Response to Reviewer 1 for the Manuscript "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 reviewer 1. 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: *The work proposes an approach for defining rainfall thresholds for "moisture-driven landslide" (MDL) forecasting in the Himalayas. The authors calculated the soil moisture content empirically by multiplying the antecedent cumulative rainfall by a decay constant k=0.9. This approach is not physically rigorous, and while it may be acceptable for defining empirical thresholds, the limitations were not sufficiently clarified.*

Response: We agree. Due to difficulties in quantifying the volume of antecedent moisture in triggering landslides, especially in data-sparse regions of the Northeastern Himalayas (NEH), where reliable and continuous soil moisture data are scarce due to complex topography and limited observational networks (Gupta et al., 2024), following earlier studies (Bennett et al., 2018a; 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. Antecedent precipitation is often used as a proxy for antecedent soil moisture 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., 2012). As suggested, while we highlight the potential limitations of our approach in the revised manuscript, we have added the reasons for using the antecedent precipitation quantified using the Antecedent Precipitation Index (API; Pathiraja et al., 2012) instead of using the modelled soil moisture. Furthermore, we present the non-parametric correlation analysis between the API and modelled soil moistures (both root-zone at 100 m depth and surface-level up to 10 cm depths) using Spearman's rank correlation at different decay constants (K = 0.8, 0.84 and 0.9) to show the agreement between the two variables. While our analysis shows a statistically significant strong correlation between the API and modelled soil moisture at different lags for all decay constants, K = 0.9 shows a substantial correlation, especially in Kalimpong, Imphal, and Gangtok, confirming its suitability for the API estimation.

Therefore, we have added the following sentences in L226 in the revised manuscript:

"Although the empirical approach for determining the API requires the calibration of additional parameters and assumptions, e.g., lag and an exponential decay constant, we use this precipitation-based index instead of modelled soil moisture primarily due to (1) to rely strongly on observational data as in the literature (Bertola et al., 2021; Blöschl et al., 2019). (2) Difficulties in quantifying the volume of antecedent moisture in triggering landslides, especially in data-sparse regions of the Northeastern Himalayas (NEH), where reliable and continuous soil moisture data are scarce due to complex topography and limited observational networks (Gupta et al., 2024). (3) Estimating soil moisture will require considering soil and vegetation properties within a complex physical modelling approach. Since the sources of large-scale climate variability that drive the soil moisture variability at synoptic and short-duration temporal scales remain the same as those that drive the rainfall variability, the use of antecedent rainfall quantified by the API is likely to capture such persistence reasonably (Pathiraja et al., 2012). 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 at the surface level (up to 10 cm), 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."

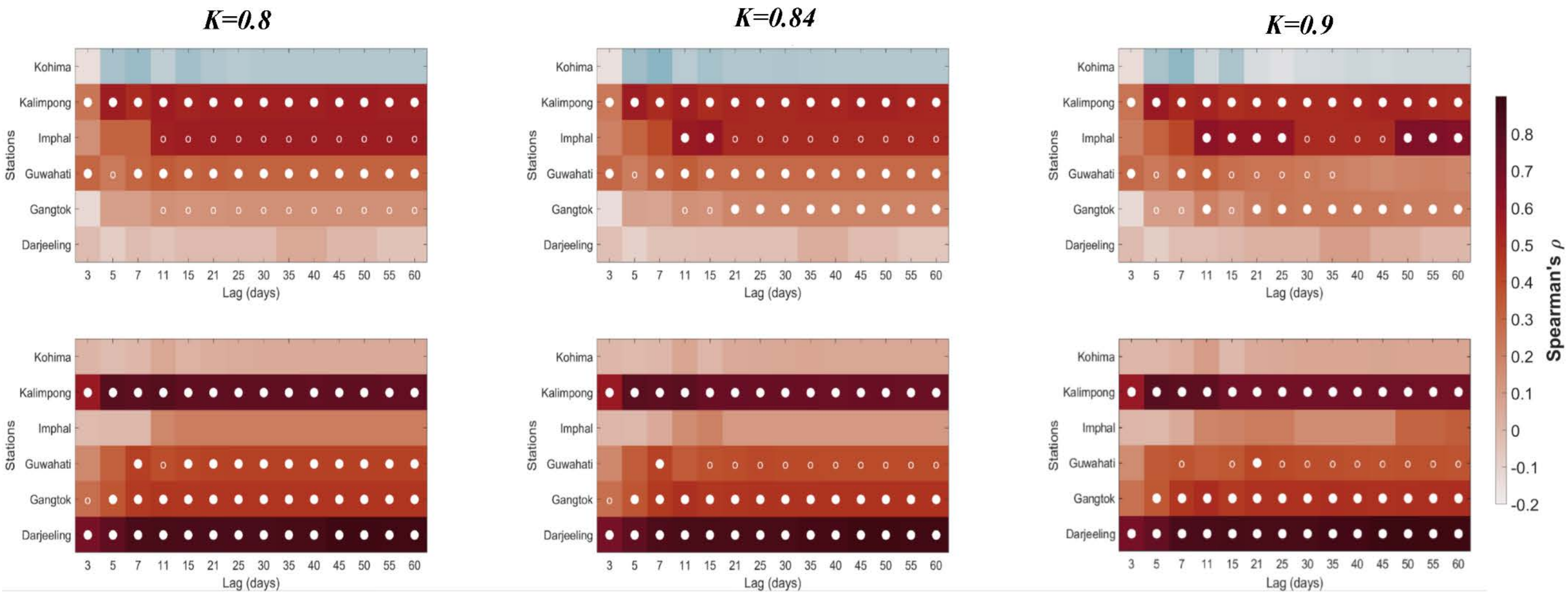

Figure S6: Spearman's rank correlation between the API and modelled Soil Moisture. The heat map shows the Spearman's rank correlation coefficient (ρ) calculated between API and GLEAM-derived soil moisture across the sites in NEH at multiple time lags, ranging from 3–60 days. The top panel represents 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(a): *The definition of MDL provided in the introduction is too limited. suggest adding details on the types of landslides considered (whether deep or shallow) and the type of movement (whether slow or fast landslides, debris flows, or slides)*

Response: Agreed and incorporated the following additional details (in Page 2, L 35) in the revised manuscript.

"MDL refers to landslides triggered by increased water infiltration or increased volumes of water due to prolonged or intense rainfall from monsoons and cyclonic depressions or snowmelt due to rain-on-snow events, which elevates the sub-surface moisture and reduces the shear strength of slope materials (Whiteley et al., 2019). These landslides include shallow and deep-seated types with a depth of less than 5 meters to extend beyond 5 meters (Cruden and Varnes, 1996; Dahal and Hasegawa, 2008). The movements range from rapid events like debris flows and earth flows, with speeds reaching up to 56 kilometers/hour, to slow-moving, such as slides and slumps, with speeds ranging from a few orders of millimeters to meters/year (Girty, 2009)."

Comment 2(b): *Additionally, two landslide catalogs were used, but only MDLs were collected from them. Since the definition of MDL is unclear to me, do these catalogs specifically contain this type of landslide, or were other similar types grouped together?*

Response: We point to the reviewer that for the Indian subcontinent, both NASA Cooperative Open Online Landslide Repository (COOLR) and the Geological Survey of India's Bhukosh portal provide comprehensive landslide data encompassing various types and triggers. For our study, we specifically filtered events associated with moisture-related triggers, identified by descriptors such as "rain," "heavy rainfall," "monsoon," "cyclone," and similar terms in the inventories in the analysis period (2006–2019). Approximately 61% of these records lacked information on landslide size or volume and were thus excluded from size distribution analysis. Among the classified events, about 19% were categorized as small, 79% as medium, and 2% as large landslides. Additionally, around 65% of entries lacked information on movement types, limiting our ability to comprehend landslide kinematics. Among classified entries, 79% showed rapid movement (≥1.5 m/day), 16% with moderate movement (≥1.5 m/month), and a minor fraction showed extremely rapid movements (≥3 m/s) (Cruden and Varnes, 1996; Murillo-García et al., 2017; Varnes, 1958).

Accordingly, we have included the following information on Pages 6, L156, in the revised manuscript

"We specifically filtered events associated with moisture-related triggers, identified by descriptors such as "rain," "heavy rainfall," "monsoon," "cyclone," and similar terms in the inventories in the analysis period (2006–2019). Approximately 61% of these records lacked information on landslide size or volume and were thus excluded from size distribution analysis. Among the classified events, about 19% MDLs were categorized as small, 79% as medium, and 2% as large slides. Additionally, around 65% of entries lacked information on movement types, limiting our ability to comprehend landslide kinematics. Among classified entries, 79% MDLs showed rapid movement (≥1.5 m/day), 16% with moderate movement (≥1.5 m/month), and < 5% showed extremely rapid movements (≥3 m/s) (Cruden and Varnes, 1996; Murillo-García et al., 2017; Varnes, 1958)."

Comment 3: *Finally, for a clearer understanding of the study's methodology, I suggest briefly mentioning in the introduction how you intend to extrapolate soil moisture from the antecedent rainfall. This missing information might lead to think that the antecedent rainfalls were directly used without deriving the soil moisture.*

Response: We agree and 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), 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., 2012). 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., 2022). 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., 2018b; 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."

Comment 4: *It is frequently stated in the manuscript that ED thresholds were purposely used to account for antecedent rainfall, something that ID thresholds do not allow. I'm not sure about that, as ED thresholds, like ID thresholds, are event-based, and they depend on how the duration is defined. For D=15 days, an E is calculated over the 15 days, and the same applies to I, with the difference that I is distributed over the entire duration (mm/day in this case). I suggest to provide a different justification for using ED threshold instead of ID.*

Response: Here we point to the reviewer that in the NEH, where landslides are predominantly moisture-driven, an accurate representation of rainfall accumulation is crucial for reliable threshold estimation. Unlike ID thresholds, which distribute rainfall intensity over a duration, ED thresholds account for the cumulative effect of rainfall over the duration of rain event, which is more effective in areas with prolonged rainfall events, rather than short bursts of high-intensity precipitation (Ebrahim et al., 2024; Guzzetti et al., 2024; Sarkar et al., 2023). Antecedent precipitation influences soil moisture and groundwater levels and results in favourable conditions for slope failure (Crozier, 1999). Further, prolonged rainfall, even with modest intensity is sufficient to saturate the soil and significantly increases the likelihood of landslides, whereas a short-duration rain event might not have the same impact.

Therefore, we have added the following sentences in the revised manuscript (on page 3, L83):

"Unlike ID thresholds, which distribute rainfall intensity over a duration, ED thresholds account for the cumulative effect of rainfall throughout the event duration, which is more effective in areas with prolonged rainfall events rather than short bursts of high-intensity precipitation (Ebrahim et al., 2024; Guzzetti et al., 2024; Sarkar et al., 2023). Prolonged rainfall, even with modest intensity, is sufficient to saturate the soil and significantly increases the likelihood of landslides, whereas a short-duration rain event might not have the same impact. Further, ED thresholds offer the following distinct advantages over ID thresholds: (1) ED thresholds typically capture total rainfall load, integrating both short-duration, high-intensity storms that trigger immediate slope failures, whereas prolonged, low-intensity rainfall that progressively weakens slopes by influencing soil moisture and groundwater levels (Crozier, 1999; Leonarduzzi and Molnar, 2020; Sarkar et al., 2023; Segoni et al., 2018; Wei et al., 2024). (2) ED thresholds better capture antecedent moisture effects, a key driver of slope failure in the NEH, where cumulative rainfall saturation precedes most landslides (Sarkar et al., 2023). (3) From an operational perspective, ED thresholds offer a cumulative effect of rainfall throughout the rain event, which is more physically consistent and relevant for predicting landslides considering antecedent rainfall conditions and soil saturation levels (Leonarduzzi and Molnar, 2020b)."

Comment 5: *I found paragraph 3.2, which relates to the methodology for defining rainy days, quite confusing. It was decided to define a day as rainy when at least 10% of the seasonal rainfall occurs. I think this method has high limitations, because, as highlighted in the text, 10% of the monsoon season's rainfall can be quite high (it was calculated to be about 13mm). In my opinion, this threshold is too high, as daily rainfall of 10mm would not be considered as a rainy event, which means that 30mm over three days would not be considered. In my opinion, they could still have an impact in the context of MDLs and could help refine the rainfall thresholds. I suggest providing further justification for this method and highlighting its limitations.*

Response: We agree with the reviewer that 10% seasonal rainfall threshold may be too high and could exclude light-to-moderate rainfall events relevant to MDLs. To improve rainfall event representation, we refined our methodology by adopting a 5% seasonal rainfall threshold for the monsoon and summer seasons while applying a fixed 1 mm/day threshold for fall and winter. This revision ensures the inclusion of moderate precipitation events (<10 mm/day) without overestimating the impact of low-intensity rainfall.

The revised thresholds for each season are as follows: winter (1 mm), summer (1.65 mm), monsoon (6.5 mm), and fall (1 mm). The 6.5 mm/day (monsoon) and 1.65 mm/day (summer) thresholds represents 5% of the seasonal median rainfall during the analysis period (2006–2019) and effectively captures a threshold above very light (IMD-defined threshold of 0.1–2.4 mm/day) to light rainfall (IMD-defined threshold of 2.5–7.5 mm/day) events (Barde et al., 2020) that can enhance surface soil moisture, contributing to landslide triggers. Additionally, the 1 mm/day threshold for fall and winter aligns with established climatological norms, defining a rainy day and ensuring the inclusion of light precipitation in hydrological assessments (Sun et al., 2006). Furthermore, Ratan and Venugopal (2013) highlighted the importance of a seasonal threshold-based approach for defining rainy days in humid tropical regions. The IMD typically classifies a rainy day with a constant threshold of 2.5 mm/day, but this measure fails to consider regional and seasonal differences (Segoni et al., 2018). To address this issue, following Ratan and Venugopal (2013), we select a seasonally varying rain threshold to define a rainy day, such that the threshold to be a percentage of the local seasonal climatological mean rainfall.

Accordingly, we have added the following sentences on Page 8, L211 in the revised manuscript:

"Following Ratan and Venugopal (2013), we select a seasonally varying rain threshold to define a rainy day, such that the threshold to be a percentage of the local seasonal climatological median rainfall. Following this approach, rain thresholds for each season are as follows: winter (1 mm), summer (1.65 mm), monsoon (6.45 mm), and fall (1 mm). The seasonal rain thresholds during the summer and monsoon seasons represent 5% of the seasonal median rainfall during the analysis period (2006–2019), which effectively captures a threshold above very light (IMD-defined threshold of 0.1–2.4 mm/day) to light rainfall (IMD-defined threshold of 2.5–7.5 mm/day) events (Barde et al., 2020), contributing MDLs. On the other hand, a low rain threshold of 1 mm/day during fall and winter agrees well with climatological norms to define a rainy day, ensuring the inclusion of even very light precipitation during relatively dry seasons of the year (Sun et al., 2006). The motivation behind imposing a higher threshold is to break longer rain events into short spell rains such that each wet spell contributes to the total number of rainy days in a season, discarding very low rain magnitudes/trace rains, frequent in humid climate regions during relatively wet times of the year."

To further illustrate the impact of the seasonal rainfall threshold of 5%, we present a comparative assessment (Figure S2) showing wet spell counts determined from daily rainfall time series with no rain threshold of 0 mm/day and a 5% rain threshold considering local climatological (2006–2019) median during the wettest phase (*i.e.*, monsoon) of the year for a representative site, Gangtok. Imposing a high threshold of 5%, previously long-duration wet spells, such as the 27-day (from 01/07/2010 to 27/07/2010) and 62-day (from 29/07/2010 to 28/09/2010) events observed during the monsoon of 2010 at Gangtok (Figure S2), based on a 0 mm/day threshold, are fragmented into shorter-duration rainfall events. For instance, the continuous 62-day wet spell is split into multiple shorter events, including 12-day and 15-day spells. This ensures that the 5% threshold effectively captures rainfall events relevant to landslide initiation while filtering out low-magnitude/trace rainfall.

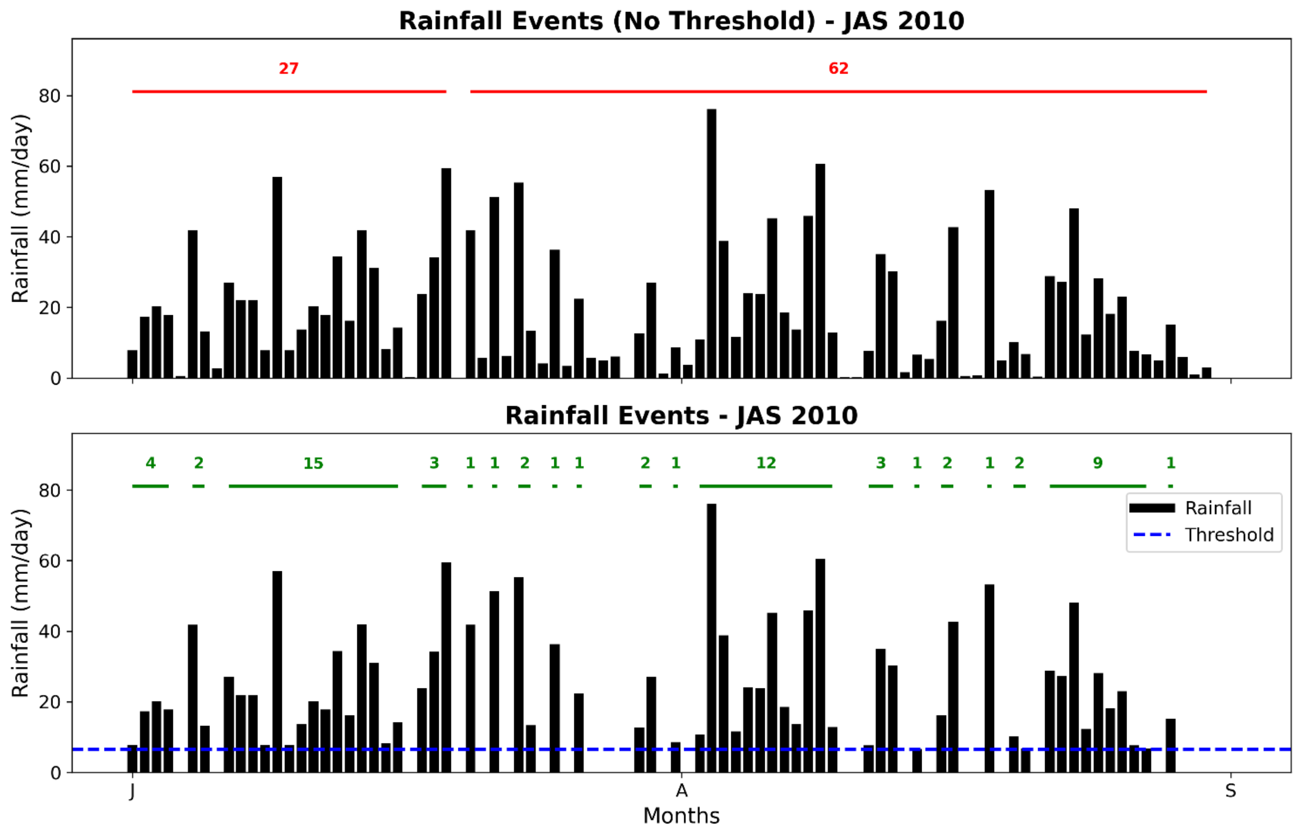

Figure S2: Illustration of wet spell determination using daily rainfall data at Gangtok (27.33°N, 88.62°E) during June–September monsoon season for the year 2010 using a threshold of (a) 0 mm/day **(b)** 5% of the local climatological (2006–2019) mean**.** The numbers on the top corner of each subplot show the length of each wet spell. In subplot (a) with 0 mm/day, the first rain event, which is 27 days (from 01/07/2010 to 27/07/2010) long, is broken down into 3 smaller rain events in subplot (b) with 5% seasonal threshold, in which spell lengths ranging from 2 to 15 days with a median spell length of 4 days. Subsequently, for the second rain event, which is 62 days (from 29/07/2010 to 28/09/2010) long with 0 mm/day threshold, is broken down into 16 smaller rain events with 5% seasonal rain thresholds with spell lengths ranging from 1 to 12 days with a median spell length of 1.5 days.

Comment 6: *The methodology for defining the lag-time, particularly in identifying the trade-off between correlation and scattering bias of triggering vs antecedent rainfall, is not clear to me and also needs further clarification.*

Response: We thank the reviewer for the feedback. We clarified this issue as below in Section 3.3, Page 9, (Lines 245-255) of the revised manuscript:

"To understand whether the triggering rainfall or antecedent rainfall governs MDL, following the literature (Kim et al., 1992) we assess the relationship between daily triggering rainfall at failure and *n*-day cumulative rainfall before the failure using a graphical diagnostic plot. The plot defines scattering bias, quantifying the dispersion of normalized ($X_n = \left(\frac{X - \min(X)}{\max(X) - \min(X)} \right)$, where X is the original series, min(X) and max(X) is the minimum and the maximum value of the time series) API values relative to the normalized triggering rainfall on a 1:1 reference line. If the scatter of points is close to the 1:1 reference line, it indicates that triggering daily rainfall at failure is of the same magnitude as the cumulative rainfall at the failure. The clustering of points above the 1:1 reference line indicates MDLs are primarily triggered by the intensity of daily rainfall at the failure due to heavy rainfall from cyclonic disturbances. In contrast, the clustering of points below the 1:1 reference line suggests that these landslides are influenced by cumulative rainfall governed by antecedent rainfall, indicating a stronger dependence on API for landslide initiation (Dahal and Hasegawa, 2008). We select the optimal lag-time when there is an agreement between the relationship of daily rainfall at failure versus the antecedent rainfall, and the maximum Kendall's τ correlation strength, ensuring that rainfall thresholds credibly capture the role of antecedent moisture accumulation in triggering landslides."

Comment 7: *In the discussion and conclusion sections, you frequently refer to landslide susceptibility ("This study provides crucial insights into the landslide susceptibility of the NEH region"). However, this term is out of context, as susceptibility refers to spatial predisposition, while rainfall thresholds are used for temporal forecasting (in the case of this study, spatialized within 30 km around each rain gauge). I would suggest you revise this part.*

Response: Thank you for pointing this out. We agree and revised this term as below:

On page 19, in L491:

This study provides crucial insights into rainfall threshold for triggering MDL in the NEH region.

In L504:

The spatial variation in rain thresholds highlights the distinct temporal variability of triggering MDLs at different locations, thus improving temporal forecasting at various lags.

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