Response to Manuscript # egusphere-2022-243 "Predictability of rainfall induced-landslides: The case study of Western Himalayan Region" by Swadhi Ritumbara Das and Poulomi Ganguli

We would like to thank the reviewer for the valuable comments and for providing us with an opportunity to improve our manuscript. In this response document, we address each of the comments raised by the reviewer. Our responses are embedded within the comments (in BLACK) in BLUE. The new additions to the revised manuscript are embedded below in BROWN.

<u>Response to Reviewer 2 Comments</u>

The paper is well written but could benefit from clarifications and better explanations of some of the steps. In my opinion, there are major issues in the methodology which need to be addressed and improved before publication.

We value the reviewer's positive comments on our work. We have made our sincere efforts to revise the manuscript in light of reviewers' comments. We have addressed each of comments raised by the reviewer in the subsequent section.

Comment 1.1: The authors consider a 30d window to determine what the triggering rainfall is and select the one with the maximum intensity. This is critical for a couple of reason. First, there is no justification for the selection of 30d and it seems unrealistic that a certain rainfall event could trigger a landslide 20 or so days after. Furthermore, let's say you have a landslide at day 40 and one at day 50. You could identify as triggering for landslide 40d the rainfall event at day 15. Now, for the landslide at day 50 you might identify a rainfall at day 35. That would mean implying that the rainfall event at day 35 was not responsible for the landslide 5d after (the one happening on day 40) but was for the one happening at day 50. This is just a practical example of how the methodology could fail.

Response: We appreciate the reviewer's feedback. We would like to point to the reviewer that the review of the literature shows that 3-, 5-, 7-, 10-, 15-, 30-day antecedent rainfall has significant influence in triggering rain-induced landslides (Kim et al., 1992; Pasuto and Silvano, 1998; Chleborad, 2003; Heyerdahl et al., 2003; Johnston et al., 2021). Further, an old rainfall event typically displays less impact in triggering landslides than the recent one (Vallet et al., 2015). The choice of a 30-day time window is based on an antecedent soil moisture condition prevalent over a catchment that may trigger flash floods followed by landslides owing to compound occurrences of extreme rain on already saturated soil (Bertola et al., 2021).

The review of the literature shows efforts to calibrate antecedent rainfall in triggering landslides and found that antecedent rainfall conditions up to 30-day are sufficient to trigger rainfall-induced landslides (Marques et al., 2008; Khan et al., 2012; Lee et al., 2014; Johnston et al., 2021). Pasuto and Silvano (1998) found the best correlation between landslide frequency and 15-day antecedent rainfall. Kanungo and Sharma (2014) analyzed that landslides are more biased towards antecedent rainfall than daily rainfall and this bias increases from 3 to 30 days. Giannecchini et al. (2012) revealed that antecedent rainfall has an important role in triggering landslides. This also depends on the type of soil where antecedent rainfall increases the pore water pressure in low permeability soils. Dahal and Hasegawa (2008) showed the correlation coefficient of antecedent rainfall corresponding to 3-, 5-, 10-, 30-days with daily rainfall and confirmed that antecedent rainfall can be considered for modelling shallow landslides. Also a study by Abraham et al. (2019) suggest that landslides are more biased towards 40-day antecedent rainfall than 30-day antecedent rainfall. Hence in the present assessment, we have considered up to 30-day duration for modelling shallow landslides.

Comment 1.2: Previous studies already showed that it's typically not the strongest intensity that triggers landslides. E.g., Staley et al. (2013), looked at debris flow and showed that "there were statistically significant differences between peak storm and triggering intensities", confirming that it's not always the strongest rain to trigger them. While the 30d window might be less unrealistic for deeper landslides and for other properties (other than maximum intensity) but not for shallow landslides or when looking at maximum intensity. Surely what happens days before the landslides is important, but more as a antecedent condition than a triggering factor.

Response: As suggested by the first reviewer, we have already revised our results considering mean intensities of rainfall in a 30-day time window preceding the day of landslides. Since from the landslide inventory records, we find most of the events in the analyzed location are small to medium in nature (see Table 1 in the response letter and Table A1 in the revision), we point to the reviewer that the choice of 30-day is sufficient for modelling rain-induced landslides. Following Brunetti et al. (2010), we have adopted a frequentist method to determine rainfall thresholds for landslides. The methodology adopted is summarized in Appendix section (**Figure A1**) in the revised manuscript. Following this, we derive new threshold curves corresponds to exceedance probability of 10%, 15%, 20%, 30% and 50% for at-sites and 1%, 5%, 10%, 20%, 30% and 50% exceedance probability levels at regional scale (Region 2). The associated threshold equations are presented in Tables 2-3.

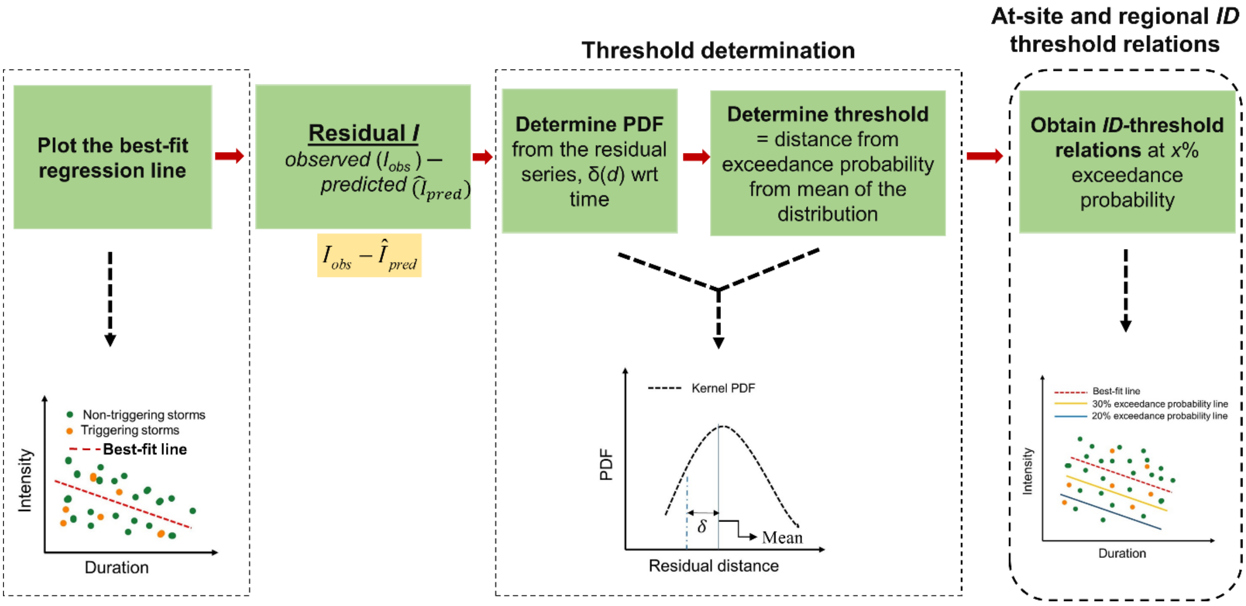

Figure 1 (Fig. S1 in revision): Detailed flowchart of the method followed to plot the threshold curves from the best-fit lines.

Table 1*. Details of landslides inventory records as adopted in this study

Stations	Distance (km)	Number of events	Classification of landslides[1]				Locational accuracy according to NASA COOLR database (in km)
			Small	Medium	Large	Very large	
Banihal	6-22	20	1	20	0	0	1-25
Katra	3-24	21	1	20	0	0	5-25
Mandi	2-22	15	2	13	0	0	1-50
Solan	7-22	16	0	16	0	0	5-25
Dehradun	1-20	12	4	8	0	0	25-50
Joshimath	1-24	16	2	13	0	1	1-50

*Table A1 in the appendix section of the revised manuscript.[1]Landslide classifications are based on the literature (Kirschbaum et al., 2015; Juang et al., 2019).

Comment 2: The authors decide to use a maximum intensity-duration threshold. That is different from both the most used applications: mean intensity-duration ID or total rainfall-duration ED threshold. For ID, mean intensity is expected to decrease with duration, capturing both strong-short events and long lasting, typically less intense, events. For ED, as duration increases, you need more overall rainfall, so ED have a positive exponent. Now, there is no expectation of a dependency between max intensity and duration, if not only that has events become longer (and/or possibly that short events, if they are convective, they have stronger intensities, but this would depend a lot on the local climatology).

Response: Agreed and incorporated as suggested in the revision. In the revised manuscript, we have considered the mean rainfall intensities instead of the maximum intensity. Our revised analysis showed, a negative exponents for derived power-law relationships for few stations, however, yet positive exponents for remaining sites (Figure 2; Fig 10. in revised manuscript). However, we would like to point to the reviewer that finally, the regional ID threshold curve for region 2 shows a negative exponent (see Figure 3 in the response document; Fig 11. in revised manuscript). Tables 2-3 presents derived rainfall *ID* threshold relations for at-site and regional estimates.

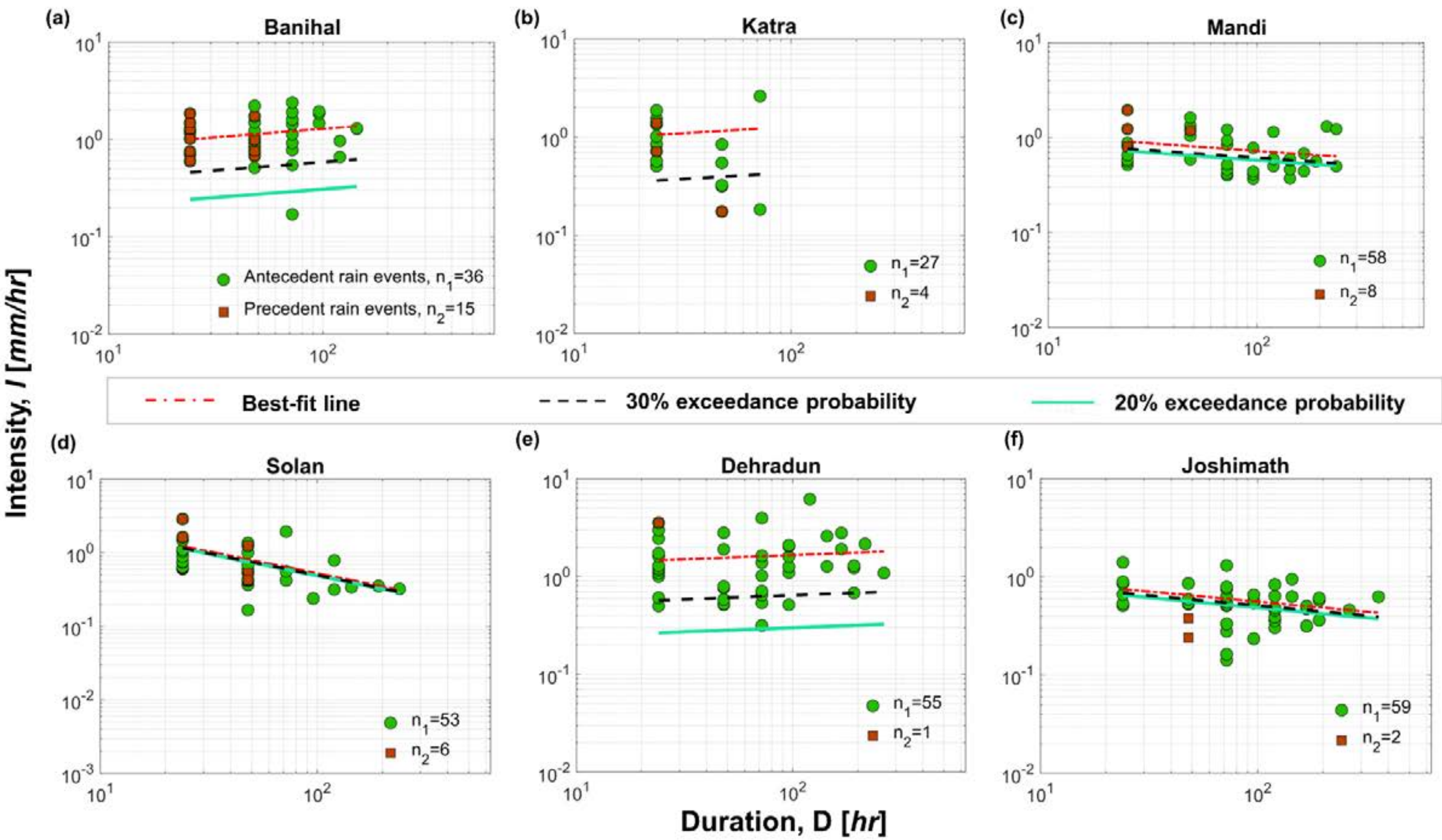

Figure 2. (Figure 10 in revision) Relation between average rainfall intensity (in mm) -versus- duration (in hours) for storms dating from 2007 to 2019 in the WHR. The red dashed line represents the best fit line. The circles indicate individual storm events; the circle in green shows antecedent rain events preceding 30-day before the landslides, whereas squares in brown show precedent rain events before the day of landslides. The dotted-black and cyan line represents threshold curves corresponding to 30% and 20% exceedance probabilities respectively. For Katra, only 30% exceedance probability curve is shown due to limited number of records available for this station. The equations for empirical *ID* threshold curves at 10%, 15%, 20%, 30% and 50% exceedance probabilities are presented in **Table 2** for all at-site locations.

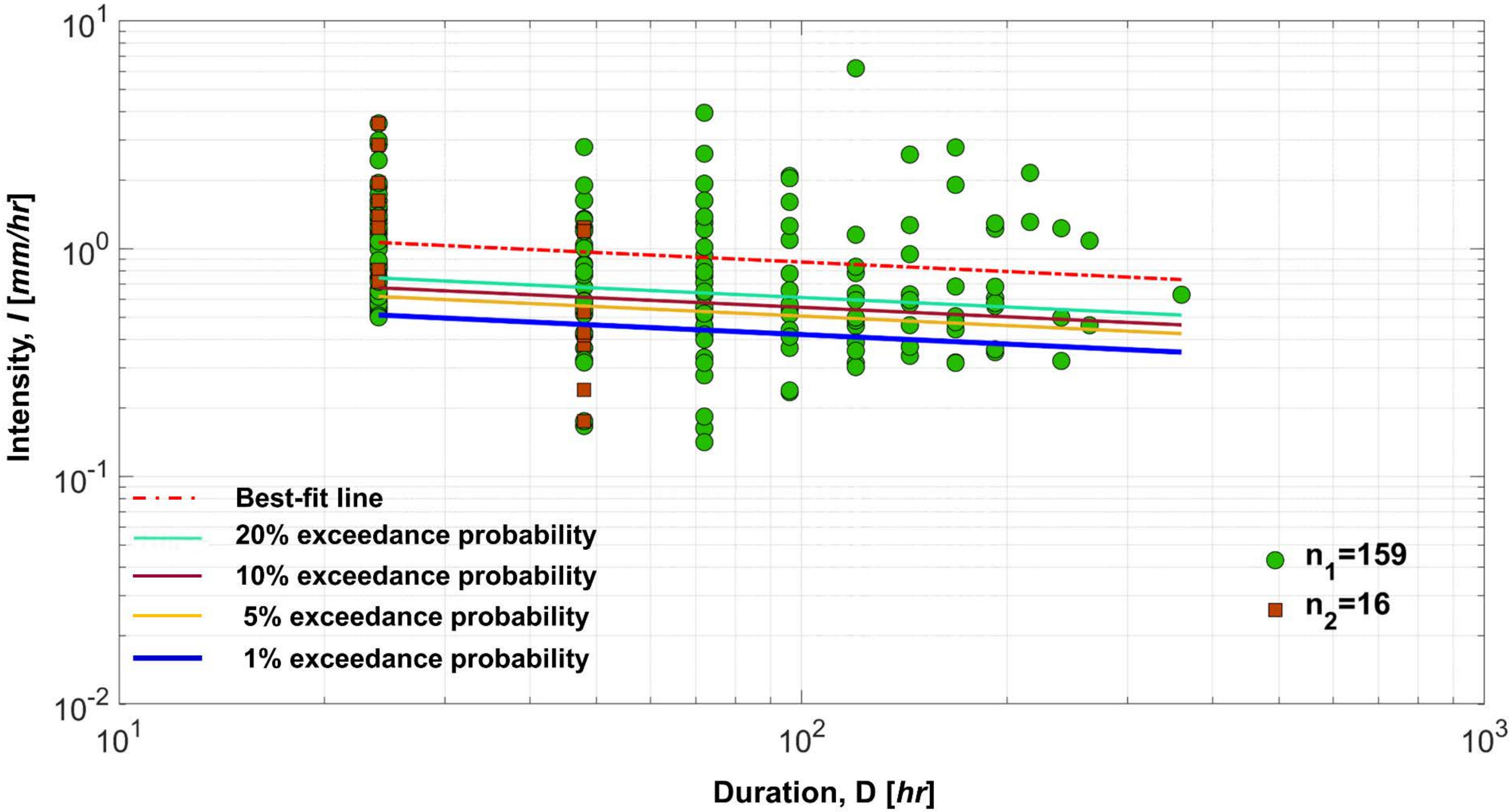

Figure 3. (Figure 11 in revision) Regional Intensity (in mm)-versus- Duration (in hours) curve for WHR. The red dashed line represents the best fit line. The circles indicate individual storm events; the circle in green shows antecedent rain events preceding 30-day before the landslides, whereas squares in brown show precedent rain events before the day of landslides. The lines parallel to the best-fit line show the threshold curves correspond to different exceedance probabilities, such as 1%, 5%, 10% and 20% levels. The associated equations for *ID* threshold equations are presented in **Table 3.**

Table 2: Intensity-Duration threshold relationships correspond to different exceedance probabilities

Stations	10%	15%	20%	30%	50%
Banihal	-*	$I_{15} = 0.06D^{0.17}$	$I_{20} = 0.14D^{0.17}$	$I_{30} = 0.26D^{0.17}$	$I_{50} = 0.584D^{0.17}$
Katra	-	-	$I_{20} = 0.003D^{0.13}$	$I_{30} = 0.24D^{0.13}$	$I_{50} = 0.7D^{0.13}$
Mandi	$I_{10} = 1.09D^{-0.16}$	$I_{15} = 1.143D^{-0.16}$	$I_{20} = 1.18D^{-0.16}$	$I_{30} = 1.25D^{-0.16}$	$I_{50} = 1.48D^{-0.16}$
Solan	$I_{10} = 7.34D^{-0.59}$	$I_{15} = 7.43D^{-0.59}$	$I_{20} = 7.5D^{-0.59}$	$I_{30} = 7.64D^{-0.59}$	$I_{50} = 7.98D^{-0.59}$
Dehradun	-	$I_{15} = 0.07D^{0.08}$	$I_{20} = 0.203D^{0.08}$	$I_{30} = 0.438D^{0.08}$	$I_{50} = 1.126D^{0.08}$
Joshimath	$I_{10} = 1.16D^{-0.21}$	$I_{15} = 1.213D^{-0.21}$	$I_{20} = 1.253D^{-0.21}$	$I_{30} = 1.318D^{-0.21}$	$I_{50} = 1.445D^{-0.21}$

*'-' shows that threshold relations could not be computed due to the lack of sufficient observations

Table 3: Regional Intensity-Duration threshold relationships correspond to different exceedance probabilities for the whole WHR

Regions	1%	5%	10%	20%	30%	50%
Region 1*	-	-	$I_{10} = 0.066D^{0.17}$	$I_{20} = 0.14D^{0.17}$	$I_{30} = 0.26D^{0.17}$	$I_{50} = 0.584D^{0.17}$
Region 2	$I_1 = 0.795D^{-0.14}$	$I_5 = 0.9585D^{-0.14}$	$I_{10} = 1.0471D^{-0.14}$	$I_{20} = 1.1563D^{-0.14}$	$I_{30} = 1.241D^{-0.14}$	$I_{50} = 1.655D^{-0.14}$

* Region 1 contains only one station, i.e., Banihal. '-' shows that threshold relations could not be computed due to the lack of sufficient observations

Comment 3: The author used a power law fit to find the threshold (can that even be called a threshold if it's defined to best fit the triggering events?). Why didn't they use other methods available from literature? Why didn't they consider also non-triggering events in the definition (since they are available)?

Response: Agreed and incorporated. First, we have considered the mean intensities instead of maximum intensity to derive the power-law relations against the event duration. Next, as explained earlier, Following Brunetti et al. (2010), we have adopted a frequentist method to determine rainfall thresholds for landslides.

Comment 4: The authors consider for each gage the landslides within a 100km radius. Is that realistic? Is the spatial variability in rainfall such that 100km can be considered more or less homogeneous, especially in the case of convective events? Furthermore, do the author make sure the same landslide do not get assigned to multiple gages (it's hard to tell from the figures, but it seems they could be less than 200km apart).

Response: Agreed; as suggested we have reduced the radial distance between stations and landslide locations to d = 25 km. We would like to point that the Global landslide catalogue does not provide enough landslide information to such a small distance. Therefore, we have also considered GSI landslide catalogue (Bhukosh, 2022) to incorporate additional landslide events for states of Himachal and Uttarakhand. We have compiled the information available from both databases and came out unique landslide events for each stations, which do not overlap between regions. Further, we point out to the reviewer that distance between stations are kept sufficiently large to avoid the chances of overlaps between landslide events. To this end, we present the great circle distances of intra-state stations in Table A3 (Table 4 in the response document) in the revised manuscript.

Table 4: Great-circle distance between inter-state sites

Intra-state Stations	**Great-circle distance (km)**
Banihal and Katra	63.35
Mandi and Solan	99.17
Solan and Dehradun	103.5
Dehradun and Joshimath	150.04

Comment 5.1: On the comparison of rainfall between the two timeframes (historical and recent). More details are provided to explain how the gridded and gage products are combined.

Response: We use the high-resolution gridded rainfall records (0.25°) archived at the India Meteorological Department's Climate Data Service Portal (https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html) to reconstruct the incomplete gauge-based daily time series using the Regularized Expectation-Maximization (Reg-EM) approach (Schneider, 2001). The gridded rainfall records are available for an extended period from 1901 to 2021. We utilize a Python-based tool to extract the rainfall records for the entire WHR region.

The EM algorithm offers an iterative procedure to compute the maximum likelihood estimate in the presence of missing records (Dempster et al., 1977). The RegEM estimates regression coefficients by ridge regression, which is a regularized regression method in which a continuous regularization parameter controls the noise filtering in the time series (Schneider, 2001). The RegEM is well established in the climatic and paleo-climatic fields and the credibility of the algorithm in infilling missing gaps in rainfall series are extensively discussed in the literature (Kalteh and Hjorth, 2009; Tsidu, 2012; Feng et al., 2013; Þórðarson et al., 2021). We have demonstrated the skill of the RegEM algorithm in infilling missing gaps in rainfall time series through a detailed validation. We evaluated the model's performance through an integrated test score as described in Beck et al. (2017). Our validation framework against daily observed rainfall time series showed the skill of the RegEM varies in the range of 0.43 (moderate) to 0.95 (excellent), which is robust in a statistical sense.

We include the process-flow describing the procedure to reconstruct daily rainfall series in Figure 4 (Figure A3 in Appendix section of the revised manuscript).

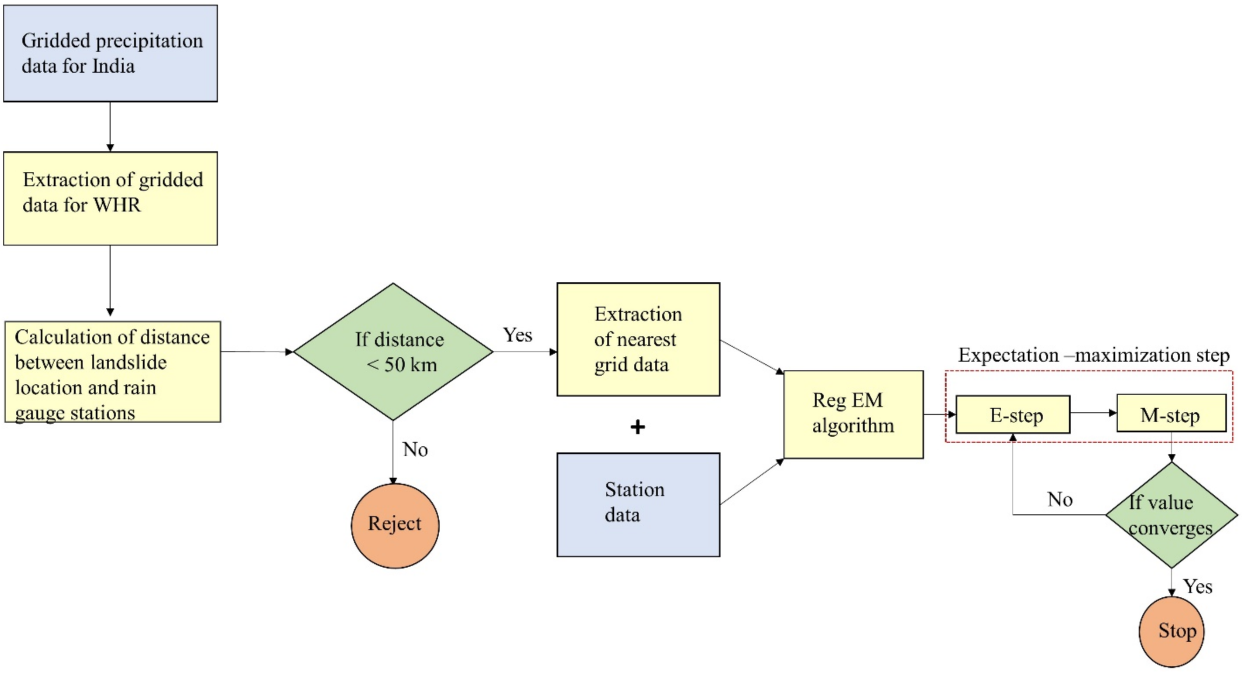

Figure 4 (Figure A3 in the revised manuscript)**:** Process flow describing procedure to reconstruct station-based daily rainfall time series using Regularized Expectation-Maximization (Reg-EM) approach (Schneider, 2001).

Comment 5.2: And how is the rainfall patterns analysis done? Does it use the gridded product? A combination of the two? The gridded product, according to the reference provided, only covers 1965-2005, which does not overlap with the landslide database timeframe, how was it then useful? How was missing data dealt with over that timeframe?

Response: For rainfall pattern analysis, we have used solely the gridded products. We considered the two time windows i.e. present (2007-2016) versus the past (1988-2006). We calculate the annual average rainfall for the two periods for each rain grids and determine their differences, which was presented as a spatial map to analyze increasing/decreasing trends in average rainfall over the WHR. Our analysis showed an increase in annual average rainfall in low-elevated regions of the WHR. We evaluate the statistical significance of increase in annual average rainfall using the non-parametric Wilcoxon rank-sum test, which compare the similarity of distributions between two independent samples of unequal sizes, at 10% significance level. The results of the test statistics in terms of p-value is presented in Table A2 (Table 5 in the response document) in the revised manuscript.

Table 5: Rain-grids with significant positive changes in the recent (2007-2016) versus past (1988-2006) rainfall magnitude

Longitude	Latitude	Difference in annual average rainfall during 2007-2016 versus 1988-2006	p-value
73	29	3.51	0.018903*
73	29.25	5.15	0.000574*
73	29.5	3.97	0.024672*
73	29.75	3.88	0.014107*
73.25	29	4.95	0.006219*
73.25	29.25	4.55	0.006848*
73.25	29.5	3.00	0.015452*
73.25	29.75	3.96	0.007458*
73.25	30	4.30	0.004701*
73.5	29	4.35	0.009955*
73.5	29.25	2.91	0.007298*
73.5	29.5	5.45	5.51E-05*
73.5	29.75	6.37	0.005262*
73.5	30	6.45	5.27E-05*
73.5	30.25	6.58	1.77E-05*
73.75	29	3.82	0.001695*
73.75	29.25	3.59	0.001666*
73.75	29.5	5.79	9.54E-06*
73.75	29.75	6.47	5.46E-05*
73.75	30	6.54	9.45E-05*
73.75	30.25	3.61	0.014701*
73.75	30.5	3.62	0.097975
74	29	5.27	0.000306*
74	29.25	6.96	0.000137*
74	29.5	8.62	4.36E-07*
74	29.75	5.59	0.010609*
74.25	29	5.08	0.006364*
74.25	29.25	8.18	1.18E-05*
74.25	29.5	8.76	8.88E-07*
74.25	29.75	7.43	0.000315*
74.5	29	6.69	0.002613*
74.5	29.25	8.53	5.69E-06*
74.5	29.5	5.17	0.003131*
74.5	29.75	5.90	0.000865*
74.5	30.75	4.26	0.044295*
74.75	29	5.31	0.013756*
74.75	29.25	7.95	0.000175*
75	29	2.16	0.021106*
75	29.25	4.55	0.019964*
75	30.25	2.27	0.05732
75.25	29.75	5.89	0.096492

75.5	32.25	25.47	0.005603*
75.5	32.5	23.87	0.047637*
75.75	30.25	5.57	0.018998*
75.75	30.5	5.20	0.018181*
75.75	32.25	17.27	0.025829*
76	30	9.35	0.000153*
76	30.75	3.72	0.060989*
76.25	30.75	9.80	0.039569*
76.5	30.75	15.81	0.00195*
76.5	33.75	26.32	0.010673*
76.75	33.5	23.68	0.013975*
76.75	33.75	18.53	0.009713*
77	33.5	15.26	0.095401
78	30.25	8.29	0.076716
79	29.5	14.44	0.045953*

*significant at a 10% significance level with p-value < 0.10. The p-values are obtained from Wilcoxon rank sum test. The null hypothesis is that rainfall time series of 2007-16 versus 1988-2006 are samples from continuous distributions with equal medians.

Comment 6.1: Based on Figure 9, it looks like there are landslides every day. Based on this Figure, you'd be better off just saying "whenever it rains between June-July-August-September, expect a landslide".

Response: We would like to point to the reviewer that here we do not fully agree with the reviewer that every rain event is associated with landslides. We present the figure for high flow seasons for both regions, which are generally susceptible to landslides due to extreme precipitation and geologic setting. Panel (b) shows region 2, which is obtained by pooling point rainfall measurements across five rain gauge stations based on climatologically similar characteristics and compares the temporal distribution of the maximum rain intensity versus landslide locations considering all events that have occurred within a 25 km radius of each station.

Comment 6.2: While the triggering events, I assume, are the rainfall of the gage closest to the rain-gage, what are the triggering events? Which gage is chosen for those? Shouldn't there always be multiple overlapping events (for each gage) of which one (or more if there are more landslide at the same time) is triggering and the other not?

Response: Here in panel (a), it is of a single station Banihal (region 1). In panel (b) we consider five rain gauge stations by pooling point rainfall measurements based on climatologically similar attributes. We consider unique rain events and landslide locations, which may occur on the same day but across different locations; the chance of overlapping events is rare. The revised figure is added below (Figure 5).

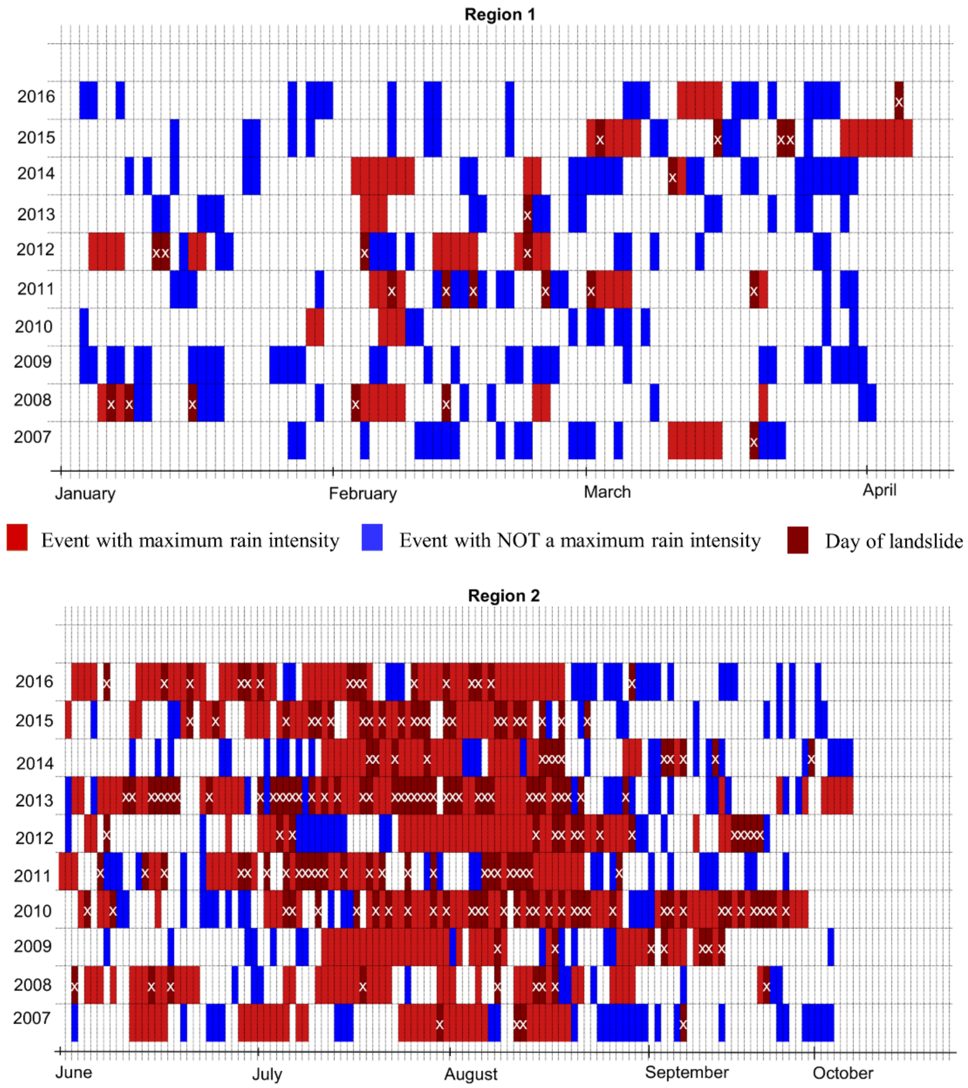

Figure 5 (Fig 9. in revision): Temporal contiguity of rain events with the maximum versus *NOT* a maximum rain intensity followed by timing of landslides for identified regimes: (a) Region 1 showing winter (January-March) season considering the site, Banihal and (b) Region 2, which is obtained by pooling point rainfall measurements across five rain gauges based on climatologically similar characteristics, depicts the southwest monsoon (June-September) season. The day of landslides, unique for each station are marked in ‘x’.

Comment 7: The scale bar in Figure 1 and 6 is deceiving. I believe it is for the smaller subplot representing where the regions are within India, but they could easily be misunderstood for representative of the study area bigger subplot, leading the reader to overestimate by a lot the size of the domain.

Response: Agreed and incorporated in the revised manuscript.

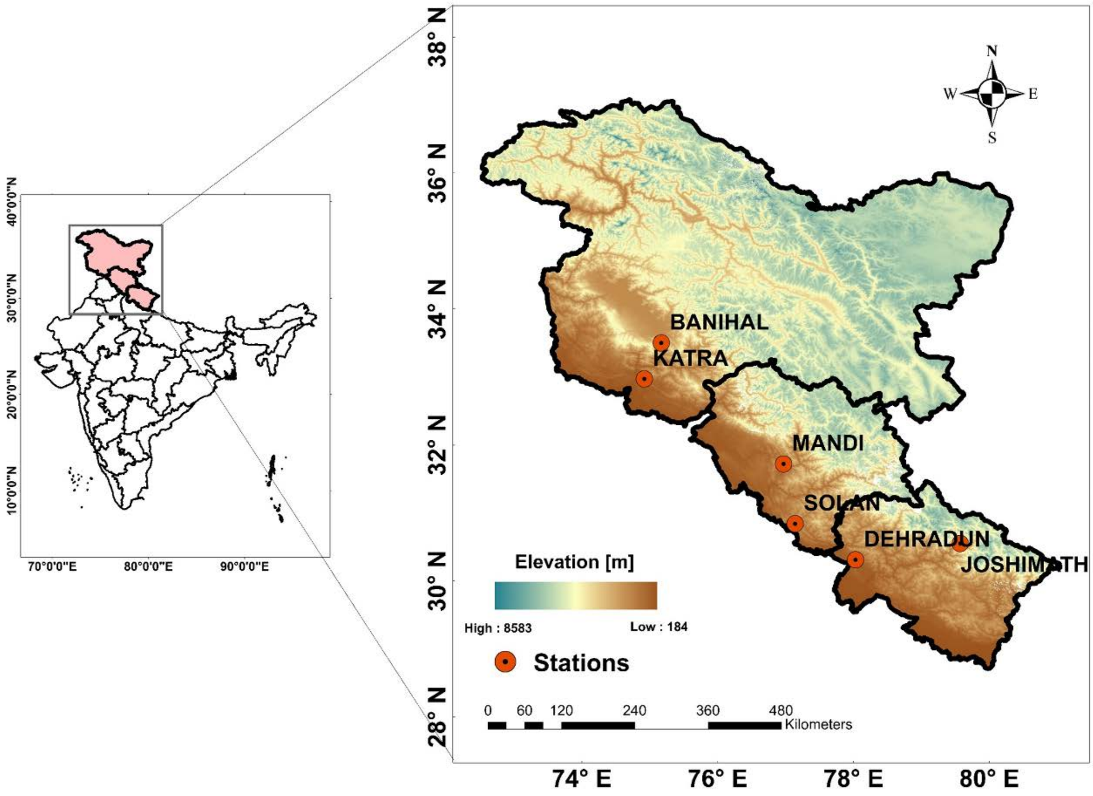

Figure 6 (Fig. 1 in revision): Spatial locations of rain gauges across the WHR (See Table 1 for details). The elevational profile shows the locations of high hills across the northern part of the WHR, which gradually decreases from the north to the south. The digital elevation model of 1-Arc second (approximately 30 m) spatial resolution was derived from the SRTM-1 Arc Second Global data product archived at USGS Earth explorer (https://earthexplorer.usgs.gov/). The elevation map of India is projected using spatial analysis software Arc GIS Desktop version 10.8.1. The inset shows the location of the WHR over the Indian subcontinent.

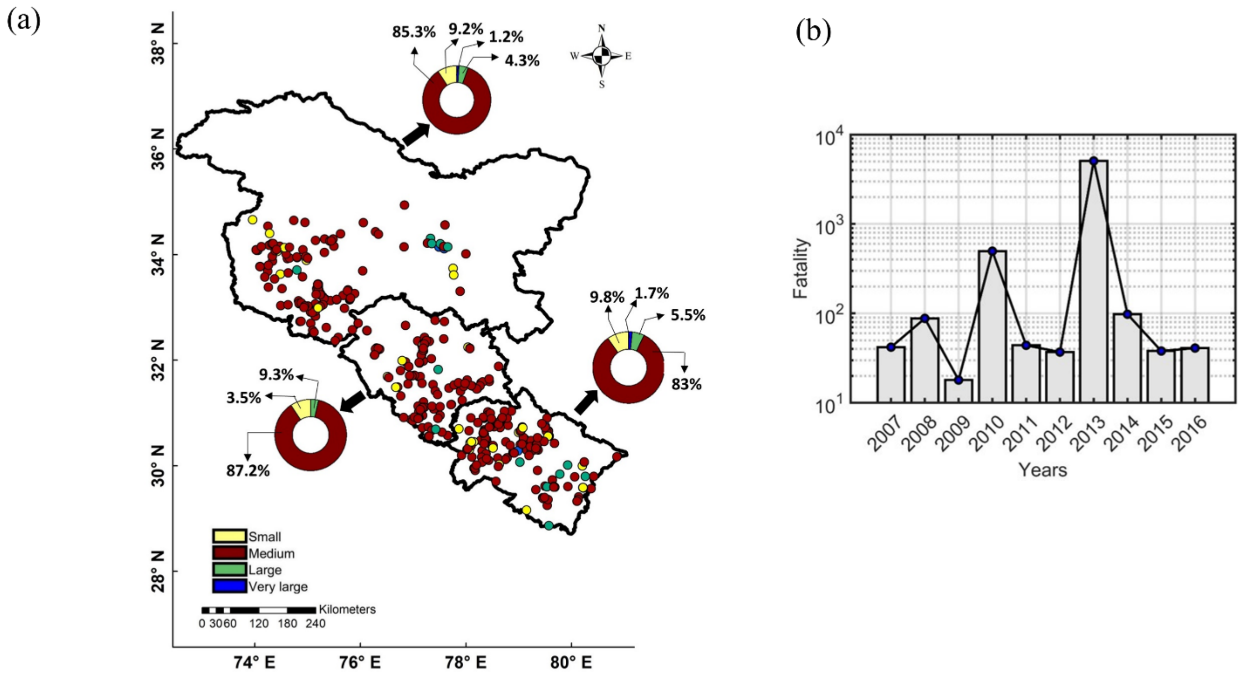

Figure 7 (Fig. 6 in revision): Spatial distribution of historical landslides versus the mortality. (a) Landslide inventory map for the period 2007-2016 and (b) temporal distribution of fatality.

Comment 8: What is the temporal resolution of rainfall? The authors refer to daily data, report values for daily durations (in the intensity-duration plots), but then use intensities in mm/h. Are hourly records available? If yes, why are the authors then using daily sums which could lead to underestimation of the threshold (e.g., Marra et al., 2019, Gariano et al., 2020, Leonarduzzi et al., 2020)? If not, why are hourly intensity reported? How are they computed?

Response: The rainfall data has daily temporal resolution. The event intensity is determined by the sum of the precipitation divided by the event duration. Here, we report intensity in terms of hours by multiplying the duration to 24. At present, we have used daily records due to the sparsity of observation records in this region. However, the gauge-based station records are considered as the best available quality controlled observations for the region. Further, we point to the reviewer that several studies so far have successfully derived rainfall *ID* threshold relations for selected regions across India (Abraham et al., 2022, 2019; Dikshit et al., 2019b, a) and elsewhere (Leonarduzzi et al., 2017; Paranunzio et al., 2019). This gives us the confidence in using daily rainfall records to derive *ID* threshold relationship at selected sites across the WHR, which are highly vulnerable to shallow-to-deep landslides, and have not been investigated earlier. We have added the following sentences in the conclusion section of the revised manuscript:

"While we acknowledge that the use of coarser temporal resolution of rainfall records may lead to underestimation of the rainfall thresholds for landslides (Marra et al., 2019, Gariano et al., 2020, Leonarduzzi et al., 2020), the availability of high-resolution ground-based observations are one of the primary constraints for the region. While the primary strength of point rain gauge measurement records lies in their ability to capture local scale processes precisely, the satellite-based rainfall measurements available at sub-daily time scales have embedded uncertainties since satellites do not measure rainfall by itself and should be related to precipitations based on one or multiple surrogate variables. These uncertainties, may cascade in the process of temporal samplings, error propagations from algorithms and satellite instruments itself (Gebremichael et al., 2005; Toté et al., 2015; Wu et al., 2012). Nevertheless, several studies so far have successfully derived rainfall *ID* threshold relations for selected regions across India (Abraham et al., 2022, 2019; Dikshit et al., 2019a, b) and elsewhere (Leonarduzzi et al., 2017; Paranunzio et al., 2019). While the availability of high-resolution sub-daily records is limited in the area, we plan to investigate the uncertainty associated with using assimilated high-resolution rainfall products, such as Multi-source Weighted-Ensemble Precipitation (MSWEP; Beck et al., 2017b) and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Nguyen et al., 2019) in rainfall *ID* threshold estimation as a future research avenue."

Comment 9: Two stations are unavailable in the timeframe of the landslide database, does it make sense to still consider them?

Response: We agree. To maintain uniformity of rainfall time series, we reconstructed the rainfall time series using a robust machine learning algorithm and maintained uniform lengths of five decades (1970-2019) across all sites. For infilling the missing gaps, we use RegEM algorithm followed by the quantile-mapping-based statistical post processing. Keeping in view the performance of the post processed data, we decide to use the infilled time series. Overall, we show a reasonably good fit between observed versus infilled time series with performance skills that ranges from 0.43 (moderate) to 0.95 (excellent), which is robust in a statistical sense. The model skill in reconstructing precipitation time series is discussed in detail on page 10, lines 253-255.

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