REVIEWER 1:

- Comment:

"Rockfall triggering and meteorological variables in the Dolomites (Italian Eastern Alps)" by Bonometti et al. aims to investigate the relationship between meteorological variables and rockfall occurrence in the Italian Eastern Alps. Specifically, a statistical modelling approach based on previous studies and on the Bayesian method has been exploited to assess the frequency of meteorological variables in the ongoing context of climate change and as potential triggers of rockfall events in the studied area in the period 1970-2019. Alongside, an in-depth analysis of the impact of long-term meteorological trends of air temperature, precipitation, temperature variations and freeze-thaw cycles at different aggregation scales on rockfall occurrence has been provided. The manuscript represents a valuable and innovative contribution to the understanding of meteorological variables-related impact on the rockfall risk. Results of this study are very interesting and properly compared to previous works on the same topic. Despite not being a mother-tongue, I think that the paper is in general well-written. However, I believe that some major revisions are needed to enhance the overall quality and clarity of the paper before acceptance for publication. While the methodology is generally well-explained from a technical point of view, there are some assumptions and flows that need clarification. Further, the paper would benefit from a more logical structure, particularly in the Results and Discussion sections. Some parts of the methodology are discussed in the Results, which is not consistent with the purpose of the section. Similarly, some results are overlooked in the Results section and rather included in the Discussion. The Introduction needs some refinements, to better highlight the aim of the work and its novelty with respect to previous mentioned works.

- Authors response

Thanks to the reviewer for the encouraging comments. We modify the manuscripts according to your suggestions.

- Comment:

L 18: This sentence is not clear, please rephrase.

- Reviewed version (from L 19 to L 28)

Our findings reveal several key correlations: in the last decade high-intensity rainfall correlates with rockfalls in autumn, showing conditional probabilities of 12.4% below 1000 m and 22.2% between 1000-2000 m. Mean air temperature correlates with rockfalls in summer, for instance, with a 12.7% probability for 21-24°C between 1000-2000 m, and in autumn, such as a 2.2% probability for 17.6-20.8°C above 2000m. Temperature amplitude shows high rockfall probabilities in spring, reaching 28.6% for 8.8-9.9°C below 1000 m, and in winter, with a 5.8% probability for 9-10°C between 1000-2000 m. Beyond these meteorological links, rockfall frequency exhibits three main peaks: November, February-April, and August. Regarding rockfall source aspect, north component has significant increment from 1970-1999 to 2000-2025 (from 4% to 12% +3%) above 2000 m, a pattern likely linked to permafrost thawing. This study underscores the critical influence of changing climate dynamics on rockfall activity in Alpine environments, providing quantitative links between specific meteorological shifts and rockfall occurrence.

- Comment:

Rather than focusing on limitations of the previous method, it seems that this is addressing a different aim. The mentioned works concentrate on the probability occurrence of extremes in the meteorological variables leading to slope failures, using a non-parametric approach to link meteorological anomalies to landslides occurrence. In contrast, this work shifts the focus to longterm trends and frequency over time, specifically investigating how these trends influence rockfall occurrences, especially considering the impacts of warming and changing weather patterns. I think that the primary aim is to assess how the variation in climate variables over time and space affect changes in rockfall frequency, rather than identifying the role of specific climate extremes as triggering events. I invite the authors to refine this part to better highlight the purpose and novelty of the work.

- Reviewed version (from L 67 to L 74)

However, during periods of climate change, variations in frequency occur across the entire range of meteorological variables, not just at their extremes. These changes can also influence the onset of rockfalls. The aim of this study is therefore to calculate the spatial and temporal frequency variations of various climate variables in the eastern Italian Alps in order to understand climate evolution and its impact on the distribution of rockfall frequency at different elevations. To this end, we propose a new method that builds on Paranunzio's (2015) methodology to include the frequencies of both anomalous and non-anomalous climate variables affecting rockfall events. This refined method was applied to a comprehensive database of rockfall events within the study area.

- Comment:

L 62-65 This part is more suited in the methodology section.

- Reviewed version (from L 65 to L 67)

This method, based on ranking climatic variable values (in ascending order for a specific scale aggregation) and computing a probability of anomalies, links extreme climate values with rockfall events, but does not fully account for their frequency.

- Comment:

A concise overview of the climate of the study area is suggested. Some text from the discussion should be moved here to better contextualize the study area from a climatological point of view.

- Reviewed version (from L 100 to L 116)

Throughout the study area, the landscape is distinctly marked by landforms such as cirques and U-shape valleys, sculpted by glacial tongues that occupied the region during the Last Glacial Maximum (LGM) and retreated to the highest valleys during the Late glacial period (Bassetti and Borsato, 2015). The topography of the study area is very irregular, characterized by valleys situated at an altitude less than 400 m, such as Val d'Adige, Valsugana, Riva del Garda e Valle del Piave, and peaks up to altitudes of over 3000 m, such as Ortles (3900 m), Presanella Group (3500 m), Marmolada (3350 m), Antelao (3264 m). In literature at these altitudes it is declared the presence of permafrost (i.e., a portion of soil or rock that remains at a temperature below freezing for at least two consecutive years). In the study area, thanks to the Alpine Permafrost Index Map (APIM) (Boeckli et al., 2011), it could be observed the presence of permafrost at altitudes above 2500 m for north-facing walls and above 2700 m for south-facing walls. The distribution of permafrost with the orientation of the rock walls shows a more frequency towards walls with orientations approximately ia a range between 300° and 50° N. The region's climate is alpine with continental characteristics and exhibits significant local variations due to microclimates. The Belluno Valley and the Po basin in the Friuli Venezia Giulia Region are influenced by humid breezes from the Adriatic Sea (Desiato et al., 2005). In contrast, the internal mountainous areas experience a typically continental climate, characterised by cold winters and mild summers. Rainfall mainly occurs as brief summer thunderstorms, whereas autumn rainfall is more prolonged (Coro et al., 2015; Frattini et al., 2008).

- Comment:

L 111 Please provide references for these datasets if available.

- Reviewed version (from L 121 to L 122)

Meteorological time-series data were collected from the SCIA website (https://scia.isprambiente.it/; Desiato et al., 2011; Padulano et al., 2021).

- Comment:

L 115 Are you thus considering all landslide events in the region regardless of the elevation? Please clarify.

- Reviewed version (from L 133 to L 137)

To establish a correlation between climatic variables and rockfall events, it was crucial to have information on the day, month, and year of occurrence. Therefore, 2971 events (out of the initial 5628) were considered, as complete date information was available for these events (Figure 1). A comprehensive dataset was generated for these events, including: identification code (ID), coordinates (x, y, z), date of event (dd/mm/yyyy), and the associated three closer weather station.

- Comment:

As far as I understand, the method focuses on the frequency of meteorological values within their characteristics value ranges in the period preceding slope failure occurrence. A more detailed explanation of these "characteristics value ranges" and how they are defined should be provided.

- Reviewed version (from L 146 to L 151)

The proposed method aims to assess both the variation of climatic conditions in an area and the effects of this variation on rockfall occurrence. This analysis computes the frequency of meteorological data by creating sampled time-series from recorded weather station data, a procedure detailed in the following sub-sections. Differently from Paranunzio et al. (2015, 2016), which focused on identifying anomalies in meteorological variables time series, this method emphasizes the frequency of statistical samples of meteorological variables within their characteristic value ranges defined as the interval between the maximum and minimum values obtained from the used time series.

- Comment:

The methodology is partially based on Paranunzio et al., particularly the time series sampling approach at different time aggregation scales. Then it differs by applying a Bayesian method to assess the relative influence of a variable to act as a trigger of a rockfall in terms of conditional probability. Thus, it seems that the computation of the non-exceedance probability, using a defined alpha level (as stated in the Introduction in reference to previous works) for the detection of potential anomalous values (in statistical sense) is not fully addressed in this paper. However, the outcomes of this approach are then presented in the discussion (L 553 on, Fig. 21.). This creates some confusion, as the linkage between the methodology and the results is not clearly explained. The paper should provide a clearer explanation of how this method connects to the presented results.

- Authors response

The reviewer is right. We did not introduce a modification of Paranunzio et al. method because we do not compute the probabilities of anomalies of meteorological variables in another way. We used the approach of Paranunzio et al. to generate statistical samples of variables, that is the aggregation scales approach, and we integrate the meteorological variable used by Paranunzio et al. (2015, 2016), by adding the following variables: temperature amplitude, icing and freeze/thaw cycles. In the proposed method we considered the frequencies of all computed statistical samples.

- Comment:

L 127 The concept is not clear to me: meteorological variables like e.g. temperature are continuous variables, thus what does the premise" this method focuses on the frequency of meteorological values" mean exactly?

- Reviewed version (from L 148 to L 151)

Differently from Paranunzio et al. (2015, 2016), which focused on identifying anomalies in meteorological variables time series, this method emphasizes the frequency of statistical samples of meteorological variables within their characteristic value ranges defined as the interval between the maximum and minimum values obtained from the used time series.

- Reviewer 1 comment:

Eq (4) Define j

- Authors response

Thanks to the reviewer. Index *j* is the summation index as specified in the summation symbol.

- Comment:

L 208 In my opinion, this statement is based on a flawed assumption. The method illustrated in Paranunzio et al. is a statistical approach based on the detection of meteorological anomalies (percentiles). As such, this allows to remove possible bias in the absolute rainfall estimates. Paranunzio et al. compute the probability distribution using the climate data recorded at the reference stations as they are and did not transpose the temperature or precipitation measurements from the meteorological stations to the geographical location and elevation of the rockfall detachment zone. This is because the application of a constant lapse rate (as in the case of temperature) would only shift the values, without influencing the probability estimate associated with V. Therefore, I think that it is not accurate to claim that the method presented in this work addresses an issue overlooked in previous methods. Rather, they provide an alternative approach to handling spatial variability in absolute values instead of percentiles. This point needs to be clarified.

- Authors response

The reviewer is right, the method takes some element of Paranunzio with a different approach to assess the variation of climate variables during time in a large region. We remove that sentence to avoid any misunderstanding.

- Reviewed version (from L 231 to L 232)

This approach, however, does not account for the fact that meteorological variables vary significantly with both elevation and spatial location.

- Comment:

L 221 Generally, an environmental lapse rate which considers air temperature decreasing with height at a rate of approx. 0.6 °C/100 m is used, but this does not take into account that the warming rate increases with elevation (see some suggested references below). It is worth to briefly discuss it in this section.

Pepin N, Bradley RS, Diaz HF et al (2015) Elevation-dependent warming in mountain regions of the world. Nat Clim Chang 5:424–430. doi:10.1038/nclimate2563.

Nigrelli, G., Fratianni, S., Zampollo, A., Turconi, L., & Chiarle, M. (2018). The altitudinal temperature lapse rates applied to high elevation rockfalls studies in the Western European Alps. Theoretical and Applied Climatology, 131, 1479-1491.

- Authors response

Thanks to the reviewer for this consideration and for the suggested references. The abovementioned papers investigate the temperature variation with altitude. Some investigated the meteorological variables considering their evolution in an hourly frequency, whereas others considered all interactions acting at high elevations such as water vapour, clouds or albedo which generates thermo-dynamical effects due to mutual warming between air and rocky outcrops. It is author's opinion, for the aim of this work, the above mechanism are too complex to be investigated with the considered variables that takes in to account only daily mean values, thereby recording these mechanisms globally and contemporary. The linear approach adopted in this work takes into account the action of all above mechanisms (Angot 1892; Dodson and Marks 1997; Barry and Chorley 2009) in a simply manner and globally.

- Reviewed version (from L 243 to L 247)

Here $V_i(t)$ is the variable value recorded by the nodal weather stations, z_i is the nodal weather elevation, z_{rf} is the rockfall elevation, c is the vertical gradient correction (with $c = 0.0065°\text{C/m}$ according to Stull, 2000), and $V_i^*(t)$ represents the corrected weather variable values. This simple linear approach, which is based on a constant vertical gradient, has been used despite the fact that is expected that warming in mountain regions depends on elevation (Pepin et al., 2015; Nigrelli et al., 2018; Pepin et al., 2022).

- Comment:

L 212 The Delaunay method assumes a smooth transition among points, but temperature gradients can be non-linear, especially in regions characterized by microclimates or highly varying topography (as raised in the previous point). The authors should be cautious of how elevation is included in the model, especially in mountain regions with high complex topography and when weather stations with high elevation difference are used. Moreover, this triangulation assumes uniformity in space, this means that stations should be distributed in a reasonably uniform manner. In the case of sparse station networks or if the stations are unevenly spaced, as often occur in complex terrain like mountain regions, the method could not accurately represent the spatial variation of the variables, leading to skewed results. Also, the sensitivity to outliers should be considered (that is, the fact that interpolation process could amplify these errors).

- Authors response

Thanks to the reviewer. We are aware that the complexity of the topography in mountain regions significantly affects the climate, generating micro-climates with non-linear variations in climate variables across the landscape. In fact, as shown in Figure 1b, the meteorological stations in our study area are irregularly distributed and decrease in number at higher altitudes. However, this problem also affects other approaches used in the literature, such as using the nearest meteorological station (Allen and Huggel, 2013; Paranunzio et al., 2015; Nigrelli and Chiarle, 2023), when the stations are located tens of kilometres away from the landslide points. We believe that triangulation partially compensates for this issue since it uses time series data from a greater number of meteorological stations around the landslide point. Weighted linear interpolation is a strong approximation, but it is the simplest approach in the absence of more detailed information. More complex weighting according to distance could be introduced without invalidating the approach.

- Reviewed version (from L 235 to L 262)

First, the weather stations were connected using a Delaunay triangulation, considering only their horizontal coordinates. Each rockfall source point then falls within one of the triangles of this triangulation. The vertices of this triangle are three weather stations, referred to as nodal weather stations, which are associated with that specific rockfall event source. The time series from these nodal weather stations were subsequently used to calculate the time series at the rockfall event source.

To obtain the rockfall site weather time-series, two corrections were applied. The altitude correction adjusts temperature time-series values using the following mathematical expressions Eq. (12):

$$V_i^*(t) = V_i(t) - c\left(z_{rf} - z_i\right)$$

Here $V_i(t)$ is the variable value recorded by the nodal weather stations, z_i is the nodal weather elevation, z_{rf} is the rockfall elevation, c is the vertical gradient correction (with $c = 0.0065°\mathrm{C/m}$ according to Stull, 2000), and $V_i^*(t)$ represents the corrected weather variable values. This simple linear approach, which is based on a constant vertical gradient, has been used despite the fact that is expected that warming in mountain regions depends on elevation (Pepin et al., 2015; Nigrelli et al., 2018; Pepin et al., 2022).

The spatial correction computes the site weather time-series based on the spatial positions of the nodal stations using the following relationship:

$$V_{rf}(t) = N_1(x,y)V_1^*(t) + N_2(x,y)V_2^*(t) + N_3(x,y)V_3^*(t)$$

where $N_i(x,y)$ $i = 1,2,3$ are the weight functions that depend on the positions of the nodal weather stations, and (x,y) represents the coordinates of the rockfall event source. The weight functions, ranging between 0 and 1, were computed by imposing a linear interpolation between the weather stations' values according to their spatial positions. This correction was applied to temperature. Figure 2 provides a schematic representation of the rockfall source, P, and the surrounding weather stations (S1, S2 and S3) forming a triangle used in the time-series computations.

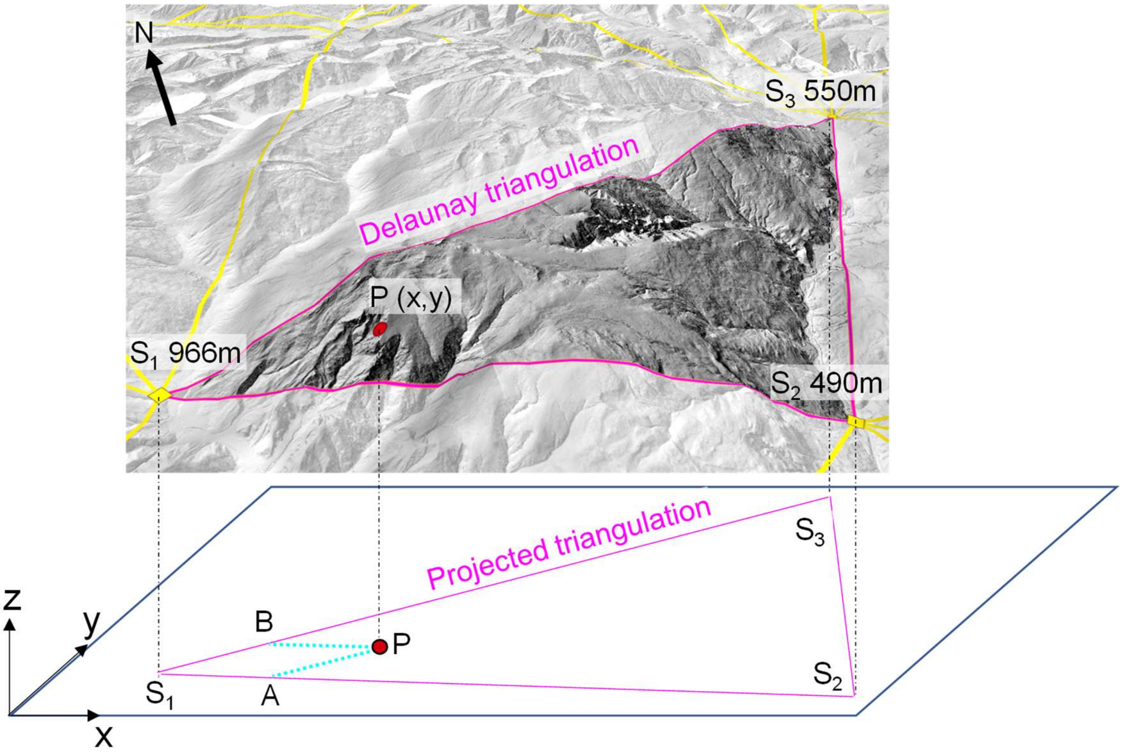


Figure 2. Schematic representation of the rockfall source point P and the weather stations (S_1, S_2 and S_3) positions forming a triangle used int time-series computations. Points A and B are the inclined projections of the point P along the edges $\overline{S_1S_3}$ and $\overline{S_1S_2}$.

Once $V_{rf}(t)$ was computed for all meteorological variables, the computed time-series and sampled time-series were subsequently obtained. This triangulation approach partially compensates for the problem of sparse weather stations that may be distant from the landslide points. However, it assumes an even spatial distribution of weather stations and a linear trend in the variables, both of which may not be accurate in complex terrain.

- Comment:

Figure 2 Define A and B

- Reviewed version (from L 257 to L 258)

Figure 2. Schematic representation of the rockfall source point P and the weather stations (S_1, S_2 and S_3) positions forming a triangle used int time-series computations. Points A and B are the inclined projections of the point P along the edges $\overline{S_1S_3}$ and $\overline{S_1S_2}$.

- Comment:

L 239 Did the authors set a minimum record length in the period 1970-2019?

- Reviewed version (from L 285 to L 295)

For the purpose of this work, three sets of meteorological stations were considered. Set A comprises all 277 selected stations and was used for the Bayesian method to analyse the frequency of climate variables. Set B contains 18 stations chosen from the original 277. These stations were specifically selected because they have a complete time series spanning the entire period from 1970 to 2019 with no data gaps. Results for mean air temperature and precipitation are presented at a 90-day aggregation scale, while results for freeze-thaw cycles are presented at 7-day scale. This enabled the observation of detailed short-term changes while avoiding overlap with other months. Additional results are provided in the supplementary materials for completeness (S1). Set C consists of 12 weather stations with complete time series. These stations were selected to analyse long-term trends at different elevations (below 1000 m, between 1000 and 2000 m, and above 2000 m a.s.l.). To ensure the selected stations were homogeneous, four stations were chosen for each elevation range. Two distinct periods were considered: 1970–2019 for stations below 2000 m and 1985–2019 for stations above 2000 m a.s.l..

- Comment:

Figure 4-5 It is not clear to what trend the arrows refer to, please clarify.

- Reviewed version (from L 336 to L 338)

Figure 5. Frequency distribution of mean temperature with an aggregation scale of 90 days during: (a) winter (DJF), (b) spring (MAM), (c) summer (JJA) and (d) autumn (SON). Arrows indicate a possible frequency trend associated with each sub-interval of mean temperature. Frequencies of the maximum and minimum temperature ranges are zoomed in at the bottom of each graph.

- Comment:

L 315-316 “which delay summer and advances winter” sounds misleading, please rephrase.

- Reviewed version (from L 401 to L 403)

These variations observed at different elevations can be attributed to the linear decrease in temperature with increasing altitude. This delays the end of the summer months and brings forward the end of the winter months at higher elevations.

- Comment:

L 356 Not sure the aim here is to assess a correlation in statistical sense.

- Reviewed version (L 466)

The sub-section aims to assess the specific relationship between rockfall events and various meteorological variables.

- Comment:

L 364 Not clear if the authors are referring to total precipitation or precipitation intensity (also in Figure 11).

- Reviewed version (from L 476 to L 477)

In both cases, an increment in conditional probability is observed for the highest values of total rainfall in the last decade, reaching 12.4% below 1000 m and 22.2% between 1000-2000 m.

- Comment:

Some key findings are presented in the Discussion rather than the Results section, which diminishes the clarity of both parts. The Results section should be dedicated solely to presenting the outcomes of the analysis. Outputs should be moved in the dedicated section, leaving comments and comparison to other works here. As an example, Section 5.1 Climate which addresses changing climate patterns and long-term trends over the last decades in the area is not suited to the Discussion section in its current form (additionally, a climatological introduction of the study area should be included in the Study area section). Similarly, some parts of the methodology are presented for the first time within this section, which contradicts its intended purpose.

- Authors response

Thanks to the reviewer. We modify the manuscript to improve the results and discussion sections. Some of the text was rearranged accordingly.

- Comment:

L 506-519 The RAPS method is mentioned in the discussion for the first time, but it should be included in the methodology, since it supports results and conclusions of the work.

- Authors response

Thanks to the reviewer. We move the mention to RAPS method in the methodology and results in the result section.

- Reviewed version (method part from L 263 to L 276)

To visualize long-term trends, fluctuations, and periodicities climatic records, the Rescaled Adjusted Partial Sums (RAPS) approach, proposed by Garbrecht and Fernandez (1994), was employed. This method is a powerful tool for analyzing time series data, particularly in hydrology and meteorology, as it facilitates the detection of irregularities and fluctuations (e.g., temperature, precipitation) that might not be evident using traditional analysis techniques. RAPS involves rescaling the partial sums of deviations from the mean of a time series, enabling the identification of significant changes or trends over time. It provides a visual representation and analysis of cumulative deviations from the mean, scaled by the standard deviation, to reveal underlying patterns and trends in the data. This technique is particularly effective for identifying breakpoints and subperiods within the data, making it valuable for studying long-term climatic trends and periodicities (Garbrecht and Fernandez, 1994, Durin et al., 2022). Mathematically, the RAPS value at time k can be expressed with the following Eq. (14):

$$RAPS_k = \sum_{t=1}^{k} \frac{Y_t - \bar{Y}}{S_y}$$

where $RAPS_k$ is the rescaled adjusted partial sum at time $(t = 1,2,..,k)$ represents the individual data points in the time series, $\bar{Y}$ is the mean of the time series, and S_y is the standard deviation of the time series. In this study, the RAPS method was utilized to compare its conclusions with those obtained from the proposed approach.

- Reviewed version (results part from L 312 to L 324)

Analogous insights were derived from the RAPS method analysis. For this study, RAPS analysis was carried out for the three altitude ranges, utilizing the 12 meteorological stations in Set C. For stations below 1000 m (Figure 4a) the RAPS values decrease from 1985 to 2008, followed by a sharp increase in the most recent years, indicating that rainfall tended to be higher than the mean value after 2008. A notable exception was observed in 2002, which documented a significant peak (red arrow in Figure 4a), likely corresponding to high rainfall events in May and November (as reported by Bollettino meteorologico e valanghe, Ufficio idrografico di Bolzano; Protezione Civile Provincia Autonoma di Trento). For stations between 1000m and 2000m (Figure 4b), a progressively increasing trend in rainfall is suggested by the downwards parabolic trend of the RAPS. Finally, above 2000m (Figure

4c), the RAPS plot exhibits a V-shape, reaching a minimum in 2007, followed by a sharp increase in the last decade.

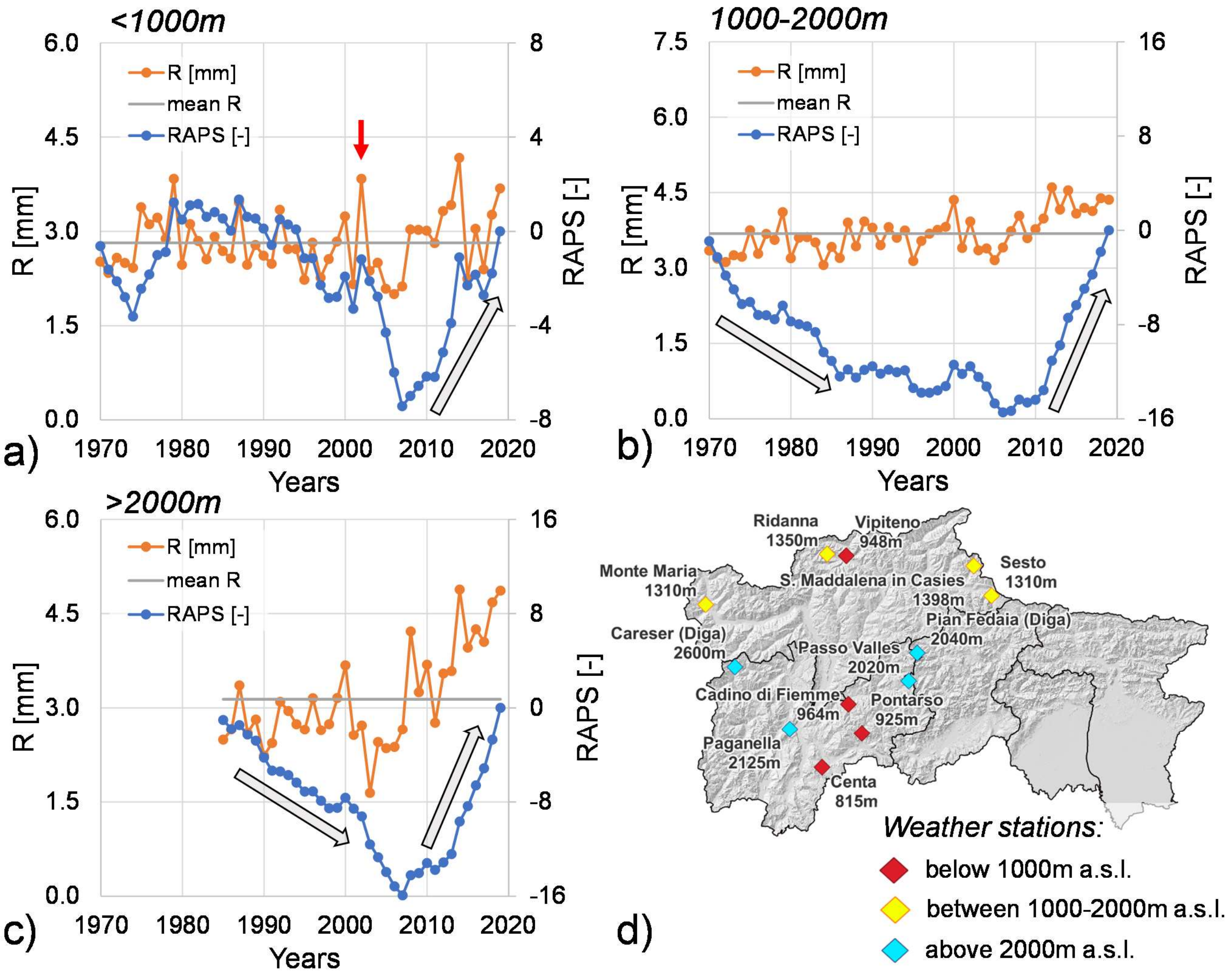


Figure 4. Annual mean rainfall values and Rescaled Adjusted Partial Sums (RAPS): (a) altitudes below 1000m (1970-2019); (b) altitudes between 1000-2000m (1970-2019); and (c) altitudes above 2000m (1985-2019). The red arrow in (a) indicates extraordinary events of 2002. (d) Spatial distribution of the 12 meteorological stations considered (Set C).

- Comment:

L 537 How did the authors measure the correlation?

- Authors response

The reviewer is right. We identify a relationship, and we do not measure a correlation. The text is changed.

- Reviewed version (from L 603 to L 604)

Our analysis indicates a relationship between winter rockfalls and precipitation, particularly daily rainfall events exceeding 31.5 mm.

- Comment:

Figure 17-20: these and related description are more suited for the results section (e.g., L 452-457, L 485-489).

- Authors response

The reviewer is right. We move them in the results section.

- Reviewed version (from L 339 to L 346)

Based on the methodology by Nigrelli and Chiarle (2023), and using the 12 stations selected for an overlapping period from 1985 to 2019, the annual average warming rates were calculated. For minimum temperature, the rates ranged between 0.23°C and 0.51°C per decade, while for maximum temperature, they ranged between 0.17°C and 0.37°C per decade (Figure 6). The highest warming rates were identified during the spring period above 2000m, with maximum increases of approximately 0.65°C for maximum temperature and 0.62°C per decade for minimum temperature.

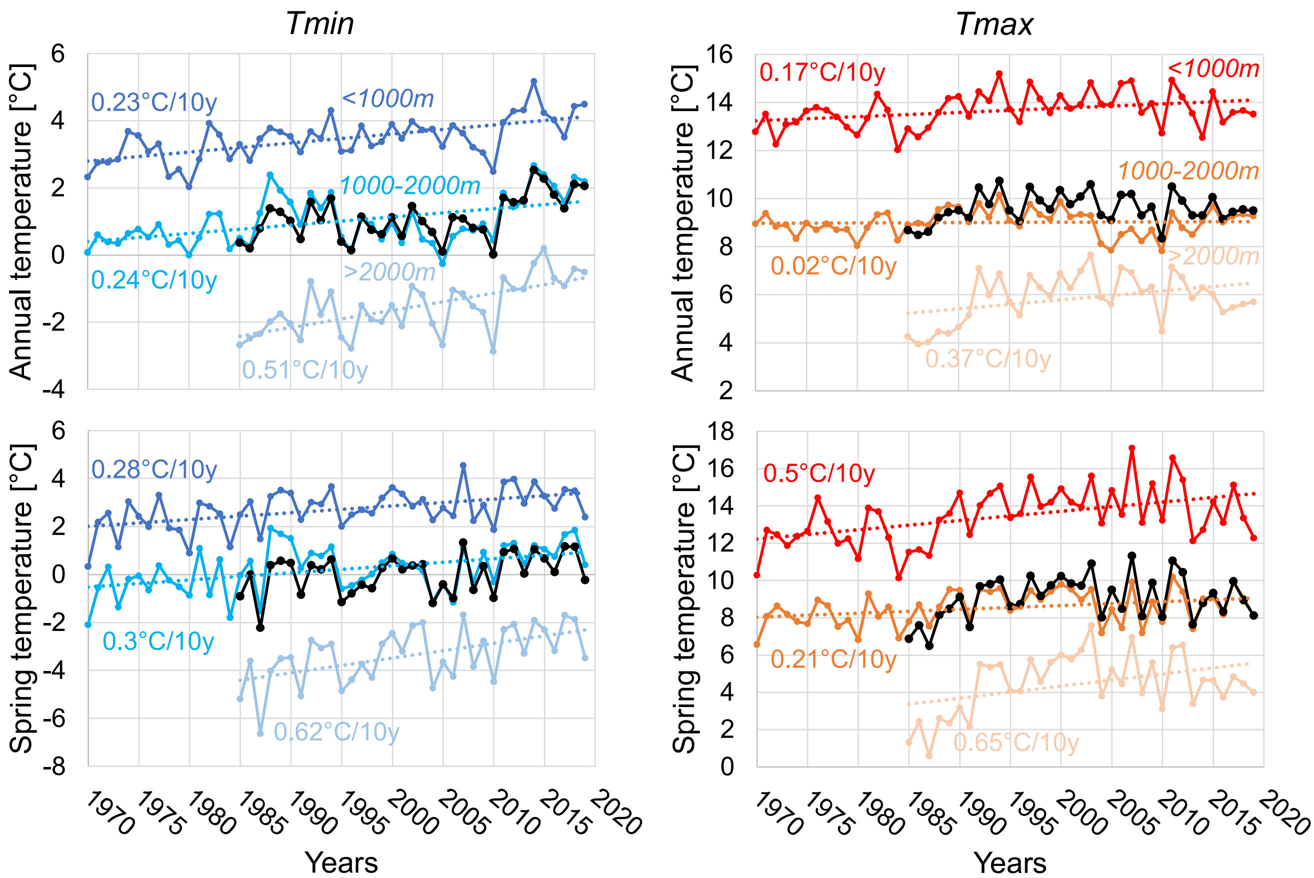


Figure 6. Annual and spring T_{min} and T_{max} trends considering 12 weather stations from 1970 to 2019 for case study. The lack line shows the mean time-series.

- Reviewed version (from L 421 to L 429)

Considering the same weather stations used for the calculation of the temperature trends and employing the approach outlined by Nigrelli and Chiarle (2023), the analysis reveals a decrease of approximately 7.3 freeze-thaw days and about 2.2 icing days per decade (Figure 13a). From the seasonal analysis, while the overall trend is generally decreasing, above 2000 m, freeze-thaw (FT) cycles show an increase at a rate of 3.3 days/10 years in winter and 2.7 days/10 years in spring (Figure 13b-c). Furthermore, in winter above 2000 m, a loss of 2.1 ice days per decade is calculated (Figure 13e).

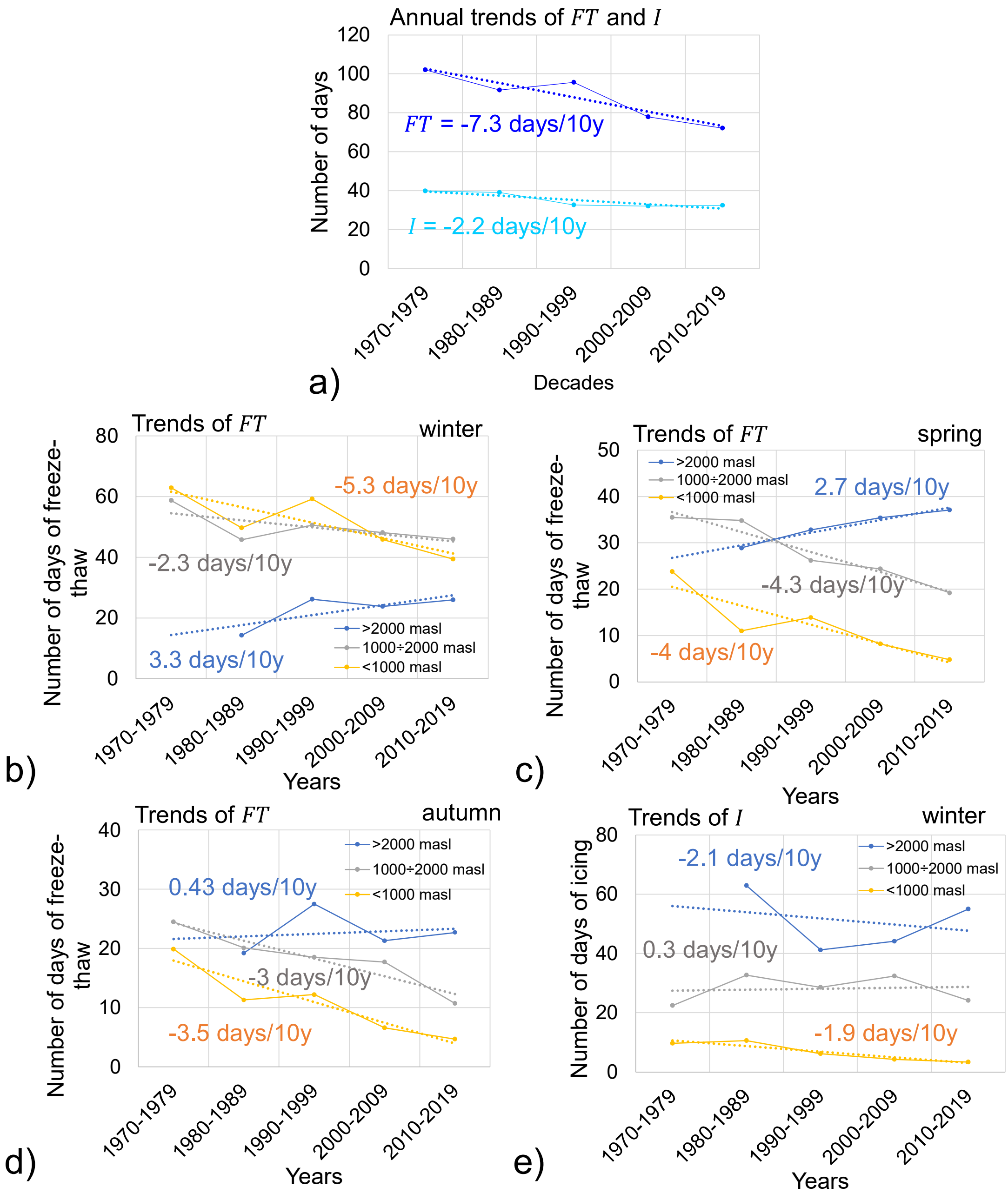


Figure 13. Annual and seasonal freeze-thaw (FT) and icing (I) trends relative to altitudes for this case study during 1970 to 2019. (a) considering 12 weather stations; (b) FT trends during winter season; (c) FT trends during spring season; (d) FT trends during autumn season; (e) I trends during winter season.

- Reviewed version (from L 347 to L 355)

To corroborate the conclusion regarding the shifting of winter and spring seasons, an analysis similar to Wang et al (2021) was performed. Considering the 12 weather stations with full time-series (Set C) from 1970 to 2019, an increase in mean temperature of approximately 1.5°C in winter and 3°C in summer was observed (Figure 7a-c). During the spring and autumn seasons, an increase in mean temperature of about 3°C and 2°C, respectively, was noted. Furthermore, this analysis revealed a shift in the onset of spring by 30 days and autumn by 20 days, consequently causing a change in the length of these two seasons (Figure 7b-d), with a more significant change occurring during spring.

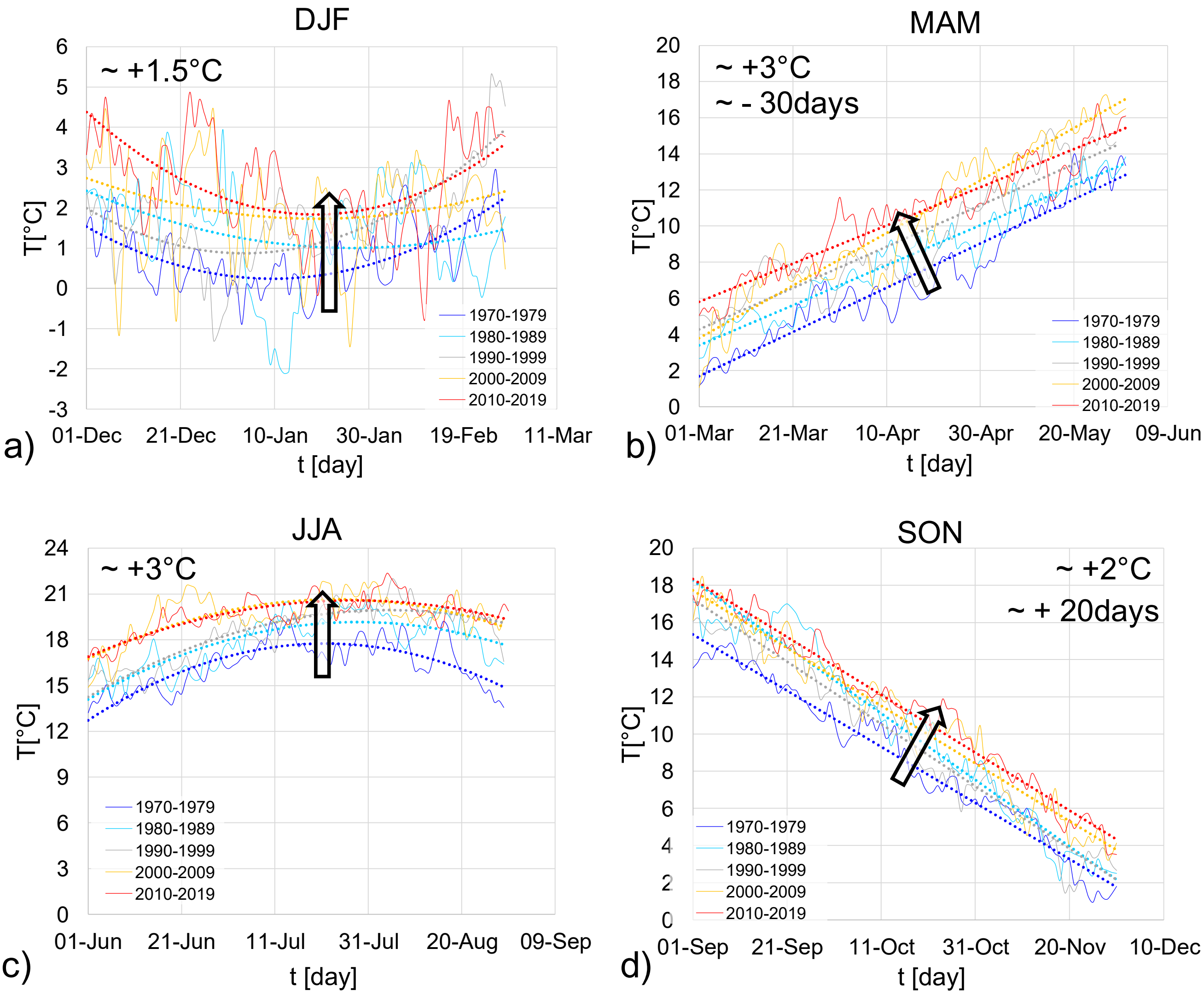


Figure 7. Daily time series of air mean temperature over 1970-2019 during: (a) winter (DJF), (b) spring (MAM), (c) summer (JJA) and (d) autumn seasons (SON).

- Comment:

Figure 21 As in the previous comment, results of this analysis (L 560 on) this should be anticipated in the Results section and briefly contextualized in the Discussion.

- Authors response

The reviewer is right. We contextualized in Discussion section.

- Reviewed version (from L 626 to L 655)

To further validate our approach, we adapted and tested the method of Paranunzio et al. (2016) in this study, comparing the results obtained with its method to those obtained using our proposed method starting in both cases from the dataset reported in this work. We analyzed the same climate variables (precipitation and mean air temperature) at identical aggregation scales (daily, weekly, monthly, and quarterly). Additionally, we investigated temperature variations (ΔT) over 1, 3, and 6 days prior to the event. The non-exceedance probability P(V) was calculated and an event is considered anomalous when its non-exceedance probability is less than $\alpha/2$ or is greater than $1.0 - \alpha/2$ being α a significance level that is equal to α=0.2 as indicated in Paranunzio et al. (2016). The obtained results are reported in Figure 21 where the frequencies of the anomalous events are reported according to the corresponding meteorological variables. For all considered variables the frequencies of anomalous events increase with the decades and more frequent anomalous events are located in the middle of the range of the considered values for each variable. This result could be due to the definition of non-exceeding probability that was estimated ordering the recorded data values. This implies that the first values in the rank could be relative higher but not the highest in the meteorological station. In contrast the conditional probability has greater values for high values of meteorological variables. This difference is attributed to the method employed for computing the conditional probability in which the meteorological probability is computed for all ranges even those in which the rockfall events did not occurred. Finally, temperature variations have to peaks one associated to negative values and another one to positive. This result is attributed to the fact that the same temperature variation could occur for increasing temperature (temperature variation positive) and for decreasing temperature (temperature variation negative) and since the anomalous events correspond to a symmetric value of non-exceeding probabilities (positive and negative anomalies) two peaks appeared.

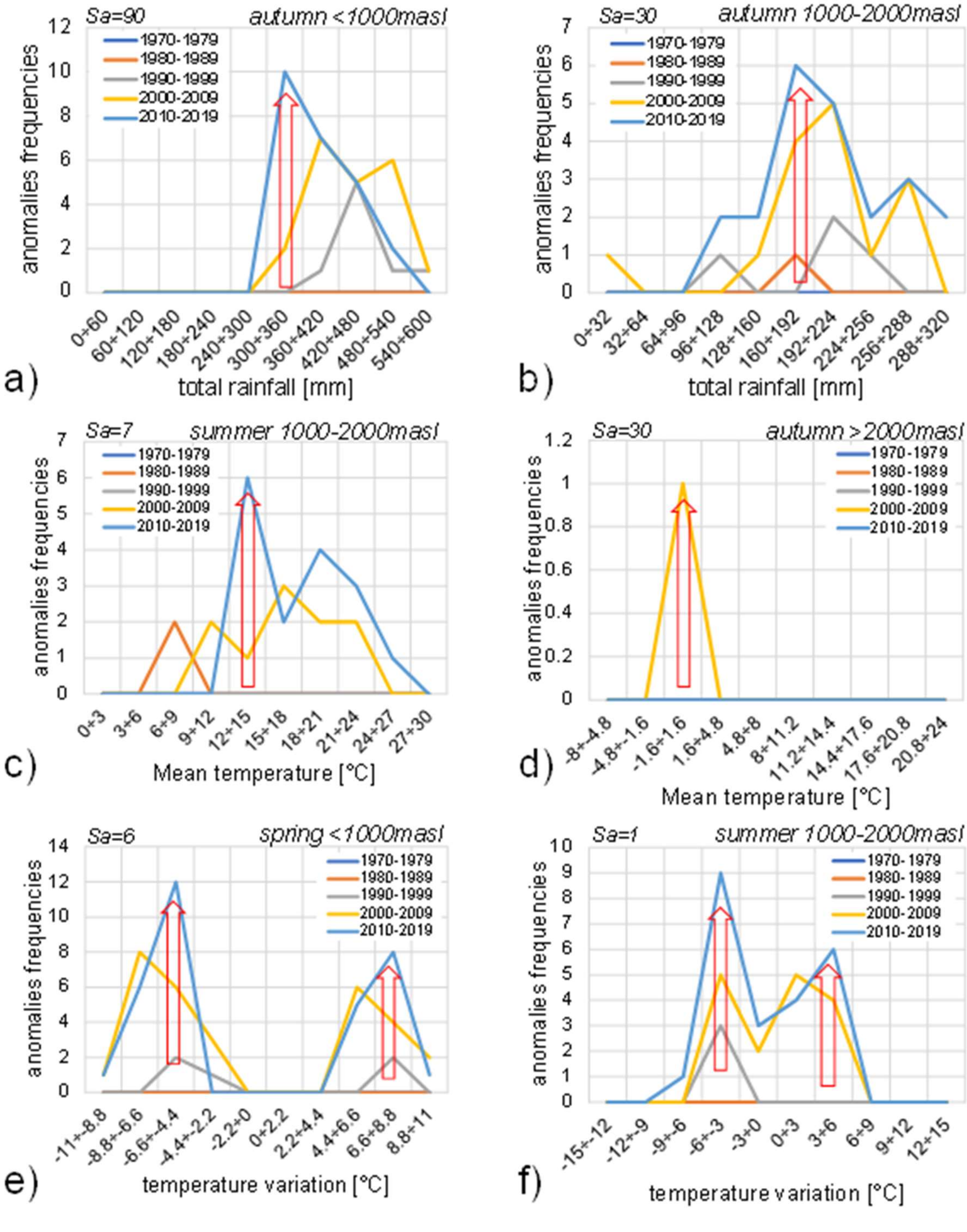


Figure 21. Distributions of anomaly frequencies by using Paranunzio et al. (2015) method, categorized by climate variable and aggregation scale as applied in this analysis. Only results for rainfall, temperature amplitude and temperature variation, as presented in Section 4.3, are reported.

Due to the complexity of meteorological but also lithological and morphological conditions under which the rockfall occurred, this analysis does not allow to unravel into detail the mechanisms why a weather variable has different effects according to the season or elevation. For such detail, it should be necessary to constrain the analysis by considering only rockfalls occurring on single lithological and morphological settings through a detailed multitemporal survey that allows to focus on specific weather variables, e.g. thermal stress (Collins and Stock, 2016; Gasc-Barbier et al., 2024; Fei et al., 2025), freeze-thaw (D'Amato et al., 2016), or rainfall (Weidner et al., 2024).

Technical corrections:

- Comment:

L 6 Alpine areas are undergoing “a high change” in…

- Reviewed version (from L 6 to L 7)

Alpine areas are experiencing substantial changes in both temperature and rainfall intensity, both critical triggers for rockfall events.

- Comment:

L 12 An anticipation of “both the onset of summer and the end of winter”…

- Reviewed version (from L 12 to L 13)

This warming has led to an earlier onset of summer and a delayed end of winter, altering seasonal lengths.

- Comment:

L 15 over “the” last…

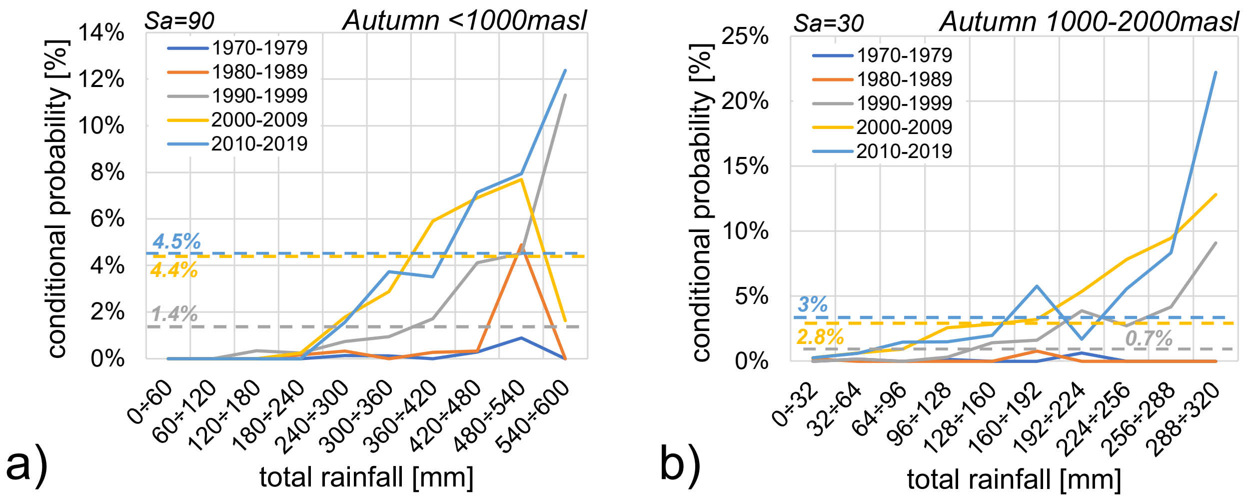
- Reviewed version (from L 14 to L 16)

Precipitation patterns are changing too, with an increasing frequency of high-intensity rainfall events, particularly in winter, and a reduction in low-intensity events across all seasons.

- Comment:

Figure 11a Correct “conditional”

- Reviewed version (L 483)



- Comment:

Figure 10 Please indicate the elevation ranges in d)

- Reviewed version (from L 458 to L 464)

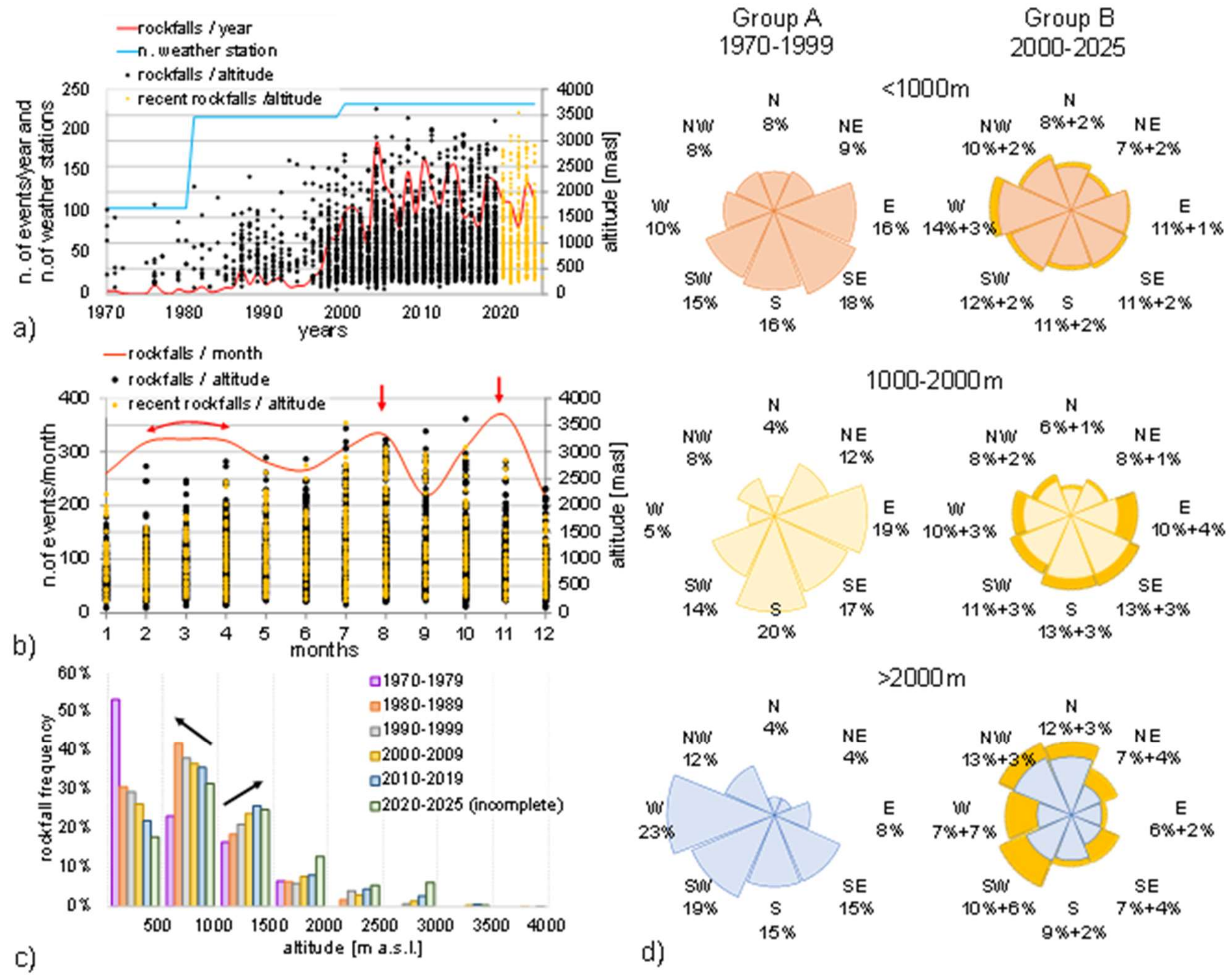


Figure 14. Analysis of rockfall events from 1970 to 2025: (a) annual frequency of rockfalls (red line), distribution of rockfall events relative to altitude (black and yellow dots), number of active weather stations (blue line); (b) monthly frequency of rockfall events relative for all years (red line), altitude distribution for all years for the different months (yellow and black dots); (c) rockfall event distribution in terms of altitude and decades; (d) comparison rockfalls frequencies occurrence in terms of aspect classes for different altitudes (0-1000 m, 1000-2000 m and greater than 2000 m) between 1970-1999 (left side) and 2000-2025 (right side). Rockfalls frequencies from 2020 to 2025 are represented in the yellow areas.

REVIEWER 2:

- Comment:

As stated in the introduction, the aim of the work is to calculate the frequency variation in time and space of different climate variables in the Italian Eastern Alps, to understand the climate evolution in the area and its influence on rockfall frequency distribution. The subject is of major interest for the understanding of rockfall failure mechanism and hazard assessment, and the manuscript represent a substantial contribution. The results are discussed in an appropriate way and compared to previous works on the same topic. I think the paper is well written. However, the methods used should be better explained. That is why I believe that some major revisions are needed to enhance the overall quality and clarity of the paper before acceptance for publication. Also, some parts of the methodology are discussed in the Results and should be moved in the Methods section.

- Authors response

Thanks to the reviewer. We move some parts of the manuscript from the results and/or discussion into the method section.

- Comment:

Minor corrections are suggested in the pdf and the more important points are developed hereafter. Some references of the text are not in the reference list. Please check that all the references are in the list.

- Authors response

Thank to reviewer. We correct the minor point for the annotated pdf and we checked the reference lists with the manuscript citation.

- Comment:

Line 16. To be clearer the expression "to study conditional probability of meteorological variables on rockfall events" should be replaced by "to study the conditional probability of meteorological variables knowing that a rockfall event occurs" (use the academic formulation). But is this true?

- Reviewed version (from L 17 to L 19)

Employing a Bayesian method, we investigated the conditional probability of rockfall occurrences knowing that a meteorological variable is within a given range.

- Comment:

I have a doubt because: (a) The equation (10) gives the conditional probability of a rockfall event knowing a meteorological variable is in a given range. (b) This sentence (line 235) "This study focuses on the effects of meteorological variables in triggering rockfall events" suggests that the results rather present the probability that rockfall events occur given that a meteorological variable is within a given range. This seems more useful.

- Authors response

(a) The doubt is correct. Equation (10) is used to compute $P(Rf|M_i)$ which represent probability of rockfall occurrences knowing that a meteorological variable is within a given range. This is consistent with the sentence modified in the abstract. (b) Thanks to reviewer. Indeed, our target was exactly to understand how the variation in the frequencies of meteorological variable affects the rockfall events. Therefore, the new sentence is now clearer.

- Reviewed version (from L 193 to L 195)

The influence of a weather variable on rockfall events can be analyzed using the Bayesian method (Bayes. 1763) to determine the conditional probability of rockfall occurrence (Rf) under the condition that a meteorological variable is within a given range.

- Comment:

In section 4.3 (Results), the sentences like " Figure 11 shows the conditional probabilities of cumulative rainfall obtained from weather stations below 1000masl" suggest the opposite. Please precise explicitly in the introduction of the section 4.3 what probabilities are presented in this section!

- Authors response

The reviewer is right. It was a mistake in writing the sentence.

- Reviewed version (from L 472 to L 475)

Figure 15 presents the conditional probabilities of rockfall events under the condition that rainfall is within a given range. Specifically, Figure 15a illustrates these probabilities for the autumn season at elevations below 1000 m a.s.l. with $S_a = 90\ days$, while Figure 15b shows the probabilities for autumn season at elevations between 1000-2000 m a.s.l. with $S_a = 30\ days$.

- Comment:

The term "rainfall intensity" refers to the rate at which rain falls over a specific period and is expressed in mm/hour. In this paper, the variable considered is the "rainfall height" or "cumulated rainfall" or simply "rainfall". The term should be corrected unless you really want to speak about the rainfall intensity (in mm/hour).

- Authors response

The reviewer is right. We modify the wrong term with “total rainfall”.

- Reviewed version (from L 476 to L 486)

In both cases, an increment in conditional probability is observed for the highest values of total rainfall in the last decade, reaching 12.4% below 1000 m and 22.2% between 1000-2000 m. When considering other aggregation scales and altitudes (detailed in supplementary materials S2.1), the highest probabilities associated with rainfall continue to occur during autumn season, specifically with a 7-days aggregation scale below 2000 m and a daily aggregation scale below 1000 m. These findings suggest a potential correlation between rockfall events and high total rainfall values during the autumn season. Furthermore, it is notable that in earlier periods, rockfalls showed a higher probability of occurrence with daily and weekly aggregation scales, whereas in the last decade, probabilities are higher with monthly and quarterly aggregation scales.

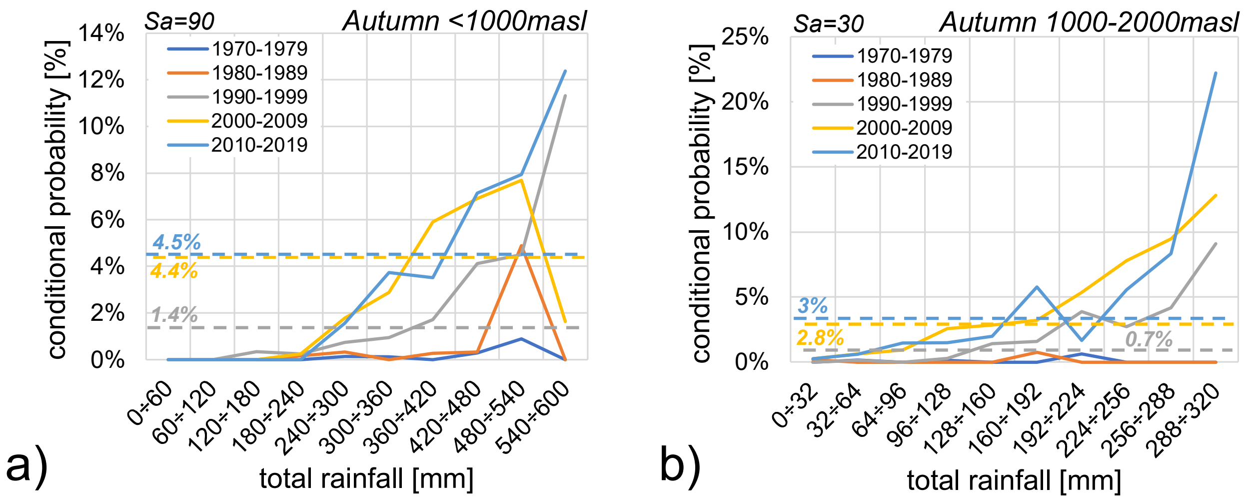


Figure 151. Conditional probabilities of rockfalls triggered by rainfall from 1970 to 2019 during autumn season: (a) below 1000 m a.s.l. considering an aggregation scale $S_a = 90\ days$; (b) between 1000-2000 m a.s.l. with an aggregation scale $S_a = 30\ days$. Rockfall probabilities are represented by the coloured dotted lines according to the decade as shown in the legend.

- Comment:

The authors should explain why they have to use the Bayesian method (equation 10). Why don't they directly calculate $P(R|M_i)$ by dividing the number of days with rockfalls when the meteorological variable is within the range i, by the number of days when the meteorological variable is within the range i? The way of calculating the different probabilities of equation 10 should be explained.

- Authors response

Thanks to the reviewer. First of all, we add in the manuscript an explanation on how the different probabilities are calculated. This is a useful suggestion. Regarding the Bayesian method, we observe that it is true (as the reviewer suggests) that the number of days with rockfalls when the meteorological variable is within the range i divided by the number of days when the meteorological variable is within the range i would provide the same correct probability. However, we believe that expressing this probability through the Bayes formula allows to formally show that this corresponds to the conditional probability of rockfall occurring given the meteorological variable being within the range i, starting from the observation of the number of rockfalls showing this variable range (i.e., the probability to have a certain variable range given the rockfall occurrence, $P(M_i|Rf)$, the prior rockfall probability, $P(Rf)$, and the prior probability to have that variable range, $P(M_i)$. Example. Say we have 10 rockfall events with rainfall between 50 and 100 mm. And assume that the rockfall probability (daily probability) is 100 events in 1000 days. Finally, assume that rainfall in the range 500-100 mm occurs 20 times in 1000 days.

In this case, we have:

$P(Rf)$ = 100/1000 = 0.1

$P(M_i)$ = 20/1000 = 0.02

$P(M_i|Rf)$ = 10/100 = 0.1

and:

$P(R|M_i) = [P(M_i|Rf) * P(Rf)] / P(M_i) = [10/\cancel{100}*\cancel{100}/\cancel{1000}] / (20/\cancel{1000}) = 10/20 = 0.5$

This corresponds to the number of days with rockfalls when the meteorological variable is within the range i (10) divided by the number of days when the meteorological variable is within the range i (20), as suggested by the reviewer. Concluding, the results is the same, but the formalization in terms of conditional probability with Bayes formula is more explaining, because it allows to put in evidence that this conditional probability depends on the prior probabilities and the observations.

- Reviewed version (from L 198 to L 205)

The conditional probability $P(Rf|M_i)$ that rockfall events occur, conditioned on the meteorological variable being within the range $i-th$, can be obtained as follows:

$$P(Rf|M_i) = P(M_i|Rf)\frac{P(Rf)}{P(M_i)}$$

where $P(Rf)$ is the overall rockfall daily probability, calculated dividing the number of rockfall events by the number of days of observation; $P(M_i)$ is the daily probability of the meteorological variable falling within the $i-th$ range, calculated dividing the number of days with the variable within that range by the number of observation days; and $P(M_i|Rf)$ is the probability of the meteorological variable being in the $i-th$ interval when a rockfall event occurs, calculated as the number of rockfall events occurred with the variable within that range divided by the total number of rockfall events.

- Comment:

Line 357. Please explain (discuss) why a weather variable has a different effect according to the season or elevation. For example, has freezing different effects if it occurs in autumn or in winter? Has a high temperature different effects if it occurs in autumn or in spring?

- Authors response

Thanks to reviewer for the questions. We analysed the results according to season, elevation or aggregation scales in order to identify the presence of some weathered signals in different conditions. In the discussion, we highlight the most significant relationships between rockfall and meteorological variables in different season or elevation classes. This information can inform about the influence of the different meteorological variables, but in our opinion, it is not sufficient to investigate the mechanisms that explains why a weather variable has a different effect according to the season or elevation. This because we are analysing a large heterogeneous inventory of rockfalls occurring on a wide range of conditions (not only meteorological, but also lithological and morphological), without constraining the analysis. In other words, the range of complexity is too large to demonstrate the mechanisms, but enough to highlight the influence of some variables in some conditions, as explained in the discussion, also comparing the results with the literature. To recognize this limitation, we add a paragraph in the discussion.

- Add version (from L 650 to L 655)

Due to the complexity of meteorological but also lithological and morphological conditions under which the rockfall occurred, this analysis does not allow to unravel into detail the mechanisms why a weather variable has different effects according to the season or elevation. For such detail, it should be necessary to constrain the analysis by considering only rockfalls occurring on single lithological and morphological settings through a detailed multitemporal survey that allows to focus on specific weather variables, e.g. thermal stress (Collins and Stock, 2016; Gasc-Barbier et al., 2024; Fei et al., 2025), freeze-thaw (D'Amato et al., 2016), or rainfall (Weidner et al., 2024).

- Collins, B. D., & Stock, G. M.. Rockfall triggering by cyclic thermal stressing of exfoliation fractures. Nature Geoscience, 9(5), 395-400, 2016.
- Fei, L., Jaboyedoff, M., Derron, M. H., Choanji, T., & Sun, C. Multiscale observations of diurnal thermal effects on rock failure and crack dynamics in soft marl layers (La Cornalle molasse rock wall, Switzerland). Engineering Geology, 108159, 2025.
- Gasc-Barbier, M., Merrien-Soukatchoff, V., Krzewinski, V., Azemard, P., & Genois, J. L.. Assessment of the influence of natural thermal cycles on dolomitic limestone rock columns: A 10-year monitoring study. Geomorphology, 464, 109353, 2024.
- Weidner, L., Walton, G., & Phillips, C.. Investigating the influences of precipitation, snowmelt, and freeze-thaw on rockfall in Glenwood Canyon, Colorado using terrestrial laser scanning. Landslides, 21(9), 2073-2091, 2024
- D'Amato, J., Hantz, D., Guerin, A., Jaboyedoff, M., Baillet, L., & Mariscal, A.. Influence of meteorological factors on rockfall occurrence in a middle mountain limestone cliff. Natural Hazards and earth system Sciences, 16(3), 719-735, 2016.

- Comment:

Variations of rockfall probability according to the decade are pointed out, but the variations according to the weather factor range should also be commented too.

- Authors response

Thanks for the suggestion. As pointed out in the previous comment, a systematic analysis of the probability as a function of single weather factors is hampered by the complexity of lithological and morphological conditions under which rockfalls have occurred. We tried to represent these variations as a function of weather factors, but the result was not clear enough.

- Comment:

It would be interesting to compare the conditional probability $P(R/M_i)$ with the rockfall probability $P(R)$.

- Authors response

Thanks for the suggestion. We add the rockfall probability $P(Rf)$ in each figure as a reference to compare the conditional probability.

- Reviewed version (from Figure 15 to Figure 20)

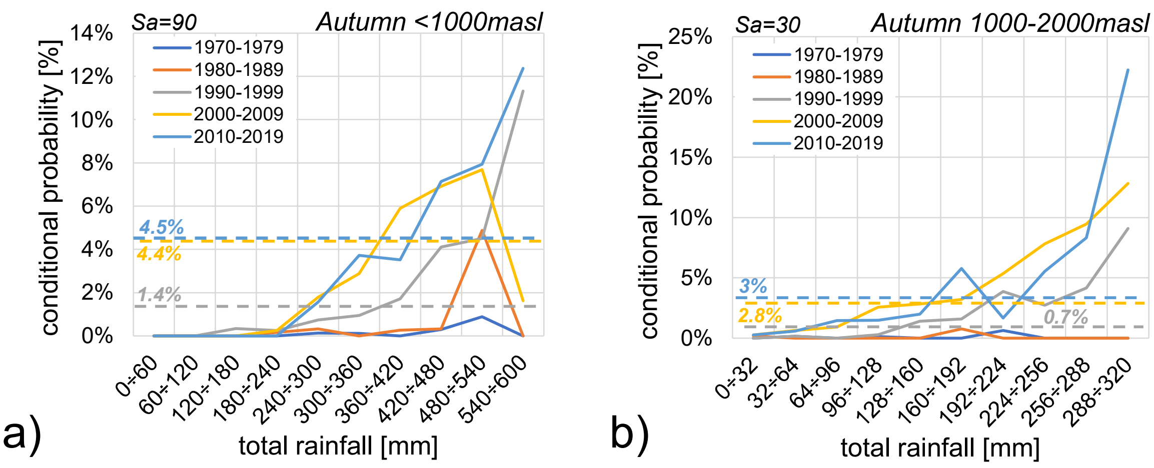


Figure 15. Conditional probabilities of rockfalls triggered by rainfall from 1970 to 2019 during autumn season: (a) below 1000 m a.s.l. considering an aggregation scale S_a=90 days; (b) between 1000-2000 m a.s.l. with an aggregation scale S_a=30 days. Rockfall probabilities are represented by the coloured dotted lines according to the decade as shown in the legend.

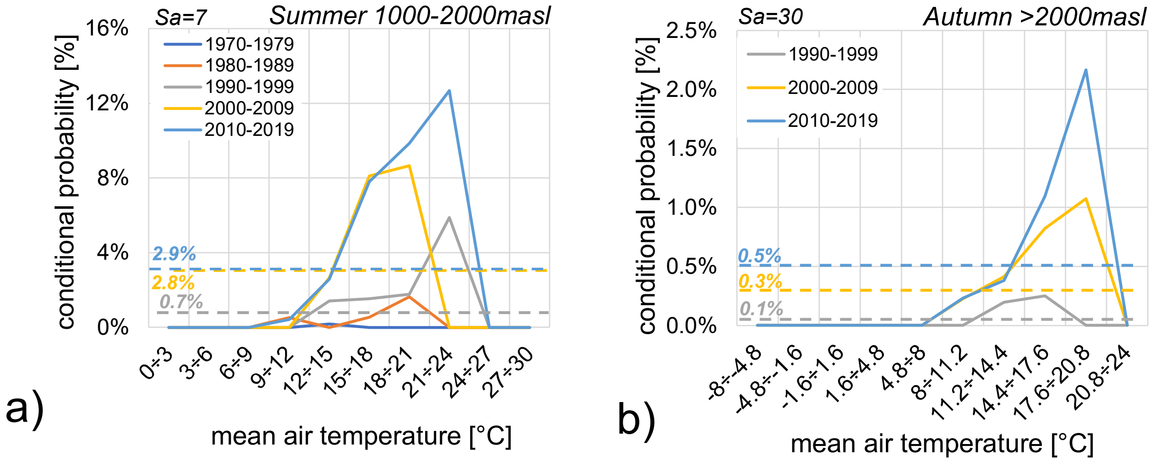


Figure 16. Conditional probabilities of rockfalls triggered by mean temperature values from 1970 to 2019: (a) during summer season between 1000-2000 m a.s.l. with an aggregation scale $S_a = 7\ days$. (b) during autumn season above 2000 m a.s.l. with an aggregation scale $S_a = 30\ days$. Rockfall probabilities are represented by the coloured dotted lines according to the decade as shown in the legend.

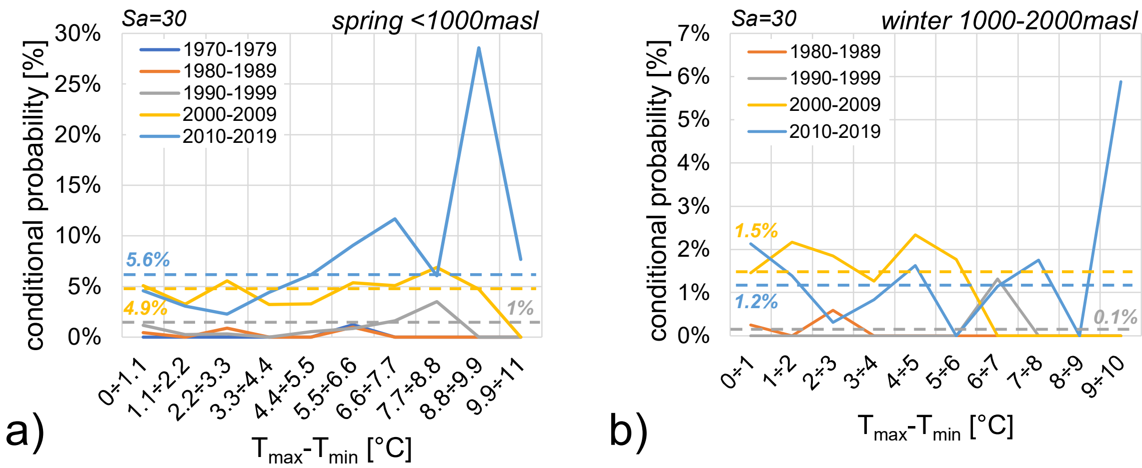


Figure 17. Conditional probabilities of rockfalls conditioned by ranges of temperature amplitude from 1970 to 2019: (a) during spring season below 1000 m a.s.l.; (b) during winter season between 1000 m-2000 m a.s.l.. Rockfall probabilities are represented by the coloured dotted lines according to the decade as shown in the legend.

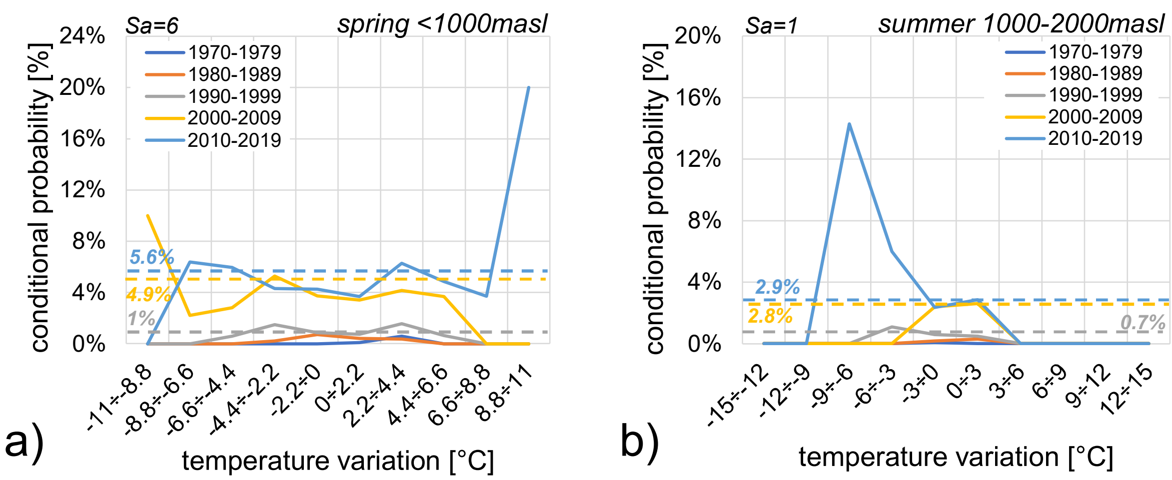


Figure 18. Conditional probabilities of rockfalls from 1970 to 2019 during: (a) summer season between 1000-2000 m a.s.l. and (b) during spring season below 1000 m a.s.l.. Rockfall probabilities are represented by the coloured dotted lines according to the decade as shown in the legend.

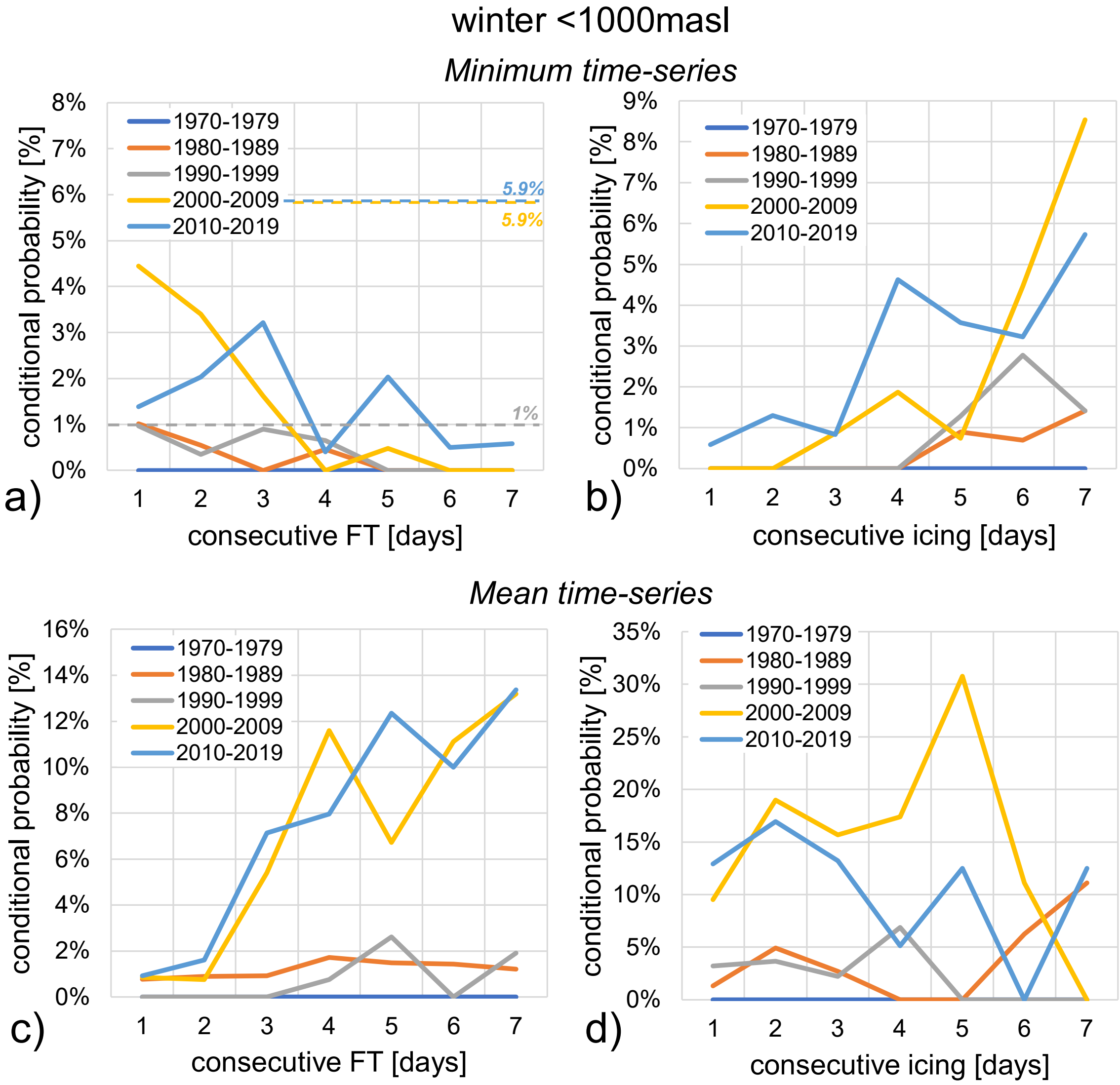


Figure 19. Conditional probabilities of rockfalls during winter below 1000 m a.s.l. from 1970 to 2019 with a 7 days aggregation scale: (a and c) triggered by freeze-thaw cycles with minimum and mean times-series; (b and d) triggered by icing with minimum and maximum time-series. Rockfall probabilities are represented by the coloured dotted lines according to the decade as shown in the legend.

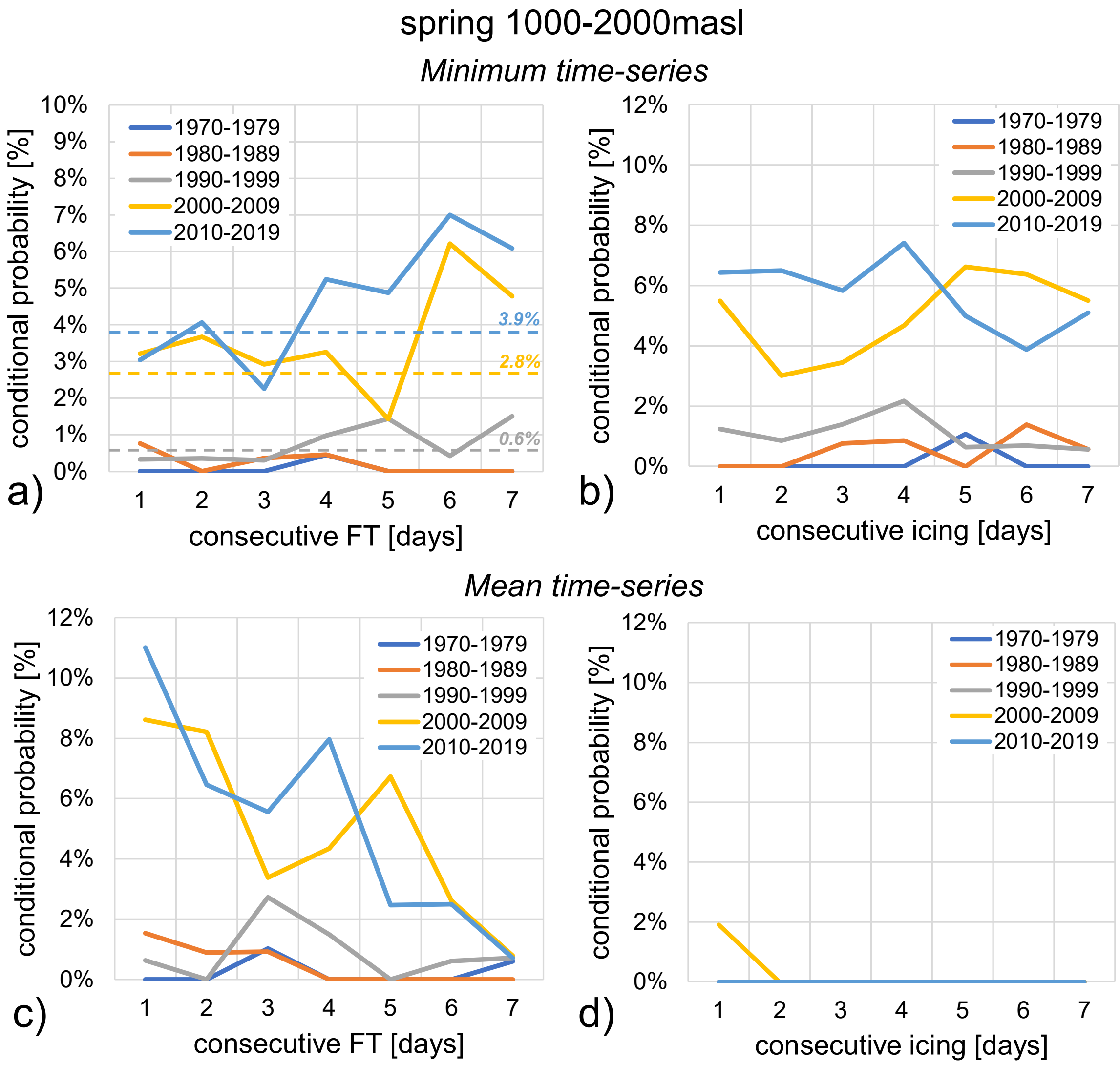


Figure 20. Conditional probabilities of rockfalls during spring between 1000 m a.s.l. and 2000 m a.s.l. from 1970 to 2019 with a 7 days aggregation scale. (a and c) triggered by freeze-thaw cycles with minimum and mean times-series. (b and d) triggered by icing with minimum and maximum time-series. Rockfall probabilities are represented by the coloured dotted lines according to the decade as shown in the legend.

- Comment:

Line 410-413: Not clear. Equation 10 gives the expression of $P(R/M_i)$ and not $P(M_i/R)$. Please name explicitly the variables considered.

- Authors response

The reviewer is right. In the new paragraph we clearly describe all the probabilities.

- Reviewed version (from L 195 to L 205)

Let Rf represent the set of rockfall events under analysis, and M_i the set of recorded data falling within a specific i-th interval of the meteorological variable. The conditional probability $P(Rf|M_i)$ that rockfall events occur, conditioned on the meteorological variable being within the range $i-th$, can be obtained as follows:

$$P(Rf|M_i) = P(M_i|Rf)\frac{P(Rf)}{P(M_i)}$$

where $P(Rf)$ is the overall rockfall daily probability, calculated dividing the number of rockfall events by the number of days of observation; $P(M_i)$ is the daily probability of the meteorological variable falling within the $i-th$ range, calculated dividing the number of days with the variable within that range by the number of observation days; and $P(M_i|Rf)$ is the probability of the meteorological variable being in the $i-th$ interval when a rockfall event occurs, calculated as the number of rockfall events occurred with the variable within that range divided by the total number of rockfall events.

- Comment:

I suggest to complete the presentation of the RAPS method with this sentence: "A trend of the rainfall is suggested by a parabolic trend of the RAPS (downward parabola for an increase)". See the figure 3 in Garbrecht and Fernandez, and the comment in the same page. A trend on the RAPS plot must not be confused with a trend of the rainfall.

Lines 517-519. The trends mentioned by Garbrecht and Fernandez are trends on the RAPS plot, but not trends for the annual rainfall. They highlight a shift that was the result of the relocation of the station. After correction no trend for the rainfall is mentioned. So, I suggest to suppress these lines. Also, to avoid any confusion, I suggest to modify the lines 520-526 as follows: " In this work, RAPS analysis by altitude, was performed considering the 12 meteorological stations (Figure 20). Below 1000m, from 1974 to 2001, an upward parabola on the RAPS plot shows a downward trend of the rainfall and a from 2005 to 2019, a down ward parabola on the RAPS plot shows an upward trend of the rainfall. In 2002, a sharp increase is noted, likely corresponding to high rainfall events in May and November (Bollettino meteorologico e valanghe, Ufficio idrografico di Bolzano; Protezione Civile Provincia Autonoma di Trento). Between 1000m and 2000m, the downward parabola shows an increase of rainfall for the whole period, which accelerates from 2005. Above 2000 m, the downward parabola from 2003 to 2019 shows an increase of rainfall for this period.

- Reviewed version (from L 313 to L 320)

For stations below 1000 m (Figure 4a) the RAPS values decrease from 1985 to 2008, followed by a sharp increase in the most recent years, indicating that rainfall tended to be higher than the mean value after 2008. A notable exception was observed in 2002, which documented a significant peak (red arrow in Figure 4a), likely corresponding to high rainfall events in May and November (as reported by Bollettino meteorologico e valanghe, Ufficio idrografico di Bolzano; Protezione Civile Provincia Autonoma di Trento). For stations between 1000m and 2000m (Figure 4b), a progressively increasing trend in rainfall is suggested by the downwards parabolic trend of the RAPS. Finally, above 2000m (Figure 4c), the RAPS plot exhibits a V-shape, reaching a minimum in 2007, followed by a sharp increase in the last decade.

- Comment:

Figure 20. Equation 14 implies that RAPSn = 0, as can be seen in the figures of Garbrecht and Fernandez. Yet, it is not the case in Fig. 20 of the manuscript. Is there a error in the calculation?

- Authors response

The review is right at the $k = n$ the RAPS has to be zero. We checked the computation and we find the error and consequently we modify the figures. See corrected figures in the previous Reviewer 1 comment.

- Comment:

Line 564-570. This paragraph is not clear. To be significant, the number of anomalies should be reported to the number of rockfalls in each season, range of elevation or range of volume.

I suggest to highlight this point: For rainfall, it appears that positive anomalies are much more frequently positive than negative (Fig. 21a-b), showing that large cumulated rainfall favours rockfall occurrence.

- Authors response

Thanks to reviewer. We modified the figure according to your suggestions and we plotted the frequencies of the anomalous events according to the same meteorological variables used by Paranunzio et al. (2016) but using the strategy shown in meteorological analysis. This choice was made to make comparable the results obtained by Paranunzio's method and those proposed by us. Consequently, we modified the text content to adapt the manuscript to the new figure and the corresponding observations. According to new figure the distinction between positive and negative anomalies was aggregated into the anomalous events frequencies because the comparison with our results was meaningless with this distinction.

- Comment:

Figure 21. Do ST, LT, WT in the figure correspond to daily, weekly, monthly and quarterly in the text? This is not clear. Please use the same terms and give explicitly the aggregation scale in the legend. What is the difference between points and bars in Fig. 21 c and d?

- Authors response

The reviewer is right. After the modification of figure 21 this problem was solved since the same approach used in the previous analyses. This was mandatory in order to make the proposed results comparable with those of Paranunzio.

- Reviewed version (from L 626 to L 655)

To further validate our approach, we adapted and tested the method of Paranunzio et al. (2016) in this study, comparing the results obtained with its method to those obtained using our proposed method starting in both cases from the dataset reported in this work. We analyzed the same climate variables (precipitation and mean air temperature) at identical aggregation scales (daily, weekly, monthly, and quarterly). Additionally, we investigated temperature variations (ΔT) over 1, 3, and 6 days prior to the event. The non-exceedance probability P(V) was calculated and an event is considered anomalous when its non-exceedance probability is less than $\alpha/2$ or is greater than $1.0-\alpha/2$ being α a significance level that is equal to $\alpha=0.2$ as indicated in Paranunzio et al. (2016). The obtained results are reported in Figure 21 where the frequencies of the anomalous events are reported according to the corresponding meteorological variables. For all considered variables the frequencies of anomalous events increase with the decades and more frequent anomalous events are located in the middle of the range of the considered values for each variable. This result could be due to the definition of non-exceeding probability that was estimated ordering the recorded data values. This implies that the first values in the rank could be relative higher but not the highest in the meteorological station. In contrast the conditional probability has greater values for high values of meteorological variables. This difference is attributed to the method employed for computing the conditional probability in which the meteorological probability is computed for all ranges even those in which the rockfall events did not occurred. Finally, temperature variations have to peaks one associated to negative values and another one to positive. This result is attributed to the fact that the same temperature variation could occur for increasing temperature (temperature variation positive) and for decreasing temperature (temperature variation negative) and since the anomalous events correspond to a symmetric value of non-exceeding probabilities (positive and negative anomalies) two peaks appeared.

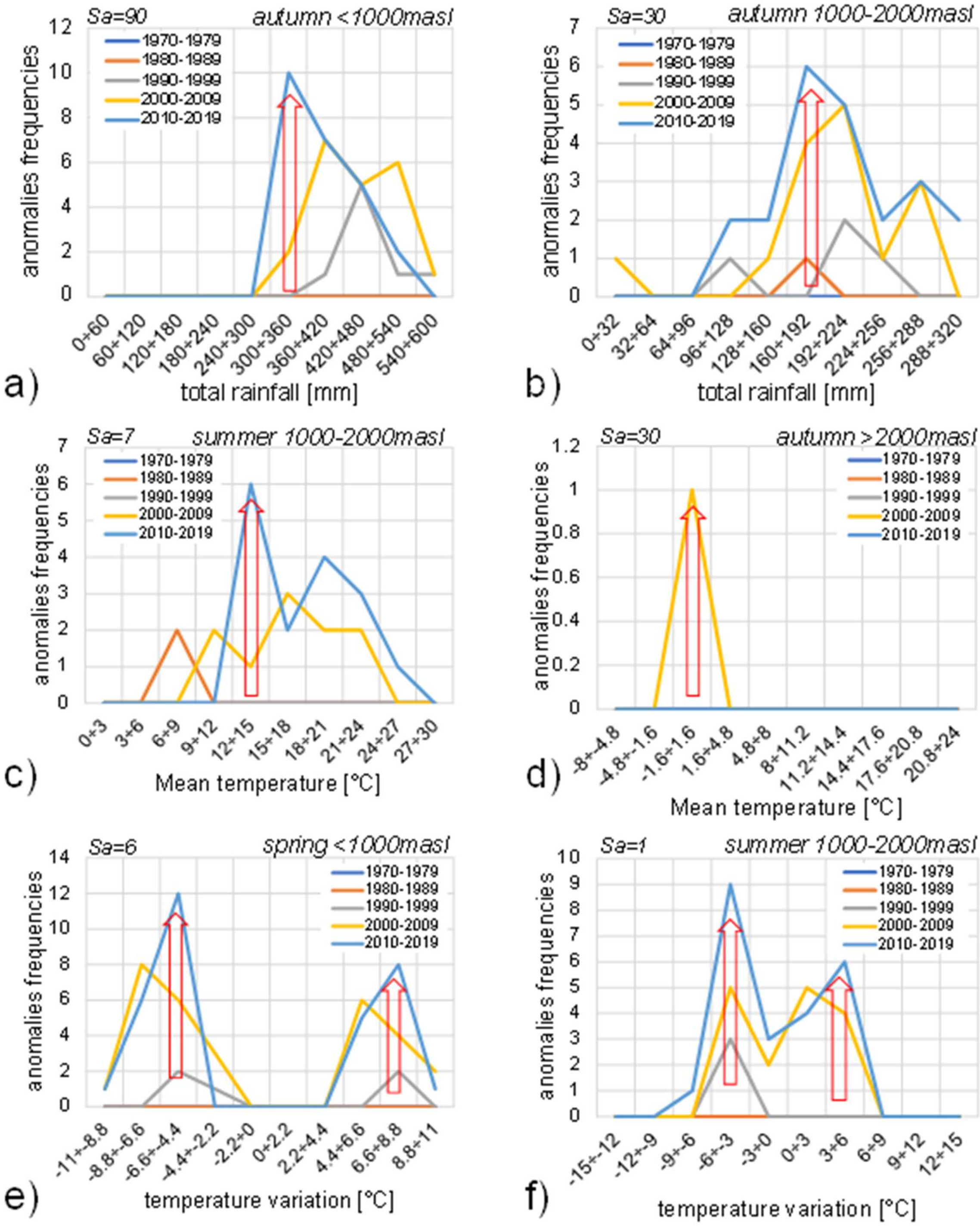


Figure 21 Distributions of anomaly frequencies by using Paranunzio et al. (2015) method, categorized by climate variable and aggregation scale as applied in this analysis. Only results for rainfall, temperature amplitude and temperature variation, as presented in Section 4.3, are reported.

Due to the complexity of meteorological but also lithological and morphological conditions under which the rockfall occurred, this analysis does not allow to unravel into detail the mechanisms why a weather variable has different effects according to the season or elevation. For such detail, it should be necessary to constrain the analysis by considering only rockfalls occurring on single lithological and morphological settings through a detailed multitemporal survey that allows to focus on specific weather variables, e.g. thermal stress (Collins and Stock, 2016; Gasc-Barbier et al., 2024; Fei et al., 2025), freeze-thaw (D'Amato et al., 2016), or rainfall (Weidner et al., 2024).