Reference Number: EGUSPHERE-2025-4791

RESPONSES TO REVIEWER TWO'S COMMENTS

We are grateful to Reviewer #2 for his/her insightful review. The provided comments have contributed substantially to improving the paper. According to them, we have made significant efforts to revise the manuscript, with the details explained as follows:

Point #1

COMMENT: *Main Critique on Methodology and Physical Interpretation: The study employs both the Response Time (RT) based on time-lag correlation and the Lag Time (LT) based on run-theory event identification to analyze drought propagation from the dual dimensions of statistical association and event evolution. However, I contend that there is a fundamental difference in their underlying physical mechanisms. RT reflects the overall synchronicity or "statistical memory" between long-series precipitation, runoff, and soil moisture. Its values are typically larger (e.g., 5–8 months in this study), primarily capturing the integrated system response driven by seasonal cycles, multi-year climate oscillations (e.g., ENSO), and the long-term water storage capacity of basins. In contrast, LT, based on discrete event tracking, focuses on the physical evolution of specific drought pulses within the hydrological cycle, reflecting the instantaneous triggering mechanism of drought signals penetrating from the atmosphere to the land surface; thus, its values are usually much smaller (e.g., 1.2–2.6 months).*

The authors must go beyond simply listing these inconsistent indices in tables and provide a rigorous physical explanation for this "numerical gap" in the Discussion section. Specifically, does the long-period RT represent the smoothing effect of basin storage or seasonal cycles on drought signals, while the short-lived LT captures the non-linear rapid response mechanism when the system exceeds a threshold under extreme stress? Without clarifying why statistical correlation and event evolution differ so significantly in magnitude from a physical perspective, readers will find it difficult to judge which indices are more valuable for early warning, and may even question the robustness of the results. Therefore, I expect the authors to add a dedicated section in the revised manuscript to deeply discuss the physical coupling behind these methodological differences and clearly indicate how to weigh the use of these distinct propagation indices under different management needs.

RESPONSE: We sincerely thank the reviewer's insightful and constructive comments regarding the methodological differences between response time (RT) and lag time (LT) and their physical implications. We fully agree with the comments that a deeper physical interpretation of the RT and LT results is essential to clarify the mechanism of drought propagation and to provide more valuable insights for drought risk management. In the revised manuscript, we have incorporated a dedicated subsection within the Discussion section (4.1. Physical interpretation of drought propagation characteristics) to explicitly address this issue. In detail, the revised section is provided as follows:

"4.1. Physical interpretation of drought propagation characteristics

In this study, two distinct methodological frameworks were employed to quantify drought propagation: (1) the response time derived from time-lag correlation analysis, and (2) the lag time based on event identification using the run theory. Response time is determined by identifying the accumulation period of a drought index (e.g., SPI) that maximizes its correlation with a target drought index (e.g., SSI at a 1-month accumulation timescale) (López-Moreno et al., 2013; Zhang et al., 2022). This approach reflects the overall synchronicity and statistical memory characteristics of various drought conditions. Thus, the response time values are strongly influenced by long-term variations in regional climatic and hydrological conditions, such as the seasonal cycle, multi-year climate oscillations, and water storage capacity. The response time refers to the system's long-term state that retains a memory of past drought conditions. The evaluation of response time is beneficial for seasonal drought predictability and long-term drought preparedness. The response time also functions as an indicator of the feasibility of using one type of drought index as a proxy for another. For example, due to the lack of comprehensive observational data, the SPI with varying accumulation periods can reflect hydrological, agricultural and groundwater drought conditions (Kumar et al., 2016).

In comparison, lag time is derived from discrete drought events identified using the multi-threshold run theory, which measures the time difference between the onset of one drought event and the onset of another drought event. By focusing on event-based dynamics, the lag time reflects the instantaneous triggering mechanism by which drought signals propagate from the atmosphere to the land surface. Numerous previous studies have analyzed the threshold of extreme stress that triggers drought propagation, using methods such as copula functions, hydrological models, and machine learning (Geng et al., 2024; Yang et al., 2025). The lag time captures the non-linear response mechanism between different drought conditions at a short time scale, which is crucial for real-time early warning and impact assessment.

Our results provide a globally consistent comparison of the response time and lag time for meteorological, hydrological, and agricultural drought propagation. The response time of drought propagation (average RT_{MH}, RT_{MA}, and RT_{HA} of 5.0 [2.7, 6.7] months, 8.7 [5.0, 11.3] months, and 5.8 [2.3, 7.3] months) is generally longer than the lag time (average LT_{MH}, LT_{MA}, and LT_{HA} of 1.23 [0.68, 1.68] months, 2.60 [1.71, 2.92] months, and 2.49 [1.68, 2.51] months). This numerical gap arises from differences in the methodology, but both approaches indicate a consistent propagation pathway for meteorological, hydrological, and agricultural droughts, with similar spatial patterns. In addition, the machine learning-based attribution method also identifies similar impact factors, which indicates the consistency of drought propagation mechanisms revealed by response time and lag time. This aligns with the conceptual framework of drought propagation, where precipitation deficits (meteorological drought) first influence runoff generation over the land surface (hydrological drought), and subsequently affect soil moisture in the root zone (agricultural drought)." **(lines 435-466 of the revised manuscript)**

<u>Point #2</u>

COMMENT: *The paper analyzes three pathways: M→H, M→A, and H→A. To what extent is the propagation of H→A independent of M? That is, if meteorological drought (M) has already* *directly driven agricultural drought (A), is the contribution of hydrological drought (H) to A merely a "shadow" of M?*

RESPONSE: We sincerely appreciate the reviewer's insightful comment. In this study, we analyzed three drought propagation pathways: from meteorological to hydrological drought, from meteorological to agricultural drought, and from hydrological to agricultural drought. Generally, drought propagation is regarded as a hierarchical top-down process. Our results demonstrate the pathway of meteorological-hydrological agricultural droughts. Meteorological drought, primarily caused by precipitation deficits, can cascade to other hydrological variables in the water cycle. As defined by the runoff variations, hydrological droughts are influenced by meteorological droughts and then propagate to agricultural droughts (deficits in soil moisture). We agree the reviewer's comment that the contribution of hydrological drought to agricultural drought is influenced by the meteorological drought. In fact, drought propagation is a complex process, as it is driven by the close interrelationships among various hydrological variables. The current analysis in our manuscript is hardly to distinguish the propagation of hydrological to agricultural droughts that is independent of the impact of meteorological drought. Accordingly, in the revised manuscript, we have added the discussion about the uncertainties in our analysis. Specifically, the revised paragraphs are provided as follows:

> "4.4. Uncertainties and implications in drought propagation evaluation
> Drought propagation evaluation relies heavily on drought indices for monitoring and characterizing various drought types. Considering the data availability and the continuity in both temporal and spatial dimensions at the global scale, we employed the SPI, SRI, and SSI to represent meteorological, hydrological, and agricultural droughts. Our results demonstrated the propagation pathway of meteorological-hydrological-agricultural droughts, which is consistent with previous studies that employed similar indices (Han et al., 2023; Mei et al., 2025). As a multifaceted phenomenon, hydrological drought is a broad term that is related not only to runoff but also to streamflow and the levels of groundwater, lakes, and reservoirs (Van Loon, 2015). Using the drought indices derived from streamflow, the propagation from agricultural to hydrological droughts has also been identified in many studies, particularly at the watershed scale (Odongo et al., 2023; Teutschbein et al., 2025). Runoff is the volume of water that originates from precipitation and flows over the land surface; it is not directly equal to the streamflow in stream channels. A deficit in runoff can directly affect the availability of soil moisture due to reduced recharge to the root zone, representing the propagation from hydrological drought to agricultural drought. In comparison, soil moisture retains precipitation that falls on the land surface and then delays the propagation time form precipitation to streamflow (McColl et al., 2017)." **(lines 513-526 of the revised manuscript)**

<u>**Point #3**</u>

COMMENT: *In desert regions with extremely low precipitation, the correlation between SPI and SRI is often meaningless. How were these extreme climatic zones handled in your global assessment, and are the conclusions applicable there?*

RESPONSE: We sincerely appreciate the reviewer's insightful comment. We agree that in hyper-arid regions—where precipitation is extremely low and highly erratic—the calculation of the SPI and SRI becomes statistically unstable, and the correlation between SPI and SRI in such environments can indeed be uninterpretable. Accordingly, we have added a discussion of the uncertainties associated with drought propagation in hyper-arid regions. The revised paragraph is provided below:

> "Due to the inherent variability of drought-related variables, significant uncertainties exist within hydrometeorological datasets (Bador et al., 2020). Our findings depend on an ensemble of three datasets (i.e., ERA5, GLDAS, and TerraClimate), which helps avoid biased and incomplete evaluations of drought propagation that could result from relying on a single dataset. We conducted a comparative analysis of drought propagation characteristics derived from multiple datasets, systematically evaluating their consistency and discrepancies (Figs. S3-S6). The results underscore the impact of input data uncertainties on the assessment of drought propagation, with notable discrepancies predominantly observed in the hyper-arid, high-latitude, and high-evaluation regions. Specifically, in hyper-arid regions—where precipitation is extremely low and highly erratic—the calculation of the SPI and SRI becomes statistically unstable; consequently, the correlation between SPI and SRI in such environments can indeed be uninterpretable. This is primarily attributed to the scarcity of in-situ stations capable of providing continuous spatial and temporal observations in these regions. The data assimilation systems and land surface models employed across different datasets to fill missing observations inevitably introduce uncertainties in both model parameters and structural configurations." **(lines 528-539 of the revised manuscript)**

<u>Point #4</u>

COMMENT: *The authors selected eight factors for attribution. What was the rationale for selecting these specific factors? Why were underlying surface characteristics, such as land use types, not included? These physical surface features often have a more direct impact on drought propagation (especially PR and LT) than NDVI.*

RESPONSE: We sincerely appreciate the reviewer's insightful comment. We agree with the reviewer's comment that there are a large number of factors that influence drought propagation, such as soil properties and geology factors. In our analysis, the selection of these factors as model predictors is due to the reason that (1) a large number of previous studies have demonstrated the importance of climatic factors in drought propagation (Apurv et al., 2017; Sattar et al., 2019; Apurv and Cai, 2020); (2) our research focused on the process of drought propagation at a $1° \times 1°$ grid scale; however, soil properties and other geological factors are not easily aggregated at such a relatively coarse spatial resolution. Accordingly, we have substantially expanded the Methods and Results section to emphasize the details of model development and evaluation. The revised sentences are provided as follows:

> "According to previous studies, climatic conditions are among the most important factors influencing drought propagation characteristics (Aryal et al., 2024). To explore the relative importance of long-term climatic conditions for drought propagation, the average values (1958–2024) of eight climatic and physiographic variables, including precipitation, temperature, potential evapotranspiration, runoff, soil moisture, aridity index, elevation, and vegetation condition, were selected as model predictors. The corresponding drought

> propagation characteristics (i.e., response time, propagation rate, and lag time) were selected as target variables. The Extreme Gradient Boosting (XGBoost) model was employed to model the relationships between climatic predictors and drought propagation target variables. The XGBoost model is an efficient and robust gradient-boosted decision tree algorithm that is widely applied in classification and regression tasks within the field of water resources engineering (Chen and Guestrin, 2016; Niazkar et al., 2024). To account for spatial autocorrelation, spatial block cross-validation was employed on the training set to prevent overfitting. The global grid was partitioned into 43 spatially contiguous blocks according to the IPCC AR6 reference land regions (Iturbide et al., 2020). In each fold, ten blocks were held out for validation, and the XGBoost model was trained on the remaining blocks. Model performance was evaluated using the coefficient of determination (R2) and root mean square error (RMSE), averaged across all held-out blocks." **(lines 225-238 of the revised manuscript)**

<u>Point #5</u>

COMMENT: *Global grid data exhibit strong spatial autocorrelation. If all grid points are fed directly into the XGBoost model, the model may suffer from overfitting or yield erroneous significance levels. Have the authors attempted to prove the robustness of the model?*

RESPONSE: We sincerely appreciate the reviewer's insightful comment. We agree that global gridded data exhibit strong spatial autocorrelation, which can lead to overfitting and thus reduce the generalizability of our findings. In our analysis, spatial block cross-validation was employed to account for spatial autocorrelation. The global grids were partitioned into 43 spatially contiguous blocks according to the IPCC AR6 reference land regions (Iturbide et al., 2020). In each fold, ten blocks were held out for validation, and the XGBoost model was trained on the remaining blocks. In the updating manuscript, we have added the sentence in the Methods section to make it clearer. The revised sentences are provided as follows:

> "According to previous studies, climatic conditions are among the most important factors influencing drought propagation characteristics (Aryal et al., 2024). To explore the relative importance of long-term climatic conditions for drought propagation, the average values (1958–2024) of eight climatic and physiographic variables, including precipitation, temperature, potential evapotranspiration, runoff, soil moisture, aridity index, elevation, and vegetation condition, were selected as model predictors. The corresponding drought propagation characteristics (i.e., response time, propagation rate, and lag time) were selected as target variables. The Extreme Gradient Boosting (XGBoost) model was employed to model the relationships between climatic predictors and drought propagation target variables. The XGBoost model is an efficient and robust gradient-boosted decision tree algorithm that is widely applied in classification and regression tasks within the field of water resources engineering (Chen and Guestrin, 2016; Niazkar et al., 2024). To account for spatial autocorrelation, spatial block cross-validation was employed on the training set to prevent overfitting. The global grid was partitioned into 43 spatially contiguous blocks according to the IPCC AR6 reference land regions (Iturbide et al., 2020). In each fold, ten blocks were held out for validation, and the XGBoost model was trained on the remaining blocks. Model performance was evaluated using the coefficient of determination (R2) and root mean square error (RMSE), averaged across all held-out blocks." **(lines 225-238 of the revised manuscript)**

"Using different drought propagation characteristics as the target variables, nine XGBoost models were established. The validation sets of these models yielded satisfactory evaluation results (Table S1), which can substantiate the attribution results." **(lines 385-387 of the revised manuscript)**

The added table:

Table S1. The performance metrics in validation sets for each XGBoost model

Model name	RT_{MH}	RT_{MA}	RT_{HA}	PR_{MH}	PR_{MA}	PR_{HA}	LT_{MH}	LT_{MA}	LT_{HA}
R^2	0.653	0.878	0.858	0.824	0.944	0.913	0.646	0.581	0.652
RMSE	1.736	1.779	1.667	4.613	3.252	4.416	1.177	4.221	1.411

<u>Point #6</u>

COMMENT: *In the Introduction, please emphasize that meteorological, hydrological, and agricultural systems are not isolated but are coupled through the hydrological cycle.*

RESPONSE: We sincerely appreciate the reviewer's valuable suggestion. We fully agree that meteorological, hydrological, and agricultural droughts are interconnected through the hydrological cycle—a connection that provides a stronger and more physically grounded foundation for our study. Accordingly, we have revised the Introduction in the updated version to incorporate this conceptual emphasis. The revised sentences are provided as follows:

"There exists a strong interrelationship among different types of droughts, owing to the close linkage of their driving factors within the hydrological cycle." **(lines 43-45 of the revised manuscript)**

<u>Point #7</u>

COMMENT: *Add a mention of the "Propagation Threshold" in the Introduction.*

RESPONSE: We sincerely appreciate the reviewer's helpful comment. Propagation threshold is an important concept for understanding drought propagation dynamics. Accordingly, we have incorporated this concept in the Introduction, and the revised sentences are provided as follows:

"Understanding drought propagation characteristics, such as propagation time, probability, and threshold, are essential for elucidating drought occurrence and evolution mechanisms, which help facilitate the effective drought monitoring and early warning systems." **(lines 46-49 of the revised manuscript)**

<u>Point #8</u>

COMMENT: *In the Data section, the spatial resolution of different datasets should be clarified, and any resampling operations must be mentioned.*

RESPONSE: We sincerely appreciate the reviewer's helpful comment. In this study, three different datasets were employed to assess the drought propagation characteristics, which have different spatial resolutions. To ensure spatial and temporal consistency, the period from 1958 to 2024 was selected as the reference period, and all datasets were uniformly interpolated onto a 1 °×1 °latitude–longitude grid using bilinear interpolation. In the updating version, we have rewritten the section "2.1 Datasets" to make it clearer, and the revised parts are provided as follows:

> "2.1 Datasets
> Monthly precipitation, runoff, and soil moisture were derived from the ERA5, the Global Land Data Assimilation System (GLDAS), and TerraClimate datasets to calculate the drought indices. ERA5 is the fifth-generation global atmospheric reanalysis product developed by the European Centre for Medium-Range Weather Forecasts. It integrates extensive records of both in-situ and satellite observations through an ensemble-based data assimilation system (Hersbach et al., 2020). Precipitation in ERA5 was generated by the atmospheric component of the Integrated Forecasting System, whereas runoff and soil moisture were simulated by a land surface model (Boussetta et al., 2021). The soil moisture in ERA5 was aggregated to 1 meter volumetric soil water using weighted data from three layers: 0–7 cm, 7–28 cm, and 28–100 cm. GLDAS is a multi-model ensemble comprising three land surface models—Noah, Catchment, and the Variable Infiltration Capacity—which integrate satellite and in-situ observations through advanced land surface modeling techniques. The soil moisture in GLDAS models has different soil layer structures, all of which were weighted to the root zone depth of 1 meter to be consistent with ERA5. TerraClimate integrates multiple datasets, including WorldClim, Climate Research Unit, and Japanese 55-year Reanalysis, to generate hydro-meteorological variables (Abatzoglou et al., 2018). The soil moisture in the TerraClimate refers to the plant extractable soil water based on the root zone storage capacity, as modeled by an empirical water balance model. To ensure spatial and temporal consistency, the period from 1958 to 2024 was selected as the reference period, and all datasets were uniformly interpolated onto a 1 °×1 °latitude–longitude grid using bilinear interpolation.
>
> In addition, the temperature and potential evapotranspiration (PET) were also obtained from the ensemble of ERA5, GLDAS, and TerraClimate datasets. Potential evapotranspiration in these datasets was calculated using the Penman-Monteith method (Abatzoglou et al., 2018). The Normalized Difference Vegetation Index (NDVI) was obtained directly from the Advanced Very High Resolution Radiometer instruments operated by the National Oceanic and Atmospheric Administration (NOAA) (Pinzon and Tucker, 2014). The elevation dataset was obtained from the ETOPO Global Relief Model developed by the National Centers for Environmental Information (https://www.ncei.noaa.gov/products/etopo-global-relief-model). The aridity index dataset was derived from the Global Aridity Index and Potential Evapotranspiration Database—Version 3 (Zomer et al., 2022)." **(lines 112-136 of the revised manuscript)**

<u>Point #9</u>

COMMENT: *More details need to be added to Section 2.4.*

RESPONSE: We sincerely appreciate the reviewer's helpful comment. In the revised manuscript, we have added more details about the lag time and propagation rate derived from the multi-threshold run theory. Specifically, the revised paragraphs are provided as follows:

> "2.4 Lag time analysis based on run theory
> Run theory is a commonly used method for analyzing drought characteristics, which defines the initiation and termination of a drought event based on the drought index. In this study, the drought events were identified using a multi-threshold run theory, which has advantages in avoiding the unreasonable splitting of persistent droughts and filtering out minor drought episodes, thus providing more accurate identification of drought events (Fleig et al., 2006; Ma et al., 2021). Potential drought events were initially identified using an intermediate threshold ($X_0 = 0$). Subsequently, the adjacent drought events with an interval of one month and whose drought index values were below a high threshold ($X_1 = 1$) within that month were combined. Finally, the potential drought events with one month length and whose drought index value is greater than a low threshold ($X_2 = -1$) were ruled out.
>
> After using run theory to identify the initiation and termination of drought events, the propagation rate and lag time between the two types of droughts can be evaluated. Taking meteorological and agricultural droughts as an example, the propagation from meteorological drought to agricultural drought is defined as the occurrence of an agricultural drought event during the period in which a meteorological drought occurs. Thus, the propagation rate (PR_{MA}) and lag time (LT_{MA}) can be mathematically expressed as follows (Sattar et al., 2019):
>
> $$P_{MA} = \frac{n}{m} \times 100\% \tag{2}$$
>
> $$LT_{MA} = \frac{\sum_{i=1}^{n} (T_{M,i} - T_{A,i})}{n} \tag{3}$$
>
> where n is number of meteorological drought events that propagate to agricultural drought events; m is the total number of meteorological drought events during the study period; TM,i is the starting time of meteorological drought event i, and TA,i is the starting time of agricultural drought event i. To elucidate the propagation of drought across different types, the SPI, SRI, and SSI at a 1-month accumulation period were used to represent meteorological, hydrological, and agricultural drought, respectively. Consistent with the analysis of drought response time, we analyzed the propagation rate and lag time between meteorological and hydrological droughts (PR_{MH} and LT_{MH}), between meteorological and agricultural droughts (PR_{MA} and LT_{MA}), and between hydrologcial and agricultural droughts (PR_{HA} and LT_{HA})." **(lines 171-189 of the revised manuscript)**

<u>Point #10</u>

COMMENT: *It is suggested to add a brief explanation of "Non-significant areas" in Section 3.1.*

RESPONSE: We sincerely appreciate the reviewer's helpful comment. In the revised manuscript, we have added a brief explanation of non-significant trend of time series trend in the Fig. 3. In detail, the revised sentences is provided as follows:

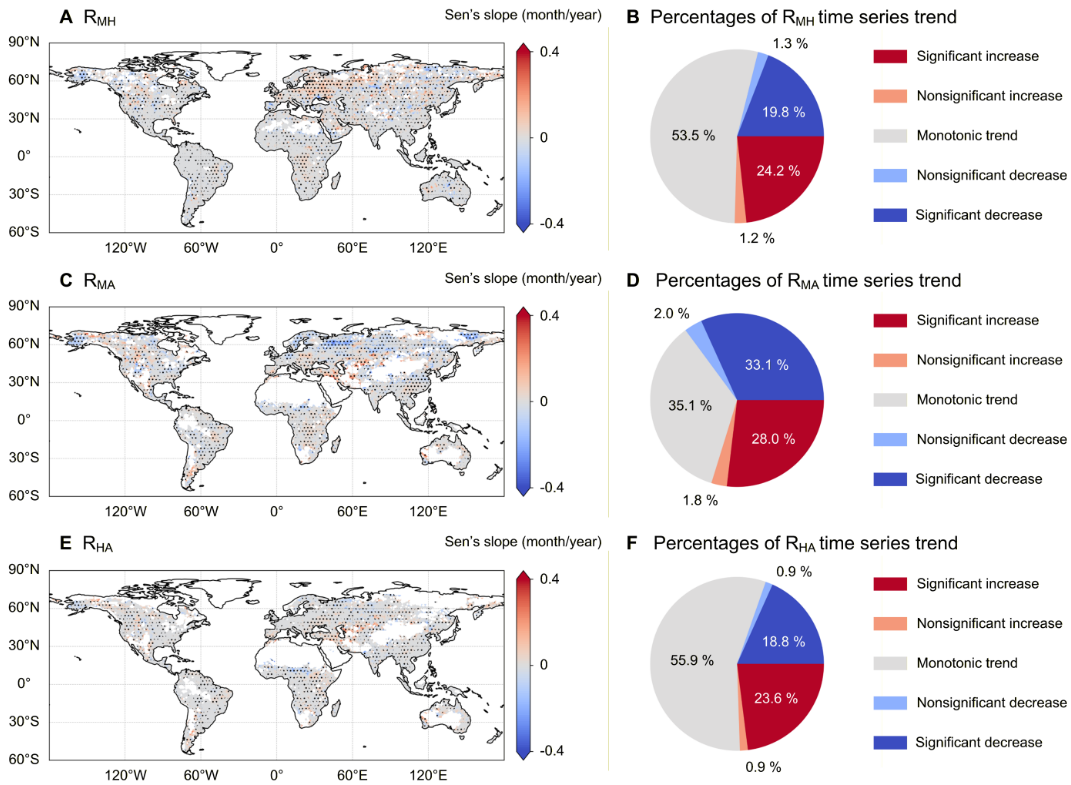

Figure 3. Spatial patterns of time series trends in RT_{MH}, RT_{MA} and RT_{HA} across global land areas. The blank grids signify that, within at least one time-window in the time series of response time obtained from the moving window, the correlation coefficient is not statistically significant. The black dots indicate the statistical significance of the time series trend, where the p-value of the TFPW-MK test is less than 0.05. A significant increase (decrease) indicates that the Sen's slope is greater (less) than 0 and that the p-value of the TFPW-MK test is less than 0.05. A nonsignificant increase (decrease) indicates that the Sen's slope is greater (less) than 0 and that the p-value of the TFPW-MK test is greater than 0.05. A monotonic trend indicates that Sen's slope is equal to 0.

Point #11

COMMENT: *Figure 2 uses a unified global timeline. Since seasons are opposite in the Northern and Southern Hemispheres, the high response values in February–April might be entirely driven by the Northern Hemisphere. Should these be discussed separately?*

RESPONSE: We sincerely appreciate the reviewer's insightful comment. We agree that drought propagation exhibits distinct seasonal variations and differs between the Northern and Southern Hemispheres. Accordingly, we have split the original Fig. 2 into separate panels for the Northern and Southern Hemispheres to better illustrate these hemispheric differences in seasonal patterns.

In the revised manuscript, the original Fig. 2 has been moved to the Supplementary Materials, and the revised version is presented below:

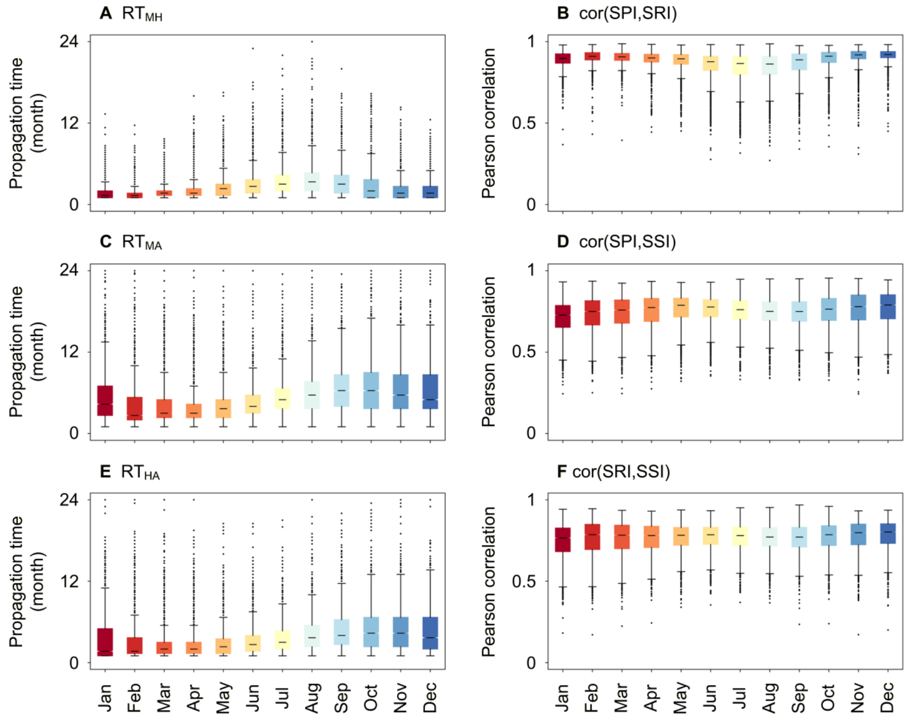

Figure S1. Box plots of RT_{MH}, RT_{MA} and RT_{HA} for each calendar month in the Southern Hemisphere, along with the corresponding Pearson correlation coefficients.

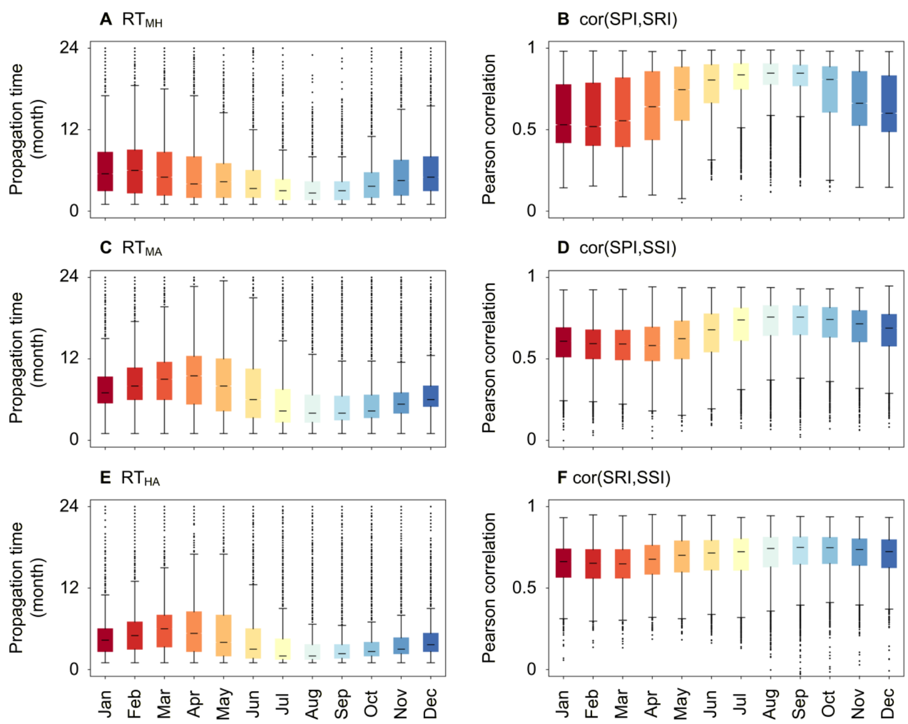

Figure S2. Box plots of RT_{MH}, RT_{MA} and RT_{HA} for each calendar month in the Northern Hemisphere, along with the corresponding Pearson correlation coefficients.

> "The response times among meteorological, hydrological, and agricultural droughts also exhibit obvious seasonal variations (Figs. S1 and S2). Shorter response times and higher correlation coefficients were observed during the summer season (June–August in the Northern Hemisphere, and December–February in the Southern Hemisphere)." **(lines 257-260 of the revised manuscript)**

Point #12

COMMENT: *Human activities can significantly alter the PR and LT of drought propagation. Have the authors considered quantifying human activities? Although this is challenging, I suggest a rough discussion on this topic.*

RESPONSE: We sincerely appreciate the reviewer's insightful comment. We agree that human activities—such as water abstraction, reservoir regulation, and land-use change—can profoundly modify natural drought propagation processes by altering catchment storage and flow pathways, thereby influencing both the propagation rate (PR) and lag time (LT). In our analysis, we focused on understanding drought propagation under the predominant influence of climate and natural conditions. Quantitatively disentangling the effect of human activities on drought propagation is indeed exceptionally challenging due to the scarcity of consistent, high-resolution datasets on human activities, particularly at the global scale. In response to the reviewer's comment, we have added a paragraph in the Discussion section addressing this topic, and the revised paragraphs are provided as follows:

> "In addition, human activities—such as water abstraction, reservoir regulation, and land-use change—can profoundly modify natural drought propagation processes by altering catchment storage and flow pathways, thereby influencing drought propagation. Future research could also focus on quantitatively disentangling the effects of human activities on drought propagation." **(lines 546-549 of the revised manuscript)**

Point #13

COMMENT: *I strongly recommend placing the propagation maps generated by each individual dataset in the Supplementary Materials.*

RESPONSE: We sincerely appreciate the reviewer's helpful comment. Accordingly, we have added the propagation maps derived from different datasets in the Supplementary Materials. In detail, the revised parts are provided as follows:

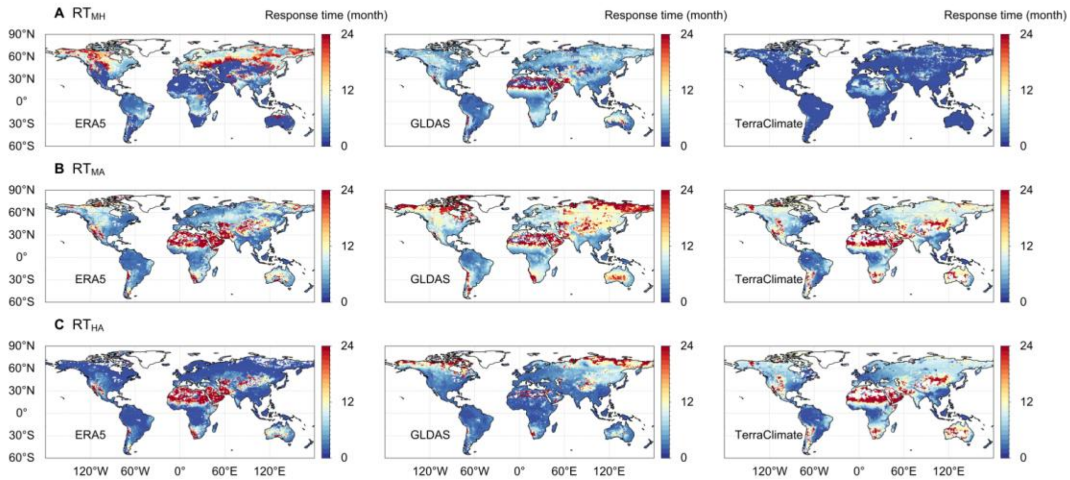

Figure S3. Spatial patterns of average RT_{MH}, RT_{MA}, and RT_{HA} across global land areas in the ERA5, GLDAS, and TerraClimate datasets.

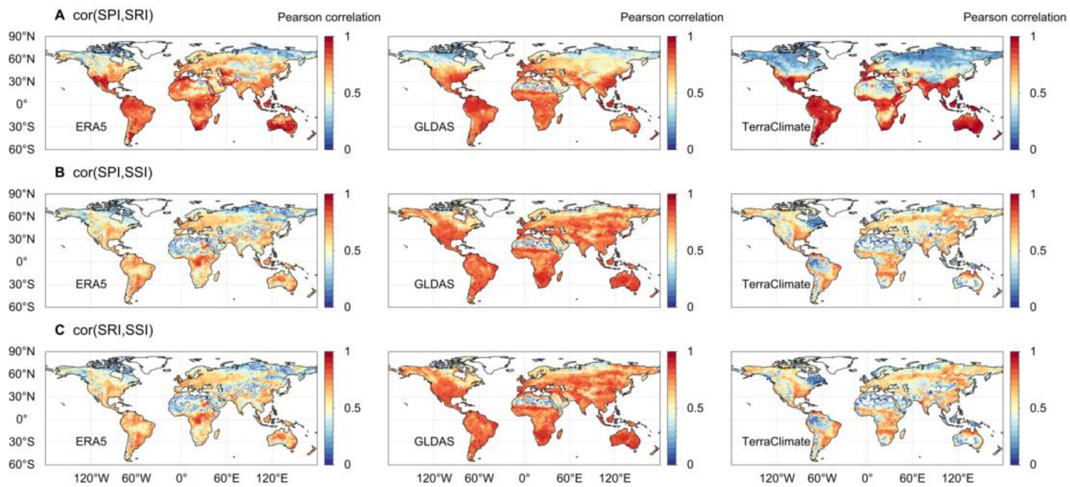

Figure S4. Spatial patterns of maximum Pearson correlation coefficients for RT_{MH}, RT_{MA}, and RT_{HA} across global land areas in the ERA5, GLDAS, and TerraClimate datasets.

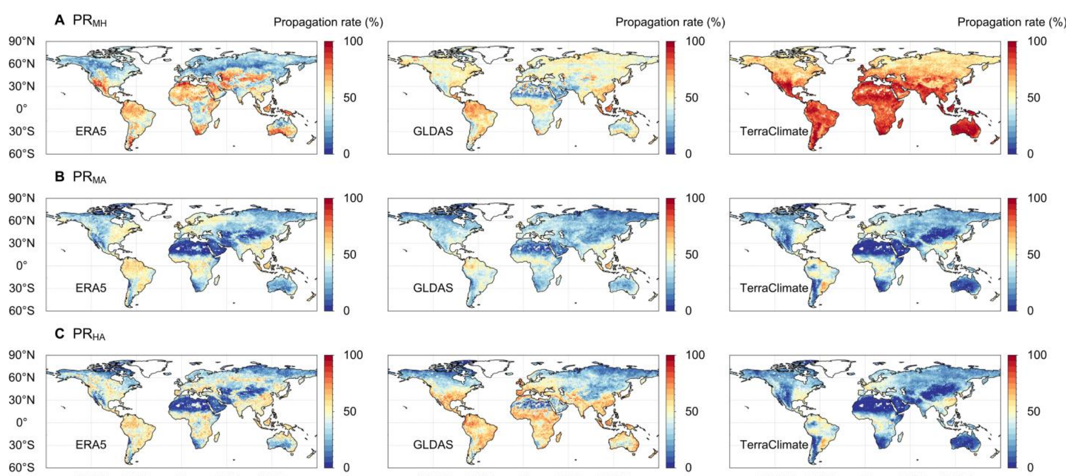

Figure S5. Spatial patterns of average PR_{MH}, PR_{MA}, and PR_{HA} across global land areas in the ERA5, GLDAS, and TerraClimate datasets.

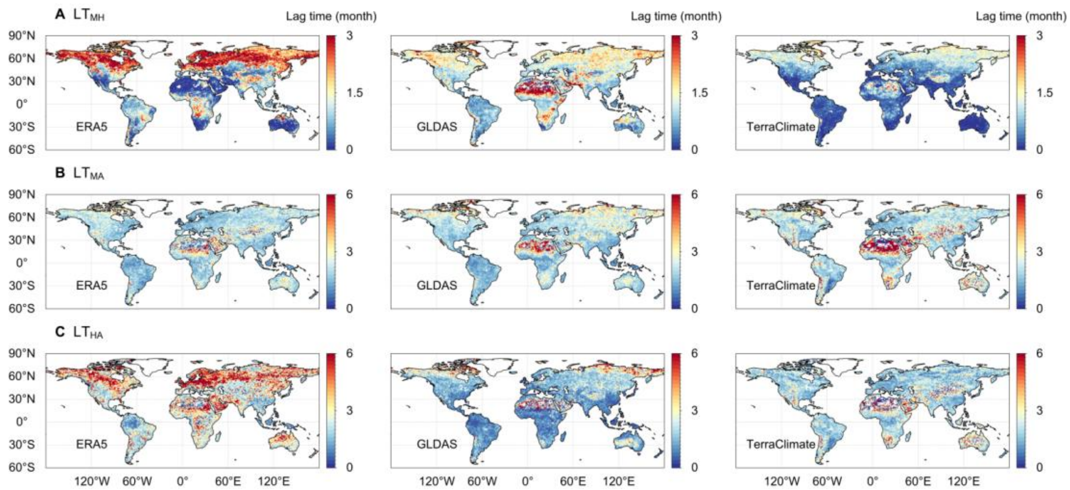

Figure S6. Spatial patterns of average LT_{MH}, LT_{MA}, and LT_{HA} across global land areas in the ERA5, GLDAS, and TerraClimate datasets.

Generally, we are deeply grateful to the reviewer's insight and careful review. His/her comments have greatly helped improve the paper. We also expressed our gratitude in the "**Acknowledgments**" of the revised manuscript.