Response letter

Manuscript title: Learning Evaporative Fraction with Memory

We greatly appreciate the thoughtful and constructive comments of the reviewers. We have carefully revised our manuscript in response to their comments, as described in the point-by-point responses below.

The comments from the reviewers are shown in black followed and our responses in blue.

Reviewer: 1

Reviewer #1 Evaluations:

Zhao et al. developed a machine learning model to predict the daily evaporative fraction (EF) across 67 eddy-covariance flux sites with different plant functional types (PFTs) worldwide. A Long Short-Term Memory (LSTM) unit is used to examine the effect of previous climatic conditions (e.g., precipitation, air temperature) – analogous to a memory effect – on EF predictions. The manuscript highlights that memory effects – ranging from 7 to 365 days – largely contribute to EF dynamic predictions, particularly across forest sites, likely due to deep roots and water use strategies compared to grassland and savanna sites. More specifically, the results show that air temperature and precipitation, rather than net radiation, emerged as the most influential drivers of EF predictions. The study provides new insights into how PFTs, soil properties, and the climate characteristics of the previous year (i) impacted EF dynamics in the following year (i + 1). This has the potential to improve the understanding of water and carbon fluxes under less frequent but more intense precipitation events due to climate change. Below are my comments.

Responses:

Thank you for your positive evaluation and for your great efforts to help us improve our paper. We also appreciate your recognition of our study’s potential to enhance the understanding of water and carbon fluxes under changing precipitation variability in the context of climate change.

In the revised version of the manuscript, we will carefully address your comments, as well as those from the other reviewers.

Major Points

Comment 1:

Your results suggest that air temperature is the most influential driver of EF predictions for forest sites (Figures 4f, 4h, and 4i), while precipitation is the dominant factor in savannas, grasslands, and shrubland sites. While the role of precipitation is clear (lines 256-275), the role of air temperature requires a more detailed explanation in the context of the memory effect on EF. For example, while Chen et al. (2018) highlighted that air temperature dominates the half-hourly ET in evergreen needleleaf forests, their analysis did not consider the memory effect.

Responses:

Thank you for pointing out this.

We agree that while the delayed effects of precipitation—via soil moisture accumulation—on vegetation are well recognized, the influence of temperature is less evaluated in literature. In response to your comment and in consideration of feedback from other reviewers (e.g., Comment 4 from Reviewer #2), we will revise the introduction to better clarify our motivation. You will see our revisions in the introduction like:

"*…Temperature anomalies, including heat and cold stresses, can impair vegetation function, alter its water availability (via temperature-induced soil moisture memory) and deplete carbon reserves, which in turn influence transpiration and daily EF variability (Staacke et al., 2025)…*"

We will also add a dedicated paragraph in the discussions to explain why and how antecedent meteorological conditions, including soil moisture and air temperature, influence vegetation functioning and, consequently, EF. In the revised text, we will review relevant literature and include evidence showing that air temperature can affect vegetation function by modulating water demand (thereby inducing temperature-related memory effects via soil moisture) and altering carbon reserves, which in turn influence vegetation transpiration and EF. The revised paragraph will read as follows:

"*...Recent studies have also highlighted temperature-related memory—often referred to as heat stress (HS) memory—at the molecular scale, revealing mechanisms and regulatory layers involved in HS memory formation and resetting. These processes play a crucial role in enhancing plant stress resilience and fitness. During episodes of excessively high temperatures, plants can suffer cellular damage, primarily due to impaired photosynthesis and respiration, accumulation of misfolded proteins, and the production of reactive oxygen species. In natural environments, plants frequently encounter multiple recurring heat stress events rather than isolated incidents. The timing of these events can vary considerably, with subsequent extremes occurring shortly after or long after the initial one (Staacke et al., 2025). This variability can significantly influence vegetation functioning and transpiration—and thereby, evaporative fraction (EF)—at later stages. Moreover, the lag time of vegetation response to high temperatures is generally longer in mid- and high-latitude regions than in low-latitude ecosystems (Xiao et al., 2024). Forests, for instance, tend to initiate resistance mechanisms earlier due to their deeper rooting systems. However, once physiological functions are affected, forests are slower to recover (Xiao et al., 2024). In contrast, grasslands, though often more vulnerable to climate extremes, typically recover more quickly (Ying et al., 2020).*

Overall, the differences in rooting depth and water-use strategies across vegetation types may create a trade-off between resistance and resilience, potentially leading to post-extreme spatial heterogeneity in vegetation responses. This underscores the importance of further investigating how such memory effects—especially temperature-induced—manifest across ecosystems and influence EF..."

The citations we will add in the revised manuscript:

Staacke, T., Mueller-Roeber, B., & Balazadeh, S. (2025). Stress resilience in plants: the complex interplay between heat stress memory and resetting. *New Phytologist*, *245*(6), 2402–2421. https://doi.org/10.1111/nph.20377

Xiao, L., Wu, X., Zhao, S., & Zhou, J. (2024). Memory effects of vegetation after extreme weather events under various geological conditions in a typical karst watershed in southwestern China. *Agricultural and Forest Meteorology*, *345*, 109840. https://doi.org/10.1016/j.agrformet.2023.109840

Comment 2:

Lines 203-205: You state that "we observed a consistent bias in the model's predictions at higher EF values for some sites, compared to lower ones. A closer examination reveals that higher EF values typically occur at forested sites, while lower EF values are found at non-forested sites". However, EF also varies depending on precipitation seasonality (dry or wet season) or growing season in each site. Additionally, Miguez-Macho and Fan (2021) show that transpiration during the wet season mainly depends on recent infiltration (topsoil groundwater). Conversely, transpiration is mainly supplied by water from past infiltrations stored in deep soil during the dry season, suggesting that the effect of deep root on evaporative fraction (EF) changes between seasons. In this sense, the memory effect on EF predictions could be higher during the dry season – EF would exhibit a higher dependence on previous precipitation events – than during the wet season. Thus, how does memory effect on EF prediction changes during the dry vs wet seasons or growing/nongrowing season? Similarly, how does model accuracy vary as a function of dry down length?

Responses:

Thank you for raising this important point and for suggesting relevant literature. Indeed, understanding how memory effects on EF predictions vary across wet and dry seasons, or between growing and non-growing seasons, is a highly valuable direction.

In our extended analysis, we compared memory contributions between dry and wet seasons as well as growing and non-growing seasons. However, we did not observe a consistent pattern across sites. That is, memory contributions were not always higher in the dry season than in the wet season, nor consistently higher during the growing season compared to the non-growing season.

We believe this inconsistency reflects the complex interactions among climatic drivers. For instance, during dry seasons, plants may rely more heavily on water stored from previous wet seasons, aligning with findings such as those by Miguez-Macho and Fan (2021), who show that transpiration in dry seasons is often sustained by deep soil moisture. However, EF is co-regulated by multiple drivers—particularly precipitation and temperature—and the dominant controls can vary depending on climate regimes (e.g., energy-limited vs. water-limited systems). In some cases, temperature anomalies (e.g., heat stress) during the wet season can induce prolonged memory effects that rival or exceed those in the dry season. Similar observations were made when comparing growing and non-growing seasons.

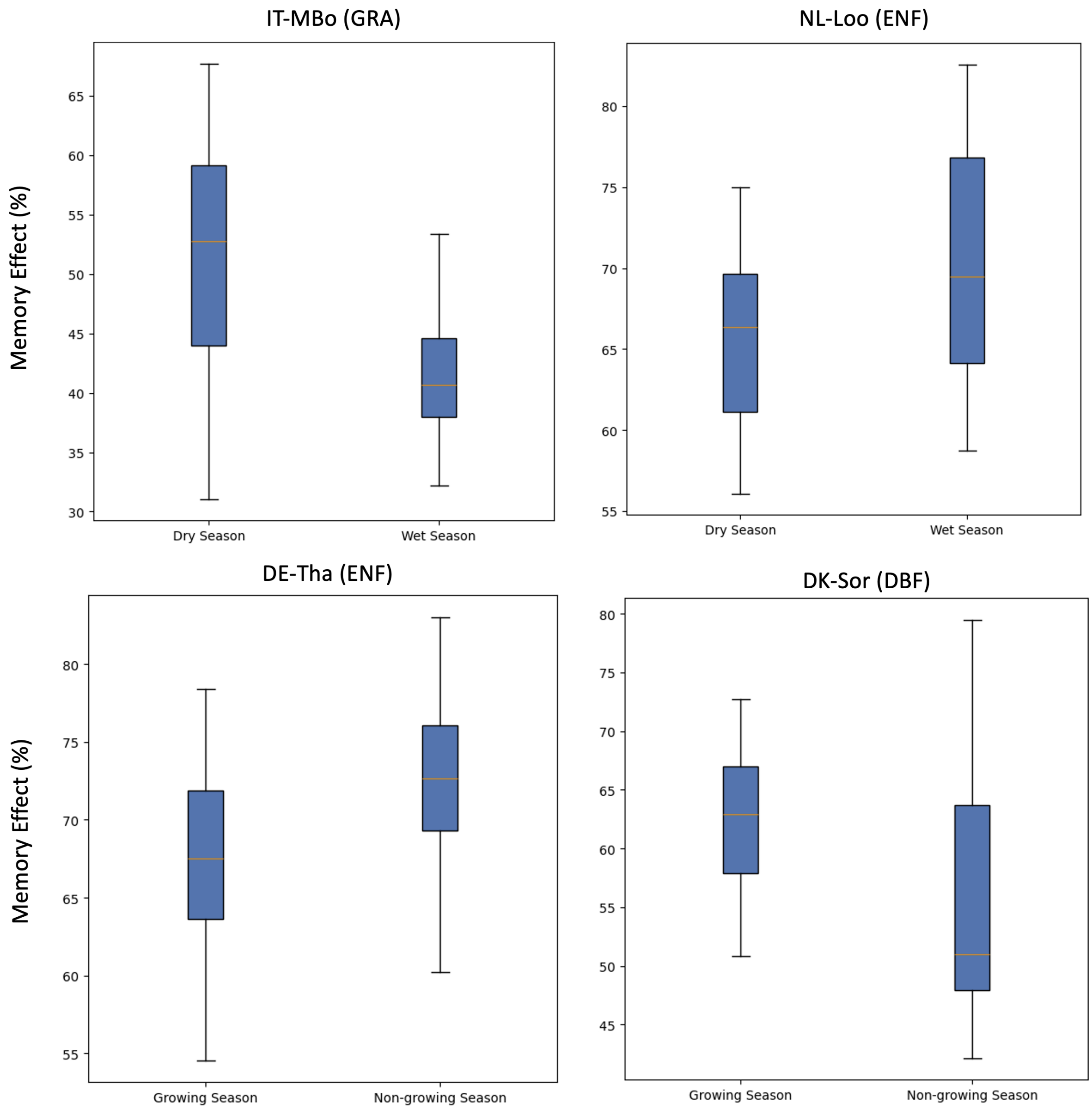

Figure R1. Memory effect comparisons between dry vs wet season and growing vs non-growing season.

This complexity suggests that memory effects are not governed by a single seasonal pattern, but rather emerge from compound effects and interactions among drivers. Our daily-scale explainable machine learning framework enables event-level analyses that can capture such nuanced behaviors. In future work, we plan to explore clustering or other data-driven classification techniques to systematically identify dominant memory regimes and their seasonality.

We appreciate the reviewer's insightful suggestion, which we have now addressed in the revised manuscript by adding the following discussion:

"*…our framework provides event-level insights that can be leveraged to explore seasonal variations in ecosystem memory and the co-regulation of EF by multiple climate drivers. These insights lay the groundwork for future classification and clustering analyses aimed at characterizing diverse memory regimes across different climate contexts…*"

We will also added relevant citations in the revised version.

Regarding the model accuracy as the function of dry-down length, this is quite an interesting idea. We'll further investigate this in the future study.

Comment 3:

Line 36. Authors state that "a slowly declining EF during periods of droughts is indicative of a deep root system". Is this the only factor modulating EF dynamics? What about the role of shallow water table depth (WTD)? For example, Chen et al. (2024) found that enhanced vegetation index (EVI) anomalies during drought years in the Amazon rainforest depend on both root deep and WTD. Thus, how could EF predictions improve by including WTD data (e.g., from Fan et al., (2013))?

Responses:

Thank you for pointing out this valuable insight.

Indeed, the rate of EF decay is not only influenced by rooting depth but also by the soil's water-holding capacity, which we have already discussed in the previous version of the manuscript (Lines 334–342). However, we also acknowledge that water table depth (WTD) is an important factor, as it can significantly affect vegetation's ability to access groundwater. For instance, as you mentioned, in the Amazon rainforest during drought years, deeply rooted vegetation can tap into groundwater or even utilize water stored in rock fractures.

That said, to our knowledge, reliable WTD data at the eddy covariance (EC) site level is still limited. Therefore, we believe it is important to be cautious about introducing additional uncertainty at this stage, especially since most of our current inputs are based on direct observations. Nevertheless, we fully agree that this is an important point worth discussing further, and we will include the following statement in the revised manuscript:

"*…In addition, previous studies have shown that vegetation functioning during drought years in the Amazon rainforest is influenced by both rooting depth and water table depth. Incorporating reliable WTD datasets in future studies could provide deeper insight into the role of subsurface water access in modulating vegetation responses and memory effects…*"

Comment 4:

In Lines 235-245, you state that EF depends on precipitation distribution throughout the year. It would be interesting to quantify how the memory effect on EF varies across regions with contrasting precipitation seasonality, characterized by metrics such as the Seasonality Index (SI; Teegavarapu, 2019) and perform a similar analysis as in Figure 6. This would allow you to assess the contribution of root depth/plant functional types in comparison to precipitation distribution.

Responses:

Thank you for pointing this out — it is indeed a very interesting idea.
We conducted an additional analysis based on the current dataset and found that memory effect contributions generally decrease with increasing seasonality index (SI). This suggests that ecosystems in highly seasonal climates tend to rely more on instantaneous climatic drivers rather than antecedent conditions. One possible explanation is that sharp dry-wet seasonal transitions shorten biologically active periods, thereby limiting the time window over which memory effects can persist.

However, it is important to note that memory is often co-regulated by multiple climatic drivers, such as precipitation and temperature, and their interactions may vary across ecosystems. Therefore, further investigation is needed to fully understand the underlying mechanisms and to disentangle the role of seasonality in regulating memory effects.

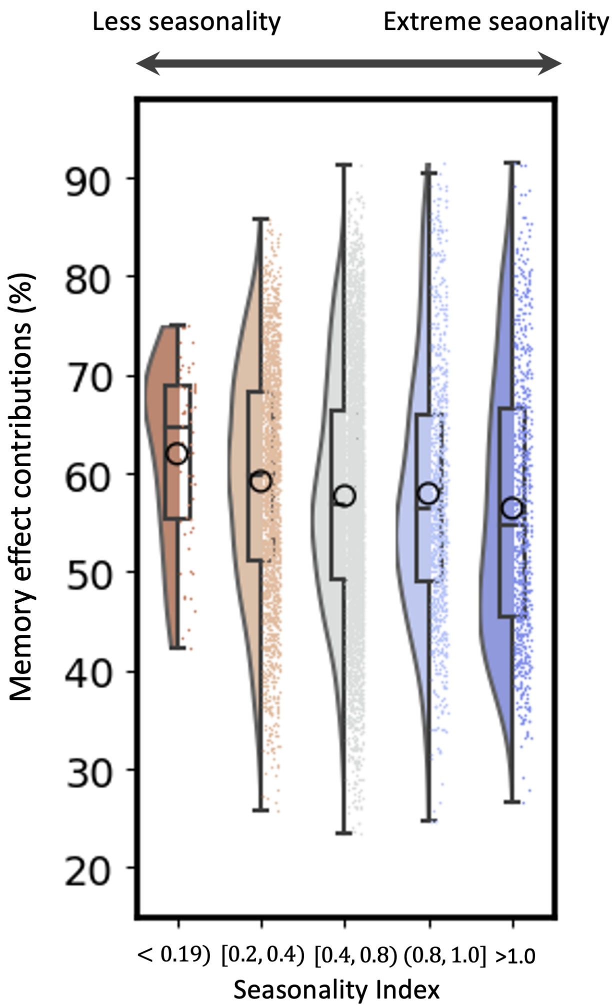

Figure R2. Relationship between memory effect and seasonality index.

Comment 5:

Lines 301-305. You state that "the maximum duration of the precipitation reveals that the legacy effect of winter precipitation, occurring 365 days prior, continues to impact water use strategies, as shown by our analysis. This observation aligns with the previous studies and experimental findings. For instance, antecedent winter precipitation from one or two years prior has been shown to influence growth in the current period". However, this may not be clear for tropical regions and regions where most of the precipitation occurs in the summer (e.g., southwestern US).

Responses:

Thank you for pointing out this important clarification. We agree that in regions where most precipitation occurs in summer—such as the tropics or the southwestern United States—legacy effects may result from summer rather than winter precipitation. To avoid confusion and better reflect this spatial variability, we will revise the sentence as follows:

"*...The maximum duration of precipitation influence suggests that legacy effects, defined as the impact of precipitation events occurring up to 365 days earlier continue to influence plant water use strategies, as shown in our site-level analysis. This is consistent with previous observational and experimental findings. While legacy effects have been widely reported for winter precipitation in temperate ecosystems, similar effects may also result from summer precipitation in regions where it dominates annual rainfall (e.g., tropical zones or monsoonal regions). Further investigation at the seasonal and event scale is warranted to differentiate the contributions of summer versus winter precipitation memory…*"

Minor Points

Comment 1:

Add a space between text and all citations (e.g., Line 31).

Responses:

Thank you. We will check and revise these throughout the manuscript.

Comment 2:

How do you define drydown? For example, Fu et al., (2022) define dry-downs like "episodes with no rain for several consecutive days during which soil moisture (SM) shows a short-term "pulse" rise after rain and then decays until the next rain event".

Responses:

Thank you for pointing out this important clarification, and we apologize for the confusion.

In our study, we define dry-down events following the approach described in McColl et al. (2020) (Global characterization of surface soil moisture drydowns), which is consistent with the definition used in Fu et al. (2022). Specifically, dry-downs are identified as periods in the soil moisture (SM) time series during which the temporal change in SM is continuously negative—i.e., SM decreases day by day. Following prior studies (e.g., Fu et al., 2022), we retain a dry-down for analysis only when SM decreases consecutively for at least 10 days after a preceding rainfall pulse.

We will clarify this in the revised manuscript with the following sentence:

"*…Dry-downs following rainfall are defined as episodes with no precipitation for several consecutive days, during which soil moisture exhibits a short-term pulse increase due to rainfall and then continuously decays until the next rainfall event, consistent with previous studies (McColl et al., 2020; Fu et al., 2022)…*"

Comment 3:

In the manuscript you used "dry-down" and drydown expressions. Please standardize the term.

Responses:

Thank you for pointing this out.

We will carefully review the manuscript and standardize the terminology by using "dry-down" consistently throughout the text.

Comment 4:

Line 95. What is the source of soil moisture data?

Responses:

Thank you for pointing this out.

The soil moisture data used in this study are observed at eddy covariance tower sites. We use the variable "SWC_F_MDS_1", which represents soil water content estimated from in situ sensors with gap-filling.

More information is available at: https://fluxnet.org/data/fluxnet2015-dataset/fullset-data-product

Comment 5:

Line 94. Describe the root depth and evapotranspiration data used in the Figure 6.

Responses:

Thank you for the suggestion.

Root depth information is obtained from the global rooting depth dataset compiled by Stocker et al. (2023), and the long-term evapotranspiration (ET) data used for dryness and wetness classifications are extracted from the TerraClimate dataset via Google Earth Engine (Abatzoglou et al., 2018).

We will include these data source descriptions in the revised manuscript under the Data section.

References:

Stocker, B. D., Tumber-Dávila, S. J., Konings, A. G., Anderson, M. C., Hain, C., & Jackson, R. B. (2023). Global patterns of water storage in the rooting zones of vegetation. Nature Geoscience. https://doi.org/10.1038/s41561-023-01125-2

Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. Scientific Data, 5, 170191. https://doi.org/10.1038/sdata.2017.191

Comment 6:

Line 115. Does MODIS extract over the full available period? Did you apply any quality control?

Responses:

Yes, MODIS LAI data were extracted over the full available period and merged with overlapping periods of EC tower observations.

We only used MODIS LAI values with good quality flags following the standard QA/QC procedures to ensure reliability.

Comment 7:

Line 120. From which soil depth are soil properties retrieved?

Responses:

Thank you for your question.

The soil property data are retrieved from the SoilGrids250m dataset, which provides estimates at seven standard soil depths: 0, 5, 15, 30, 60, 100, and 200 cm. In our analysis, we take the arithmetic mean across these depths to represent the overall soil property values for each site.

Comment 8:

Line 131. A descriptor of precipitation seasonality such as the Seasonality Index (SI; Teegavarapu, 2019), can provide additional information about its distribution throughout the year.

Responses:

Thank you. Please see our response to your comment 4.

Comment 9:

Lines 166-167. You state that "whole datasets were separated by site, with one site from each PFT randomly selected for testing and validation, and the remaining sites used for training". How many EBF sites are included in your analysis? Based on Figure S1, I assume that only one is included.

Responses:

Thank you.

Yes, we confirm that there are five EBF sites in our dataset. We apologize for the missing information in Figure S1. In the revised manuscript, we will update Figure S1 accordingly and incorporate the analysis of the EBF sites to ensure a complete and accurate representation of all the sites included in this study.

Comment 10:

Figure 4j. Why is the evergreen broadleaf forest (EBF) not included in this panel, but it shows in Figure 4g? The same question applies to figure 5.

Responses:

Thank you for pointing out this issue, and we apologize for the confusion.

The absence of evergreen broadleaf forest (EBF) in Figure 4j and Figure 5 was due to a plotting oversight. EBF was indeed included in the analysis, as reflected in Figure 4g. We will correct this error and ensure that EBF is properly represented in both Figure 4 and Figure 5 in the revised manuscript.

Comment 11:

Figure 6: 1) How do you rank rooting depth? 2) Are the RD values in panel B the mean values for all sites within each soil sand fraction level? 3) Why did you define the aridity index as ET/PET instead of the more traditional definition of P/PET?.

Responses:

Thank you for pointing this out.

1) We ranked rooting depth (RD) by percentile rather than using absolute values because the RD dataset is not continuous and exhibits strong skewness—forests tend to have significantly larger values compared to the much smaller values observed in some grassland sites. Therefore, we used percentile ranking to better capture the general tendency between rooting depth and memory effect, rather than aiming for a strict quantitative interpretation.

2) Yes, the RD values shown in panel B are the mean values for all sites within each soil sand fraction level.

3) We apologize for the confusion regarding terminology. We used ET/PET in this analysis because it is a strong indicator of plant water stress. To avoid misunderstanding, we will revise the label from "aridity index" to "plant water stress index" in the manuscript to more accurately reflect what the metric represents.

Additionally, we have now plotted the relationship between the classical aridity index (P/PET) and the memory effect. The results are shown below:

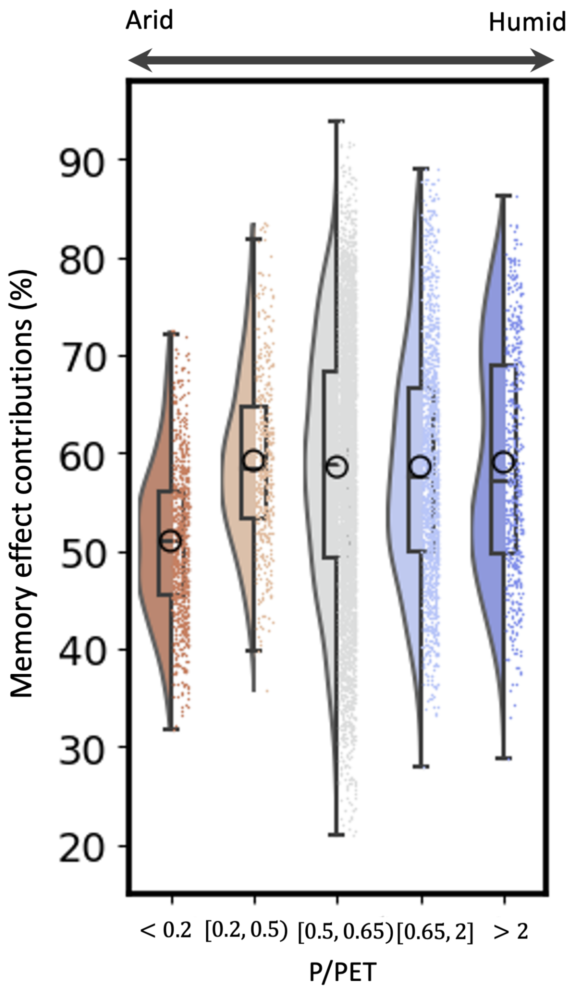

Figure R3. Relationship between memory effect and aridity index.

We observe a general increasing trend in memory effect contributions from arid (P/PET < 0.2) to more humid conditions (P/PET > 2). This suggests that ecosystems in more humid regions tend to rely more on antecedent climatic conditions, potentially due to less varying soil moisture regimes and deeper rooting systems that enable longer memory timescales. However, memory effects are also influenced by multiple interacting factors such as vegetation type, rooting depth, and seasonal dynamics. Therefore, the underlying mechanisms warrant further investigation, potentially through advanced clustering algorithms that can better capture the complexity and heterogeneity of ecosystem memory behaviors across climate regimes.

Comment 12:

Figure 3. I suggest replacing at least one grassland or savanna site with an EBF site.

Responses:

Thank you.

We will include the EBF site in Figure 3 as suggested.

Comment 13:

Figure 4. Please indicate the number of sites included for each PFT.

Responses:

Thank you.

We will revise Figure 4 and update it in the revised manuscript accordingly. The updated number of sites within each plant functional type (PFT) category is as follows:

- Evergreen Needleleaf Forest (ENF): 23
- Grassland (GRA): 12
- Deciduous Broadleaf Forest (DBF): 12
- Mixed Forest (MF): 7
- Evergreen Broadleaf Forest (EBF): 4
- Open Shrubland (OSH): 4
- Woody Savanna (WSA): 3
- Savanna (SAV): 2

The missing information will also be corrected and included in Figure 4j.

Comment 14:

Table S1. Please indicate the sites selected for your analysis.

Responses:

Thank you.

We will revise Table S1 to include only the sites that were ultimately used in the analysis.

Comment 15:

Figures 4-6. In line 105 you mention that only sites with > 10 years of records were included in your analysis. So, the note "sites with more than 10 years of observations are summarized here" is not needed in figures descriptions may be redundant.

Responses:

Thank you.

We will remove the repeated statements from the figure descriptions in Figures 4–6 in the revised manuscript.

Comment 16:

Please check some minor grammar issues, for example: Line 9. plant "water stress"? Line 17 and 275, "precipitation" and "VPD", Line 18. Add comma after "(OSH")

Responses:

Thank you.

We will correct these issues and carefully review the revised manuscript to ensure consistency and proper grammar throughout.

Comment 17:

References

Chen, S., Stark, S.C., Nobre, A.D., Cuartas, L.A., De Jesus Amore, D., Restrepo-Coupe, N., Smith, M.N., Chitra-Tarak, R., Ko, H., Nelson, B.W., Saleska, S.R., 2024. Amazon forest biogeography predicts resilience and vulnerability to drought. Nature 631, 111–117. https://doi.org/10.1038/s41586-02407568-w

Chen, Y., Xue, Y., Hu, Y., 2018. How multiple factors control evapotranspiration in North America evergreen needleleaf forests. Science of The Total Environment 622–623, 1217–1224. https://doi.org/10.1016/j.scitotenv.2017.12.038

Fan, Y., Li, H., Miguez-Macho, G., 2013. Global Patterns of Groundwater Table Depth. Science 339, 940943. https://doi.org/10.1126/science.1229881

Fu, Z., Ciais, P., Feldman, A.F., Gentine, P., Makowski, D., Prentice, I.C., Stoy, P.C., Bastos, A., Wigneron, J.-P., 2022. Critical soil moisture thresholds of plant water stress in terrestrial ecosystems. Sci. Adv. 8, eabq7827. https://doi.org/10.1126/sciadv.abq7827

Miguez-Macho, G., Fan, Y., 2021. Spatiotemporal origin of soil water taken up by vegetation. Nature 598, 624–628. https://doi.org/10.1038/s41586-021-03958-6

Teegavarapu, R.S.V., 2019. Changes and Trends in Precipitation Extremes and Characteristics, in: Trends and Changes in Hydroclimatic Variables. Elsevier, pp. 91–148. https://doi.org/10.1016/B978-0-12810985-4.00002-5

Responses:

Thank you for providing these helpful references to improve our manuscript. We have incorporated and cited them in the appropriate sections, as detailed in our previous responses.