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Key Points:

- RS captures GPP's directional response to VPD and SWC deficit relative to EC measurements but misses the magnitude
- The discrepancy in absolute changes between RS and EC is ecosystem-specific and consistent across all examined RS products
- Integrating ecosystem-specific VPD effects and non-linear SWC deficit responses may improve RS GPP simulations

Supporting Information:

Supporting Information may be found in the online version of this article.

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Can Large-Scale Satellite Products Track the Effects of Atmospheric Dryness and Soil Water Deficit on Ecosystem Productivity Under Droughts?

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Abstract Drought stress, characterized by increased vapor pressure deficit (VPD) and soil water content (SWC) deficit, significantly impacts ecosystem productivity (GPP). Accurately assessing these factors in satellite remote sensing (RS) GPP products is crucial for understanding the large-scale ecological consequences of drought. However, the accuracy of RS GPP in capturing the effects of VPD and SWC deficit, compared to EC flux data, remains under-investigated. Here we evaluated 10 RS GPP products and their mean (RSmean) concerning VPD and SWC deficit across diverse ecosystems along a dryness gradient. Our results revealed that RSmean and individual products generally capture the GPP response direction (VPD: mainly negative, SWC deficit: mixed positive/negative) but consistently misestimate the absolute GPP changes. This discrepancy is ecosystem-specific and consistent across all RS products, underscoring the need to enhance RS products to better account for ecosystem-specific VPD effects and non-linear SWC deficit responses, thereby improving RS GPP accuracy under drought.

Plain Language Summary Droughts significantly affect how productive ecosystems are by reducing the amount of water in the air (vapor pressure deficit, VPD) and in the soil (soil water content, SWC). Researchers use satellite remote sensing (RS) products to study these drought impacts on ecosystem productivity (GPP) across large areas. However, current satellite tools often inaccurately estimate the effects of VPD and SWC deficit, leading to uncertainties in GPP estimation during droughts. In our study, we examined the performance of 10 mainstream RS GPP estimates and their average (RSmean) to assess how well they track ecosystem productivity responses to VPD and SWC deficit across various ecosystems along a dryness gradient. We found that although RSmean and individual RS GPP products can capture the trend of GPP in response to VPD and SWC deficit, they do not accurately match the actual value changes in GPP observed on the ground. This misestimation varies by ecosystem and is consistent across all RS products. To improve the accuracy of GPP estimation under droughts, we recommend that future RS GPP account for ecosystem-specific VPD effects and non-linear SWC deficit effects. This would enable a more reliable assessment of the drought impacts on vegetation productivity at large scales.

1. Introduction

Droughts, characterized by elevated atmospheric vapor pressure deficit (VPD) and soil water content (SWC) deficit, significantly impact terrestrial gross primary productivity (GPP) (Sippel et al., 2018). The IPCC's sixth assessment report (AR6) predicts that global warming will intensify droughts, potentially threatening terrestrial carbon sinks by suppressing GPP (Caretta et al., 2022). Therefore, accurately estimating GPP's response to droughts is crucial for understanding ecosystem vulnerability under future climate scenarios (Chen et al., 2023).

The effects of VPD and SWC deficit on GPP are fundamentally linked to the soil-plant-atmosphere continuum (Sperry et al., 2016). This involves soil water extraction by plant roots, its transport to leaves, and subsequent transpiration via stomata (Passioura, 1982). Increased VPD triggers stomatal closure to minimize water loss,

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thereby reducing GPP (Grossiord et al., 2020). Similarly, reduced SWC also induces stomata closure due to decreased plant xylem conductance and regulation of abscisic acid, further decreasing GPP (Buckley, 2019).

Recent studies utilizing ground eddy-covariance (EC) flux measurements have examined the relative roles of VPD and SWC in regulating GPP across various ecosystems and climate gradients. These studies suggest that VPD predominantly affects GPP across extensive aridity gradients and serves as a more significant water stressor than SWC deficit in humid ecosystems (e.g., mesic forests) (Kimm et al., 2020; Novick et al., 2016; Sulman et al., 2016; S. Xu et al., 2023). Conversely, in semi-arid and arid ecosystems (e.g., grasslands), SWC deficit has a greater negative impact on GPP when SWC falls below a critical threshold (Fu et al., 2022; Stocker et al., 2018). Collectively, these studies highlight the importance of considering the distinct roles of VPD and SWC deficit in assessing the drought stress impacts on plant productivity across different climates and ecosystems.

While EC flux tower sites provide valuable ground-truth data to examine the impacts of drought stress on GPP, their limited number and spatial coverage present constraints (Pastorello et al., 2020). To enable large-scale monitoring of drought effects on ecosystem productivity, satellite remote sensing (RS)-based GPP products have been developed and widely used (Jiao et al., 2021; Ryu et al., 2019).

Despite the advantages of using RS GPP for assessing drought effects on productivity, uncertainties persist. Different RS GPP data sets can yield varying results due to diverse assumptions about drought impacts across stress dimensions (i.e., VPD vs. SWC deficit) and ecosystem types (Bao et al., 2022; Wang et al., 2022; Zhang et al., 2015, 2023). For example, GPP estimation based on vegetation optical depth (VOD), derived from satellite-based surface microwave emission, is sensitive to canopy water content, making it a better indicator of SWC deficit effects on plants (Lyons et al., 2021; Wild et al., 2021). Conversely, certain GPP estimations (e.g., Moderate Resolution Imaging Spectroradiometer, MODIS GPP products) are found to better capture the VPD effects, as they incorporate an atmospheric water stress function (Hwang et al., 2008; Pei et al., 2020; Yuan et al., 2014). Previous studies also show that in mesic ecosystems (e.g., Eastern European forests), where VPD predominantly influences GPP dynamics, MODIS GPP aligns well with EC GPP measurements, showing a more pronounced decrease with rising VPD compared to VOD-based GPP. In contrast, in arid ecosystems (e.g., Western North America dryland), where SWC deficit mainly drives GPP dynamics, VOD-based GPP is more sensitive to SWC changes and aligns better with EC observations, while MODIS GPP tends to underestimate GPP loss related with SWC deficit (Hwang et al., 2008; Wild et al., 2021).

To address these uncertainties, this study aims to comprehensively evaluate 10 mainstream satellite RS GPP products (Table S1 in Supporting Information S1) by analyzing their performance in capturing the effects of VPD and SWC deficit on GPP. We assembled globally available EC data to benchmark these RS GPP products under various SWC-VPD gradients and ecosystem types. Specifically, we addressed three questions: (a) How well does the mean value of 10 GPP products (RSmean) capture the patterns (including direction and magnitude) of GPP response to VPD and SWC deficit under various VPD-SWC conditions compared to those derived from EC observations? (b) Are the GPP response patterns, from RSmean and EC data, consistent across forest, non-forest, and cropland ecosystems? (c) Do different RS GPP products exhibit convergent or divergent performance in capturing GPP responses to VPD and SWC deficit? By addressing these questions, we hope to improve our understanding of the reliability of using RS GPP products for drought stress impact assessments and provide a critical benchmark for future improvements in accurately characterizing both VPD and SWC deficit effects.

2. Materials and Methods

2.1. Materials

We used two main types of data: (a) EC flux data from FLUXNET2015 and European flux networks, and (b) Satellite RS-based GPP products.

2.1.1. Ground EC and Meteorological Measurements

We reviewed EC sites from FLUXNET2015 and European Flux networks, which process data using a standardized pipeline (Pastorello et al., 2020), detailed in Text S3 of the Supporting Information S1. A total of 80 sites, spanning from 2001 to 2015, were selected based on the availability of daily GPP, soil moisture content (SWC), and three key meteorological variables: VPD, incoming shortwave radiation (SW) and air temperature

(Ta). Surface SWC measurements were used due to the significantly fewer sites with deep-depth SWC data. Details on the 80 sites are provided in Table S2 and Figure S3 of the Supporting Information S1.

2.1.2. Satellite RS-Based GPP Products

We analyzed ten widely used global GPP products (Table S1 in Supporting Information S1): MODIS (S. W. Running et al., 2004), VPM (Zhang et al., 2017), ECLUE (Y. Zheng et al., 2020), GOSIF (Li & Xiao, 2019a, 2019b), VODCA2 (Wild et al., 2021), BESS (Jiang & Ryu, 2016), P-model (Stocker et al., 2019), and FLUXCOM (RF/ANN/MARS) (Jung et al., 2020). These products were chosen for two main reasons. First, they employ diverse and representative GPP estimation methodologies (Zhu et al., 2024). Second, these products are publicly available, covering long-term periods (at least 2001–2015) with relatively high temporal resolution, ranging from daily to 8-day intervals. Detailed descriptions and processing methods are provided in Texts S1 and S2 of the Supporting Information S1.

2.2. Methods

To evaluate the effectiveness of satellite RS GPP products in assessing GPP response to drought stress (VPD and SWC deficit), we conducted three key analyses. First, we selected EC sites to minimize potential scale mismatches between RS and EC measurements (Section 2.2.1). Second, we trained artificial neural network (ANN) models to link VPD and SWC with GPP, deriving GPP sensitivity to drought stress using these models (Section 2.2.2). Finally, we compared the RS GPP drought stress sensitivity results with the corresponding EC results (Sections 2.2.2 and 2.2.3). A flowchart summarizing these analyses is presented in Figure S2 of the Supporting Information S1. Evaluations were performed for both the mean value of the 10 GPP products (RSmean, Sections 3.1 and 3.2) and individual products (Section 3.3).

2.2.1. EC Sites Selection

Given the spatial footprint differences between ground EC measurements (<1 km) and RS GPP (with pixel size of 0.5°, approximately 50 km), we conducted additional site screening to minimize scale mismatch. We implemented a two-step process to select EC sites with homogeneous vegetation cover that could represent the corresponding RS GPP pixel (Text S4 in Supporting Information S1). This resulted in the selection of 36 sites (sites indicated by * in Table S2 of the Supporting Information S1) grouped into three major ecosystem types: forests (evergreen needle forest—ENF, evergreen broadleaved forest—EBF, deciduous broadleaved forest—DBF, and mixed forest—MF), non-forests (grassland—GRA), and croplands (CRO) as per Fernández-Martínez et al. (2020).

2.2.2. ANN Models Training and Sensitivity Analyses

To assess GPP sensitivity to VPD and SWC deficit, we employed ANN models, a data-driven machine learning method widely used in ecological research (Green et al., 2020; Stocker et al., 2018). At each site, we adopted the feed-forward ANN model from Fu et al. (2022), following a three-step process: (a) data screening; (b) model training and evaluation; and (c) determining GPP sensitivity to VPD and SWC deficit based on the trained models (Text S5 in Supporting Information S1). Detailed definitions of sensitivity to VPD and SWC deficit are provided in Text S6 of the Supporting Information S1. An example site (US-Blo), illustrating the ANN model's estimation of GPP sensitivity to VPD and SWC deficit is included in Figure S5 of the Supporting Information S1.

2.2.3. Metrics for Comparing RS GPP Sensitivity to VPD and SWC Deficit With EC Measurements

We used a difference metric to evaluate any systematic bias in RS GPP sensitivity relative to EC results using Equation 1:

$$\text{Difference} = \text{median}\,(S_{RS}) - \text{median}\,(S_{EC}) \tag{1}$$

where S_{RS} and S_{EC} denote GPP sensitivity to VPD or SWC deficit derived from RS and EC data, respectively, across all relevant sites.

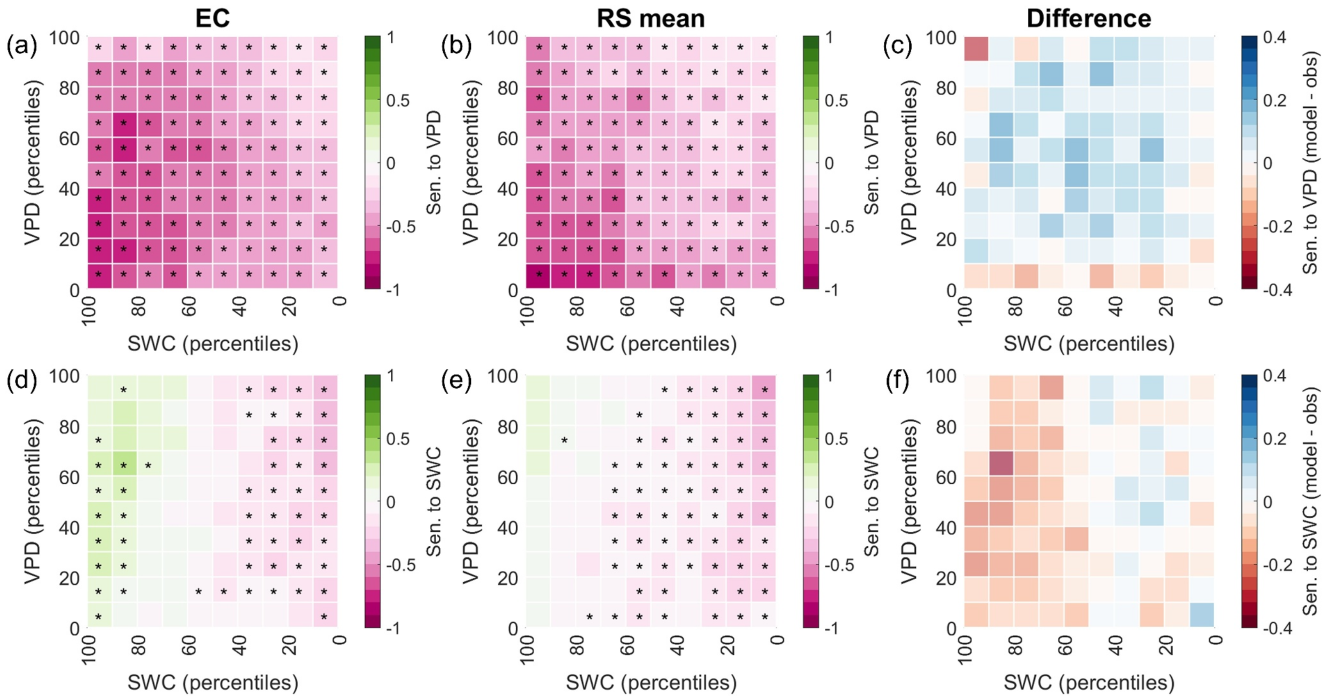

Figure 1. Sensitivities of GPP to VPD and SWC deficit based on EC data and RSmean (mean value of 10 RS GPP data sets). Sensitivities of GPP to VPD for (a) EC data and (b) RSmean; Sensitivities of GPP to SWC deficit for (d) EC data and (e) RSmean; Differences (RSmean minus EC) of GPP sensitivities to (c) VPD and (f) SWC deficit. Median of sensitivities across all sites are used. An asterisk "*" indicates that the sensitivities are significantly different from zero based on *t*-tests ($p < 0.05$) across all sites for each VPD-SWC bin.

3. Results

3.1. Overall GPP Sensitivity to Drought Stress: EC Versus Satellite RSmean

Our results demonstrate that RSmean, the mean value of 10 GPP products, captures the general direction of GPP response to VPD and SWC deficit across the full VPD-SWC gradients (Figures 1a, 1b, 1d, and 1e). However, it fails to reproduce the absolute GPP changes compared to EC measurements (Figures 1c and 1f).

The analysis of GPP sensitivity to VPD using EC data reveals a predominantly negative response across the entire VPD-SWC space, with variations in the distribution of these negative sensitivity values (Figure 1a). Similarly, RSmean exhibits a primarily negative sensitivity to VPD (Figure 1b), but consistently underestimates the negative GPP sensitivity values across a broad VPD-SWC range compared to the EC results (Figure 1c).

For SWC deficit, EC data shows a mixed response, with positive and negative sensitivities depending on the specific VPD-SWC conditions (Figure 1d). Positive sensitivity dominates when SWC is high (>60th percentiles of SWC), while negative sensitivity prevails as SWC decreases (<60th percentiles of SWC). In contrast, RSmean exhibits distinct sensitivity patterns, with a broader VPD-SWC range characterized by negative sensitivity and a narrower range of positive sensitivity (mainly when SWC is >90th percentiles) (Figure 1e). Consequently, significant differences in the magnitude of GPP-SWC deficit sensitivity are observed between EC and RSmean data, with RSmean tending to underestimate the positive (negative) sensitivity under high (low) SWC conditions (Figure 1f).

3.2. Variation in GPP Response to Drought Stress Across Different Ecosystem Types

Our Results indicate that RSmean captures the overall direction of GPP response to VPD and SWC deficit in forests (DBF, ENF, and MF), non-forests (GRA), and croplands (CRO), consistent with the EC results (Figure 2). However, there are differences in the sensitivity magnitude between RSmean and EC across these ecosystem types (Figure 2).

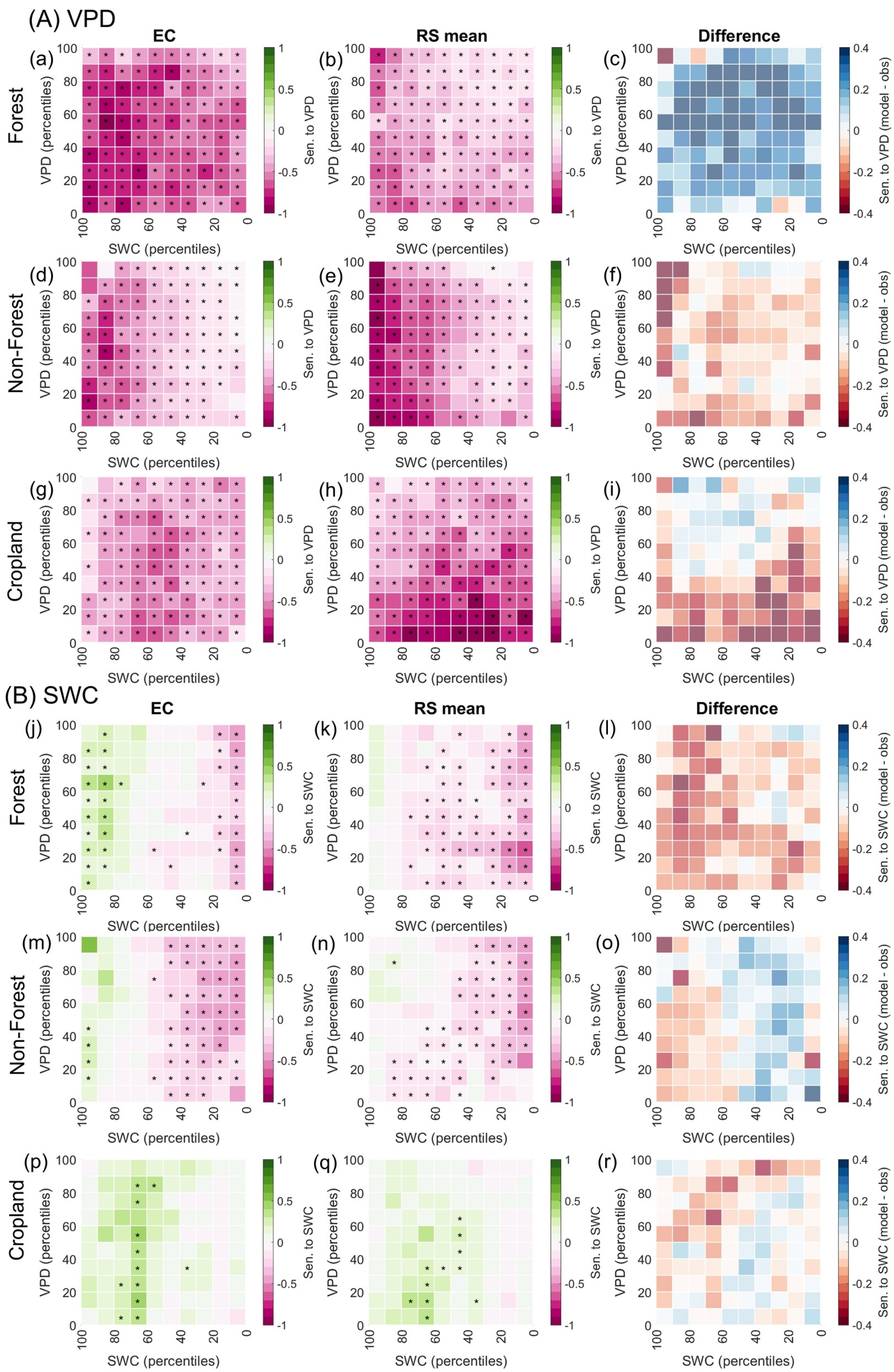
(A) VPD
EC
RS mean
Difference
Forest
Non-Forest
Cropland
VPD (percentiles)
SWC (percentiles)
Sen. to VPD
Sen. to VPD (model - obs)
(B) SWC
Sen. to SWC
Sen. to SWC (model - obs)

Figure 2.

EC data consistently show a negative sensitivity to VPD across the entire VPD-SWC space for all three ecosystem types (Figures 2a, 2d, and 2g). Notable differences exist in GPP-VPD sensitivity among ecosystem types, with forests and non-forests showing more pronounced negative sensitivity compared to croplands when SWC is high. RSmean also captures similar negative sensitivity to VPD across ecosystem types (Figures 2b, 2e, and 2h), but variations in sensitivity magnitude are observed (Figures 2c, 2f, and 2i). Forests exhibit a greater underestimation of negative GPP sensitivity to VPD, while non-forests and croplands tend to overestimate it.

GPP-SWC deficit sensitivity derived from EC data displays significant variations across ecosystem types. Forests and non-forests exhibit mixed positive and negative sensitivities (Figures 2j and 2m), while croplands are predominantly characterized by positive sensitivity (Figure 2p). Non-forests show more negative sensitivity values compared to forests (Figures 2j and 2m). RSmean generally aligns with the sensitivity direction observed in EC data for forests and non-forests (positive vs. negative) and for croplands (predominantly positive) (Figures 2k, 2n, and 2q). However, in terms of sensitivity magnitude, RSmean primarily underestimates negative GPP-SWC deficit sensitivity in non-forests, particularly when SWC is below the threshold (i.e., 70th percentiles) (Figure 2o), while all three ecosystem types underestimate the positive effects of SWC deficit across most of the VPD-SWC space (Figures 2l, 2o, and 2r).

3.3. Performance of Each RS Product in Capturing GPP Response to Drought Stress

Consistent with EC results, each RS product captures the negative effects of VPD across the three ecosystem types examined (Figure 3a), with forests and non-forests displaying a decreased negative VPD sensitivity with drying-down SWC gradient, while croplands showing an opposite pattern (Figures 3c, 3e, and 3g). Specifically, all products display similar responses to VPD in forests, albeit with a systematic underestimation of negative VPD effects (Figure 3c, Figures S7a and S7c in Supporting Information S1) compared to non-forests and croplands (Figure 3e, Figures S8a and S8c in Supporting Information S1; Figure 3g, Figures S9a and S9c in Supporting Information S1). In non-forests, all products exhibit convergent negative VPD responses with discrepancies between RS and EC results (Figure 3e, Figures S8a and S8c in Supporting Information S1). For croplands, RS products display comparable negative VPD responses, though the P-model and VODGPP show larger biases (Figure 3g, Figures S9a and S9c in Supporting Information S1).

Regarding the response to SWC deficit, RS products generally capture a mixture of positive and negative sensitivities across the high to low SWC gradient (Figure 3b). This includes similar mixed positive and negative sensitivities observed in both forests and non-forests, and predominantly positive sensitivities in croplands (Figure 3d, Figure S7b in Supporting Information S1; Figure 3f, Figure S8b in Supporting Information S1; Figure 3h, Figure S9b in Supporting Information S1). In forests, RS products tend to underestimate positive effects when SWC is high (>10th percentiles), subsequently underestimate negative effects under low SWC conditions (<10th SWC percentiles and >80th VPD percentiles) (Figure S7d in Supporting Information S1). In non-forests, all RS products underestimate positive effects when SWC is above 10th percentiles and negative effects when SWC is below 70th percentiles (Figure S8d in Supporting Information S1). For croplands, most RS products (excluding VODGPP) continuously underestimate positive effects (Figure S9d in Supporting Information S1).

4. Discussion and Conclusion

RS-based GPP products are essential for assessing drought effects on terrestrial carbon fluxes and benchmarking Earth system models (Sippel et al., 2018). This study comprehensively evaluates the capacity of 10 RS GPP products, including their mean value (RSmean) and individual products, to capture the relative effects of VPD and

Figure 2. Comparison of GPP sensitivities to VPD and SWC deficit using EC data and RSmean (mean value of 10 RS GPP data sets) across different ecosystem types. Median values of sensitivities within each ecosystem type are used. Section A: GPP sensitivities to VPD for forests (a), (b), non-forests (d), (e), and croplands (g), (h), with left panels (a, d, g) showing EC data and middle panels (b, e, h) showing RSmean. The differences (RSmean minus EC) in GPP sensitivities to VPD are in the last panel for forests (c), non-forests (f), and croplands (i). Section B: GPP sensitivities to SWC deficit for forests (j), (k), non-forests (m, n), and croplands (p, q), with left panels (j, m, p) showing EC data and middle panels (k, n, q) showing RSmean. The differences in GPP sensitivities to SWC deficit are displayed in the last panel for forests (l), non-forests (o), and croplands (r). An asterisk "*" indicates that the sensitivities are significantly different from zero based on *t*-tests ($p < 0.05$) across all sites for each VPD-SWC bin.

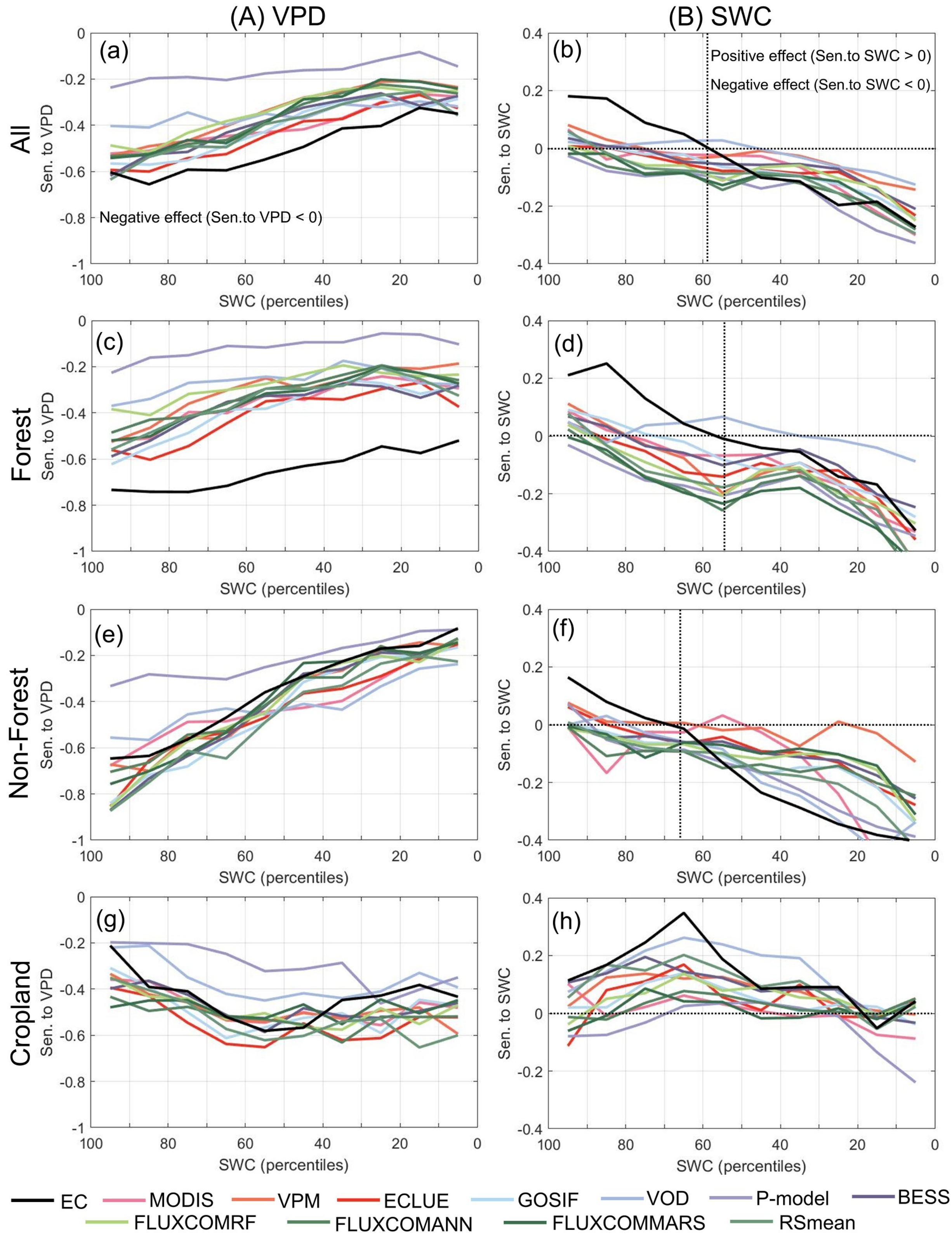
(A) VPD
(B) SWC
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
All
Forest
Non-Forest
Cropland
Sen. to VPD
Sen. to SWC
SWC (percentiles)
Positive effect (Sen.to SWC > 0)
Negative effect (Sen.to SWC < 0)
Negative effect (Sen.to VPD < 0)
EC
MODIS
VPM
ECLUE
GOSIF
VOD
P-model
BESS
FLUXCOMRF
FLUXCOMANN
FLUXCOMMARS
RSmean

Figure 3.

SWC deficit—two key dimensions describing droughts—on GPP across diverse VPD-SWC gradients and ecosystem types.

Consistent with previous research (Fu et al., 2022), EC data reveal negative GPP responses to VPD and mixed positive and negative responses to SWC deficit (Figures 1a and 1b). Both RSmean and all RS products capture the general direction of these responses (Figures 1d, 1e, 3a, and 3b, Figures S6a and S6b in Supporting Information S1), but tend to underestimate the absolute magnitude of GPP changes compared to EC data. This underestimation is evident in the negative GPP sensitivity to VPD across the entire VPD-SWC space, and the positive (negative) sensitivity of GPP to SWC deficit under high (low) SWC conditions (Figures 1c, 1f, 3a, and 3b, Figures S6c and S6d in Supporting Information S1). These findings suggest that while RS products can capture drought effects on plant productivity, their ability to quantify absolute GPP loss due to drought remains uncertain.

The significant magnitude difference observed between RS and EC may be attributed to the limited accuracy of RS products in modeling drought stress (i.e., high VPD and low SWC) (Liu et al., 2020; Lu et al., 2022). The 10 products in this study can be classified into three types based on their representation of water stress: (a) atmospheric dryness indicators (MODIS, ECLUE, GOSIF, BESS, and FLUXCOM), (b) combined atmospheric dryness and soil moisture deficit indicators (P-model), and (c) plant water content indicators (VPM, VOD).

EC results show that GPP sensitivity to VPD varies across different ecosystems (Figures 2a, 2d, and 2g). This finding aligns with previous studies (Grossiord et al., 2020; S. Xu et al., 2023), which indicate that the GPP-VPD response curves vary with plant species and ecosystem types. However, RS GPP products often use uniform coefficients (e.g., a fixed slope in the stomatal conductance model within BESS model) or empirical response equations (e.g., MODIS) to broadly represent the GPP-VPD relationships, neglecting species and ecosystem-specific variations (Pei et al., 2020, 2022). This approach fails to capture the actual GPP response to VPD as observed in EC flux data (Figures 1d and 3a, Figure S6c in Supporting Information S1). Discrepancies between RS and EC results vary across different ecosystem types (Figures 2c and 3c, Figure S7c in Supporting Information S1; Figures 2f and 3e, Figure S8c in Supporting Information S1; Figures 2i and 3g, Figure S9c in Supporting Information S1), suggesting that RS GPP may not fully capture ecosystem-specific responses. These findings emphasize the need to refine RS methodologies to quantify differential VPD effects across diverse ecosystem types.

The effect of VPD on GPP is also regulated by SWC (Green, 2024). Our results indicate that RS GPP can capture the GPP-SWC deficit relationship to some extent, as declines in SWC often coincide with increased atmospheric dryness (Seneviratne et al., 2010), where VPD serves as a significant water stress factor captured by several RS products (Jiang & Ryu, 2016; Jung et al., 2020; Li & Xiao, 2019b; S. W. Running et al., 2004; Zhang et al., 2017; Y. Zheng et al., 2020). However, recent studies suggest that under extreme conditions—very dry or very wet SWC—the VPD-SWC relationship decouples. In very dry soil, stomatal closure occurs to prevent excessive hydraulic conductance losses, outweighing VPD in constraining plant productivity (Seneviratne et al., 2010; Stocker et al., 2018). Conversely, in wet conditions, decreases in SWC can reduce stomatal conductance but may still increase productivity (Fu et al., 2022; Green, 2024). This decoupling can hinder the performance of RS GPP products, explaining the biases in capturing SWC deficit effects compared to EC data under extreme conditions (Figures 1f and 3b, Figure S6d in Supporting Information S1).

The underestimation of the negative effects of SWC deficit is more pronounced in non-forests (Figure S8d in Supporting Information S1) than in forests, where it is significant only under conditions of high VPD (>80th percentiles) and low SWC (<10th percentiles) (Figure S7d in Supporting Information S1). Consistent with previous research (Stocker et al., 2019), we found that LUE-based GPP (MODIS and VPM) and the process-based GPP (BESS) products underestimate the negative effects of SWC deficit in non-forests (Figure 3f, Figure S8d in Supporting Information S1). This may be due to insufficient consideration of SWC deficit effects.

Figure 3. Comparison of GPP sensitivities to VPD and SWC deficit across SWC gradient using EC data (black line) and each of 10 RSGPP products (color lines) at different ecosystem types. Left panels (a, c, e, g) show GPP-VPD sensitivity, while right panels (b, d, f, h) show GPP-SWC deficit sensitivity. Panel (a), (b) presents the results from all sites, followed by forest sites (c), (d), non-forest sites (e), (f), and cropland sites (g), (h). Each solid line represents the median of sensitivity of GPP to VPD and SWC deficit in each SWC bin. In the left panels (a, c, e, g), a sensitivity <0 indicates a negative effect of VPD on GPP, while in the right panels (b, d, f, h), a sensitivity >0 (or < 0) indicates that a positive (negative) effect of SWC deficit on GPP. The vertical dashed line in the right panels (a, c, e) represents the SWC percentile where the sensitivity value derived from EC is zero.

Stocker et al. (2019) address this by incorporating an empirical soil moisture stress function into the P-model, which improved GPP estimation performance under very dry soil moisture conditions (purple line in Figure 3f). Additionally, VODGPP, utilizing microwave RS estimates of VOD (Konings et al., 2019), shows the least bias in capturing GPP-SWC response in non-forests (dark blue line in Figure 3f; Figure S8d in Supporting Information S1), but significantly underestimates SWC deficit effects in forests under dry SWC conditions (dark blue line in Figure 3d; Figure S7d in Supporting Information S1). This difference aligns with previous findings and may be due to VOD's reliance on plant water content, which decreases significantly in non-forests but not in forests (Teubner et al., 2021; Wang et al., 2022).

Regarding the underestimation of positive SWC deficit, all GPP products underestimate these effects under high SWC conditions (>10th percentiles) (Figures 1d and 3a, Figure S6d in Supporting Information S1). A recent study has suggested that RS products use monotonic functions to simulate SWC effects on GPP, which differs from the bell-shaped curve relationship of GPP-SWC as observed in our study and others based on EC observations. Incorporating a Gaussian function into LUE models could improve this misrepresentation (Tagesson et al., 2021). The underestimation is more pronounced in forests and croplands (Figures 2l and 3d, Figure S7d in Supporting Information S1; Figures 2r and 3h, Figure S9d in Supporting Information S1) compared to non-forests (Figures 2o and 3f, Figure S8d in Supporting Information S1). These findings highlight a limitation in RS GPP products, particularly under extreme wet and dry soil conditions, emphasizing the need to enhance these products to better capture the relationships between GPP and SWC deficit across diverse moisture conditions and ecosystem types.

Interestingly, our results show distinct differences in the response of forests and non-forests to water stress. Forests are more sensitive to the negative VPD effects than non-forests (Figures 2a and 2d), but less sensitive to the negative SWC deficit effects within the VPD-SWC spaces (Figures 2j and 2m). These differences can be attributed to their diverse root systems (H. Xu et al., 2023; C. Zheng et al., 2023). Forests, with deeper root systems, have a higher capacity for absorbing soil water, potentially mitigating their sensitivity to SWC changes and making them less reactive compared to non-forest ecosystems, such as grasslands, under elevated SWC deficit (Hoek van Dijke et al., 2023). This differential response emphasizes the importance of modeling ecosystem-specific characteristics when evaluating drought impacts.

It is critical to note that the flux tower data set used in this study predominantly represents temperate ecosystems, while tropical and boreal ecosystems—accounting for over 83% of global forest carbon sinks from 1990 to 2019 (Pan et al., 2024)—are significantly underrepresented due to current data limitations. This underrepresentation complicates the generalization of our findings across global forest biomes, as boreal and tropical forest ecosystems may exhibit unique physiological responses to environmental stressors. For example, boreal trees demonstrate more conservative water use strategies, often closing stomata to minimize water loss, leading to a higher negative sensitivity of GPP to increasing VPD (Lin et al., 2015; Massmann et al., 2019). In contrast, tropical trees generally employ more aggressive water use strategies, prioritizing carbon fixation over water conservation, resulting in less negative sensitivity of GPP to increasing VPD (Massmann et al., 2019). Additionally, within tropical regions, dry tropics dominated by deciduous trees and shrublands face greater soil moisture constraints compared to evergreen rainforests, as they need to avoid xylem embolism, thus showing higher negative sensitivity of GPP to SWC deficit (Hasselquist et al., 2010). These forest type-specific responses are inadequately captured in current models, which tend to underestimate the negative impacts of SWC deficit on GPP in dry tropical regions and poorly account for VPD limitations in boreal zones. This discrepancy is concerning, given that climate change is expected to lengthen dry seasons in the tropics (H. Xu et al., 2022) and increase atmospheric aridity (VPD) in boreal regions (Mirabel et al., 2023). Addressing these gaps requires prioritizing the deployment of flux towers in underrepresented ecosystems and improving parameterizations for their GPP-drought sensitivities, ultimately enhancing the accuracy of satellite-derived GPP products and refining simulations of drought impacts on global forest carbon dynamics (Fang et al., 2024).

Our study highlights two critical steps to advance future research. First, when comparing with EC measurements, the station values for RS GPP products were extracted from the nearest pixel. To mitigate this uncertainty, we selected RS data and flux tower sites with the identical PFT and its dominance exceeding 60%. However, this approach also introduces uncertainties in evaluating model performance. Second, biases in RS model simulations (as examined in this study) were influenced by input data, but obtaining all model input variables is challenging.

Performing on-site scenario using consistent input data can help better diagnose and understand the inconsistencies between RS and EC in characterizing GPP-water stress response.

In summary, our study provides a comprehensive evaluation of existing RS products, their accuracy and limitations in tracking water stress on GPP under droughts. We evaluated the performance of 10 RS GPP products, as well as RSmean, in response to VPD and SWC deficit across different ecosystem types, using EC measurements as benchmarks. Our analysis indicated that while RSmean and each individual product capture the general directional response of GPP to VPD and SWC deficit across the full VPD-SWC gradient, they fail to reproduce the absolute value of GPP changes compared to EC measurements. Importantly, the discrepancies between RS and EC data are ecosystem-specific and consistent across all RS products examined. These findings suggest that incorporating ecosystem-specific VPD effects and non-linear SWC deficit responses could enhance RS-based GPP simulations under droughts.

Data Availability Statement

The eddy covariance measurements are available online at the FLUXNET2015 (https://fluxnet.org/data/fluxnet2015-dataset/) and ICOS European flux (https://www.icos-cp.eu/data-products/ecosystem-release). The MODIS GPP (MOD17A2H) data are available from (S. Running et al., 2015) at NASA Earth Observing System Data and Information System (EOSDIS) Land Processes (LP) Distributed Active Archive Center (DAAC). The VPM GPP data can be from Zhang et al. (2017). The ECLUE GPP data can be found from Y. Zheng et al. (2020). The GOSIF GPP data can be downloaded from Li and Xiao (2019b). The VODCA2 GPP data can be accessed via Wild et al. (2021). The BESS GPP data can be downloaded from Jiang and Ryu (2016). The P-model GPP data (s1b_fapar3g_v2_global.d.gpp.nc) are available in Stocker et al. (2019). The FLUXCOM data can be downloaded via Jung et al. (2019). MODIS land cover product (MCD12C1) data are available in Sulla-Menashe and Friedl (2018).

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