Zhang, Z., Wei, Z., 2022. Global assessment of partitioning transpiration from evapotranspiration based on satellite solar-induced chlorophyll fluorescence data. *J. Hydrol.* 612, 128044.
- Lu, J., et al., 2021. Projected land evaporation and its response to vegetation greening over China under multiple scenarios in the CMIP6 models. *J. Geophys. Res. Biogeosci.* 126, e2021JG006327.
- Marchin, R.M., Medlyn, B.E., Tjoelker, M.G., Ellsworth, D.S., 2023. Decoupling between stomatal conductance and photosynthesis occurs under extreme heat in broadleaf tree species regardless of water access. *Glob. Change Biol.* 29, 6319–6335.
- Miralles, D.G., Gentile, P., Seneviratne, S.I., Teuling, A.J., 2019. Land-atmospheric feedbacks during droughts and heatwaves: state of the science and current challenges: land feedbacks during droughts and heatwaves. *Ann. N. Y. Acad. Sci.* 1436, 19–35.
- Miralles, D.G., Vilà-Guerau de Arellano, J., McVicar, T.R., Mahecha, M.D., 2025. Vegetation–climate feedbacks across scales. *Ann. N. Y. Acad. Sci.* 1–15. <https://doi.org/10.1111/nyas.15286>.
- Miralles, D., Teuling, A., van Heerwaarden, C., et al., 2014. Mega-heatwave temperatures due to combined soil desiccation and atmospheric heat accumulation. *Nat. Geosci.* 7, 345–349.
- Nelson, J.A., et al., 2024. X-BASE: the first terrestrial carbon and water flux products from an extended data-driven scaling framework. *Fluxcom. X. Biogeosci.* 21, 5079–5115.
- Schwingshackl, C., Hirschi, M., Seneviratne, S.I., 2017. Quantifying spatiotemporal variations of soil moisture control on surface energy balance and near-surface air temperature. *J. Clim.* 30, 7105–7124.
- Seneviratne, S.I., et al., 2010. Investigating soil moisture–climate interactions in a changing climate: a review. *Earth Sci. Rev.* 99, 125–161.
- Simard, M., Pinto, N., Fisher, J.B., Baccini, A., 2011. Mapping forest canopy height globally with spaceborne lidar. *J. Geophys. Res.* 116, G04021.
- Still, C.J., Berry, J.A., Collatz, G.J., DeFries, R.S., et al., 2009. ISLSCP II C4 vegetation percentage. In: Hall, F.G., et al. (Eds.), ISLSCP Initiative II Collection. Data set. Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, TN, USA. Available online from: <https://doi.org/10.3334/ORNLDAAAC/932>.
- Stocker, B.D., et al., 2020. P-model v1.0: an optimality-based light use efficiency model for simulating ecosystem gross primary production. *Geosci. Model Dev.* 13 (3), 1545–1581. <https://doi.org/10.5194/gmd-13-1545-2020>.
- Tan, S., Wang, H., et al., 2023. Towards a universal evapotranspiration model based on optimality principles. *Agric. For. Meteorol.* 336, 109478.
- Tan, S., Wang, H., Prentice, I.C., Yang, K., 2021. Land-surface evapotranspiration derived from a first-principles primary production model. *Environ. Res. Lett.* <https://doi.org/10.1088/1748-9326/ac29eb>.
- Taylor, C.M., et al., 2011. Frequency of Sahelian storm initiation enhanced over mesoscale soil-moisture patterns. *Nat. Geosci.* 4, 430–433.
- Taylor, C.M., de Jeu, R.A.M., Guichard, F., Harris, P.P., Dorigo, W.A., 2012. Afternoon rain more likely over drier soils. *Nature* 489, 423–426.
- Tian, L., Zhang, Y., Zhu, J., 2014. Decreased surface albedo driven by denser vegetation on the tibetan plateau. *Environ. Res. Lett.* 9 (10), 104001.
- Vargas Zeppetello, L.R., McColl, K.A., Bernau, J.A., et al., 2023. Apparent surface conductance sensitivity to vapour pressure deficit in the absence of plants. *Nat. Water* 1, 941–951. <https://doi.org/10.1038/s44221-023-00147-9>.
- Villalobos, F.J., Fereres, E., Testi, L., De Melo-Abreu, J.P., 2024. Wind and turbulent transport. Principles of Agronomy for Sustainable Agriculture. Springer International Publishing, Cham, pp. 47–58.
- Wang, H., Prentice, I.C., Keenan, T.F., et al., 2017. Towards a universal model for carbon dioxide uptake by plants. *Nat. Plants* 3, 734–741.
- Wang, K., Zhao, D., Zhu, Y., Gao, X., Deng, S., Chen, Z., Wang, S., Cui, Y., 2023. Albedo-dominated biogeophysical warming effects induced by vegetation restoration on the loess plateau. *China Ecol. Indic.* 154, 110690.
- Wilcox, R.R., 2010. Fundamentals of Modern Statistical methods: Substantially Improving Power and Accuracy, 319. Springer, New York, pp. 153–154 (5862).
- Williams, I.N., Torn, M.S., 2015. Vegetation controls on surface heat flux partitioning, and land-atmosphere coupling. *Geophys. Res. Lett.* 42, 9416–9424.
- Yang, Y., Roderick, M.L., Guo, H., et al., 2023. Evapotranspiration on a greening Earth. *Nat. Rev. Earth Environ.* 4, 626–641. <https://doi.org/10.1038/s43017-023-00464-3>.
- Zhang, Y., et al., 2022. Evaluating the vegetation–atmosphere coupling strength of ORCHIDEE land surface model (v7266). *Geosci. Model Dev.* 15, 9111–9125. <https://doi.org/10.5194/gmd-15-9111-2022>.
- Zhang, Y., Kong, D., Gan, R., Chiew, F.H.S., McVicar, T.R., Zhang, Q., Yang, Y., 2019. Coupled estimation of 500 m and 8-day resolution global evapotranspiration and gross primary production in 2002–2017. *Remote Sens. Environ.* 222, 165–182. <https://doi.org/10.1016/j.rse.2018.12.031>.
- Zhou, S., Zhang, Y., Williams, A.P., Gentile, P., 2019. Projected increases in intensity, frequency, and terrestrial carbon costs of compound drought and aridity events. *Sci. Adv.* 5, eaau5740.
- Zhu, Z., Piao, S., Myeni, R., et al., 2016. Greening of the Earth and its drivers. *Nat. Clim. Change* 6, 791–795. <https://doi.org/10.1038/nclimate3004>.
- Zomer, R.J., Xu, J., Trabucco, A., 2022. Version 3 of the global aridity index and potential evapotranspiration database. *Sci. Data* 9, 409.
- Zscheischler, J., Orth, R., Seneviratne, S.I., 2015. A submonthly database for detecting changes in vegetation–atmosphere coupling. *Geophys. Res. Lett.* 42, 9816–9824.