Responses to reviewers' comments for EGUSPHERE-2026-1199

Global vegetation responses to wet and dry soil moisture extremes

RC1:

This study presents a global-scale analysis of vegetation greenness responses to both dry and wet soil moisture extremes using long-term NDVI data and a machine-learning-based attribution framework. The manuscript is well structured, and the separation of drivers into pre-extreme conditions, extreme characteristics, and environmental background is conceptually clear and useful. The results confirming consistent vegetation browning during dry extremes and more heterogeneous responses during wet extremes are interesting and pretty important. I include my comments below, which I hope help the authors to strengthen the paper.

Reply:

The authors thank the reviewer for their positive summary and constructive comments that have helped improve the manuscript. We have detailed replies to each comment below, marked in blue.

1. The Introduction provides a useful overview of previous studies but does not clearly articulate the specific research gap that this study aims to address.

Reply:

The gap that we aim to fill is to have a consistent comparison of predictors and mechanisms of vegetation's response to wet and dry extremes, respectively, on a large spatial scale. We rephrased the introduction and clarified the research gap on lines 61-63 and lines 75-79. And we also explicitly express the difficulty of filling this gap (lines 80-82).

Line 61-63:

"While the overall relevance of dry and wet extremes for vegetation function is well established, important knowledge gaps remain regarding the spatial variability of their impacts and the mechanisms driving this variability."

Line 75-79:

"However, it remains unclear to what extent environmental background conditions, characteristics of the extremes (e.g., severity and timing), and pre-extreme vegetation states jointly shape vegetation responses across regions and biomes, particularly for wet extremes."

Line 80-82:

"In addition, differences in datasets and methodological approaches among previous studies have made it difficult to disentangle and compare the dominant predictors on vegetation responses to wet and dry extremes at the global scale."

2. (1) The study defines wet and dry extremes based on the 5th and 95th percentiles of soil moisture, both overall and seasonally. While this ensures statistical consistency, it does not necessarily correspond to ecologically meaningful thresholds. The identified "extremes" may reflect statistical anomalies rather than true ecological stress events.

   (2) In addition, the manuscript employs two types of thresholds, but their respective roles are not clearly reflected or discussed in the Results.

Reply:

(1) We agree with the reviewer that percentile-based thresholds define statistical rather than explicitly ecological extremes. However, the 5th and 95th percentiles of soil moisture are designed to capture rare departures from the local hydroclimate background, which are often associated with conditions that are relevant for vegetation stress or enhanced water availability. While these thresholds do not guarantee ecological impacts across all regions, they provide a consistent, spatially comparable definition of hydrological extremes. In addition, in the attribution analyses in Figures 3-5, we only consider dry and wet soil moisture extremes during which NDVI is lower than usual. While this does not equal ecological stress, it contributes to focusing our analysis more strongly on negative vegetation responses. At the same time, we acknowledge that it is difficult to assess actual stress at the spatio-temporal scales and extent of our analysis with the corresponding available data products. We clarified this distinction in the revised manuscript.

Lines 508-511:

"This study identifies wet and dry soil-moisture extremes relative to the local climatology and overall records at each grid cell. This percentile-based framework is well-suited for global analysis, but it does not necessarily capture absolute hydrological thresholds of vegetation's response to extremes such as root-zone waterlogging or imply that all detected events correspond to ecologically stressful conditions."

And we also added a future direction to better imply vegetation functioning's response to hydrological extremes in lines 525-527:

"Future work could also benefit from emerging indicators of vegetation functioning, such as solar-induced chlorophyll fluorescence (SIF), once sufficiently long observational records become available."

(2) The two thresholds were designed to ensure that detected hydrological extremes are both rare within the long-term soil moisture distribution and anomalous relative to the respective seasonal background conditions. We agree that their complementary roles were not sufficiently reflected in the original manuscript. We therefore clarified these roles in the Methods (lines 110-113) and added text in the Results (lines 231-233).

Without the overall threshold, regularly occurring seasonal wet or dry periods could be identified as extremes, whereas without the seasonal threshold, detected events would be concentrated in climatologically wet or dry seasons, making it difficult to distinguish seasonal effects from true hydrological anomalies. Together, the two thresholds enable a more consistent comparison of vegetation responses across regions and seasons.

Lines 110-113:

“The combined use of overall and seasonal thresholds ensures that detected events are both rare in the context of the long-term soil moisture distribution and anomalous relative to the typical seasonal conditions. This avoids identifying regularly occurring seasonal dry or wet periods as hydrological extremes.”

Lines 231-233:

“As a result of the combined threshold approach, the detected extremes represent soil moisture that is rare within the long-term record and anomalous for the respective time of year, facilitating consistent comparisons across regions and seasons.”

3. The Random Forest–based attribution framework identifies important predictors but does not establish causal relationships between drivers and vegetation responses. Currently, the manuscript often interprets variable importance as indicating mechanistic control. Could you please justify it?

Reply:

We thank the reviewer for this important comment. We agree that the Random Forest framework identifies statistical associations and predictor importance rather than revealing causal relationships. Our intention in the attribution analysis is not to claim causal proof, but to identify dominant factors associated with vegetation responses and to interpret these patterns with established ecological understanding.

To avoid overstating causality directly from random forest results, we revised the manuscript to use more cautious wording throughout (e.g., replacing “controls” or “drivers” with “influential predictors”). We additionally clarified in the Method (lines 187-190) that the attribution analysis provides insights into potential mechanisms, but the mechanistic interpretation relies on ecological knowledge and should not be interpreted as direct causal inference.

Lines 187-190:

“The RF framework identifies predictors that are strongly associated with vegetation responses, while mechanistic interpretations are based on existing ecological understanding rather than direct causal inference.”

4. What about the Random Forest model performance?

Reply:

The average cross-validation (out-of-bag, OOB) scores of the selected random forest models across all regions ranged from 0.22 to 0.62 (SD = 0.11), while performance varied across IPCC regions and between wet and dry extremes. The details are shown in the supplementary (Figure S5 and S6). Considering the relevance of this information, we added the range and standard deviation of out-of-bag scores for all IPCC regions in the main text and described how this influences the reliability of results (lines 343-358).

Lines 343-358:

"The robustness and interpretability of these regional attribution patterns depend on the explanatory performance of the RF models and the degree of concurvity among the selected predictors (Figure S5). The average OOB scores of the selected RF models across all regions ranged from 0.22 to 0.62 (SD = 0.11), while the average concurvity values ranged from 0.23 to 0.66 (SD = 0.11). RF model performance varied across IPCC regions and between wet and dry extremes. Lower OOB scores and higher concurvity values were generally found in regions with relatively fewer retained events, such as Eastern Central Asia (ECA) for wet extremes and Russian-Arctic (RAR) for dry extremes (Figure S4). Lower explanatory power was also observed in regions where vegetation responses to hydrological extremes were comparatively weak or spatially heterogeneous, such as Western Central Africa (WAF) for wet extremes and Central Africa (CAF) for dry extremes (Figure 2). In contrast, regions with stronger and more spatially coherent NDVI anomalies during extremes generally showed higher OOB scores and lower concurvity among predictors. Overall, OOB scores were slightly lower for wet extremes than for dry extremes, consistent with the more heterogeneous vegetation responses observed during wet extremes. Nevertheless, the RF models generally retained moderate-to-high explanatory power and low-to-moderate concurvity across most regions, indicating that the identified attribution patterns are robust and that the selected predictors capture meaningful variability in vegetation responses to hydrological extremes."

5. Converting 16-day NDVI to daily values may introduce artifacts. Please clarify the potential impacts.

Reply:

We used the 16-day MODIS NDVI product because it provides comparatively robust and spatially consistent vegetation estimates through the incorporation of multiple observations and strict quality-control procedures within each compositing period (Didan & Barreto, 2019). This choice was intended to better preserve observation-based vegetation responses during hydrological extremes while minimizing artifacts related to cloud contamination, view-angle effects, and atmospheric correction. Although vegetation products with nominal daily resolution exist, these products often also rely on compositing, smoothing, or moving temporal windows and therefore do not necessarily represent fully independent daily vegetation observations. We added this explanation for dataset choice concisely in the manuscript as well (lines 131-134).

Lines 131-134:

"We used the 16-day NDVI product because it provides comparatively robust and spatially consistent vegetation estimates through the incorporation of multiple observations and strict quality-control procedures within each compositing period (Didan & Barreto, 2019)."

Since the dataset user guide documentation indicates “The goal of the compositing methodology is to extract a single value per pixel from all the retained filtered data, **which will represent the pixel for the particular 16-day period**”, we applied the “nearest neighbor” method for interpolation in our actual analysis. At the same time, we agree that our interpolation application can introduce uncertainties. In order to quantify this, we used an alternative interpolation method (linear) to repeat the calculation for wet extremes. The spatial pattern comparison shows a limited influence of the way of interpolation (Figure R1). And we added the uncertainty of interpolation in lines 517-525.

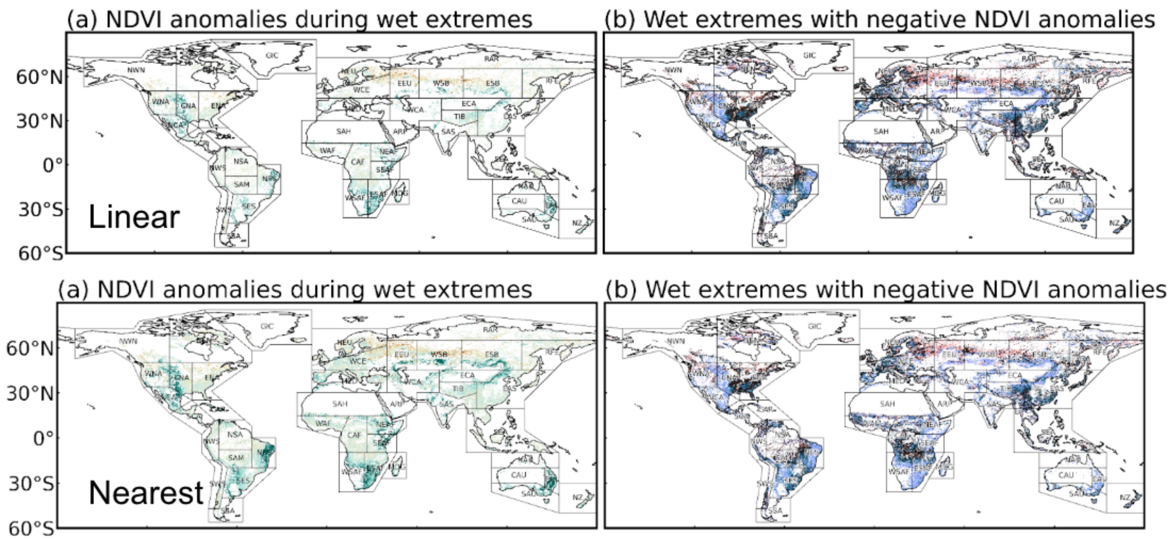

Figure R1: Comparison of spatial patterns of vegetation responses to wet extremes using NDVI interpolated with linear (upper) and nearest-neighbor (lower) methods.

Lines 517-525:

“In addition, the NDVI data used in this study are based on 16-day composite products that were temporally interpolated to daily resolution to align with daily soil moisture extremes. This interpolation may smooth short-term vegetation dynamics and introduce uncertainties in the timing and magnitude of rapid responses. As a result, fine-scale variability in vegetation responses may be dampened, and the exact alignment between NDVI and extreme events should be interpreted with a degree of caution. Future work could benefit from higher-temporal-resolution vegetation products to better capture vegetation responses during hydrological extremes, although such products would also likely require careful filtering and smoothing to mitigate day-to-day noise associated with cloud contamination and atmospheric effects.”

Reference:

Didan, K., & Barreto-Muñoz, A. (2019). MODIS Collection 6.1 (C61) Vegetation Index Product User Guide. The University of Arizona, Vegetation Index and Phenology Lab: Tucson, AZ, USA.

6. It is not clear which years the study period covers. Please specify.

Reply:

The results of this study are based on the period 2000-2023, noted on line 98 and also added in the caption of Figure 1.

Line 98:

*"Daily soil moisture data from ERA5-Land with a 0.1° resolution from **2000-2023** were used to identify hydrological extremes since soil moisture is directly related to water availability of vegetation (Liu et al., 2020)."*

Caption of Figure 1:

*"Figure 1: Number and average duration of wet and dry extremes during **2000-2023**."*

7. Consider adding a table summarizing all predictors under pre-extreme condition, extreme characteristics, and environmental background for clarity.

Reply:

We appreciate this suggestion. For clarity, we have considered summarising the predictors in a dedicated table in Supplementary Table 1. And they are also described in detail in the manuscript, Method 2.3, lines 145-151.

Supplementary Table 1:

Table S1: Summary of all predictor variables used in the attribution analysis

Category	*Full name of variables*	*Number of variables*
Pre-extreme Vegetation Condition	Pre-extreme NDVI percentile	1
Extreme Characteristics	Extreme severity, seasonal timing of the extreme, accumulative shortwave radiation anomaly, accumulative vapour pressure deficit anomaly	4
Environmental Background	Tree cover, short vegetation cover, deciduous vegetation cover, evergreen vegetation cover, aridity index, topography, soil texture, long-term mean air temperature	8

Line 145-151:

"(1) Pre-extreme Vegetation Condition: The vegetation's greenness state before the current extreme event.

(2) Extreme Characteristics: Event-specific features such as extreme severity, seasonal timing of the extreme, shortwave radiation, and vapour pressure deficit (VPD) during the extreme.

(3) Environmental Background: Grid cell properties including tree cover, short vegetation cover, deciduous vegetation cover, evergreen vegetation cover, aridity index, topography, soil texture, and long-term mean air temperature."

8. One of the main findings is that vegetation responses to wet extremes are highly heterogeneous (both positive and negative NDVI anomalies). The explanation of heterogeneous responses to wet extremes is need.

Reply:

We agree that the strong heterogeneity of vegetation responses to wet extremes is one of the key findings of this study and deserves further discussion. We have therefore expanded the Discussion section to clarify two aspects of this heterogeneity. First, wet extremes are primarily driven by precipitation events, which are inherently more spatially heterogeneous than the large-scale atmospheric anomalies commonly associated with dry extremes. Consequently, wet conditions and wet-extreme characteristics vary substantially across regions (lines 406-409). Second, the ecological consequences of excess soil moisture depend more on local environmental conditions than dry extremes, including soil drainage capacity, topography, climatic background, and vegetation characteristics. As a result, similar wet extremes can lead to markedly different vegetation responses across regions. This interpretation is consistent with our attribution analysis, which shows a comparatively stronger influence of environmental background conditions on vegetation responses during wet extremes than during dry extremes (lines 430-442).

Lines 406-409:

"In contrast, wet extremes are primarily driven by precipitation events, which are often highly heterogeneous in space. Combined with local differences in soil drainage and water-storage capacity, this leads to more spatially variable wet conditions and consequently more regionally concentrated patterns of responses to wet extremes."

Lines 430-442:

"These mechanistic differences explain why environmental background exerts a stronger influence on vegetation responses during wet extremes in some regions. The consequences of excess moisture depend heavily on factors such as drainage capacity (linked to soil texture and topography), climatic constraints on evapotranspiration, and the thermal environment that shapes recovery potential (reflected in long-term mean air temperature and aridity). Vegetation cover types and conditions also modify how strongly waterlogging affects root functioning, leading to divergent greenness responses (Figure S9). In contrast, the direct water-stress exerted by dry extremes leaves less room for background conditions to mediate the impacts. Vegetation responses primarily reflect the characteristics of the dry extreme itself. As a result, wet-extreme responses are substantially more heterogeneous across regions

than dry-extreme responses, because the ecological consequences of excess soil moisture are more strongly modulated by local environmental conditions."

9. In Figure 1, please clarify whether "Number of events" refers to annual counts or totals over the study period.

Reply:

It is the total amount of events during the whole 2000-2023 period. This information has been added to the caption of Figure 1.

Caption of Figure 1:

*"Figure 1: Number and average duration of wet and dry extremes **during 2000-2023.**"*