Response to Reviewer 2's Comments for the Manuscript # NHESS-2024-152 "Derivation of Moisture-driven Landslide Thresholds for Northeastern Regions of the Indian Himalayas" by D. Monga and P. Ganguli

We would like to thank the reviewers, editorial board member and associate editor for the valuable comments and for providing us an opportunity to improve our manuscript. We appreciate the positive comments of the reviewer 2. In subsequent sections, we will address each of the comments raised by the reviewer. Our **responses** are embedded within the comments (in **BLACK**) in BLUE. The **new texts** added in the manuscript in line (L) are in BROWN**.**

Comment 1: ***Unclear Terminology*** *One of the main results of the study is the definition of the MDL thresholds. However, Figures 5 and 6 depict empirical thresholds based on cumulative rainfall (E, mm) vs. duration (D, days), without any explicit reference to the AMC as computed using Crozier's formulation. This creates ambiguity, as throughout the manuscript, AMC and antecedent rainfall are treated as interchangeable terms. It is important to clearly distinguish between these concepts and make the methodology clearer. Indeed, by conflating AMC and antecedent rainfall, the methodology becomes challenging to follow, and the manuscript risks misrepresenting the nature of the thresholds (rainfall-driven vs. moisture-driven).*

Response: We agree. First, we clearly explain the role of AMC in influencing the MDL in the revised manuscript. We then stress that due to difficulties in estimating AMC in data sparse areas of NEH, following the literature (Bennett et al., 2018; Heggen, 2001; Nepal et al., 2021; Zheng et al., 2014), we use a surrogate measure of antecedent moisture based on precipitation depth prior to the rainfall-conditioning landslides. It should be noted that Antecedent precipitation, often quantified using the Antecedent Precipitation Index (API; Pathiraja et al., 2012; see Fig. S1 in revised manuscript, Fig. S2 in earlier version of the manuscript), is often used as a proxy for antecedent soil moisture instead of using the modelled soil moisture in the literature (Bertola et al., 2021; Blöschl et al., 2019), as it is one of the dominant controls of soil moisture at depths, which impacts on rainfall to runoff generation, leading to MDLs (Pathiraja et al., 2012a). Further, in the subsequent revision, we have used the term "Antecedent Precipitation Index (API)" throughout to avoid ambiguity. For example, on page 13, sub-section heading 4.2 was revised to "4.2 Correlation of API versus Triggering Rain Events"

We have incorporated the following sentences on Page 3, L82 in the revised manuscript:

"Antecedent precipitation is often defined using the antecedent precipitation index (API, see Eq. 1; Figure S1), a surrogate metric of AMC, as it is one of the dominant controls of soil moisture at depths, which impact on rainfall-to-runoff generation, leading to MDLs (Pathiraja et al., 2012b). Since there is no physical parameter that exclusively captures the AMC, soil moisture is often linked with the AMC due to the significant correlation between triggering MDL and soil moisture (Abraham et al., 2021). Since credible soil moisture data over long periods are rarely available, especially in the data-sparse region of the Himalayas (Gupta et al., 2024), surrogate climate variables, primarily based on precipitation data, are commonly used to represent the AMC (Ali and Roy, 2010). Following the literature (Bennett et al., 2018; Heggen, 2001; Nepal et al., 2021; Woldemeskel and Sharma, 2016; Zheng et al., 2014), here, we use the API, which is the weighted precipitation depth in the *n*-daily time steps prior to the landslide triggering rainfall (Capecchi and Focardi, 1988; See Figure S1), as a surrogate for the AMC."

In response to Comment 5 from Reviewer 1, we have adopted a *5%* seasonal rainfall threshold for the monsoon and summer seasons, while applying a fixed *1 mm/day* threshold for fall and winter since these seasons comprise dry periods with very few rain events compared to other two seasons in the NEH. The updated thresholds with explicitly differentiating triggering (red) versus antecedent (blue) rainfall events are shown in Figures 5 to 6 for better interpretability in the revised manuscript (Figures 1 and 2 in the response letter).

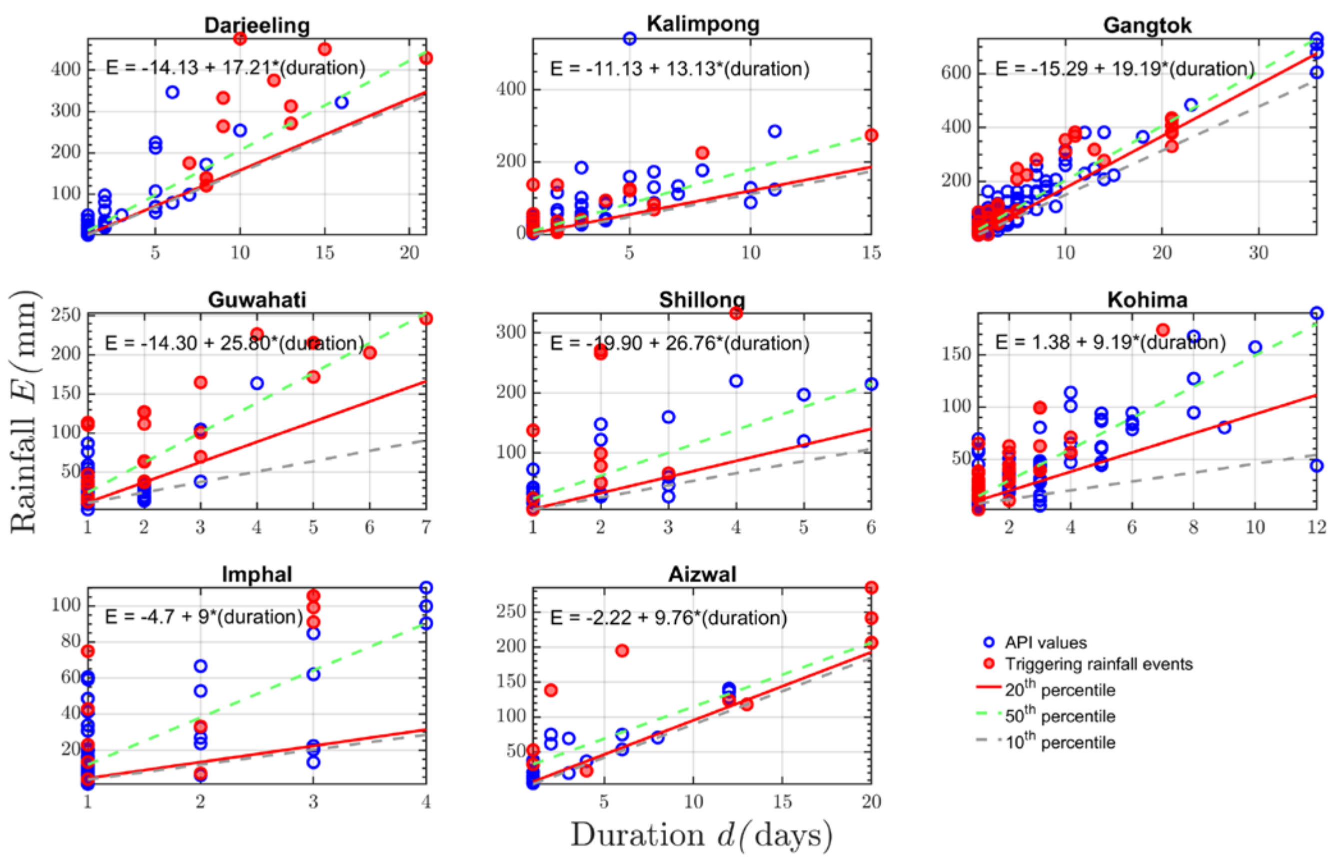

Figure 1: Empirical rain thresholds showing the relation between cumulative rainfall Event (*E*) vs. event Duration (*D*). The API and triggering rainfall events are marked in blue (unfilled) and red (filled) circles. The ED thresholds are shown for the 10th (in grey), 20th (in red), and 50th (in green) percentile levels, showing the least, low and median thresholds

for triggering MDLs following the literature (Abraham et al., 2021). The figure highlights regional variations in rainfall threshold triggers, with Guwahati and Shillong, showing relatively higher thresholds, indicating lower susceptibility for MDLs.

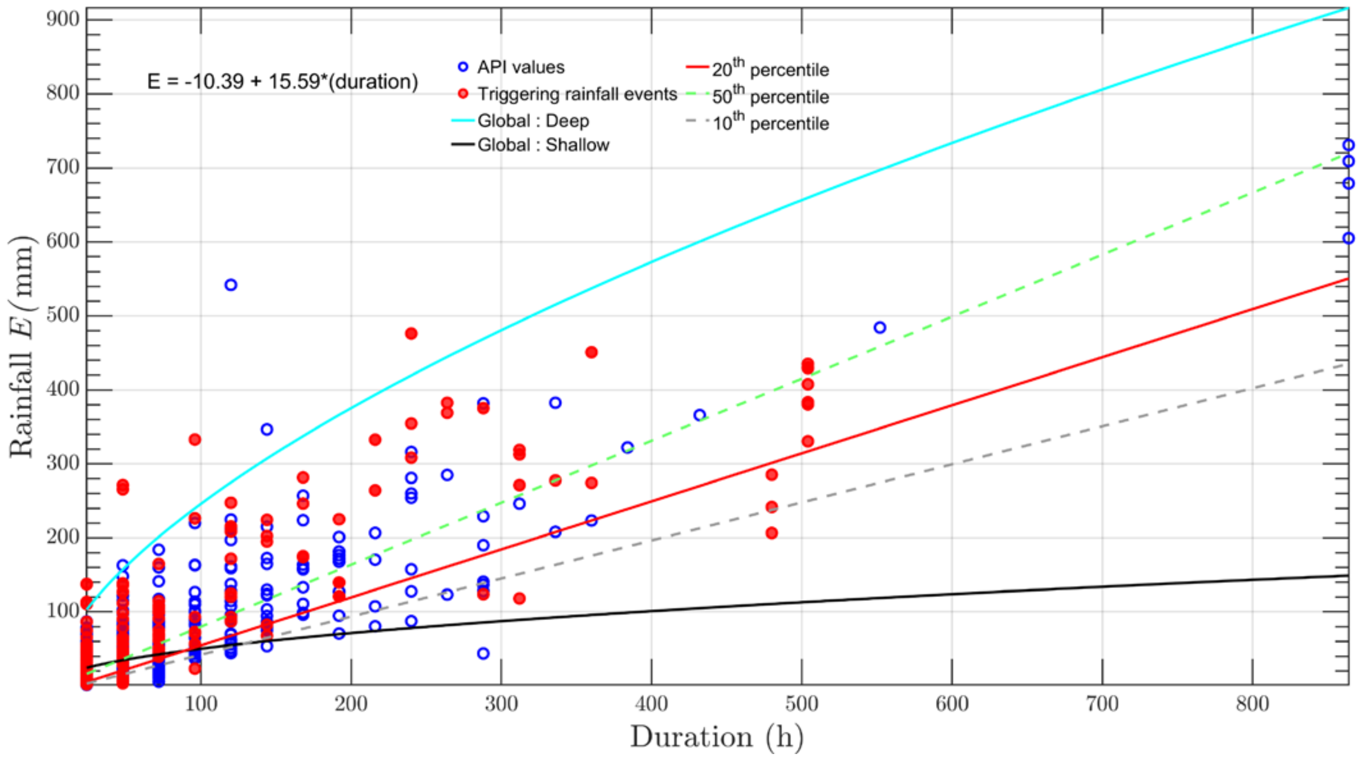

Figure 2: Regional Empirical ED thresholds for the NERI. The 10th, 20th, and 50th percentiles are shown in grey, red and green lines respectively. While the API values are shown in blue unfilled circles, triggering rainfall events are shown using red filled circles. The derived regional rain thresholds for MDLs at NERI are compared with global thresholds for deep (in cyan) and shallow (in black) landslides, indicating the regional susceptibility for shallow to deep landslides.

Comment 2(a): *The choice of the decay constant K = 0.9 is a crucial aspect of the methodology, as it directly influences the calculation of AMC and, consequently, the derived thresholds. However, the justification for this value relies solely on a study conducted in a different region, without further validation or region-specific analysis.*

Response: We agree. To validate applicability of the decay constant $K = 0.9$ for the Northeastern Himalayas (NEH), we assessed the correlation between soil moistures (both surface level and root-zone depth) and API, determined using K=0.9 at various time lags. For soil moisture, we use the modelled soil moisture archived in GLEAM version 4.2 (Global Land Evaporation Amsterdam Model (GLEAM; https://www.gleam.eu/) repository estimates soil moisture from a global land-surface model. For analyzing correlation between API and soil-moisture at lags, we employed the non-parametric Spearman's rank correlation metric, which assesses the monotonic association between variables and offers a robust measure of association for outliers. The correlation coefficients were computed for different decay constants (K = *0.8, 0.84, and 0.9*) across multiple time lags, revealing that K = *0.9* consistently shows the strongest correlation for both surface-level (*0-10cm*) and root-zone (*0-100cm*) soil moisture, particularly for sites Kalimpong, Imphal, and Gangtok, with a signature of robust correlation for remaining sites as well. The statistically significant correlation values reinforce the robustness of K = *0.9* in capturing antecedent moisture conditions relevant to landslide trigger in the NEH region.

Therefore, we have added the following sentences in **L227** in the revised manuscript:

"To validate further, we evaluated the association between API and soil moisture records retrieved from the soil moisture archive modelled using a land-surface model, Global Land Evaporation Amsterdam Model (GLEAM; https://www.gleam.eu/), at different temporal lags across the sites in the NEH. We use the non-parametric correlation metric, Spearman's rank correlation, which measures the monotonic association between two variables (see Figure S6) and is robust to outliers.

We introduced a new sub-section in the results section under the following heading to identify time lags showing the significant association between the API and soil moisture (on page 13, L341):

4.2 Association between Antecedent Precipitation Index and Soil Moisture at Different Lags

The site-specific Spearman's correlation coefficients between API and GLEAM-derived soil moisture for different decay constants *(*K = 0.8, 0.84, and 0.9*)* show that K = 0.9 exhibits stronger correlations across multiple lag times, particularly in Kalimpong, Imphal, and Gangtok, reinforcing its suitability for API estimation. This could be because the humid climate of NEH, which experiences heavy rainfall, especially during the monsoon season, K = 0.9, heavily weighs the antecedent precipitation immediately before the triggering rainfall event (Bennett et al., 2018). The statistically significant ($p < 0.10$) correlation value at the root- zone depth (at 100 cm) ranges from 0.27 to 0.72, whereas for the surface level (up to 10cm), the correlation value ranges from 0.36 to 0.89. These further confirms K = 0.9 as an optimal decay constant for the API estimation, effectively capturing antecedent moisture conditions at various lags."

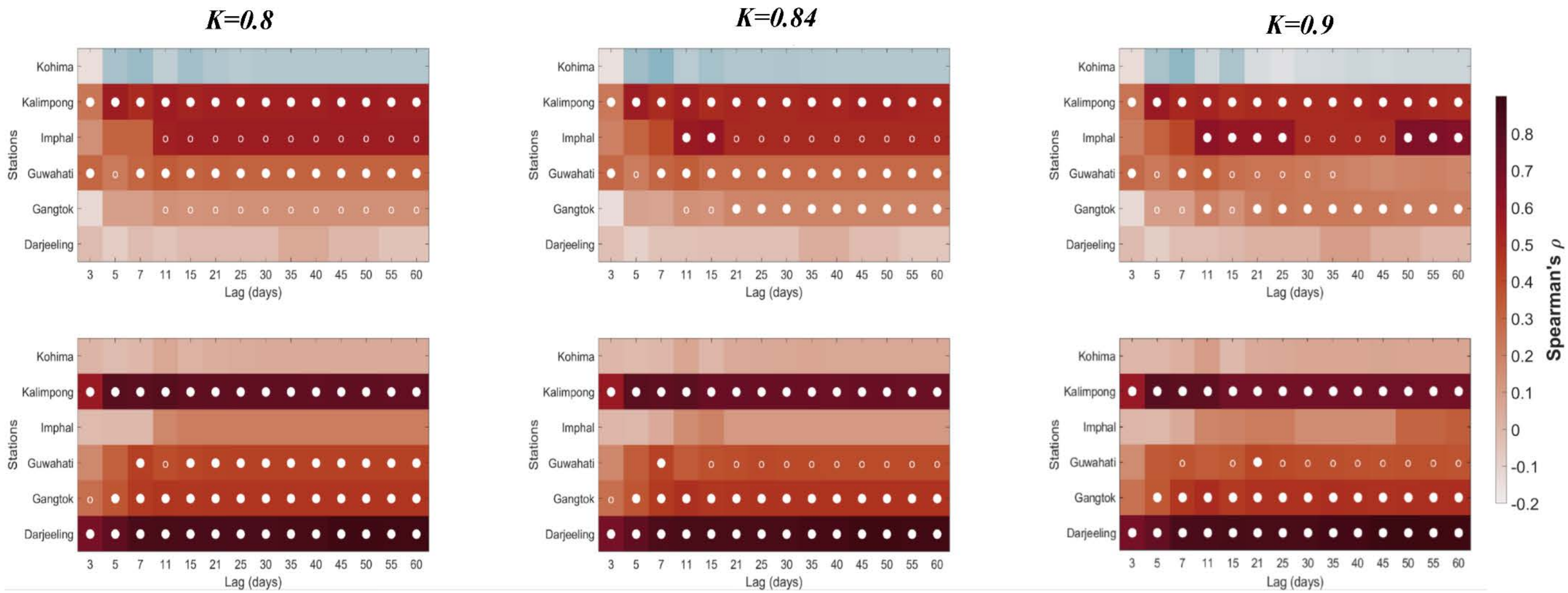

Figure S6: Spearman's rank correlation between the API and modelled Soil Moisture. The heat map shows the Spearman's rank correlation coefficient (ρ) calculated between API and GLEAM-derived soil moisture across the sites in NEH at multiple time lags, ranging from 3–60 days. The top panel represents correlation between API and root-zone moisture (at 100 cm), while the bottom panel shows the correlation between API and surface-level (up to 10 cm) soil moisture. The columns show the decay constants, ranging from K = 0.8, 0.84, and 0.9. The lags with statistically significant correlations are marked with filled ($p < 0.05$) and unfilled ($p < 0.10$) circles.

Comment 2(b): *Considering the sensitivity of landslide thresholds to AMC modeling, a more in-depth analysis is necessary to validate the chosen decay constant for the Northeastern Himalayas. For instance, a sensitivity analysis could be carried out to strengthen the reliability of the findings.*

Response: We agree. We further expanded our explanation in result section in the sub-section 4.2 in revised manuscript with a new Supplementary Figure (Fig. S7):

"Further, to investigate the variations of mean API at various lags for different decay constants (*K* = 0.8, 0.84, and 0.9) at NEH, we compare mean API values across multiple time lags ranging from 3–60 days. As shown in Figure S7, API values show substantially large variability at shorter time lags (3–15 days), with noticeable differences apparent around 30 days before reaching to a relatively stable values beyond 30 days' time lag. Notably, *K = 0.9* consistently yields higher API values across all lag durations, confirming its effectiveness in representing antecedent precipitation conditions relevant to landslide trigger. The large variability in API values at lower time lags can be due to multiple factors (Guzzetti et al., 2007), such as (1) diverse lithological, morphological, soil conditions and vegetation; (2) meteorological condition leading to slope instability.

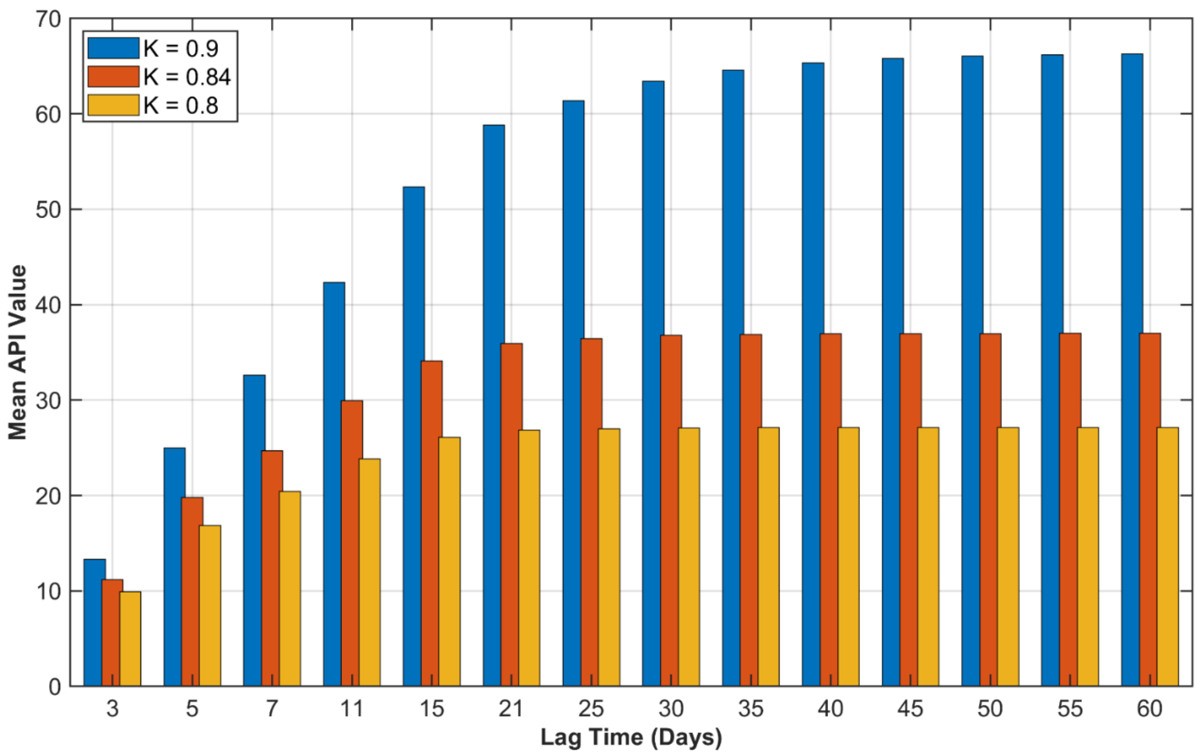

Figure S7: Variations in API values across different decay constants over multiple time lags.

Comment 3(a): A discussion comparing the results with important existing studies is essential. Highlighting such comparisons would allow readers to place these findings in a broader context and assess their significance.

Response: We agree. Accordingly, we have included a comparative assessments of existing literature with our findings on Page 17, L445 under the sub-section **5.2 Comparative Assessment of derived MDL thresholds with Existing Rain Thresholds in the Literature**, in the revised manuscript:

5.2 Comparative Assessment of derived MDL thresholds with Existing Rain Thresholds in the Literature

"While direct comparison with existing studies with ours may not be possible due to methodological differences (daily versus hourly rainfall records) and approaches (*i.e.*, approach to handle rainy days), different study area domain and analysis periods, we compare our findings with an existing study (Teja et al., 2019; hereafter TE19), focusing on estimated rainfall thresholds over Kalimpong. While assessment of TE19 is limited to 288 hrs/12 days, we find for lower time lags, for example, ≤ 5-day the order of differences (ours estimate − TE19) ranging from $d \in [-22$ to $-6]$ mm, with gradually declining differences with the increase in lag time, however, with a positive difference of around 46 mm at 12-day time lag. The discrepancies in ED thresholds between the two studies are likely due to (1) temporal resolution and period of record availability of rainfall time series: while TE9 used hourly rainfall record from 2010-2016, we used daily rainfall data from 2006-2019. (2) Methodological differences: TE19 considered have used CTRL-T tool (Melillo et al., 2018), which adapts a bootstrapping statistical technique coupled with frequentist method (Brunetti et al., 2010) to derive rain thresholds to trigger landslides. One of the limitations of the frequentist approach is that they assume residual (pointwise difference in linear regression fits of accumulated rainfall vs event duration − observed scatter between accumulated rainfall and event duration) to be normally distributed, which may not be the case for extreme precipitation events, which often shows a highly skewed distribution. In contrast, we implemented a non-crossing quantile regression, which provides a robust, distribution-free threshold estimation. In addition (3), our study applies seasonal rainfall thresholds to define rainy days during summer and monsoon, against the fixed threshold to define rainy days in TE19."

Comment 3(b): While the study identifies environmental controls influencing rainfall thresholds, further discussion is needed to assess their impact in a broader context. A more detailed comparison with studies that have examined similar environmental controls would enhance the manuscript.

Response: We agree. Accordingly, we have included the following sentences in the revised manuscript:

In the Introduction (Page 4, Line 116): “Understanding the contributions of potential environmental controls — such as LULC, slope, elevation, TWI, CND, and geological composition—in shaping the spatial variability of rainfall thresholds is critical for improving landslide risk assessments and enhancing the predictive capabilities of LEWS. For instance, variations in LULC and slope have been shown to significantly influence rainfall-driven slope instability (Rabby et al., 2022; Segoni et al., 2018).”

In Section 3.5 (Page 12, Lines 303), we elaborate on how these environmental factors influence the spatial variability of landslide-triggering rainfall thresholds:

“Environmental controls, such as LULC, slope, elevation, TWI, CND, and geological composition, influence the spatial heterogeneity of landslide-triggering rainfall thresholds. Morphological characteristics, TWI and CND play a crucial role in modulating rainfall thresholds by controlling water accumulation and subsurface flow (Gupta et al., 2024).”

Additionally, in Section 4.4 (Page 16, Lines 413), we expand on the regional variability in rainfall thresholds, emphasizing the role of geological and hydrological controls:

“The spatial distribution of rainfall thresholds across the study area exhibits significant regional heterogeneity, governed by lithology, topography, and hydrological factors. Notably, Shillong and Guwahati, characterized by dense forests and igneous/metamorphic formations, require higher rainfall to trigger landslides due to stronger soil cohesion and reduced infiltration rates (Dey et al., 2024; Sarma et al., 2015). In contrast, Aizwal and Imphal, underlain by highly porous sedimentary formations, show lower rainfall thresholds due to rapid infiltration and moisture saturation-induced instability (Verma, 2024). These geological differences, combined with slope steepness and proximity to river networks, further influence regional threshold variability.

In Section 4.4 (Page 16, Line 431):

MI analysis highlights vegetation (*MI* = 0.52) as one of the dominant controls, which is followed by CND (*MI* = 0.48) and slope (*MI* = 0.42), confirming their roles in runoff and soil moisture retention in threshold modulation. Our findings agree with earlier assessments over the Himalayas that also suggest among topographic factors, elevation, slope and drainage density significantly modulate MDL likelihood (Prasad et al., 2021; Kumari et al., 2024; Sana et al., 2025). Areas with steep slopes and specific lithological characteristics, such as highly fractured sedimentary formations, tend to have lower rainfall thresholds due to rapid infiltration and reduced shear strength, amplifying rainfall-induced slope instability (Lee et al., 2024; Rabby et al., 2022; Segoni et al., 2018).”

On Page 16, Line 431: High TWI values indicate areas with prolonged soil saturation, with low rainfall thresholds required for landslide trigger, whereas proximity to drainage networks (CND) can accelerate runoff and saturation, leading to higher threshold variability (Bogaard and Greco, 2018; Borga et al., 2002; Gupta et al., 2024; Sørensen et al., 2006)

Building on these findings, Section 5.2 (Page 21, Line 466) discusses the implications for LEWS and landslide risk assessment:

"The observed spatial variability in rainfall thresholds underscores the need for integrating site-specific environmental controls in LEWS. Regions dominated by sedimentary formations and steep slopes exhibit lower thresholds due to rapid infiltration and moisture accumulation, increasing rainfall-induced slope instability. In contrast, regions with igneous/metamorphic formation require higher cumulative rainfall for landslide trigger due to stronger cohesion and reduced permeability. These insights emphasize the necessity of refining rainfall thresholds by incorporating hydrometeorological, morphological and lithological variability for improved landslide prediction and risk management (Dey et al., 2024; Rabby et al., 2022; Sana et al., 2025; Segoni et al., 2018; Verma, 2024)."

References

Abraham, M. T., Satyam, N., Rosi, A., Pradhan, B., and Segoni, S.: Usage of antecedent soil moisture for improving the performance of rainfall thresholds for landslide early warning, CATENA, 200, 105147, https://doi.org/10.1016/j.catena.2021.105147, 2021.

Ali, G. A. and Roy, A. G.: A case study on the use of appropriate surrogates for antecedent moisture conditions (AMCs), Hydrol. Earth Syst. Sci., 14, 1843–1861, https://doi.org/10.5194/hess-14-1843-2010, 2010.

Bennett, B., Leonard, M., Deng, Y., and Westra, S.: An empirical investigation into the effect of antecedent precipitation on flood volume, J. Hydrol., 567, 435–445, https://doi.org/10.1016/j.jhydrol.2018.10.025, 2018.

Bertola, M., Viglione, A., Vorogushyn, S., Lun, D., Merz, B., and Blöschl, G.: Do small and large floods have the same drivers of change? A regional attribution analysis in Europe, Hydrol. Earth Syst. Sci., 25, 1347–1364, https://doi.org/10.5194/hess-25-1347-2021, 2021.

Blöschl, G., Hall, J., Viglione, A., Perdigão, R. A. P., Parajka, J., Merz, B., Lun, D., Arheimer, B., Aronica, G. T., Bilibashi, A., Boháč, M., Bonacci, O., Borga, M., Čanjevac, I., Castellarin, A., Chirico, G. B., Claps, P., Frolova, N., Ganora, D., Gorbachova, L., Gül, A., Hannaford, J., Harrigan, S., Kireeva, M., Kiss, A., Kjeldsen, T. R., Kohnová, S., Koskela, J. J., Ledvinka, O., Macdonald, N., Mavrova-Guirguinova, M., Mediero, L., Merz, R., Molnar, P., Montanari, A., Murphy, C., Osuch, M., Ovcharuk, V., Radevski, I., Salinas, J. L., Sauquet, E., Šraj, M., Szolgay, J., Volpi, E., Wilson, D., Zaimi, K., and Živković, N.: Changing climate both increases and decreases European river floods, Nature, 573, 108–111, https://doi.org/10.1038/s41586-019-1495-6, 2019.

Bogaard, T. and Greco, R.: Invited perspectives: Hydrological perspectives on precipitation intensity-duration thresholds for landslide initiation: proposing hydro-meteorological thresholds, Nat. Hazards Earth Syst. Sci., 18, 31–39, https://doi.org/10.5194/nhess-18-31-2018, 2018.

Borga, M., Dalla Fontana, G., and Cazorzi, F.: Analysis of topographic and climatic control on rainfall-triggered shallow landsliding using a quasi-dynamic wetness index, J. Hydrol., 268, 56–71, https://doi.org/10.1016/S0022-1694(02)00118-X, 2002.

Brunetti, M. T., Peruccacci, S., Rossi, M., Luciani, S., Valigi, D., and Guzzetti, F.: Rainfall thresholds for the possible occurrence of landslides in Italy, Nat. Hazards Earth Syst. Sci., 10, 447–458, https://doi.org/10.5194/nhess-10-447-2010, 2010.

Capecchi, F. and Focardi, P.: Rainfall and landslides: research into a critical precipitation coefficient in an area of Italy., Balkema, 1131–1136, 1988.

Dey, A., Sarma, C. P., and Krishna, A. M.: Rainfall-Induced Landslide Hazard Analysis of Noonmati-Sunsali Hill Series in Guwahati City, Assam: A Physically-Based Model Approach, in: Proceedings of the Indian Geotechnical Conference 2022 Volume 6, vol.

484, edited by: Jose, B. T., Sahoo, D. K., Oommen, T., Muthukkumaran, K., Chandrakaran, S., and Santhosh Kumar, T. G., Springer Nature Singapore, Singapore, 13–25, https://doi.org/10.1007/978-981-97-3393-4_2, 2024.

GLEAM, Global Land Evaporation Amsterdam Model: https://www.gleam.eu/, last access: November 2024.

Gupta, V., Syed, B., Pathania, A., Raaj, S., Nanda, A., Awasthi, S., and Shukla, D. P.: Hydrometeorological analysis of July-2023 floods in Himachal Pradesh, India, Nat. Hazards, 120, 7549–7574, https://doi.org/10.1007/s11069-024-06520-5, 2024.

Guzzetti, F., Peruccacci, S., Rossi, M., and Stark, C. P.: Rainfall thresholds for the initiation of landslides in central and southern Europe, Meteorol. Atmospheric Phys., 98, 239–267, https://doi.org/10.1007/s00703-007-0262-7, 2007.

Heggen, R. J.: Normalized Antecedent Precipitation Index, J. Hydrol. Eng., 6, 377–381, https://doi.org/10.1061/(ASCE)1084-0699(2001)6:5(377), 2001.

Kumari, K., Ganguli, P., Purushothaman, N. K., and Das, B. S.: Spatial footprints of moisture-driven landslides in Western Himalayas from 2007 to 2022, Nat Hazards, https://doi.org/10.1007/s11069-024-07086-y, 2024.

Lee, J.-S., Pradhan, A. M. S., Song, C.-H., and Kim, Y.-T.: Lithological terrain-based rainfall thresholds for possible initiation of shallow landslides in South Korea, Stoch. Environ. Res. Risk Assess., 38, 175–191, https://doi.org/10.1007/s00477-023-02568-0, 2024.

Melillo, M., Brunetti, M. T., Peruccacci, S., Gariano, S. L., Roccati, A., and Guzzetti, F.: A tool for the automatic calculation of rainfall thresholds for landslide occurrence, Environ. Model. Softw., 105, 230–243, https://doi.org/10.1016/j.envsoft.2018.03.024, 2018.

Nepal, S., Pradhananga, S., Shrestha, N. K., Kralisch, S., Shrestha, J. P., and Fink, M.: Space–time variability in soil moisture droughts in the Himalayan region, Hydrol. Earth Syst. Sci., 25, 1761–1783, https://doi.org/10.5194/hess-25-1761-2021, 2021.

Pathiraja, S., Westra, S., and Sharma, A.: Why continuous simulation? The role of antecedent moisture in design flood estimation, Water Resour. Res., 48, https://doi.org/10.1029/2011WR010997, 2012a.

Pathiraja, S., Westra, S., and Sharma, A.: Why continuous simulation? The role of antecedent moisture in design flood estimation, Water Resour. Res., 48, https://doi.org/10.1029/2011WR010997, 2012b.

Prasad, P., Loveson, V. J., Das, S., and Chandra, P.: Artificial intelligence approaches for spatial prediction of landslides in mountainous regions of western India, Environ. Earth Sci., 80, 720, https://doi.org/10.1007/s12665-021-10033-w, 2021.

Rabby, Y. W., Li, Y., Abedin, J., and Sabrina, S.: Impact of Land Use/Land Cover Change on Landslide Susceptibility in Rangamati Municipality of Rangamati District, Bangladesh, ISPRS Int. J. Geo-Inf., 11, 89, https://doi.org/10.3390/ijgi11020089, 2022.

Sana, E., Kritika, Kumar, A., Robson, E., Prasanna, R., Kala, U., and Toll, D. G.: Investigation of landslides triggered by unprecedented rainfall events during 2023 monsoon in Himachal Pradesh, India, Landslides, https://doi.org/10.1007/s10346-025-02471-5, 2025.

Sarma, C. P., Krishna, A. M., and Dey, A.: Landslide hazard assessment of Guwahati region using physically based models, 2015.

Segoni, S., Piciullo, L., and Gariano, S. L.: A review of the recent literature on rainfall thresholds for landslide occurrence, Landslides, 15, 1483–1501, https://doi.org/10.1007/s10346-018-0966-4, 2018.

Sørensen, R., Zinko, U., and Seibert, J.: On the calculation of the topographic wetness index: evaluation of different methods based on field observations, Hydrol. Earth Syst. Sci., 10, 101–112, https://doi.org/10.5194/hess-10-101-2006, 2006.

Teja, T. S., Dikshit, A., and Satyam, N.: Determination of Rainfall Thresholds for Landslide Prediction Using an Algorithm-Based Approach: Case Study in the Darjeeling Himalayas, India, Geosciences, 9, 302, https://doi.org/10.3390/geosciences9070302, 2019.

Verma, R.: Kinematic Analyses of Elephant Rock Section, NH-44A, Aizawl, Mizoram, India, https://papers.ssrn.com/abstract=4759125, 14 March 2024.

Woldemeskel, F. and Sharma, A.: Should flood regimes change in a warming climate? The role of antecedent moisture conditions, Geophys. Res. Lett., 43, 7556–7563, https://doi.org/10.1002/2016GL069448, 2016.

Zheng, M., Liao, Y., and He, J.: Sediment Delivery Ratio of Single Flood Events and the Influencing Factors in a Headwater Basin of the Chinese Loess Plateau, PLoS ONE, 9, e112594, https://doi.org/10.1371/journal.pone.0112594, 2014.