We thank the Associate Editor and three anonymous Referees for handling and assessing our manuscript. We are also grateful to the three referees for their insightful observations and critiques. Following their recommendations and concerns, we will carefully revise our manuscript to clarify the methods and significance of this research.
Hereafter, we provide preliminary responses to these observations before addressing them in detail in a revised manuscript.
The comments of the Associate Editor and the three Referees are in *italic black* font style. Our preliminary responses are in regular blue font style.

<u>Responses to the Associate Editor (EC1)</u>

EC1: Comments and responses

Dear Authors,
We have now received three referee comments (RCs). Based on the RCs, major revisions may be needed before the manuscript may be considered for publication.
Please respond to the three Referee Comments. RC2, in particular, provided detailed critiques and suggestions for improving the manuscript.
Upload a revised manuscript and a detailed response to the RCs by March 10, 2023.
Best,
Sagy Cohen, Associate Editor

Thank you again for handling our manuscript. We are grateful to the three referees for their insightful comments and critiques. We understand and respect the critiques given by RC2. However, we do feel that most of them originated from an intrinsic misunderstanding of our study hypothesis and methods, which might be due to an unclear explanation in the original manuscript. Hereafter, we provide preliminary responses to all observations of the referees to explain how we will revise our manuscript and clear out any potential misunderstandings.

We will carefully revise our manuscript following the recommendations of the three referees and upload a revised manuscript and detailed responses by the due date.

<u>Responses to Referee 1 (RC1)</u>

RC1: Comment 1 and response

In the introduction part, the authors should clearly indicate the research gap and the novelty of this research.

Thank you again for assessing our manuscript. We understand your concerns regarding the clarity of the research gap and novelty in our manuscript, which can be originated from an unclear explanation in the Introduction section. We will substantially revise the Introduction section in a revised manuscript to improve the presentation of our research gap and novelty.

RC1: Comment 2 and response

The research object of this paper is mainly shallow landslides. It is recommended to highlight the uniqueness of the research object in the abstract and introduction.

We acknowledge that most landslides triggered during the examined rainfall event are shallow (depth = 1 to 2 m), as indicated by Chigira et al. (2018). Still, some of the landslides could be relatively deep, as we observed a few landslides with large areas (area > 10,000 m^2) in the FAD of the landslide inventory (Figure 2 of the original manuscript).

Because we did not use any fundamental criteria to differentiate shallow landslides (e.g., area < 10,000 m^2 in Marc et al. (2019)) due to the unavailability of validation data (i.e., high-resolution DEM data taken before and after the examined event), we believe that adding “shallow landslides” may cause some confusion for readers. Therefore, we prefer not to limit the study to shallow landslides.

RC1: Comment 3 and response

In Figure 1b, the north arrow is missing.

We will add the missed north arrow in Figure 1b. Also, we will add the missed label and unit in the color bar of Figure 1a.

RC1: Comment 4 and response

In Figure 3, the contour of the study area should be added. The color bars in Figure 3 lack labels and units. Please check similar issues in other figures.

We have added the contour lines of the study area in Figure 3 (please see Fig. RC1.1). However, we feel that the figure becomes unclear for readers as it overlays multiple different information (i.e., rainfall intensity, landslide distribution, TD, MLD, and contour lines). We believe that adding the contour lines may make the figure difficult to understand. Therefore, we prefer not to add it. On the other hand, we will add the missed labels and units in the color bars in Figure 3 and all other figures in the Supplement file.

RC1: Comment 5 and response

The discussion part needs to be reorganized.

We will reorganize the discussion section in a revised manuscript with sub-sections to make it more accessible for readers.

RC1: Comment 6 and response

Figure 4c: "TD 5.68 & MLD = 1.14" should be changed to "TD = 5.68 & MLD = 1.14".

We will re-create Figure 4 to correct this mistake.

RC1: Comment 7 and response

Line 255: The 100-year rainfall anomaly was higher in the low landslide-density grid cell in P3 (Fig. 5i) than in the low landslide-density grid cell in P1 (Fig. 5c) (< 1.5 times). Why could the comparison of the 100-year rainfall anomaly explain the substantial difference in landslide density between the two grid cells (≈ 110 times for TD).

This important question leads us to notice an insufficient explanation regarding the use of the 100-year rainfall anomaly in our study. Therefore, we will substantially clarify it in our revised manuscript.

It is worth noting that the 100-year rainfall anomaly was proposed in our study to assess the rainfall intensity for multiple timespans (i.e., rainfall intensity maxima) in terms of rarity and extremity rather than rainfall intensity. For instance, a 100-year rainfall anomaly for a 3-h timespan higher than 1 means that the 3-h maximum rainfall intensity was extreme and rare compared to previously experienced 3-h rainfall intensity in the study area as it has a return level of > 100-year return period. Thus, the 100-year rainfall anomaly can provide important information on the potential of the multiple rainfall timespans to induce landslides, as high return level rainfall is generally needed for landsliding (Iida, 1999; Segoni et al., 2015). Accordingly, it can be a standard method to compare the potential of rainfall intensity maxima observed in the different R/A grid cells to trigger landsliding, irrespective of the differences in rainfall intensity maxima.

We found that the 100-year rainfall anomaly was higher in the low landslide-density grid cell in P3 (Fig. 5i) than in the low landslide-density grid cell in P1 (Fig. 5c). This means that rainfall timespans in the former were more extreme (i.e., high potential to cause landslides) than those experienced over the latter. Accordingly, the differences in the 100-year rainfall anomaly, which dictate the potential of rainfall periods to cause landsliding, could explain the substantial difference in landslide density over the two R/A grid cells.

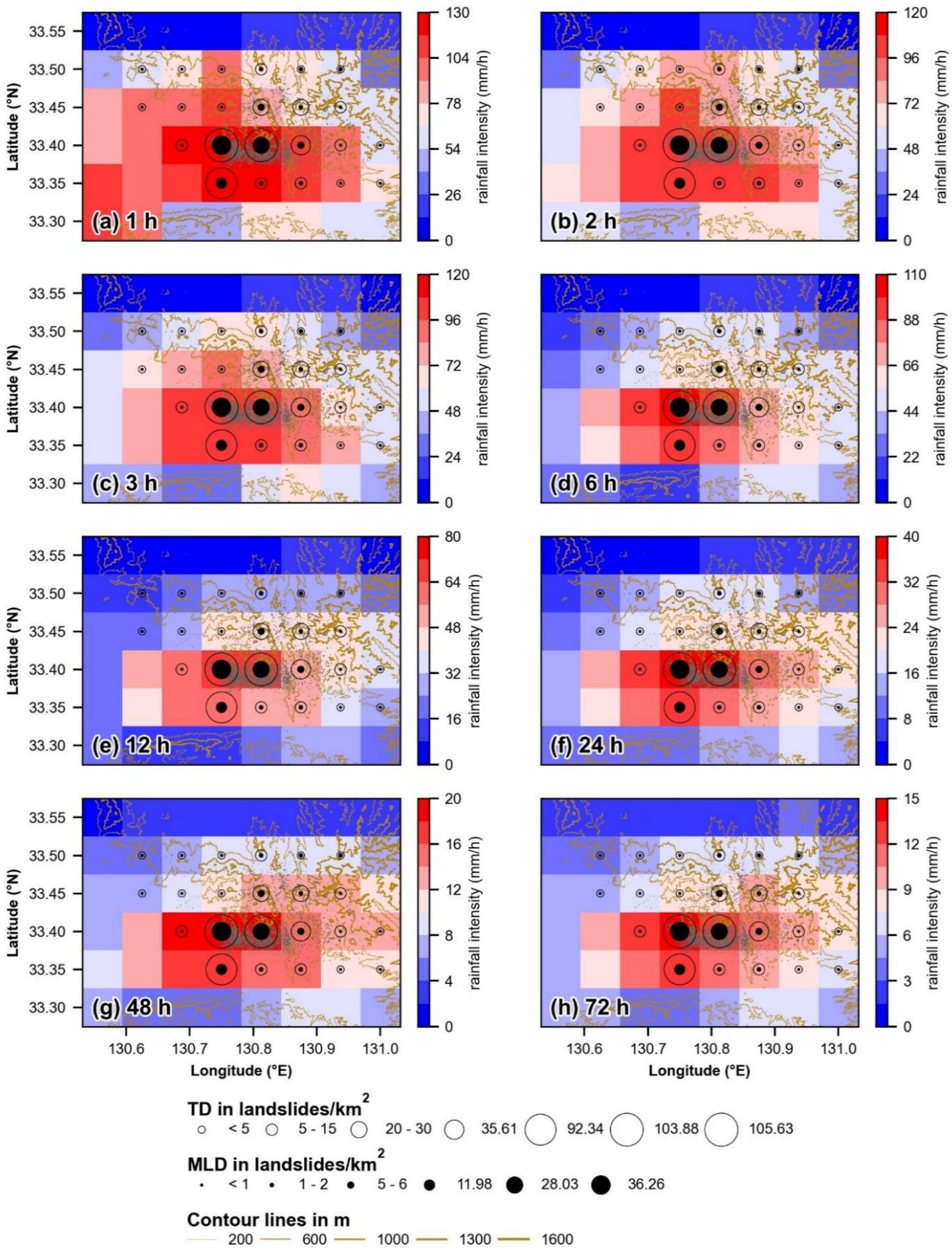

Figure RC1.1. Spatial distribution maps of rainfall intensity maxima for 1 to 72 h timespans within the P_{std} in mm/h, triggered landslides (grey polygons), and landslide density metrics (circles). The brown lines show the contour lines of the study area.

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<u>Responses to Referee 2 (RC2)</u>

RC2: Comment 1 and response

The study relates a large data set of landslides with rainfall characteristics in Japan, using 7,500 landslides over an area of 400km^2. The study uses radar precipitation at 25km2 resolution with 1 to 72 h durations. Land cover and lithology are deemed homogenous in the study site.
A power-law distribution is used to identify the landslide size cutoff for moderate and large sizes. Landslide densities are only calculated where slopes exceeded a threshold of 16.26 degrees (slopes that include >90% of slides). Landslides are separated into total landslide density (TD), which includes all the observations, and medium and large landslide size density (MLD), which includes the slides greater that the size cutoff (>439 m2).
A standardized rainfall that accumulates maximum rainfall over 72h period is used as Pstd. Within this Pstd, multiple time periods that record maximum intensities were also identified (1h to 72h). That aided the authors to develop a rainfall intensity-duration relation threshold curves based on I-D data.
Figure 3 presents a map of 1h to 72h maximum rainfall depths (25km2 resolution) along with TD and MLDs. Higher landslide densities are observed where rainfall intensities are high.
More landslides occurred with rainfall exceeded 100 year return interval.

Thank you for assessing our manuscript. We like to clarify a potential misunderstanding about how we calculated landslide density in this study. Our study intended to examine the interplay between rainfall intensity for multiple timespans, which can be assessed by their return levels, and the spatial variation of landslide density. Given that the rainfall information was derived from a 5-km radar-driven gauge-adjusted precipitation dataset (referred to as R/A), we calculated landslide density by considering the number of landslides that occurred within each R/A grid cell. This is different from other studies that intended to examine how landslide density varies with slope angle, and therefore they calculated landslide density by counting the number of landslides that occurred within particular ranges of local hillslope angles (Coe et al., 2004; De Rose, 2013; Prancevic et al., 2020).

So, differently from what is stated, "*Landslide densities are only calculated where slopes exceeded a threshold of 16.26 degrees (slopes that include >90% of slides)*", landslide densities considered the number of **all** landslides (for total landslide density "TD") and **all** landslides with area > 439 m^2 (for medium and large landslides density "MLD") occurred within each R/A grid cell (i.e., ≈ 25 km^2). The threshold of 16.26° (considered in our study as a minimum slope threshold to allow landsliding and referred to as $S_{threshold}$) was used to calculate the area of the R/A grid cells where the slope > 16.26° (referred to hereafter as $A_{S>16.26°}$). The two Landslide density metrics were, therefore, calculated by dividing the number of landslides (i.e., **all** landslides for TD and **all** landslides with an area > 439 m^2 for MLD) that occurred within each R/A grid cell by $A_{S>16.26°}$ following the equation (1) and (2).

$$\mathrm{TD} = \frac{\text{Total number of all landslides within the R/A grid cell}}{A_{S>16.26^\circ}} \quad (1)$$

$$\mathrm{MLD} = \frac{\text{Number of medium and large landslides within the R/A grid cell}}{A_{S>16.26^\circ}} \quad (2)$$

Such a normalization method is fundamental to reduce bias in the numbers of triggered landslides within the different R/A grid cells caused by the differences in the distribution of local topographic features (Prancevic et al., 2020), as landslides commonly occur in hilly and mountainous areas rather than plains (Lombardo et al., 2021). Therefore, it makes assessing the relationship between rainfall information and landslide densities in the R/A grid cells less biased by the differences in local slope conditions. We note that such a normalization method has been also adopted in some previous works by considering a 10° slope as the minimum slope threshold for landsliding (Marc et al., 2019) or the slope at which > 90 % of landslides occurred (Prancevic et al., 2020).

RC2: Comment 2 and response

Observations: P1, P2, P3-- can you clarify how the populations of landscape slopes similar in these groups, do you report any statistics somewhere? Where are those populations? Are they identified within each selected rainfall grid or can they be located in different rainfall grids?

It is worth noting that each of the pairs (i.e., P1, P2, and P3) represents two R/A grid cells with similar local slope conditions within $A_{S>16.26^\circ}$ but different landslide density metrics (i.e., TD and MLD). The selection of the three pairs was based on the distribution of local slope conditions in $A_{S>16.26^\circ}$ of the different R/A grid cells rather than landslide data. In other words, we examined all slope pixels (resolution = 10 m) in $A_{S>16.26^\circ}$ and did not limit the analysis to only landslide slope pixels. By selecting these pairs, we intended to explicitly focus on rainfall controls and avoid any possible influence of the differences in local slope conditions of $A_{S>16.26^\circ}$ of the R/A grid cells on landslide occurrence.

The three pairs were selected by first comparing the distribution of slope conditions in $A_{S>16.26^\circ}$ of all R/A grid cells (i.e., 23) using the Kruskal-Wallis static (Kruskal and Wallis, 1952) to validate the existence of significant differences in local slope conditions. To better highlight these differences, we provided a Figure showing the distribution of local slope degrees in $A_{S>16.26^\circ}$ of the different R/A grid cells referred to in this figure by the corresponding TD (please see Fig. RC2.1). Subsequently, we employed Dunn's post hoc test for detecting the R/A grid cells with a similar mean rank sum of slopes, meaning similar slope conditions. We note that the result of Dunn's test has been already shown in Table S1 in the Supplement file, as stated in our preprint (P8, L198). From this result, we could find three pairs of R/A grid cells characterized by similar slope conditions (as Dunn's test could not reject the null hypothesis) and different landslide density metrics. Therefore, to explicitly reveal the controls of rainfall information on landslide density, we mainly focused on these three pairs (i.e., P1, P2, and P3) as each pair of R/A grid cells includes two R/A grid cells with similar local slope conditions.

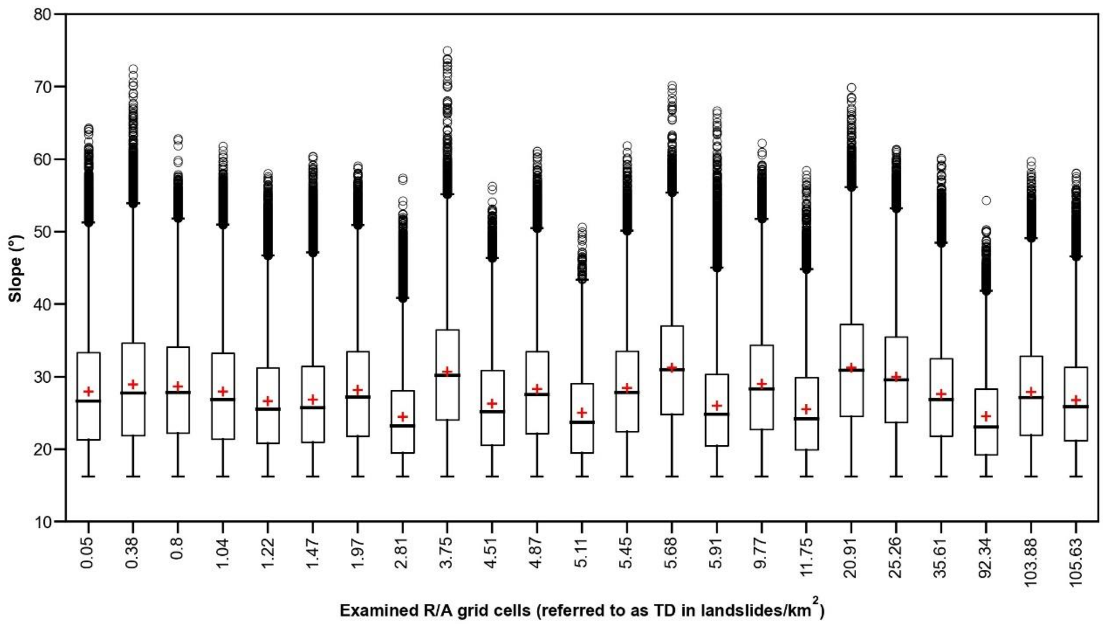

Figure RC2.1. Distribution of local slope degree within $A_{S>16.26°}$ of the R/A grid cells. Note that the distributions are shown as box-and-whisker plots. The box delimitates the 25th and 75th percentiles. The black line indicates the median. The red cross '+' displays the mean. The circles 'o' designate the outliers.

RC2: Comment 3 and response

Lines 195-220: I'm not sure what the objective here, if one is interested to find out where rainfall plays a stronger role, then shouldn't you go and investigate the local conditions (area, slope, soil veg properties) of individual slides.

Here, we compared the relation between rainfall intensity maxima and landslide density in three pairs of R/A grid cells with similar slope conditions (i.e., P1, P2, and P3). We intended to explore the potential interplay between the rainfall intensity maxima and the spatial variation of landslide density metrics (i.e., TD and MLD).

We agree that one of the methods is to investigate local conditions (e.g., slope, soil, vegetation properties, etc.). However, there are mainly one or two controlling factors in some specific regions which are worth exploring. In our study area in particular, two interesting previous works have investigated the importance of multiple predisposing factors (e.g., slope, land cover, elevation) in landslide occurrence using statistical machine-learning methods (Ozturk et al., 2021; Dou et al., 2020). Both works showed that rainfall is the main factor controlling landslide occurrence in our study area, followed by the slope and land use parameters. These findings were also consistent with the in-field observation of Chigira et al. (2018). It is worth noting also that several previous works showed the feasibility to assess only rainfall conditions for landslide prediction by exploring the spatial relation between rainfall conditions and landslide density (Chen et al., 2013; Chang et al., 2008; Dai and Lee, 2001; Gao et al., 2017; Marc et al., 2019), as rainfall is the main factor for landsliding. Given this, we mainly focused on rainfall controls on landslide density in this study.

I think the selection process of P groups are based on some random selection routine, if you shuffle these landslides into another set of 3 populations you may get all three look like P1 and P2 with smaller differences in rainfall rate differences, then what would you do.?

From this comment, we believe you interpreted the selection of the three pairs as it was based on a random selection from the landslide data. Very differently, the three selected pairs of R/A grid cells were selected based on local slope conditions in the R/A grid cells. Please see our response to your second comment (RC2: Comment 2 and response), where we have cleared out how we selected the three pairs of R/A grid cells.

We believe this potential misunderstanding might be originated from unclear explanation of the selection method and intention of the three pairs (P1, P2, and P3). Therefore, we will clarify this by substantially revising our manuscript (in particular, Section 2.3.)

I also could not figure out what those two different groups are within each plot in Figure 4. Why do the gray symbols have smaller landslide densities than red symbols? I think those were referred to as "pairs" but not sure how paired and why with different densities? Beyond all what is the purpose of pairing.

In Figure 4, each plot compared rainfall intensity for multiple timespans (i.e., rainfall intensity maxima) recorded in two R/A grid cells with similar slope conditions (for the $A_{S>16.26°}$), but different numbers of landslides as can be revealed by the two landslide density metrics (i.e., TD and MLD). For instance, in Fig. 4a, the gray symbols reflect the rainfall intensity maxima recorded in the R/A grid cell where TD = 0.05 and MLD = 0 landslides/km^2. The red dots reflect the rainfall intensity maxima observed in the R/A grid cell where TD = 35.61 and MLD = 11.98 landslides/km2. The black line showed the average rainfall intensity maxima in the two R/A grid cells in comparison.

The pairing approach we used in this paper aimed at selecting the R/A grid cells with similar slope conditions to avoid any possible influence of the differences in slope conditions on landslide density and explicitly focus on rainfall controls, as we explained in our response to your second comment (RC2: Comment 2 and response).

RC2: Comment 4 and response

Rainfall data is very coarse for a rugged terrain to obtain any detailed and new science with respect to landslide process understanding and how rainfall controls it. The study may be useful for regional early warning systems, though still very coarse.

We agree that high-resolution rainfall data would provide more detailed information on spatial rainfall patterns. However, long-term gridded rainfall data with a spatial resolution finer than 5 km, needed in our study to estimate rainfall return levels, is currently unavailable in Japan. Indeed, the R/A dataset used in this study is, so far, the highest-resolution and most reliable long-term gridded precipitation data available. Due to its relatively high resolution, long-term records, and accuracy, several studies used the R/A dataset as referential data for analyzing localized heavy rainfall (e.g., Kato, 2020; Hirockawa et al., 2020; Saito and Matsuyama, 2015), evaluating precipitation forecasts and estimates (e.g., Kubota et al., 2009; Iida et al., 2006; Yin et al., 2022), and constraining empirical relationships between rainfall information and landslide occurrence (e.g., Saito et al., 2010; Marc et al., 2019; Ozturk et al., 2021). All these works showed the usefulness of the R/A precipitation product in capturing the spatial pattern of extreme rainfall events experienced over the Japanese archipelago. Interestingly, Ozturk et al. (2021) evaluated the performance of a coarsened R/A dataset to ≈ 10-km resolution in landslide forecasting using a logistic regression model and showed a comparable performance between the 5-km and 10-km R/A dataset, meaning that the spatial rainfall pattern over the mountainous study areas Ozturk et al. (2021) focused on can be satisfactorily captured even with a 10-km spatial resolution R/A data. Therefore, as our objective was to assess the spatial relation between rainfall characteristics and landslide density, rather than explicitly examine the landsliding process of each of the triggered landslides, we believe that a resolution of 5 km could be sufficient due to its performance in capturing the spatial pattern of the studied rainfall event and given the unavailability of alternative product with finer resolution and long-term records.

How do you take the next step from coarse-grain analysis to finer scale hazard mapping?

We believe that the R/A data can be downscaled to finer resolution by employing machine learning and data fusion methods (e.g., Peleg et al., 2018; Salcedo-Sanz et al., 2020) to address finer scale hazard analysis. However, several drawbacks can limit the application of these methods, such as the need for dense rain gauges network over mountainous regions, which is generally difficult to obtain. We believe that rainfall data downscaling is another research issue that needs to be addressed in detail in the future and is beyond the objective of the current study.

RC2: Comment 5 and response

What is the point of Figure 5, what is the question you are trying to address?

It is worth recalling that all rainfall intensity maxima (i.e., maximum rainfall intensities for multiple timespans within the P_{std}) could explain the spatial variation of landslide density, as shown in Table 1 and Fig. 4. However, it is difficult to set a method to compare all rainfall intensity maxima between the different R/A grid cells that experienced landslides during the examined rainfall event. On the other hand, the return levels would assess the rainfall intensity maxima in terms of extremity and rarity comparing to rainfall intensity previously experienced in the R/A grid cells. Accordingly, it can provide important information on the potential of these rainfall intensity maxima to induce landslides, as high return level rainfall is generally needed for landsliding (Iida, 1999; Segoni et al., 2015), irrespective of the rainfall intensity. Thus, rainfall return levels can be a standard method to compare the potential of rainfall intensity maxima to cause landslidiing at the spatial scale, irrespectively of the spatial disparity of rainfall intensity maxima of the examined rainfall event. Given this, In Figure 5, we compared the return levels of rainfall intensity maxima recorded over two R/A grid cells with similar local slope conditions and different landslide densities (i.e., P1, P2, and P3). Here, we intended to investigate whether the landslide density increases in the R/A grid cells where rainfall intensities reach high return levels that are rarely experienced.

As far as I understood you have some randomly selected data pairs with different landslide densities and they seem to show some narrow range of variable ID trends, but this is expected isn't it.

Sorry, you misunderstood how we selected the three pairs of R/A grid cells. The selection of these pairs was based on local slope conditions in the R/A grid cells rather than a random selection of landslide data. Please see our response to your second and third comments for more explanation (RC2: Comment 2 and response, RC2: Comment 3 and response).

Another point I did not understand—in Figs 3 and 4, do each of the circles average many points with different landslide densities?

Fig. 3 shows the spatial distribution of rainfall intensities for multiple timespans, triggered landslides, and landslide density metrics. Each white and black circle is the TD and MLD in the corresponding R/A grid cell, respectively.

No, in Fig. 4, each plot compared rainfall intensities for multiple timespans recoded in two R/A grid cells with similar slope conditions (for the $A_{S>16.26°}$), but different numbers of landslides as can be revealed by the two landslide density metrics (i.e., TD and MLD). So, the circles (red and gray) are the rainfall intensities for multiple timespans recorded in two R/A grid cells. For instance, in Fig. 4a, the gray symbols reflect the rainfall intensities for multiple timespans recorded in the R/A grid cell where TD = 0.05 and MLD = 0 landslides/km^2. The red dots reflect the rainfall intensities for multiple timespans recorded in the R/A grid cell where TD = 35.61 and MLD = 11.98 landslides/km^2. The black line showed the average of rainfall intensities between the two R/A grid cells in comparison.

RC2: Comment 6 and response

Not having a clear research question and/or hypotheses makes it difficult to follow this paper.

Our scientific question was to investigate the potential interplay between rainfall intensity for multiple timespans, which characterize the temporal rainfall pattern and can be assessed by their return levels, and the spatial pattern of landslide distribution during the examined triggering rainfall event (i.e., landslide density spatial pattern). In other words, we intended to assess whether the spatial variation of landslide density during the examined triggering rainfall event is governed by the return levels of rainfall intensity for multiple timespans rather than rainfall intensity of a specific timespan (e.g., 48 h maximum rainfall intensity).

We understand your concern about the clarity of our research question and hypothesis. Therefore, we will substantially improve the introduction section in a revised manuscript to clearly state our research question and hypothesis.

In addition, the methods rely on some comparisons of three similar slope populations (P1,2,3), and pairing of data among them, the purpose of which was not clear.

Sorry, you misunderstood how and why we select the three pairs of R/A grid cells with similar slope conditions. Please see our response to your second and third comments for more explanation (RC2: Comment 2 and response, RC2: Comment 3 and response).

To clear this out and avoid any potential future misunderstanding, we will improve the Methods section in a revised manuscript.

If the whole point of the paper is to show that rainfall patterns and return intervals matter, that is no surprise to anyone, that is why those intensity-duration thresholds were used for nearly a century.

First, it is worth noting the existence of two empirical approaches for quantifying rainfall characteristics that triggered landslides. The first approach is the traditional intensity-duration (ID) thresholds that determined the minimum rainfall conditions necessary for likely triggering landslides. The second approach, mainly used in this paper, relates the spatial variation of landslide density with rainfall information beyond the ID thresholds.

The objective of this paper was to mainly investigate the potential interplay between rainfall intensity for multiple timespans, which characterize the temporal rainfall pattern and can be assessed by their return levels, and the spatial variation of landslide density. We showed that landslide density is constrained by the return levels of rainfall variables for multiple timespans rather than the intensity of a single rainfall timespan (e.g., Maximum rainfall intensity for 48 h). Our finding is different from other studies' findings that related the spatial variation of landslide density to a single rainfall variation for a specific timespan. Also, this is different from the ID thresholds that generally linked the occurrence of landslides to specific rainfall conditions in terms of intensity and duration. So, given this, we believe that the findings of our paper are novel and addressed a significant gap in the understanding of rainfall controls on landslide density.

In addition, the rainfall data is at 5km spatial resolution, which for mountain ranges, is very coarse, and radar rainfall is usually not a good option for estimating mountain rainfall.

We are aware of the intrinsic drawbacks of weather radars in reliably observing precipitation, which could be attributed to various meteorological, topographic, and technical factors (e.g., beam blockage, ground clutter, anomalous beam propagation, and range effects) (e.g., Borga et al., 2022). Therefore, we agree with the Referee's statement: "*radar rainfall is usually not a good option for estimating mountain rainfall*." However, we believe this is the case for the raw uncorrected radar-driven precipitation data (e.g., Young et al., 1999). Differently, the R/A dataset used in this study was processed by a quality control algorithm involving various correction procedures for precipitation observation errors (Makihara, 2000; Hotta, 2018; Nagata, 2011). For instance, ground clutter and beam blockage due to mountains are corrected using a 2-km Pseudo Constant Altitude Plan Position Indicator (PCAPPI) that processes echo intensity data from multiple elevation angles. Additionally, the R/A product involves a Gauge-adjustment algorithm that calibrates precipitation estimates with gauge measurements. These correction procedures made the R/A product valuable for providing reliable rainfall estimates over the mountainous areas in Japan, which cannot be captured by rain gauged due to a sparse network. Therefore, it is often used as benchmark rainfall data in multiple studies over mountainous areas (please see RC2: Comment 4 and response).

It is worth noting, finally, that several previous studies showed the usefulness of corrected radar-driven precipitation datasets in observing the rainfall over mountains (e.g., Germann et al., 2006; Shimada et al., 2016; Nelson et al., 2016; Marra et al., 2022). Therefore, we believe that the R/A product used in our study provides reliable rainfall estimates over the mountainous areas in Japan.

And finally, which is probably more important than any of the comments I made above, besides local slopes, the authors have not factored in elevation in their analysis. Elevation is also a good predictor of rainfall and variations in soils and vegetation. They used a slope threshold in their analysis to select landslides but a quick grouping by elevation would probably reveal a strong elevation control.

It is worth recalling that the slope threshold (16.26°) was used only for deriving normalized landslide densities over the R/A grid cells while accounting for the number of **all** landslides (for TD) and **all** landslides with area > 439 m^2 (for MLD).

Of course, we agree that the elevation can have a strong control on landslide occurrence in addition to other predisposing factors for landslide occurrence (e.g., slope, land cover, rainfall, etc.). However, there are mainly one or two controlling factors in some specific regions which are worth exploring. For our study case in particular, Ozturk et al. (2021) evaluated the importance of multiple predisposing factors for landslide occurrence, including elevation and rainfall, using multivariate logistic regression. Their findings indicated that the rainfall information is the main control for the spatial distribution of triggered landslides, followed by the slope parameter. On the other hand, the elevation parameter was found to be very less important in controlling landslide occurrence according to their findings.

To further assess how landslide occurrence varies with elevation, we have plotted the histograms of landslide elevations (i.e., 7,676 landslides) from a 10-m DEM (please see Figure RC2.2.). We found that the landslides occurred in hillslopes with a wide range of elevation from ≈ 50 to ≈ 800 m a.s.l. Although most of the landslides occurred in hillslopes with an elevation in the range of ≈ 50 to ≈ 600 m a.s.l., still, this elevation range is wide, meaning that landslide do not preferentially occurred on hillslopes with a specific elevation.

Given this, we believe that the elevation has a weak control on the spatial distribution of the landslides we focused on in this study. To avoid any similar queries by readers, we will add this information in the revised manuscript to clearly state the importance of rainfall controls in our examined study case.

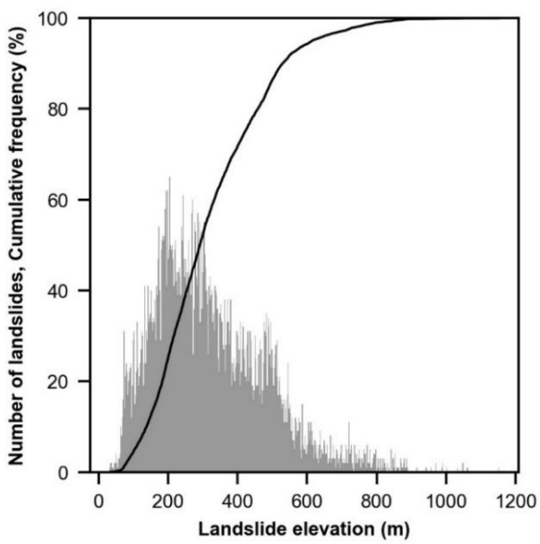

Figure RC2.2. Non-cumulative (gray histogram) and cumulative (black line) frequency distribution of landslide elevations (bins = 500). Note that landslide elevations were calculated as the median of DEM pixel values at landslide scars.

All in all, the paper left me with no new information. If the authors would want to salvage this paper, they would probably reconsider a set of new methods and pose clear questions and objectives.

We respect your critiques. However, we feel that most of them originated from an intrinsic misunderstanding of the research methods, especially the method of landslide density calculation and pairs selection. Considering the research objective was to mainly investigate the potential interplay between a wide range of rainfall explanatory variables, which characterize the temporal rainfall pattern, and the spatial variation of landslide density, we believe that the methods used in our study could sufficiently address the research question.

Finally, we apologize for any misunderstandings which might be originated from unclear explanations of the research methods and hypothesis in the original manuscript. We will substantially improve the manuscript to clearly state our research questions and explain the methods.

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<u>Responses to Referee 3 (RC3)</u>

RC3: Comment 1 and response

This paper analyzed > 7,500 landslides in a region of Japan and insisted that the landslide density would be high when the rainfall return period exceeded 100 years. This paper deals with an interesting topic; the interpretation of results is reasonable for me. I hope the authors consider the comments below to make this paper more attractive to readers.

Thank you again for commenting on our manuscript. We sincerely appreciate your constructive suggestions that would improve our manuscript. Please see below how we will revise the original manuscript to consider your recommendations.

RC3: Comment 2 and response

The authors assume the stable conditions of rainfall. The meaning of "100 years" would differ in changing climate conditions. I want the authors to consider and mention climate change. The first step may be to examine trends in rainfall.

This is a very important observation. We agree and acknowledge that the 100-year rainfall return level may shift over time due to climate change. Therefore, in the revised manuscript, we will follow your recommendation and examine the possible alteration of the estimated 100-year rainfall return level due to climate change. We will first assess trends in the annual maxima series (AMS) of rainfall intensities for multiple durations we used for estimating the 100-year rainfall return level. To this end, we will employ non-parametric statistical tests for assessing the significance and magnitude of the possible trends in rainfall (e.g., the Mann-Kendall test and the Sen's slope estimator test). Then, we will carefully revise our manuscript to add the new trend analysis tests and highlight the possible alteration of the 100-year rainfall return level in the future due to climate change.

RC3: Comment 3 and response

The authors analyzed using the return period of rainfall and did not mention the absolute amount (intensity) of rainfall. I am wondering whether the absolute amount of rainfall may be more important than the return period for understanding the distribution of the landslides.

As explained in our manuscript (P2, L32–39 and P6, L 132–143), constraining the absolute amount (intensity) of rainfall responsible for all landslides (i.e., 7,676) triggered during the examined rainfall event is difficult due to the disparate hydromechanical responses of affected hillslopes to forcing rainfall. Therefore, in this study, we used multiple timespans from 1 to 72 h within a standardized period (P_{std}) of 3 days that accumulated the maximum rainfall amount during the triggering event to examine the relationship between rainfall information and landslide density. In doing so, we intended to consider multiple combinations of rainfall durations that could represent the effective rainfall duration needed for triggering the various landslides.

If we consider the rainfall intensity maxima for a specific duration (e.g., 24, 48, or 72 h) recorded during the examined rainfall event as the meaning of absolute rainfall intensity, we could find a significant statistical correlation between landslide density and the absolute rainfall intensity (Table 1 and Fig. 3). This means that the absolute rainfall intensity could also be important for explaining the spatial distribution of landslide density. But, this correlation did not necessarily mean that landslide density increased with increased absolute rainfall intensity for a specific timespan (e.g., 24, 48, or 72 h). Indeed, as shown in Fig 4c, the landslide density metrics in two grid cells with similar slope conditions were different despite the similarity in the rainfall intensity for 24–72 h durations and slope conditions. This led us to conclude that all rainfall intensity maxima matter for landslide occurrence. Therefore, despite the absolute rainfall amount or intensity could explain the distribution of landslides from a statistical prospect, rainfall return level is a better proxy for landslide density as it can thoroughly assess the rainfall intensities for multiple timespans. We will clear this out better by improving the manuscript.

RC3: Comment 4 and response

The results section includes not only "results" but also "discussion". It may be better to combine these two sections as the "results and discussion" section.

Because combining the results and discussion sections may make the paper difficult to follow by readers, we believe that separated "results" and "discussion" sections may address our findings better. We will carefully revise the "results" section to avoid any possible preliminary discussion of the study results.

RC3: Comment 5 and response

I guess there are several studies focusing on the same landslides because these landslides would affect a large-scale impact on this region. The authors did not mention the factor determining the density of the grids with any return periods of < 100 years. Are there any tips from the previous studies?

We could find a few previous studies that focused on the same examined study case, but using different landslide inventories, such as Dou et al. (2020) and Ozturk et al. (2021). Both works used statistical machine-learning methods to investigate the importance of numerous predisposing factors in landslide occurrence. Their findings showed that rainfall is the main factor controlling landslide occurrence in our study area, followed by the slope and land use parameters. These findings provided useful insights about possible influence of terrain settings (i.e., slope and land cover) on landslide occurrence in the R/A grid cells with return periods < 100 years.

Therefore, in the revised manuscript, we will settle for improving the paragraph (P14 L329-

L333) to add the potential influence of terrain settings (e.g., land cover) on landslide occurrence when rainfall return levels are lower than 100 years.

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