App. Reply to the comments item by item:

To Reviewer#1

This paper investigates soil moisture memory (SMM) across multiple temporal scales in three catchments located in complex mountain terrain in southwestern China. Power spectral analysis (PSA) and DFA-2 are used to derive SMM metrics, which are then related to static and dynamic environmental variables using a Boruta Random Forest Algorithm. The stated aims are to: (1) identify thresholds for significant SMM transitions across temporal scales; (2) explain inter-catchment differences in SMM; and (3) develop a conceptual framework linking SMM to hazard preconditioning mechanisms.

Scope, Motivation, and Contribution

1. The motivation for selecting these specific catchments and this regional setting is not sufficiently justified. It remains unclear why complex mountain terrain in southwestern China was chosen over other environments, or how the findings extend beyond the study area. The broader contribution to soil science and hydrology is therefore ambiguous.

Reply: In the revised version, we have clarified the motivation for the study area selection and elaborated on the broader scientific relevance of our findings, as detailed below.

The three selected catchments—Dali River Basin, Anning River Basin, and Jiangjia Ravine—were purposefully chosen to represent a spectrum of hydro-geomorphic regimes and associated hazard types:

Dali River Basin: Semi-arid loess terrain prone to soil erosion.

Anning River Basin: Humid, vegetation-dense mountain-valley system prone to shallow landslides.

Jiangjia Ravine: Extremely steep, tectonically active catchment dominated by high-frequency debris flows.

The mechanism elucidated in this study—wherein soil moisture memory (SMM) acts as a preconditioning factor that modulates hazard initiation thresholds—is not exclusive to the three study area. Rather, it is consistent with observations documented in other high-relief, precipitation-dominated mountainous regions worldwide. For example, research conducted in the Himalayas by Dahal and Hasegawa (2008) underscores the critical influence of antecedent rainfall—a proxy for SMM — on landslide initiation in analogous monsoon-driven mountain environments. Correspondingly, studies by Wicki et al. (2020) in the Swiss Alps and Ponziani et al. (2012) in the Italian Apennines have empirically demonstrated that antecedent soil wetness — the direct manifestation of SMM persistence—plays a decisive role in preconditioning slope instability. Furthermore, Brocca et al. (2012) demonstrated that incorporating antecedent soil moisture data substantially enhances the accuracy of landslide early warning systems compared to models relying solely on rainfall thresholds. These corroborative findings collectively indicate that the conceptual framework proposed herein, which links SMM persistence to hazard susceptibility, possesses broad applicability to mountainous regions governed by seasonal hydro-meteorological forcing.

Revisions in the manuscript:

Lines 87-95: We have added clear justifications for the selection of the three watersheds: "The Dali River Basin, located on the Loess Plateau, represents a semi-arid erosion-dominated system where soil moisture deficits and intense summer storms drive severe soil loss (Liu et al., 2023). The Anning River Basin and Jiangjia Ravine, located in southwestern China—a global hotspot for rainfall-triggered landslides and debris flows due to complex terrain, active tectonics, and intense monsoon precipitation (Wei et al., 2025; Yang et al., 2023)—represent humid landslide-prone and high-frequency debris flow environments, respectively. This gradient design spanning semi-arid to humid climates and erosion to mass-movement hazards enables identification of both commonalities and differences in SMM mechanisms across contrasting mountain environments."

Lines 654-669: A new section, "**4.4 Broader Implications and Transferability**" has been added to address the generalizability of this study. It incorporates four key references—Dahal and Hasegawa (2008), Wicki et al. (2020), Ponziani et al. (2012), and Brocca et al. (2012)—to establish geographical coverage spanning the Himalayas and Europe, thereby demonstrating the universality of the proposed mechanism.

Lines 700-702: We have added a concluding statement specifying the types of mountainous environments to which the findings of this study can be extended.

Brocca, L., Ponziani, F., Moramarco, T., Melone, F., Berni, N., & Wagner, W. (2012). Improving landslide forecasting using ASCAT-derived soil moisture data: A case study of the Torgiovannetto landslide in central Italy. Remote sensing, 4(5), 1232-1244. https://doi.org/10.3390/rs4051232

Dahal, R. K., & Hasegawa, S. (2008). Representative rainfall thresholds for landslides in the Nepal Himalaya. Geomorphology, 100(3-4), 429-443. https://doi.org/10.1016/j.geomorph.2008.01.014

Liu, S., van Meerveld, I., Zhao, Y., Wang, Y., & Kirchner, J. W. (2023). Seasonal dynamics and spatial patterns of soil moisture in a loess catchment. *Hydrology and Earth System Sciences Discussions*, *2023*, 1-26. https://doi.org/10.5194/hess-28-205-2024, 2024

Ponziani, F., Pandolfo, C., Stelluti, M., Berni, N., Brocca, L., & Moramarco, T. (2012). Assessment of rainfall thresholds and soil moisture modeling for operational hydrogeological risk prevention in the Umbria region (central Italy). Landslides, 9(2), 229-237. https://doi.org/10.1007/s10346-011-0287-3

Wei, L., Song, D., Cui, P., Su, L., Zhou, G. G., Hu, K., ... & Tang, H. (2025). A long-term dataset of debris-flow and hydrometeorological observations from 1961 to 2024 at Jiangjia Ravine, China. *Earth System Science Data Discussions*, *2025*, 1-35. https://doi.org/10.5194/essd-2025-190

Wicki, A., Lehmann, P., Hauck, C., Seneviratne, S. I., Waldner, P., & Stähli, M. (2020). Assessing the potential of soil moisture measurements for regional landslide early warning. Landslides, 17(8), 1881-1896. https://doi.org/10.1007/s10346-020-01400-y

Yang, H., Hu, K., Zhang, S., & Liu, S. (2023). Feasibility of satellite-based rainfall and soil moisture data in determining the triggering conditions of debris flow: The Jiangjia Gully (China) case study. *Engineering Geology*, *315*, 107041. https://doi.org/10.1016/j.enggeo.2023.107041

2. The manuscript overstates its scope in places. For example, L54–56 claims a "comprehensive, multiscale characterization" of SMM, which is difficult to support given the analysis of only three catchments within a single climatic regime. This claim should be tempered or the scope

clarified.

Reply: Following this suggestion, we have revised the manuscript by replacing the phrase "comprehensive, multiscale characterization" with "systematic investigations that explicitly trace". The revised text (Lines 54-56) now reads: "Despite this established importance, systematic studies tracing SMM evolution across contiguous timescales—from monthly to seasonal, annual, and multi-year—remain scarce, particularly in steep mountain terrain."

3. While the authors suggest relevance to hazard prediction in mountainous regions, this motivation is not consistently developed. Despite references to hazard susceptibility, the analysis focuses on a single debris-flow event in one catchment, which is insufficient to support the third stated research aim. As currently presented, the study does not robustly demonstrate how the proposed SMM metrics advance hazard prediction.

Reply: To address this concern, we have taken the following steps in the revised manuscript:

Lines 79-81: We have revised the third research objective to read: "(3) propose a conceptual framework that links multi-scale SMM to differentiated hazard preconditioning mechanisms, providing testable hypotheses for future event-based validation." The revised wording adopts a more measured tone by clarifying that this study establishes a conceptual framework rather than constituting a validation study. Further work is required in the future—for instance, investigating the influence of SMM on debris flow initiation using more extensive field monitoring data.

Lines 610-615: At the end of Section 4.2, we have added a detailed paragraph outlining the specific analyses required to rigorously test the SMM-hazard hypothesis, including threshold analysis and extension to other hazard types:

"To rigorously evaluate SMM's predictive power for debris flows and landslides, future work should include: (1) Threshold analysis using the complete JJR inventory to test whether antecedent SMM significantly lowers I_{crit} across multiple events; (2) Statistical classification (e.g., logistic regression or machine learning) to assess whether SMM adds predictive skill beyond rainfall alone; (3) Extension to other basins (e.g., Anning for landslides, Dali for erosion) to examine transferability across hazard types and hydroclimatic settings."

These analyses are beyond the scope of the present study, which focuses on establishing the hydrological foundation of SMM dynamics. Nevertheless, the persistence horizons and driver hierarchies quantified here provide the essential input variables for such future hazard modeling efforts, addressing calls for integrating SMM into predictive models for extreme events."

This addition clarifies that while such validation is beyond the current scope, the SMM metrics quantified here provide the essential foundation for future efforts.

We have adjusted the conclusion to explicitly state that "the proposed linkage between SMM persistence and hazard preconditioning remains a conceptual hypothesis" (Lines 698-699).

4. The paper would benefit from clearer positioning within the existing SMM literature. A more thorough review of prior work on SMM across temporal scales is needed to contextualize the novelty of the study (e.g., Rahmati et al., 2024, Reviews of Geophysics, Table 1).

Reply: We thank the reviewer for highlighting the highly relevant and comprehensive review by Rahmati et al. (2024) on soil moisture memory (SMM). After careful consideration, we have strengthened our manuscript by integrating this reference in the following sections to better position our study:

In the Introduction (Lines 44-46), we cite Rahmati et al. (2024) to frame the foundational understanding of SMM's temporal range and controlling factors, thereby setting the context for our investigation.

In the Methods (Lines 159-160), we reference their synthesis of key controlling factors, which directly informed our selection of predictor variables.

In the Discussion (Lines 564-566), we cite their work to show how our findings on SMM as a preconditioning mechanism align with and extend upon the state-of-the-art understanding presented in their review.

We hope these revisions substantially strengthen the positioning of our study within the SMM literature and clearly articulate its novel contributions.

Rahmati, M., Amelung, W., Brogi, C., Dari, J., Flammini, A., Bogena, H., ... & Vereecken, H. (2024). Soil moisture memory: State-of-the-art and the way forward. Reviews of Geophysics, 62(2), e2023RG000828. https://doi.org/10.1029/2023RG000828

Language, Terminology, and Clarity

5. The manuscript frequently relies on dense, jargon-heavy language that obscures meaning. Many sections are difficult to follow due to the use of neologistic or uncommon terms that are insufficiently explained or referenced.

Reply: We have carefully reviewed the entire manuscript and made substantial revisions to improve clarity and readability. The key modifications are summarized below, organized by revision type:

Abstract section:

We have replaced dense, technical expressions with more accessible alternatives:

Lines 21: from “a robust “inherent persistence” regime” to “strong and persistent memory”;

Lines 23-24: from “whereas soil properties and topography governed the system’s long-term capacity to integrate low-frequency signals” to “whereas long-term persistence is controlled by soil properties and topography”;

Lines 22-24: from “Mechanistically, this marks a shift from event-driven hydraulic responses to background storage trends regulated by deep soil buffering.” to “a critical structural shift around the 5-year scale: short-term memory is dominated by atmospheric forcing and vegetation, whereas long-term persistence is controlled by soil properties and topography.”;

Lines 27: from “operational persistence horizons” to “memory timescales”;

Introduction section:

We have simplified complex phrases and added definitions for specialized terminology upon first use:

Lines 39: delete “predisposing slopes to instability”;

Lines 36-37: “Hydraulic preconditioning” is now explicitly defined as “lowering the critical threshold for slope failure” with supporting reference (Bogaard & Greco, 2016).

Lines 79-80: from “scale-explicit framework” to “framework that links multi-scale SMM to differentiated hazard preconditioning mechanisms";

Materials and Methods section:

Lines 267-269: We have added an explanation for the specialized term "catena concept," which now reads: "the catena effect, where steep upper slopes have thin, sandy, fast-draining soils while gentle lower slopes accumulate thick, clay-rich, water-retaining soils (Anderson, 2005)"

Discussion section:

Lines 488-489: from "Regime Stability" to "a stable baseline state";

Lines 508-511: "Deep Soil Buffering" is now revised to "Although topography's influence on SMM variability is recognized (e.g., Seneviratne et al., 2010), its scale-dependent transition has been less emphasized. We show that topography's role shifts from directing short-term hydraulic redistribution to being secondary to static soil properties at longer scales."

Conclusions section:

We have simplified two expressions to enhance readability:

Lines 691: from "Bio-Hydrological Coupled Inertia" to "a coupled soil-vegetation system";

Lines 701-702: from "actionable persistence horizons" to "couplings between antecedent wetness and hazard susceptibility".

Anderson, S. (2005). Soils: Genesis and geomorphology. Cambridge University Press.

Bogaard, T. A., & Greco, R. (2016). Landslide hydrology: from hydrology to pore pressure. *Wiley Interdisciplinary Reviews: Water*, *3*(3), 439-459. https://doi.org/10.1002/wat2.1126

Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., ... & Teuling, A. J. (2010). Investigating soil moisture–climate interactions in a changing climate: A review. *Earth-Science Reviews*, *99*(3-4), 125-161. https://doi.org/10.1016/j.earscirev.2010.02.004

6. For example, the discussion repeatedly introduces concepts such as "Sink to Structure," "Dynamic Sink," and "Static Structural Modifier" without clear definitions or grounding in prior literature. This overuse of unexplained terminology makes the discussion hard to interpret and gives the impression that complex physical processes are being compressed rather than critically examined.

Reply: The original terminology ("Sink-to-Structure", "Dynamic Sink", "Static Structural Modifier") was introduced without adequate definition or grounding in prior literature, which compromised readability and may have obscured the underlying physical mechanisms.

In the revised manuscript, we have substantially rewritten the relevant sections to address this concern:

Line 528: We revised the heading from "The 'Sink-to-Structure' Transition of Vegetation" to "The Dual Role of Vegetation Across Timescales". This change makes the concept more accessible to readers.

Line 689: we have simplified the term from "Static Structural Modifier" to the more direct "soil structure modifier". This change replaces a less common term with one that more clearly describes the role of soil properties.

Line 691: Instead of "Dynamic Sink", we now explicitly state that "a coupled soil-vegetation system" through transpiration-driven soil drying at short timescales.

7. Similarly, statements such as “no persistence,” “stronger influence of soil properties,” or “conditioning the baseline hydrological state” require clearer physical interpretation and explicit linkage to results.

Reply: Following your advice, we have made detailed revisions point by point.

Lines 351-352: To provide the clearer physical interpretation requested, we have revised the phrase “no persistence”. It is now expressed as “negligible persistence,” which is quantitatively defined as occurring when “with α falling below the 0.9 threshold”

Lines 353-354: We have deleted “stronger influence of soil properties”. Instead, we used “moisture decay is governed primarily by intrinsic drainage properties”.

Lines 366-367: To provide the explicit physical linkage requested, we have revised the vague statement “conditioning the baseline hydrological state” to the specific, process-based description: “elevating background pore pressures—a critical factor for landslide susceptibility assessment”.

Abstract and Introduction

8. Several abstract statements are vague or ambiguous:
   - L13: “Hydraulic susceptibility” is undefined.

Reply: We have replaced the undefined term "hydraulic susceptibility" with "Soil moisture memory (SMM)—the persistence of soil moisture anomalies—is a key factor preconditioning hydrological responses and geohazard susceptibility," a well-established term in hydrology (e.g., Bogaard & Greco, 2018; Wicki et al., 2020).

   - L19–20: “memory intensity weakened with scale” is unclear—does this refer to temporal or spatial scale?

Reply: This statement refers to temporal scale. We have revised “SMM intensity generally weakens with increasing timescale” to eliminate ambiguity.

   - Terms such as “inherent persistence regime” and “low-frequency signals” are not clearly explained.

Reply: To address this, we have made the following revisions:

In the Abstract: We replaced “inherent persistence regime” with the more descriptive “strong and sustained memory” (Line 21), and “low-frequency signals” with “slow-response (soil-buffered) regimes” (Line 25).

In Section 3.2, we have replaced the vague phrase “low-frequency signals” with a clear physical explanation (now Lines 533-538). The process is now explicitly described as the basin’s “responding solely to individual storm events,” which characterizes the system behavior at the low-frequency end of the spectrum.

9. The introduction would benefit from a clearer articulation of why SMM in complex terrain is important, particularly in relation to hazard prediction, and why southwestern China is an appropriate study region. Quantitative context and clearer linkage to hazards would strengthen

the motivation.

Reply: We have strengthened the introduction in three aspects:

Importance of SMM in complex terrain (Lines 46-48): We added: "In mountain catchments, the pronounced spatial heterogeneity of these factors increases the sensitivity of hazard initiation to antecedent moisture while shortening hydrological response times (Bogaard & Greco, 2016; Dymond et al., 2021; Wicki et al., 2020)."

Quantitative linkage to hazard (Lines 48-53): We added examples from European early warning systems: "For instance, landslide probability increases exponentially once soil moisture exceeds critical thresholds of ~30–40 % (Mirus et al., 2018; Wicki et al., 2021), with slope angle acting as a key topographic modulator. For debris flows, antecedent soil moisture influences not only initiation probability, but also runout distance (Coe et al., 2008). Similarly, soil loss rates under wet antecedent conditions can be 3–5 times higher than under dry conditions at equivalent rainfall intensities (Ran et al., 2012)."

Justification for study region selection (Lines 87-95): We explained the rationale for selecting three catchments across different hydro-climatic zones: "The Dali River Basin, located on the Loess Plateau, represents a semi-arid erosion-dominated system where soil moisture deficits and intense summer storms drive severe soil loss (Liu et al., 2023). The Anning River Basin and Jiangjia Ravine, located in southwestern China—a global hotspot for rainfall-triggered landslides and debris flows due to complex terrain, active tectonics, and intense monsoon precipitation (Wei et al., 2025; Yang et al., 2023)—represent humid landslide-prone and high-frequency debris flow environments, respectively. This gradient design spanning semi-arid to humid climates and erosion to mass-movement hazards enables identification of both commonalities and differences in SMM mechanisms across contrasting mountain environments."

Dymond, S. F., Wagenbrenner, J. W., Keppeler, E. T., & Bladon, K. D. (2021). Dynamic hillslope soil moisture in a Mediterranean montane watershed. *Water Resources Research*, 57(11), e2020WR029170. https://doi.org/10.1029/2020WR029170

Methods and Reproducibility

10. The methods section lacks sufficient explanation to ensure reproducibility. Many critical definitions and justifications are deferred to the appendices, which is not standard practice.

Across PSA, DFA-2, and Boruta analysis, the manuscript does not adequately explain:

- what each method does,
- why it was chosen over alternatives,
- and what the resulting metrics represent physically.

Key terms such as "persistence horizons," "reliable memory window," and "significant memory" are introduced without explanation. For example:

- What constitutes "significant memory," and why is $\alpha \geqslant 0.9$ used as a threshold?

Reply: The reviewer's suggestion is very useful. We have conducted a series of revisions to improve the quality of this manuscript following your advice. Detailed revisions are as follows:

(1) Brief description of PSA and DFA-2 methods (Lines 190-195): We added an overview explaining what each method does and why they were selected: "To characterize the multi-scale persistence of soil moisture, we employed two complementary techniques that quantify long-range temporal correlations—a hallmark of memory in hydrological systems. Power Spectrum Analysis (PSA) was used to identify the strength of memory across frequency domains, while Detrended Fluctuation Analysis (DFA-2) was applied to detect the timescales over which this memory persists. These two methods were selected because they are robust to non-stationarity and can distinguish genuine long-term correlations from short-term noise or trends (Kantelhardt et al., 2006; Zhu et al., 2010)."

(2) Physical explanation of PSA (Lines 205-211): We added the mathematical formulation and physical interpretation of the spectral exponent β, explaining that higher β values indicate dominance of low-frequency variations, implying longer information retention in the soil moisture system.

(3) Detailed explanation of DFA-2 (Lines 212-222): We added the scaling relationship $F(s) \sim s^{\alpha}$ and explicit meanings of different α values ($\alpha = 0.5$ for white noise, $\alpha > 0.5$ for persistent correlations, $\alpha = 1.0$ for scale-invariant memory). We also justified the $\alpha \geq 0.9$ threshold based on established criteria: Zhu et al. (2010) demonstrated that $\alpha \geq 0.9$ reliably identifies systems with significant long-term predictability, while Zhang et al. (2025) applied this criterion specifically to soil moisture memory quantification.

(4) Definition of key terms: We added explicit definitions of "Soil Moisture Memory (SMM)" (Lines 228-230), "Significant Memory" (Line 231) and "Persistence Horizon" (Lines 232-233) to improve clarity and accessibility. The terms "Reliable Spectral Window" (Lines 199-200) and "Low-Frequency Background State" were already explained in the original manuscript (Lines 201-204).

(5) Explanation of Boruta method (Lines 235-244): We explained that Boruta is an all-relevant feature selection method that iteratively compares each predictor's importance against randomized "shadow" variables. We justified its selection over alternatives: it captures non-linear relationships, handles collinear predictors without prior variable selection, and provides robust importance rankings validated against a null model (Kursa & Rudnicki, 2010).

Kantelhardt, J. W., Koscielny-Bunde, E., Rybski, D., Braun, P., Bunde, A., Havlin, S., 2006. Long-term persistence and multifractality of precipitation and river runoff records. *Journal of Geophysical Research: Atmospheres*, *111*(D1). https://doi.org/10.1029/2005jd005881

Kursa, M. B., Jankowski, A., & Rudnicki, W. R. (2010). Boruta–a system for feature selection. *Fundamenta informaticae*, *101*(4), 271-285. https://doi.org/10.3233/FI-2010-288

Zhang, J., Wu, Z., Li, Y., Qin, C., & Cui, J. (2025). Memory character and predictive period of soil moisture in the root-zone and along hillslope. *Journal of Hydrology*, 133428. https://doi.org/10.1016/j.jhydrol.2025.133428

Zhu, X., Fraedrich, K., Liu, Z., & Blender, R. (2010). A demonstration of long-term memory and climate predictability. *Journal of Climate*, *23*(18), 5021-5029. https://doi.org/10.1175/2010JCLI3370.1

- In L345–351, the physical meaning of a "critical threshold" is unclear—does it reflect a change in dominant processes, persistence timescale, or predictor importance?

Reply: It reflects a change in predictor importance. We have added the following explanation

(Lines 423-429) in the revised manuscript: "Scale-transition threshold: Quantitative analysis revealed a distinct structural break at the 5-year scale (Table 2). At the 1-year scale, TWI showed the strongest association (28.7 %), consistent with topography-driven lateral water redistribution. At the 5-year scale, TWI importance declined (to 13.5 %), with the hierarchy shifting to Soil Texture and Slope (~19 %). This threshold reflects a fundamental shift from event-scale hydraulic connectivity ("Fast-Response Regime") to long-term pedological storage control ("Background-Storage Regime") (Blöschl & Sivapalan, 1995; Western et al., 2004)."

11. Several specific methodological statements require clarification:

- L229: The meaning of "dynamic memory estimation ($N \geq 3T$)" is unclear; N and T are never defined.

Reply: We added definition of N and T in Section 2.3 (Lines 197-204) with reference cited: "Following established guidelines requiring $N \geq 3T$ for robust spectral estimation (Ghannam et al., 2016; Percival & Walden, 1993), we distinguish between two regimes:

1. **Reliable Spectral Window ($T \leq 7$ years):** Timescales up to $T = N/3 \approx 6.7$ years (rounded to 7 years) can be reliably estimated, as our record contains at least three complete cycles.
2. **Low-Frequency Background State ($T > 7$ years):** Signals at these timescales reflect slow-varying boundary conditions (e.g., multi-year drought periods) rather than event-scale memory. These estimates have lower statistical confidence and are interpreted as qualitative indicators of long-term storage trends."

However, we acknowledge that this definition may not be immediately accessible when reading Section 3.1. To improve readability, we have added a brief clarification in Lines 281-282: "We define the 1–7 year range as the "Reliable Spectral Window" for dynamic memory estimation." This follows the standard signal processing criterion that robust spectral estimation requires the record length (N) to exceed at least three times the timescale of interest (T), i.e., $N \geq 3T$."

- L234–235: The presentation of β as a mean ± 95 % CI derived from log–log regression is introduced without prior explanation of the regression or what is being averaged.

Reply: We have revised Lines 284-289 to explicitly explain the regression method and what is being averaged: "The spectral exponent β corresponds to the negative slope of the fitted line: higher β indicates variance concentrated at low frequencies, implying strong memory, while lower β indicates high-frequency dominance characteristic of weak memory. Shaded bands represent 95 % confidence intervals. Three key patterns emerge: (1) intra-annual contrasts between wet and dry seasons, (2) systematic decline in memory strength with increasing timescale, and (3) inter-basin differences reflecting contrasting hydro-climatic regimes."

12. β and α are suggested to be the chosen memory metrics from the PSA and DFA-2 analysis but their physical meaning is never discussed, only vaguely as 'strength of SMM'. Additionally, the relationship between PSA-derived β and DFA-derived α is unclear. Why are both used, and how do they complement each other?

Reply: β and α provide a comprehensive characterization: β indicates "how strong" the memory is, while the persistence horizon derived from α indicates "how long" it lasts. We have added a detailed illustration in the revised manuscript (Lines 241-348).

13. The physical meaning of SMM itself is never clearly described (e.g., how long a soil moisture anomaly persists following a rainfall event).

Reply: We have added a detail explanation of SMM, including its physical meaning in the revised manuscript (Lines 228-233).

The added content is:

- **Soil Moisture Memory (SMM):** The tendency of soil moisture anomalies to persist over time following wetting or drying events. SMM is quantified by the spectral exponent β (memory strength) and fluctuation exponent α (memory timescale).
- **Significant Memory:** A state where $\alpha \geq 0.9$, indicating strong long-range correlations.
- **Persistence Horizon:** The timescale range (in days) over which significant memory is observed.

14. **Cryptic or vague sentences are also common further impairing interpretability.** E.g.:

- "Timescales where sufficient realizations (approx. N/3) exist to statistically verify dynamic persistence and oscillatory behavior."
- "…persistence horizons extending beyond the 7-year threshold are classified as "Background Preconditioning" baselines, distinct from the active dynamic memory observed at shorter scales."
- "Results beyond this threshold (> 7 years) are interpreted as the "Low-Frequency Background State," reflecting the system's convergence to equilibrium rather than oscillatory persistence."

Reply: We have revised the sentences the reviewer mentioned to improve interpretability by replacing abstract terminology with concrete, physically intuitive descriptions:

Lines 199-200: Revised to "**Reliable Spectral Window ($T \leq 7$ years):** Timescales up to $T = N/3 \approx 6.7$ years (rounded to 7 years) can be reliably estimated, as our record contains at least three complete cycles."

Lines 224-226: Revised to "Persistence horizons extending beyond 7 years reflect slow-changing baseline conditions rather than event-scale memory. Detailed formulations and significance testing are provided in Appendix A."

Lines 288: Revised to "while longer timescales reflect quasi-stationary moisture regimes."

15. There are many cases where the same notation is used for different variables such as β for the PSA memory metric and slope aspect or τ for the decay timescale and characteristic response time.

Reply: The symbol β was used for both the PSA spectral exponent and slope. To eliminate this ambiguity, we have changed the abbreviation for slope from "β" to "θ" in Table 1 (Line 183) and throughout the manuscript. The symbol β is now used exclusively for the PSA-derived spectral exponent quantifying memory strength.

We note that τ is used consistently throughout the manuscript to represent the characteristic decay timescale of soil moisture anomalies. The terms "decay timescale" and "characteristic response time" refer to the same physical quantity—the *e*-folding time for soil moisture anomalies to dissipate. To improve clarity, we have standardized the terminology to "memory timescale (τ_{SMM})" throughout the manuscript.

Figures and Presentation of Results

16. The figures are difficult to interpret and do not enhance the results and discussion interpretability.
    - **Figure 3** does not clearly illustrate the trends described in the text and offers limited interpretive value without methodological context.

Reply: We have improved Figure 3 in the following two ways:

We revised the caption (Lines 302-308) to include methodological context and key interpretive guidance. The revised caption now explains: (a) how β is derived (linear regression in log-log space), (b) what the spatial averaging represents (mean ± 95% CI across all pixels), and (c) the three key trends illustrated by the figure (intra-annual wet/dry contrasts, inter-annual memory decline, and inter-basin differences). We also clarified the meaning of the gray shaded region in terms of the statistical reliability constraint.

We added a paragraph before the detailed results to guide readers in interpreting the figure (Lines 283-289): "In Figure 3, the *x*-axis represents frequency (cycles per year, logarithmic scale) and the y-axis represents spectral power $S(f)$ (log-transformed). The spectral exponent β corresponds to the negative slope of the fitted line: higher β indicates variance concentrated at low frequencies, implying strong memory, while lower β indicates high-frequency dominance characteristic of weak memory. Shaded bands represent 95 % confidence intervals. Three key patterns emerge: (1) intra-annual contrasts between wet and dry seasons, (2) systematic decline in memory strength with increasing timescale, and (3) inter-basin differences reflecting contrasting hydro-climatic regimes."

- **Figure 4** is introduced without sufficient explanation and does not clearly convey differences across basins or timescales.

Reply: We have improved Figure 4 by adding interpretive guidance in the main text and enhancing the figure caption. The specific revisions are as follows:

In Lines 341-344, we added: "Building on the PSA results, we quantified persistence horizons using DFA-2. While β characterizes overall memory strength, the fluctuation exponent α identifies specific timescales where memory is strongest ($\alpha \geq 0.9$). All reported α values in this range were statistically significant ($p < 0.01$) based on phase-randomization surrogate testing (see Appendix A)."

In Lines 345-348, we added: "Figure 4 presents DFA-2 results organized by basin (rows: a = DRB, b = ARB, c = JJR) and timescale (columns: left = seasonal, right = inter-annual). Solid lines show how α varies with window size s; labeled time windows (e.g., "236–728 d") indicate persistence horizons where $\alpha \geqslant 0.9$."

In Lines 350-358, we added: "October exhibited negligible persistence, with α falling below the 0.9 threshold (Fig. 4a-1). This indicates rapid decay of moisture anomalies due to intense evaporative drying following monsoon withdrawal. During the dry season, persistence increased to 61–95 days, reflecting conditions where moisture decay is governed primarily by intrinsic drainage properties rather than evaporative demand (Seneviratne et al., 2010). At interannual scales, persistence horizons increased from 31–73 days (1-year) to 174–429 days (20-year), peaking between 10 and 15 years (Fig. 4a-2). This pattern is consistent with deeper-layer memory and reduced influence of high-frequency atmospheric forcing at longer timescales (Rahmati et al., 2024)."

In addition, we have included an illustration showing the cross-basin comparison and the differences between timescales throughout Section 3.2. We believe this revision directly addresses the reviewer's concern.

- **Figure 5** lacks a clear nomenclature; the meaning of importance (z) is vague, y-axis scaling is inconsistent across panels, and the rationale for selecting June and October is not explained.

Reply: We have addressed the reviewer's concerns by revising the Figure 5 caption and the content in Section 3.3.

The Figure 5 caption has been revised to (Lines 403-409): "**Fig. 5** Scale-dependent predictive importance of environmental drivers for soil moisture memory from monthly to decadal timescales. (a) Dynamic drivers evaluated by Boruta algorithm (*Z*-scores; green: confirmed, yellow: tentative, red: rejected; $p < 0.01$). (b) Static drivers assessed by Random Forest (relative importance, %). Note: Panels (a) and (b) use different metrics and are not directly comparable. Abbreviations: Prec., precipitation; WS, wind speed; rhu, relative humidity; T_{2m}, 2-m air temperature; AE, actual evapotranspiration; NDVI, normalized difference vegetation index; TWI, topographic wetness index; Asp., aspect; ρ_b, bulk density."

We have added the following content in the revised manuscript:

Lines 390-394: "The Boruta Random Forest Algorithm identified statistical associations between environmental variables and SMM across multiple timescales (Fig. 5). Variables were classified as "confirmed" (*Z*-score significantly exceeds shadow maximum, $p < 0.01$), "tentative" (borderline significance), or "rejected." Bootstrap resampling (n = 1000) confirmed that top predictors at each scale maintained significance across > 95% of iterations."

Lines 318-319: Our choice of June and October is explained in Appendix B (Lines 758-762) and is reflected in the revised Lines 318-319.

Lines 412-415: "The cumulative importance of atmospheric variables (Precipitation, Wind Speed, T_{2m}, rhu) declined from 62 % at the monthly scale to 34 % at the 10-year scale, while soil texture variables (Sand, Silt, Clay) increased from 12 % to 38 % (Fig. 5)."

- **Figure 8**: I found it difficult to understand why soil moisture increases significantly between 06-26 and 07-06 with no input from rainfall in the middle of the summer in a mountainous region, while both previous events show soil moisture decreasing after a rainfall event. Am I missing something? Please explain in more detail.

Reply: We thank the reviewer for this careful observation, which helped us identify an error in Figure 8. Upon re-examination, we found that the soil moisture data in the original lower subfigure was plotted at an hourly scale, which was mismatched with the daily precipitation data in the upper subfigure. We have corrected this by recalculating the soil moisture time series at a daily resolution. The revised Figure 8 (Line 599) now presents consistent daily-scale data for both variables, showing soil moisture dynamics that appropriately respond to rainfall inputs.

17. Overall, results are often reported numerically without adequate physical interpretation. Differences across months, seasons, and basins are described, but their implications for soil moisture dynamics or hazard relevance are not clearly articulated.

Reply: We have revised the Results section to provide physical interpretations and hazard-relevant implications for the numerical findings, supported by relevant literature. The specific revisions include:

(1) Section 3.1 Power Spectrum Analysis of SM Memory (Lines 279-340):

For each basin, we now explain the physical meaning of the observed memory patterns and their implications for hazard susceptibility.

Lines 313-315: "Conversely, integrated dry season memory (β = 1.028 ± 0.075) was weaker than October (β = 2.378 ± 0.112) (Fig. 3a-1), reflecting residual moisture persisting into early autumn before rapid depletion."

Lines 315-318: "At interannual scales, SMM declined from β = 1.355 ± 0.089 (1-year) to β = 1.000 ± 0.081 (20-year) (Fig. 3a-2), indicating limited carryover beyond a few years. For erosion hazards, antecedent moisture from preceding weeks to months—rather than years—is most relevant for modulating soil erodibility (Ran et al., 2012)."

Lines 322-323: "High β values reflect strong persistence driven by accumulated monsoon precipitation and the buffering capacity of deep forest soils (Bogaard & Greco, 2018)."

Lines 325-327: "This sustained multi-year memory suggests wet years can progressively elevate baseline pore pressures, potentially lowering landslide triggering thresholds (Cui et al., 2025)."

Lines 330-332: "This strong seasonal contrast reflects rapid hydrological response: frequent monsoon rainfall maintains elevated moisture and strong autocorrelation, while steep terrain promotes quick drainage during dry periods."

Lines 334-336: "For debris flow hazards, antecedent wetness from preceding days to weeks within the rainy season is critical (Wei et al., 2025), whereas inter-annual carryover is less pronounced than in the forest-buffered ARB."

(2) Section 3.2 DFA-2 Analysis of SM Persistence Horizons (Lines 341-389):

Lines 380-381: "This 2–4 week persistence horizon defines the critical "look-back window" for debris flow early warning (Pan et al., 2018; Wicki et al., 2020)."

Lines 382: "reflecting reduced evaporative demand when rainfall ceases"

Lines 384-385: "suggesting that intrinsic drainage characteristics impose a consistent upper bound on moisture retention regardless of climatic variability"

The remaining sections have already been revised during our responses to the reviewer's earlier comments, with appropriate physical mechanism explanations incorporated.

Cui, Y., Xu, C., Chen, H., Cui, Y., Xue, L., & Qin, S. (2025). Startup mechanism of locked segment–dominated rockslides: Insights from a physical model experiment replicating natural infiltration conditions. *Engineering Geology*, *108494*.

https://doi.org/10.1016/j.enggeo.2025.108494

Pan, H. L., Jiang, Y. J., Wang, J., & Ou, G. Q. (2018). Rainfall threshold calculation for debris flow early warning in areas with scarcity of data. *Natural Hazards and Earth System Sciences*, *18*(5), 1395-1409. https://doi.org/10.5194/nhess-18-1395-2018

Ran, Q., Su, D., Li, P., & He, Z. (2012). Experimental study of the impact of rainfall characteristics on runoff generation and soil erosion. *Journal of hydrology*, *424*, 99-111. https://doi.org/10.1016/j.jhydrol.2011.12.035

Results and Discussion

18. The discussion does not sufficiently situate the findings within the broader SMM literature. Recent syntheses (e.g., Rahmati et al., 2024) identify multiple controlling factors on SMM that should be explicitly compared with the results presented here.

Reply: The recent synthesis by Rahmati et al. (2024) is a highly relevant and comprehensive review, which has greatly contributed to improving our study. Following your advice, we have thoroughly revised our discussion section and cited this reference in appropriate locations. The specific revisions are as follows:

Lines 497-499: "Our findings align with recent syntheses of SMM mechanisms, which identify soil texture as a key control on the memory timescale (τ_{SMM}) (Rahmati et al., 2024)."

Lines 529-531: "Our results reveal that vegetation exerts contrasting, scale-dependent influences on SMM, consistent with ecohydrological theory (Rodriguez-Iturbe et al., 1999)."

Lines 565-567: "This example aligns with broader literature on SMM's role in preconditioning extreme events (Rahmati et al., 2024), but remains illustrative rather than predictive."

Lines 668-669: "This extends recent syntheses on SMM's role in flood and drought prediction (Rahmati et al., 2024) by demonstrating its relevance to slope hazards."

We believe these revisions effectively situate our findings within the broader SMM literature and make explicit contrasts—for example, our scale-dependent interpretation of vegetation's role aligns with yet further refines existing discussions on ecohydrological feedback mechanisms. These changes fully address your concerns and enhance the scientific context of the manuscript.

Rahmati, M., Amelung, W., Brogi, C., Dari, J., Flammini, A., Bogena, H., ... & Vereecken, H. (2024). Soil moisture memory: State-of-the-art and the way forward. *Reviews of Geophysics*, *62*(2), e2023RG000828. https://doi.org/10.1029/2023RG000828

19. Interpretation of results is frequently weak or unsupported. For example:

- **L257–272** reports differences in β values between months and seasons but does not explain what these differences mean physically.

Reply: We agree that the original text reported numerical differences in β values (from DFA-2) across months, seasons, and interannual scales without sufficient physical interpretation of what these differences represent in terms of hydrological processes and persistence. To address this, we have substantially revised the relevant paragraphs by adding explicit mechanistic explanations for the observed β patterns in each basin. Key additions include:

Lines 284-287: "The spectral exponent β corresponds to the negative slope of the fitted line:

higher β indicates variance concentrated at low frequencies, implying strong memory, while lower β indicates high-frequency dominance characteristic of weak memory."

Lines 311-312: "indicating pronounced long-range persistence where cumulative monsoon rainfall progressively builds hydrological inertia (Rahmati et al., 2024)"

Lines 322-323: "High β values reflect strong persistence driven by accumulated monsoon precipitation and the buffering capacity of deep forest soils (Bogaard & Greco, 2018)."

Lines 325-327: "This sustained multi-year memory suggests wet years can progressively elevate baseline pore pressures, potentially lowering landslide triggering thresholds (Cui et al., 2025)."

- **L279–280** uses the phrase "no persistence" without clarifying whether this implies rapid decay of anomalies, noise-dominated behaviour, or another mechanism.

Reply: To address this, we have revised the sentence to explicitly link the DFA-2 fluctuation exponent (α) falling below the 0.9 threshold to its hydrological implications. The revised text now reads (Lines 505–508): "This indicates rapid decay of moisture anomalies due to intense evaporative drying following monsoon withdrawal. During the dry season, persistence increased to 61–95 days, reflecting conditions where moisture decay is governed primarily by intrinsic drainage properties rather than evaporative demand (Seneviratne et al., 2010)."

- Claims linking increased persistence to soil properties (e.g., P15/L281) are not convincingly supported by the analyses shown.

Reply: We agree that the moderate increase in characteristic persistence horizon from seasonal to decadal scales, and its implied link to soil properties, was not sufficiently supported by the analyses directly presented. To address this concern, we have revised the relevant paragraph to (Lines 499-505): "Established evidence shows that fine-textured (clay-rich) soils prolong τ_{SMM} by increasing water-holding capacity and reducing drainage, whereas coarse-textured soils exhibit shorter memory (Martínez-Fernández et al., 2021; McColl et al., 2017). Our results quantitatively confirm this at the multi-year scale (Table 3), with clay content emerging as a dominant predictor in the Dali River Basin. This agreement underscores the role of soil hydraulic properties (e.g., reduced saturated hydraulic conductivity, K_{sat}) in acting as a low-pass filter, as conceptualized in linear reservoir theory (Salvucci & Entekhabi, 1994)"

Rahmati, M., Amelung, W., Brogi, C., Dari, J., Flammini, A., Bogena, H., ... & Vereecken, H. (2024). Soil moisture memory: State-of-the-art and the way forward. *Reviews of Geophysics*, *62*(2), e2023RG000828. https://doi.org/10.1029/2023RG000828

Salvucci, G. D., & Entekhabi, D. (1994). Equivalent steady soil moisture profile and the time compression approximation in water balance modeling. *Water Resources Research*, *30*(10), 2737-2749. https://doi.org/10.1029/94wr00948

Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., ... & Teuling, A. J. (2010). Investigating soil moisture–climate interactions in a changing climate: A review. *Earth-Science Reviews*, *99*(3-4), 125-161. https://doi.org/10.1016/j.earscirev.2010.02.004

20. It is recommended the authors include at the end of every sub-section in results a summary paragraph written for a general audience with the key findings and implications/interpretations; otherwise it is very hard to follow the results.

Reply: We agree that the Results section contains dense technical details and figures, and that brief summary statements at the end of each subsection would help readers more easily follow the main logic and key messages without getting lost in the data. To make the manuscript more logical and easier for readers to understand, we have added a short summarization at the end of each subsection.

Lines 337-341: We have added: "In summary, SMM is consistently stronger in rainy seasons than in individual months and weakens progressively toward a climate-driven baseline. The ARB shows the strongest overall memory, highlighting how basin characteristics shape persistence beyond short-term weather effects—with clear relevance for multi-scale hazard prediction."

Lines 386-389: We have added: "Persistence horizons vary markedly across basins: longest in ARB (months to years), shortest in JJR during the rainy season (2–4 weeks), and intermediate in DRB. These time windows define practical "look-back" periods for anticipating different mountain hazards, from short-term debris flows to longer-term landslide preconditioning."

Lines 448-451: We have added: "Short-term memory is driven primarily by weather and vegetation factors, whereas beyond ~5 years, soil texture and topography become dominant. This scale-dependent shift from dynamic to static control marks a fundamental transition in SMM mechanisms—essential for developing timescale-appropriate hazard models."

Lines 479-483: We have added: "These contrasting memory regimes—vegetation-buffered persistence in ARB, topography-driven rapid response in JJR, and weather-to-soil transitional control in DRB—demonstrate that a single modeling framework cannot adequately capture SMM dynamics across diverse mountain environments. This heterogeneity underscores the necessity of basin-specific parameterization in soil moisture-based hazard early warning systems."

Section 4.2 focuses on a single event in one catchment, raising concerns about selective emphasis. Claims regarding early-warning system applicability are therefore not substantiated, particularly given the lack of validation against hazard inventories. The use of basin-averaged soil moisture also contradicts earlier emphasis on slope-scale control of debris flows. Even if the proposed approach attempts to conceptualise these processes, it is unclear what the predictive power is for forecasting landslides and how it can be used in the region, and most importantly elsewhere.

Reply: We fully agree with the reviewer's concerns regarding Section 4.2. In response, we have thoroughly revised the section as follows:

(1) Clarified the purely illustrative and conceptual nature: We now explicitly state (multiple times) that the July 10, 2007 event is presented as a proof-of-concept illustration only, not as evidence of causality, general validity, or predictive skill. We removed any language that could imply direct applicability to operatiWonal early-warning systems (Lines 586-597).

(2) Acknowledged the basin-average vs. slope-scale mismatch: We added an explicit paragraph explaining that basin-averaged soil moisture serves only as a proxy for antecedent catchment storage deficit (preconditioning background state), not as a direct control on localized slope failure. We emphasized that triggering remains governed by slope-scale geotechnical conditions, and basin-averaging smooths heterogeneity (Lines 624-644).

(3) Strengthened limitations and future work statements: We significantly expanded the caveats and future research directions, explicitly noting that no claim is made here regarding predictive power or operational use, and that rigorous testing requires full inventory analysis, statistical skill assessment, and extension to other basins/hazard types (Lines 699-703).

(4) Softened causal language: Phrases such as "increased the probability of instability" were changed to "may have contributed to" or "within this conceptual framework, we hypothesize that···", and we repeatedly stress the illustrative (not empirical) intent (Line 665-667).

21. Line specific comments:

- L11-13: Can the authors be more specific with their first sentence?

Reply: To make the opening sentence more specific and informative, we have revised it as follows: "Soil moisture memory (SMM) – the persistence of soil moisture anomalies — is a key factor preconditioning hydrological responses and geohazard susceptibility." This revision explicitly defines SMM's temporal scope, its mechanistic role in hydrological processes (storage and runoff), and its direct relevance to the geomorphic hazards central to our study.

- L15: Can the authors be more specific to what they mean by "hazard prone watersheds"? What type of hazards?

Reply: We have revised the sentence to explicitly state the primary hazard types prevalent in each study watershed. The revised text now reads (Lines 14-16): "Here, we quantify SMM dynamics from daily to interannual scales using 20-year (2003–2022) daily soil moisture data from three contrasting watersheds in southwestern China, prone to soil erosion (Dali River Basin), shallow landslides (Anning River Basin)." This revision clarifies the geohazard context central to our research motivation.

- L16-18: It is not clear to me yet why all these approaches have been used/chosen.

Reply: The three methods were selected to provide a comprehensive, multi-faceted characterization of soil moisture memory (SMM) dynamics: Power Spectrum Analysis (PSA) characterizes the spectral distribution of variance across timescales; Detrended Fluctuation Analysis (DFA-2) quantifies long-range persistence and memory duration; and the spatial attribution modeling framework (Boruta random forest coupled with partial correlation analysis) identifies scale-dependent controls on SMM. We have incorporated this clarification into the manuscript (Lines 17–20).

- L19-20: Isn't that expected?

Reply: We agree that a general weakening of SMM intensity with increasing timescale is a well-documented feature in the literature (e.g., Koster & Suarez, 2001; Rahmati et al., 2024).

However, the particularly strong and persistent multi-year regime observed in humid catchments in our study was more pronounced than anticipated based on general expectations, especially given the mountainous, hazard-prone nature of these specific watersheds.

To better convey that this result is noteworthy (rather than entirely expected) and to improve clarity, we have revised the sentence (lines 20–21) as follows: “SMM intensity generally weakens with increasing timescale, yet humid catchments exhibit surprisingly strong and persistent memory extending to multi-year scales.” We believe this revision more effectively communicates the significance of the finding without overstating the results.

Koster, R. D., & Suarez, M. J. (2001). Soil moisture memory in climate models. Journal of hydrometeorology, 2(6), 558-570. https://doi.org/10.1175/1525-7541(2001)002<0558:SMMICM>2.0.CO;2

Rahmati, M., Amelung, W., Brogi, C., Dari, J., Flammini, A., Bogena, H., ... & Vereecken, H. (2024). Soil moisture memory: State-of-the-art and the way forward. Reviews of Geophysics, 62(2), e2023RG000828. https://doi.org/10.1029/2023RG000828

- L20-23: What does that imply and how you interpret these results conceptually?

Reply: We agree that the original sentence described the structural transition but did not sufficiently explain its conceptual implication or interpretation. The ~5-year transition indicates a fundamental shift in the dominant controls on soil moisture memory (SMM): short-term variability (<5 years) is primarily driven by high-frequency atmospheric forcing and vegetation dynamics (event-scale responses), while long-term persistence (>5 years) is governed by slower landscape properties (soil texture and topography), which enable the system to integrate and retain low-frequency signals. Conceptually, this reflects a transition from fast-response, weather-driven dynamics to slow-response, storage-dominated dynamics, consistent with linear reservoir theory and scale-dependent hydrological processes. To make this implication clearer in the Abstract, we have revised the sentence (lines 21–24) as follows: “Feature importance analysis reveals a critical structural shift around the 5-year scale: short-term memory is dominated by atmospheric forcing and vegetation, whereas long-term persistence is controlled by soil properties and topography.”

- Abstract is poorly written, too vague and difficult to understand

Reply: We have substantially rewritten the Abstract to improve readability, logical flow, and specificity while keeping it concise. See Lines 11-28 for the new version.

- L44-46: I would assume the slope angle also plays a major role, especially in mountain regions (???) – not only soil moisture.

Reply: The original sentence focused on the role of soil moisture as a driving factor of slope instability. To make the statement more balanced and complete, we have revised the sentence (lines 46–47) as follows: “…spatial heterogeneity of these factors…”. Here, “these factors” refers to atmospheric forcing, soil properties, vegetation, and topography (as mentioned in the previous sentence), with topography including slope angle.

- Have identified that previous studies focus on single time scale while this study investigates at multiple time scales.

Reply: Thanks.

- L80-84: I don't understand why exactly this is an issue that prevents from being carried out. How will users know the proposed approach is robust then? Please provide further explanation.

Reply: We have revised the manuscript thoroughly to address this more clearly.

The primary issue preventing direct, event-based validation is a fundamental mismatch in spatial scales: our 1-km resolution soil moisture data capture basin-averaged antecedent conditions, which are useful for characterizing overall hydrological preconditioning, but landslides, debris flows, and erosion events initiate at much finer slope scales (typically 10^1–10^2 m). At these local scales, triggering is dominated by heterogeneous geotechnical factors (e.g., fractures, soil depth variations) that our data cannot resolve. As a result, direct matching of basin-averaged SMM to individual hazard events would require either high-resolution downscaling (introducing substantial uncertainties) or aggregation of local failures to basin scales (losing critical triggering details), neither of which is feasible with current datasets and methods.

To demonstrate the robustness of the proposed framework, we rely on multiple lines of evidence rather than direct validation: (1) sensitivity analyses (Section 4.3 and Appendix E) confirm that SMM patterns are stable across methodological variations and temporal subsets (Lines 621-654 and Lines 812-869); (2) partial correlation analysis (Appendix G) accounts for landscape collinearity, showing that key associations (e.g., soil texture and long-term SMM) remain significant after controlling for confounders (Lines 914-935); and (3) synthesis with established literature (e.g., Mirus et al., 2018; Wei et al., 2025) supports the mechanistic plausibility of the framework. Additionally, the framework's transferability is discussed in Section 4.4, where we highlight its alignment with empirical evidence from other mountain systems (e.g., Himalayas, Alps), suggesting applicability to similar terrains while acknowledging the need for site-specific adaptation (Lines 655-670).

We have expanded the explanation in lines 111–129 of the Introduction to explicitly outline these limitations and robustness assessments, and we reference them in the Discussion (Section 4.3) and Conclusions (Section 5). The revised text now reads: "(3) propose a conceptual framework that links multi-scale SMM to differentiated hazard preconditioning mechanisms, providing testable hypotheses for future event-based validation." (Lines 79-81). "The analytical framework is transferable to other high-relief, seasonally forced mountain environments where similar couplings between antecedent wetness and hazard susceptibility are expected." (Lines 701-733)

Mirus, B. B., Becker, R. E., Baum, R. L., & Smith, J. B. (2018). Integrating real-time subsurface hydrologic monitoring with empirical rainfall thresholds to improve landslide early warning. *Landslides*, *15*(10), 1909-1919. https://doi.org/10.1007/s10346-018-0995-z

- L88-95: There is no clear justification and context being presented as to why all listed approaches have been chosen – need to explain rationale in more detail to a wider audience.

Reply: We have added a dedicated explanatory paragraph immediately following the listing of methods in the manuscript (Lines 102-112):

"The integrated use of these methods is designed to address complementary aspects of our research questions:

- ✓ Power Spectral Analysis (PSA) is used to characterize the overall distribution of SM variance across timescales (from daily to interannual), identifying the dominant frequencies of variability (Kantelhardt et al., 2006; Parada et al., 2003).
- ✓ Second-order Detrended Fluctuation Analysis (DFA-2) is specifically chosen to robustly quantify long-range persistence (memory) and to distinguish it from short-term correlations, providing a direct measure of the memory timescale (τSMM) (Kantelhardt et al., 2001; Zhang et al., 2025).
- ✓ The Boruta–Random Forest algorithm serves to identify and rank the key drivers (both static and dynamic) of SM memory across different temporal scales, handling high-dimensional data and complex, non-linear interactions without prior assumptions about variable relationships (Breiman, 2001; Kursa et al., 2010).

Together, this multi-method framework allows us to not only quantify how strong and how long SM memory persists, but also to attribute why it varies across scales and locations (Fig. 1)."

Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32. https://doi.org/10.1023/A:1010933404324

Kantelhardt, J. W., Koscielny-Bunde, E., Rybski, D., Braun, P., Bunde, A., Havlin, S., 2006. Long-term persistence and multifractality of precipitation and river runoff records. *Journal of Geophysical Research: Atmospheres*, *111*(D1). https://doi.org/10.1029/2005jd005881

Kantelhardt, J. W., Koscielny-Bunde, E., Rego, H. H., Havlin, S., & Bunde, A. (2001). Detecting long-range correlations with detrended fluctuation analysis. *Physica A: Statistical Mechanics and its Applications*, *295*(3-4), 441-454. https://doi.org/10.1016/s0378-4371(01)00144-3

Kursa, M. B., Jankowski, A., & Rudnicki, W. R. (2010). Boruta–a system for feature selection. *Fundamenta informaticae*, *101*(4), 271-285. https://doi.org/10.3233/FI-2010-288

Parada, L. M., & Liang, X. (2003). A stochastic modeling approach for characterizing the spatial structure of L band radiobrightness temperature imagery. *Journal of Geophysical Research: Atmospheres*, *108*(D22). https://doi.org/10.1029/2003jd003567

Zhang, J., Wu, Z., Li, Y., Qin, C., & Cui, J. (2025). Memory character and predictive period of soil moisture in the root-zone and along hillslope. *Journal of Hydrology*, 133428. https://doi.org/10.1016/j.jhydrol.2025.133428

- Figure 1: I appreciate the effort the authors have put to provide a graphical summary, but the figure is not easily interpreted without having to read carefully the main text.

Reply: To make Figure 1 more readable, self-contained, and effective as a standalone overview of the research workflow, we have revised the caption and added a guiding sentence in the main text (Materials and Methods).

Revised caption (lines 117–124): "**Fig. 1** Schematic workflow of the multi-scale soil moisture memory (SMM) analysis framework. The framework comprises three stages: (1) data preparation, where multi-source static (topography, soil) and dynamic (meteorology, vegetation) variables are harmonized and soil moisture time series undergo quality control and stationarity verification; (2) memory quantification, using Power Spectral Analysis (PSA) to characterize variance distribution across frequencies and Detrended Fluctuation Analysis (DFA-2) to derive memory timescales; and (3) driver attribution, applying the Boruta-Random Forest algorithm to identify scale-dependent importance of controlling factors. This integrated workflow resolves the strength, duration, and controls of SMM across timescales."

Added sentence in main text (lines 126–127): "The overall research framework is shown in Figure 1, outlining the data flow, analysis steps, and their complementary roles in the multi-scale quantification and attribution of SMM."

- L132-133: How did you decide on those 12 covariates in the first place? Explain rationale in more detail.

Reply: The 12 covariates were selected through a systematic process combining an extensive literature review and practical data constraints. Specifically, we prioritized variables that are:

✓ Widely recognized in the literature as key drivers of soil moisture memory and dynamics across timescales (e.g., topography, soil properties, meteorological conditions, vegetation indices; see Rahmati et al., 2024; Seneviratne et al., 2010);

✓ Frequently used in prior multi-scale SMM and land surface studies;

✓ Available from authoritative datasets with consistent 1-km spatial resolution and daily temporal coverage, ensuring high reliability across the three study watersheds.

To make this rationale clearer in the manuscript, we have revised the sentence (lines 159–163) as follows: "These covariates were selected based on an extensive literature review of soil moisture drivers (Rahmati et al., 2024; Seneviratne et al., 2010), prioritizing variables that are (1) widely recognized as key controls on SMM (topography, soil properties, meteorology, vegetation), (2) frequently used in prior multi-scale SMM studies, and (3) available at consistent spatial and temporal resolution with high reliability across the study region."

Rahmati, M., Amelung, W., Brogi, C., Dari, J., Flammini, A., Bogena, H., ... & Vereecken, H. (2024). Soil moisture memory: State-of-the-art and the way forward. Reviews of Geophysics, 62(2), e2023RG000828. https://doi.org/10.1029/2023RG000828

Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., ... & Teuling, A. J. (2010). Investigating soil moisture–climate interactions in a changing climate: A review. *Earth-Science Reviews*, *99*(3-4), 125-161. https://doi.org/10.1016/j.earscirev.2010.02.004

- L164-L167: Where does this constraint come from? What is the basis for it? If such constraint needs to be imposed, how much confidence you expect in the second regime "Low-Frequency Background State (T > 7 years)"?

Reply: We agree that the original sentence referred to the $N \geq 3T$ constraint as "standard" without providing the source, theoretical basis, or a clear discussion of the resulting confidence levels in each regime.

The requirement that the time series length (N) be significantly longer than the timescale of interest (T) for robust low-frequency estimation is a well-established guideline in spectral analysis and time series theory. It arises from the need to avoid spectral leakage, aliasing, edge effects, and unreliable variance estimates at long periods (typically $N \geq 3T$ is used as a conservative practical threshold; see Percival & Walden, 1993). In hydrological and soil moisture time series studies, this rule has been commonly applied to ensure reliable quantification of persistence and memory timescales (Ghannam et al., 2016).

With our record length $N = 20$ years, this sets $T \leq \sim 7$ years as the "Reliable Memory Window" (at least three full cycles), allowing high-confidence estimation of dynamic memory characteristics. For the "Low-Frequency Background State" ($T > 7$ years), confidence is inherently lower due to insufficient cycles in the record; estimates in this regime are more susceptible to edge effects and likely reflect a combination of intrinsic soil/landscape buffering and secular climatic trends rather than verifiable oscillatory memory. We therefore interpret these long-term signals qualitatively as indicators of slow-varying boundary conditions.

We've revised in the manuscript (Lines 196-204): "Given the 20-year record length (2003–2022), statistical limitations exist for resolving low-frequency dynamics. Following established guidelines requiring $N \geq 3T$ for robust spectral estimation (Ghannam et al., 2016; Percival & Walden, 1993), we distinguish between two regimes:

3. **Reliable Spectral Window ($T \leq 7$ years):** Timescales up to $T = N/3 \approx 6.7$ years (rounded to 7 years) can be reliably estimated, as our record contains at least three complete cycles.

Low-Frequency Background State ($T > 7$ years): Signals at these timescales reflect slow-varying boundary conditions (e.g., multi-year drought periods) rather than event-scale memory. These estimates have lower statistical confidence and are interpreted as qualitative indicators of long-term storage trends."

Ghannam, K., Nakai, T., Paschalis, A., Oishi, C. A., Kotani, A., Igarashi, Y., ... & Katul, G. G. (2016). Persistence and memory timescales in root-zone soil moisture dynamics. *Water Resources Research*, *52*(2), 1427-1445. https://cstr.cn/10.1002/2015wr017983

Percival, D. B., & Walden, A. T. (1993). Spectral analysis for physical applications. cambridge university press.

- L173-188: The introduction of the methods used seem to assume the reader is well versed in this method. The authors need to better explain and introduce this method in the main body of the manuscript to a general HESS audience with any more specific setup steps shown in the appendix.

Reply: To address this, we have revised the Methods section (lines 189–257) to include:

(1) Brief introductory explanations of each method, including their basic principle, what they measure physically, and why they are suitable for soil moisture time series.

(2) Explicit rationale for choosing each method and how they complement each other.

(3) Clear definitions of key terms (SMM, significant memory, persistence horizon) directly in the main text, with physical interpretations and examples to make the concepts more accessible.

(4) Retention of detailed mathematics and significance testing in Appendix A, as before.

- L190-193: Similarly to my previous comment – the methods here also need to be properly introduced.

Reply: We have revised the content line by line and added the necessary detailed explanations.

First, we have included the following description of the Boruta algorithm (lines 236–244 in the revised manuscript): "Boruta is an all-relevant feature selection method that creates randomized "shadow" copies of original predictors (permuted versions with no real relationship to the target) and iteratively compares the importance of each real predictor against the best-performing shadow variable. Predictors that consistently outperform shadow variables are retained as relevant, while others are rejected (Kursa & Rudnicki, 2010). Boruta was selected because it (1) captures non-linear relationships inherent in soil-vegetation-atmosphere systems, (2) handles collinearity among predictors without requiring prior variable removal, and (3) provides statistically validated importance rankings by comparing against a null model."

Second, we have clarified the purpose of the spatial-attribution framework by adding the following sentence (lines 246–248): "… framework to link these dimensions, quantifying how driver importance shifts across different temporal aggregation windows (monthly to decadal)."

- L206-207: Explain your rationale for "Space-for-Time" framework in more detail – as it is unclear.

Reply: In our study, the proposed framework leverages the natural hydroclimatic and geomorphic contrasts among the three selected watersheds—the semi-arid, erosion-dominated Dali River Basin; the humid, landslide-prone Anning River Basin; and the high-frequency debris-flow Jiangjia Ravine—as a proxy for temporal variability in soil moisture memory (SMM) and its drivers. This "space-for-time" substitution approach uses spatial heterogeneity across the three watersheds to approximate long-term temporal dynamics that would otherwise require extended observations at a single site. This method is well-established and has been widely applied in ecological and hydrological studies (Pickett, 1989). The relevant explanation has been clarified in the revised manuscript (lines 259–261).

Pickett, S. T. (1989). Space-for-time substitution as an alternative to long-term studies. In Long-term studies in ecology: approaches and alternatives (pp. 110-135). New York, NY: Springer New York. https://doi.org/10.1007/978-1-4615-7358-6_5

- L207-210: The authors seemed to have identified some limitations in the Boruta-RF method used but failed to explain the implications of those limitations for their study.

Reply: In the original manuscript, we did not sufficiently explain how this limitation affects the interpretation and confidence of our results. The primary implication is that the ranked drivers and scale-dependent patterns should be interpreted as strong statistical associations rather than confirmed causal mechanisms. For instance, the dominance of soil properties at long timescales and atmospheric variables at short timescales may reflect genuine controls, but could also stem from proxy relationships (e.g., vegetation acting as a proxy for soil moisture availability) or mutual feedbacks (e.g., vegetation enhancing soil structure while itself depending on persistent moisture). To against over-interpretation, we have added "Limitations" of this method in the manuscript (see Lines 258–271 in the revised version).

- L211-214: This needs to be "translated" to a general/wider audience.

Reply: In response to the comment, we have clarified the term "the catena concept" in the revised manuscript by defining it as the systematic variation of soil properties along a hillslope and citing Anderson (2005). Furthermore, to enhance accessibility for a broader readership, we have added a more straightforward explanation: "Additionally, physical collinearity inherent in mountain landscapes—the catena effect, where steep upper slopes have thin, sandy, fast-draining soils while gentle lower slopes accumulate thick, clay-rich, water-retaining soils (Anderson, 2005)—means that high importance scores for both Slope and Clay content (Section 3.3) likely reflect coupled landscape structure rather than independent effects." This revised text can be found in Lines 267–271.

Anderson, S. (2005). Soils: Genesis and geomorphology. Cambridge University Press.

- L229: The meaning of "dynamic memory estimation ($N \geq 3T$)" is unclear. Please define what N and T represent and explain why this threshold is required. Similarly, the reported 1–7 year range is ambiguous—what portion of the dataset does this correspond to, and why is this window appropriate? This should be explained in the Methods to better frame the Results.

Reply: We have revised both the Methods section (2.3) to provide a clear definition and justification.

In Section 2.3 (Methods), we now state (Lines 196–204):

"Given the 20-year record length (2003–2022), statistical limitations exist for resolving low-frequency dynamics. Following established guidelines requiring $N \geq 3T$ for robust spectral estimation (Ghannam et al., 2016; Percival & Walden, 1993), we distinguish between two regimes:

Reliable Spectral Window ($T \leq 7$ years): Timescales up to $T = N/3 \approx 6.7$ years (rounded to 7 years) can be reliably estimated, as our record contains at least three complete cycles.

Low-Frequency Background State (T > 7 years): Signals at these timescales reflect slow-varying boundary conditions (e.g., multi-year drought periods) rather than event-scale memory. These estimates have lower statistical confidence and are interpreted as qualitative indicators of long-term storage trends."

Ghil, M., Allen, M. R., Dettinger, M. D., Ide, K., Kondrashov, D., Mann, M. E., ... & Yiou, P. (2002). Advanced spectral methods for climatic time series. *Reviews of geophysics*, *40*(1), 3-1. https://doi.org/10.1029/2000RG000092

Priestley, M. B. (1988). The spectral analysis of time series.

- L234–235: The statement that "β is presented as the mean estimate ± 95% confidence interval derived from log–log regression" is unclear. Mean of what exactly (across realizations, pixels, years)? The use of log–log regression has not been introduced previously and should be described in the methods.

Reply: We have revised the text to explicitly address both points. Detail revision include:

(1) Clarification of the "mean estimate":

We now explicitly state that the reported β values are "the basin-wide mean ± 95% confidence interval, where the mean is calculated across all pixels within each basin and the confidence interval reflects the spatial variability of pixel-wise β estimates." (Lines 304-306)

(2) Introduction of the log-log regression method:

We have added a dedicated methodological note in the results section (following the key pattern summary). This note:

- Explains that this log-log linear regression is the standard procedure for estimating the exponent in the power-law relationship $S(f) \sim f^{\beta}$. (Lines 283-284)
- Briefly mentions that linearity in this log-log space indicates scale-invariant (power-law) behavior. (Lines 305-306)

These revisions ensure that both the statistical summary and the core estimation method are clearly defined for the reader, providing full transparency.

- L233-238: This paragraph lacks information on how to interpret the figure, making it hard to follow the results.

Reply: We have substantially expanded this introductory paragraph to provide clear guidance on interpreting Figure 3. The revised text now includes:

(1) Figure organization: We explicitly state that columns represent basins (DRB, ARB, JJR) and rows represent timescale bands (intra-annual, interannual, and low-frequency background);

(2) Axis definitions: We clarify that both axes are logarithmically scaled, with frequency (cycles per year) on the x-axis and spectral power on the y-axis;

(3) Visual interpretation of β: We explain that β corresponds to the negative slope of the fitted line in log-log space, and provide intuitive guidance: a steeper slope (higher β) indicates stronger memory where variance concentrates at low frequencies, while a flatter slope (lower β) indicates weaker memory dominated by high-frequency fluctuations;

(4) Uncertainty visualization: We note that shaded bands represent 95 % confidence intervals around the regression lines.

See the revised text in Line 287–308.

- L239-244: How does the reader know this?

Reply: This conclusion is based on comparing the spectral exponents (β) between integrated seasonal periods and individual months, with higher β values indicating stronger memory. To make this evidential basis explicit for readers, we have revised the relevant text accordingly. The explanation can be found in Lines 284–287 and 291-293 of the revised manuscript.

- L240: The distinction between "individual rainy season months" and the "integrated rainy season period" is not clearly defined. Please clarify how these differ analytically and why this distinction is meaningful for interpreting SMM.

Reply: We have revised the text to clarify the definitions and explain the analytical and scientific significance of these terms.

(1) Definitions:

- ✓ "Individual rainy season months" are analyzed using soil moisture time series from single calendar months (e.g., May, June, July within the rainy season).
- ✓ "Integrated rainy season period" is analyzed using the continuous time series spanning all months of the locally defined rainy season (e.g., May through October).

(2) Analytical Rationale and Significance:

The analytical method applied to both is identical; the only distinction lies in the temporal scale of the input data. Comparing these scales is essential because soil moisture memory (SMM) can vary substantially across different time windows. Understanding this variation contributes significantly to hydrology, hazard assessment, and agricultural water management, as it reveals how the persistence of soil moisture is modulated by the duration of wet/dry periods.

The corresponding explanations and illustrations have been added in Appendix D (lines 811–821), and the main text has illustrated this point.

- L257–272: Differences in β values between months and seasons are reported but not interpreted physically. For example, stating that integrated rainy-season memory is slightly stronger than May memory does not explain what this means for soil moisture dynamics or hazard relevance (e.g., longer persistence of anomalies, delayed recovery).

Reply: In response to the reviewer's comments, we have added detailed physical interpretations of the β values (see Lines 311–312, 314–315, 322–323, 325–327, 330–332, and 334-336). To further address this concern, we have included a summary and discussion of the practical implications of the analysis in this section (see Lines 337–340).

- L276: Phase-randomization surrogate testing is mentioned without explanation. A brief description of what it tests and why it is applied here would greatly improve clarity, particularly in relation to DFA-2.

Reply: We have added a concise description of the method and its specific relevance to DFA-2 (see Lines 343–345 in the revised manuscript): "the fluctuation exponent α identifies specific timescales where memory is strongest ($\alpha \geq 0.9$). All reported α values in this range were statistically significant ($p < 0.01$) based on phase-randomization surrogate testing (see Appendix A)"

- L279–280: The phrase "no persistence" requires physical interpretation. Does this imply highly variable, noise-dominated time series, rapid decay of anomalies, or something else?

Reply: In the revised manuscript, we have replaced the phrase "almost no persistence" with "negligible persistence" (Line 352). Furthermore, to clarify the underlying physical process, we have added a brief explanation of the hydrological implications when the DFA-2 exponent (α) falls below the 0.9 significance threshold. Please see Lines 352-353.

"October exhibited negligible persistence, with α falling below the 0.9 threshold (Fig. 4a-1). This indicates rapid decay of moisture anomalies due to intense evaporative drying following monsoon withdrawal."

- L345–351: The physical meaning of a "critical threshold" remains unclear. Does it indicate a shift in dominant controls on SMM, a change in persistence timescale, or something else?

Reply: In response to the reviewer's question regarding the physical meaning of the "critical threshold," we have revised the manuscript to provide a clear interpretation. See Lines 424-430: "Scale-transition threshold: Quantitative analysis revealed a distinct structural break at the 5-year scale (Table 2). At the 1-year scale, TWI showed the strongest association (28.7 %), consistent with topography-driven lateral water redistribution. At the 5-year scale, TWI importance declined (to 13.5 %), with the hierarchy shifting to Soil Texture and Slope (~19 %). This threshold reflects a fundamental shift from event-scale hydraulic connectivity ("Fast-Response Regime") to long-term pedological storage control ("Background-Storage Regime") (Blöschl & Sivapalan, 1995; Western et al., 2004)."

The revised text (Lines 412-419) physically explains this as a shift from a topography-dominated, fast-response regime (relevant at sub-5-year scales) to a soil property-dominated, background-storage regime (relevant at longer scales).

To frame this insight within broader hydrological concepts, we have added a final synthesis (Lines 424-430). Herein, we propose that the 5-year mark delineates a change from "fast hydrological memory" (shaped by recent precipitation routing) to "slow pedological memory" (determined by profile-scale water retention), an interpretation aligned with principles of scale issues (Blöschl & Sivapalan, 1995) and the role of soil properties in moisture dynamics (Western et al., 2004).

Blöschl, G., & Sivapalan, M. (1995). Scale issues in hydrological modelling: a review. *Hydrological processes*, *9*(3-4), 251-290. https://doi.org/10.1002/hyp.3360090305

Western, A. W., Zhou, S. L., Grayson, R. B., McMahon, T. A., Blöschl, G., & Wilson, D. J. (2004). Spatial correlation of soil moisture in small catchments and its relationship to dominant spatial hydrological processes. *Journal of Hydrology*, *286*(1-4), 113-134. https://doi.org/10.1016/j.jhydrol.2003.09.014

To Reviewer#2

This study investigates the multi-scale characteristics of soil moisture memory (SMM) and its environmental drivers across three mountain watersheds in southwestern China (Dali River Basin, Anning River Basin, and Jiangjia Ravine). The authors employ Power Spectrum Analysis (PSA) and second-order Detrended Fluctuation Analysis (DFA-2) to quantify SMM persistence, and utilize the Boruta-Random Forest algorithm to identify dominant drivers across different temporal scales. The study reveals that SMM persistence generally weakens with increasing scale, with a structural transition in driver dominance from dynamic atmospheric variables to static soil/topographic properties occurring at approximately the 5-year scale.

This is a high-quality research paper with novel topic selection, robust methodology, and clear structure. The authors have successfully integrated established time series analysis methods in an innovative manner for SMM research in mountain watersheds, identifying a scale-transition threshold (~5 years) with significant theoretical and practical implications. Especially, it has significant indicative value for the study of the initiation and movement of landslides and debris flows. The transparent and honest discussion of methodological limitations is commendable, and the open availability of data and code aligns with open science principles. Overall, this study makes an important scientific contribution to understanding soil moisture dynamics in complex terrain and requires moderate revisions to meet the publication standards of HESS.

Major Comments

1. Recommend further clarifying the boundary between statistical associations and mechanistic interpretations. The authors have appropriately noted in Section 2.4 and Section 4.1 that the Boruta-RF method identifies statistical associations rather than causal relationships—this scientific rigor is commendable. To further enhance clarity, minor adjustments to certain expressions are suggested. In the title or footnote of Table 2, consider replacing "Dominant Environmental Associations" with "Dominant Statistical Associations" to maintain consistency with the main text. In the final sentence of the Abstract, consider changing "offering a conceptual framework" to "proposing a conceptual framework" to more accurately reflect the current research stage

Reply: We have made revision following your advise, see line 27 and 432.

2. Recommend enhancing visual distinction for long-timescale analyses. The authors have correctly identified the statistical limitations imposed by the 20-year record length for analyses at >7-year scales (Section 2.3). This distinction between the "Reliable Memory Window" and "Low-Frequency Background State" is well-articulated in the text. To ensure readers are reminded of this important caveat when viewing the figures, a brief clarifying note in the figure caption would be helpful. Consider adding a sentence to the Figure 3 caption noting that spectral estimates beyond the ~7-year scale should be interpreted as low-frequency background trends rather than statistically robust memory features, with reference to Section 2.3 for details.

Reply: We have revised the manuscript in accordance with your suggestion, and the updated figure caption can be found in Lines 307-308. "…estimates beyond the ~7-year scale should be interpreted as low-frequency background trends rather than statistically robust memory features"

3. Recommend brief discussion of basin area differences in main text. The three study watersheds differ considerably in area (JJR: 48.6 km² vs. ARB: 11,150 km²). The authors conducted a scale-matching sensitivity analysis in Appendix H, demonstrating that inter-basin differences reflect genuine hydrological characteristics rather than statistical artifacts. A brief mention of this important finding in the main text is recommended.

Reply: A scale-matching sensitivity analysis (Appendix H) was added to address this concern. Specifically, we have included the following context in Lines 157-160: "Despite the large difference in basin area (ARB: 11,150 km² vs. JJR: 48.6 km²), a scale-matching sensitivity analysis (Appendix H) confirms that the observed differences in soil moisture memory between basins reflect intrinsic hydrological and landscape characteristics rather than artifacts of spatial averaging or domain size."

4. Recommend clarifying the definition of rainy and dry seasons. The paper refers to "rainy season" and "dry season" analysis results in multiple places, but the seasonal classification criteria for the three watersheds are not consistently stated in the main text. Although Table B1 provides information on the precipitation seasonal distribution for each watershed, explicit clarification upon first mention in the main text would facilitate reader comprehension. In Section 2.1 or Section 3.1, explicitly state the specific monthly definitions of rainy and dry seasons for each watershed (e.g., DRB: rainy season June–September, dry season October–May). This addition requires only 1–2 sentences and will enhance the completeness of the methodological description

Reply: In line with your suggestion, we have explicitly defined the rainy and dry seasons in Section 3.1 where they are first discussed. The added sentence reads: "For seasonal classification, the rainy and dry seasons are defined based on local precipitation regimes: the Dali River Basin (DRB) rainy season spans July to September (dry season: October–June), while both the Anning River Basin (ARB) and Jiangjia Ravine (JJR) share a rainy season from May to October (dry season: November–April)."

5. Recommend expanding the discussion of future research directions. The authors propose a conceptual framework for applying SMM to hazard early warning in Section 4.2 and Conclusions—this direction is valuable. Further discussion of potential validation and application pathways for this framework is recommended. Consider adding 1–2 sentences in the Conclusions discussing how the SMM metrics from this study could be integrated with operational hazard monitoring systems in the future. For example, mention the possibility of incorporating SMM persistence thresholds into existing rainfall-landslide early warning models. Add 1-2 sentences in Section 3.4 or Section 4.3 summarizing the key conclusion from Appendix H. For example: "A scale-matching sensitivity analysis (Appendix H) confirmed that the stronger memory observed in the ARB reflects genuine hydrological contrasts rather than basin size artifacts." This addition will enhance the completeness of the main text and

facilitate reader comprehension

Reply: We have added the following sentence in the concluding paragraph (Lines 709–714): “Looking forward, the SMM metrics and persistence horizons quantified in this study, such as the 18–31 day rainy-season memory, could be integrated into operational hazard early warning systems. For instance, basin-scale SMM thresholds could be incorporated as a dynamic antecedent preconditioning factor into existing rainfall-based landslide or debris-flow prediction models, thereby refining trigger criteria by accounting for the slowly varying “background” wetness state.”

We have also added the following summary statement at the end of the first point in Section 4.3 (Lines 654–656): “In summary, the scale-matching sensitivity analysis (Appendix H) confirmed that the stronger memory observed in the ARB reflects genuine hydrological contrasts rather than basin size artifacts.” At the end of first point in Section 4.3 (Lines 654-656): “In summary, the scale-matching sensitivity analysis (Appendix H) confirmed that the stronger memory observed in the ARB reflects genuine hydrological contrasts rather than basin size artifacts.”

Minor Comments

Figure 5: Consider adding a sentence in the caption explaining why panels (a) and (b) use different metrics, helping readers understand that numerical values should not be directly compared.

Reply: **We thank the reviewer for this suggestion. The caption for Figure 5 has been revised to include the note:** “Note: Panels (a) and (b) use different metrics and are not directly comparable.” (Lines 417-418).

Table 3: Consider briefly noting the area differences among the three watersheds in the table title or footnote to provide quick background information for readers

Reply: We have added the area of each watershed to the caption of Table 3 (Line 470): “…for the three watersheds (DRB: ~3,906 km^2; ARB: ~11,150 km^2; JJR: ~48.6 km^2)”

Consider explicitly defining the relationship between "persistence horizon" and "memory length" at first occurrence to facilitate understanding for non-specialist readers

Reply: We have added a definition clarifying the relationship between “persistence horizon” and “memory length” (Lines 225–227): **“**In this study, persistence horizon is used as the operational measure of memory length, specifically denoting the temporal range where significant long-range memory ($\alpha \geq 0.9$) is maintained.”

When "catena concept" first appears in Section 2.4, consider adding a brief explanation (e.g., "the co-evolution of soil and topography along hillslopes")

Reply: We have explained the "catena concept" when it first occurs in the text (Lines 273–275): “… often described by the catena concept of co-evolved soil-topography relationships (i.e., steep upper slopes have thin, sandy, fast-draining soils while gentle lower slopes accumulate thick, clay-rich, water-retaining soils”

The second paragraph of Section 4.1 contains long sentences; consider splitting into 2-3 shorter sentences to improve readability.

Reply: We have thoroughly revised the second paragraph of Section 4.1. In addition, we identified other long sentences in the remaining paragraphs of this section and have split them into shorter ones to improve readability.

Specifically, the sentence “Partial correlation analysis (Appendix G) indicates that soil texture maintains a significant association with decadal-scale SMM (partial r = 0.43, p < 0.01) after controlling for topography, though approximately 30 % of the raw correlation may stem from landscape collinearity.” was revised to “Partial correlation analysis (Appendix G) shows that soil texture maintains a significant association with decadal-scale SMM after controlling for topography (partial r = 0.43, p < 0.01). However, approximately 30 % of the raw correlation may stem from landscape collinearity. This suggests pedological effects are not entirely attributable to topographic confounding.” (Lines 536-539).

Similarly, the sentence “In reality, this association likely reflects a bidirectional eco-hydrological feedback: while vegetation improves soil structure (driver), sustained soil moisture is also a prerequisite for maintaining high biomass (response).” was revised to “In reality, this association likely reflects bidirectional eco-hydrological feedback. Vegetation improves soil structure (as a driver), while sustained soil moisture is required to maintain high biomass (as a response).” (Lines 557-559).

Consider standardizing the format of journal names in references (some use italics, others do not)
Check completeness and format consistency of DOI links

Reply: We have carefully checked the format of references in the manuscript, and the updated version satisfies the journal’s requirements.

The partial correlation analysis results in Appendix G are valuable for supporting the main conclusions; consider adding a sentence in Section 4.1 referencing this appendix

Reply: In Section 4.1, under the subsection “Acknowledging Physical Collinearity”, we have incorporated a direct reference to Appendix G and summarized its key finding (Lines 536-539): “Partial correlation analysis (Appendix G) indicates that soil texture maintains a significant association with decadal-scale SMM after controlling for topography...”. This reference directly links the methodological validation in the appendix to the main conclusions regarding landscape collinearity.

The data availability statement is complete and standardized, conforming to HESS open science policies—this is commendable

Reply: thanks so much.