1950–2100 climate trends in avalanche activity in Haute-Maurienne, French Alps

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Abstract. TS1 Avalanche activity in alpine regions is sensitive to climate change. However, without consistent historical data, it is challenging to estimate past trends in avalanche activity and assess future avalanche scenarios from climate projections. To tackle this challenge, we use avalanche observations and simulated snowpack conditions to train a machine learning gradient-boosting regression model, which predicts the number of avalanches per day. We focus on a small alpine domain with high-quality data: the Haute-Maurienne valley in the French Alps, where avalanche paths span elevations from approximately 1800 to 2700 m a.s.l. First, we demonstrate that accounting for the uncertainties in avalanche occurrence dates and using only the most recent period (2006–2023) with homogeneous observations during the training step is essential for achieving consistent results. We then use this machine learning model to reconstruct the past avalanche activity (1958–2023) from reanalysed meteorological and snow data, and to project future avalanche activity (1950–2100) from a downscaled ensemble of snow-climate simulations. We evaluate climatic trends in avalanche activity using three indicators: the number of avalanches per winter season, the number of avalanches per month, and the annual maximum number of avalanches in one week, which quantifies the largest avalanche cycles. Based on reanalysed snow-climate simulations, the model estimates that avalanche activity decreased in the past: the mean number of avalanches per year declined by ~~4.7~~ % per decade between 1958 and 2023, with a stronger decrease in spring avalanche activity, and the 30-year return level associated with large avalanche cycles decreased at a slower rate of ~~1.7~~ % per decade. In the future, avalanche activity is also expected to decrease. For the emission scenarios RCP4.5 and RCP8.5, the annual number of avalanches is expected to decrease by 4.6 % per decade and 8.8 % per decade, respectively, mainly due to a reduction in spring avalanche activity. Large avalanche cycles, quantified by the 30-year return level, are also expected to decrease in intensity but at slower rates: 2.2 % per decade for RCP4.5 and 5.5 % per decade for RCP8.5. This study quantifies the impact of climate change on avalanche activity in an exemplary alpine valley. It demonstrates that combining statistical learning with climate simulations can help produce reference scenarios for mitigation strategies in high mountain environments.

1 Introduction

Snow avalanches are rapid mass movements of snow down a steep slope (Schweizer et al., 2003). They represent a significant natural hazard in snow-covered mountainous regions, threatening human lives, settlements, and infrastructure. Studying avalanche risk is essential in populated areas of mountainous regions, such as the European Alps, due to the economic and human stakes involved (Fuchs et al., 2007; Cappabianca et al., 2008; Eckert et al., 2012; Techel et al., 2016). In these areas, mitigation strategies are mandatory and mainly rely on heavy protective structures or restrictive land-use policies, which are designed to remain effective over several decades (Höller, 2007). Therefore, implementing effective risk mitigation strategies requires anticipating potential non-stationarity in risk components, among which is the possible impact of climate change on avalanches (Fuchs et al., 2013; Eckert and Giacona, 2023).

Table 3. Scores for the four models. Training periods are expressed as winter seasons denoted by the year in which they end (e.g. 2007–2023 corresponds to the winter seasons spanning from 2006/2007 to 2022/2023). The mean absolute errors correspond to a number of avalanches. The values in brackets are percentages calculated from the average value of each indicator. The model in bold is the one selected for the rest of this study.

Model version	Training period	Uncertainties on the triggering date	Annual MAE	Monthly MAE	Worst week MAE
$\boldsymbol{M_{d_1-d_2}^{2007-2023}}$	**2007–2023**	**taken into account**	**32.5 (26.5 %)**	**2.3 (16.9 %)**	**4.5 (12.5 %)**
$M_{d_1-d_2}^{1961-2023}$	1961–2023	taken into account	56.6 (46.2 %)	5.9 (43.7 %)	14.9 (41.2 %)
$M_{d_2}^{2007-2023}$	2007–2023	not taken into account	50.8 (41.5 %)	5.3 (39.3 %)	8.7 (24.2 %)
$M_{d_2}^{1961-2023}$	1961–2023	not taken into account	56.8 (46.4 %)	5.5 (41.0 %)	18.8 (52.3 %)

fined indicators of avalanche activity (Fig. 6). In addition, we compute the temporal linear trends of these indicators using a Bayesian framework (Abril-Pla et al., 2023). The linear trends are systematically expressed in % per decade relative to the 1975–2005 climatology, with its median value and the 10th–90th percentile posterior credible interval.

The predicted number of avalanches per winter season shows large inter-annual variability but an average decreasing trend (Fig. 6a). For instance, years with more than 200 avalanches are rather frequent (approximately every three years on average) before the late 1980s and become rare thereafter. As expected, the trends from the raw observations are completely off from these assessments, which highlights that raw observations over a long period may be affected by sampling biases. Quantitatively, our model predicts a median decreasing linear trend of ~~−4.7~~ % per decade in the annual number of avalanches over the period 1958–2023, with a 10th–90th percentile credible interval ranging from ~~−9.9~~ % to +0.4 % (Appendix Fig. A1).

The decrease of the annual number of avalanches is not uniform during the winter season as shown by contrasting 30-year periods at the beginning and at the end of the dataset: 1958–1988 and 1993–2023 (Fig. 6b). For instance, the resulting trends indicate a median slope of ~~−1.5~~ % (with a credible interval ranging from ~~−7.5~~ % to ~~+4.5~~ %) per decade in the avalanche activity in December, January, and February (DJF) and of ~~−8.4~~ % (between ~~−13.2~~ % and −3.5 %) per decade in March, April and May, with a peak at −14.3 % for the April avalanche activity (Appendix Fig. A1). Therefore, the decrease in avalanche activity in the past has been greater in spring than in winter.

The weekly maximum number of avalanches for each winter season is shown in Fig. 6c. As we use a Bayesian framework to fit the GEV distribution on the data, the slope distribution of the return levels is directly provided within the inference procedure. The results show a decreasing slope of the 30-year return level by ~~−1.7~~ % (between −7.3 % and ~~+3.9~~ %) per decade relative to the mean return level between 1975 and 2005. This downward trend is less significant than the one observed in the total number of avalanches, suggesting that the magnitude of large cycles has decreased at a lower rate than the total number of avalanches.

3.3 1950–2100 climate simulations

The same machine learning model is applied to all members of the climate simulations (18 per scenario), and the avalanche activity is quantified by the three previously defined indicators. In contrast to the single reanalysis, the linear trends derived from climate simulations for a given scenario are not only made uncertain by the inter-annual variability but also by the inter-model variability. To compute the probability distribution function of the trend slope, we arbitrarily assumed that all GCM/RCM pairs are equiprobable and evaluated the overall credibility interval by pooling posterior samples derived from individual projections (see Appendix Fig. A1).

The annual number of avalanches clearly shows a decreasing trend under advanced climate change and its consequences for snowpack characteristics (Fig. 7a). The mean number of avalanches in the historical simulations is around 25 % higher than that in the reanalysis. However, the trends are similar with a historical decrease at a median rate of −5.9 % per decade, but with large uncertainties (10th–90th percentile posterior credible interval ranging from −17.1 % to ~~7.7~~ %). The projections for the 21st century show a decrease in the annual number of avalanches at median rates of −4.6 % per decade for the RCP4.5 scenario and −8.8 % for the RCP8.5 scenario with respect to the period spanning from the winter seasons 1975 to 2005. The associated uncertainties are shown in Table 4. In other words, the results indicate a reduction of approximately 37 % (respectively 65 %) in the mean number of avalanches over the 2070–2100 period compared with the 1975–2005 baseline in the RCP4.5 scenario (resp. RCP8.5).

The expected decline of avalanche activity is heterogeneous between seasons (Fig. 7b). First, the higher number of avalanches predicted by historical climate simulations compared to the reanalysis mainly arises from stronger activity in March and April, while DJF avalanche activity is broadly consistent between the two datasets. Then, the projected

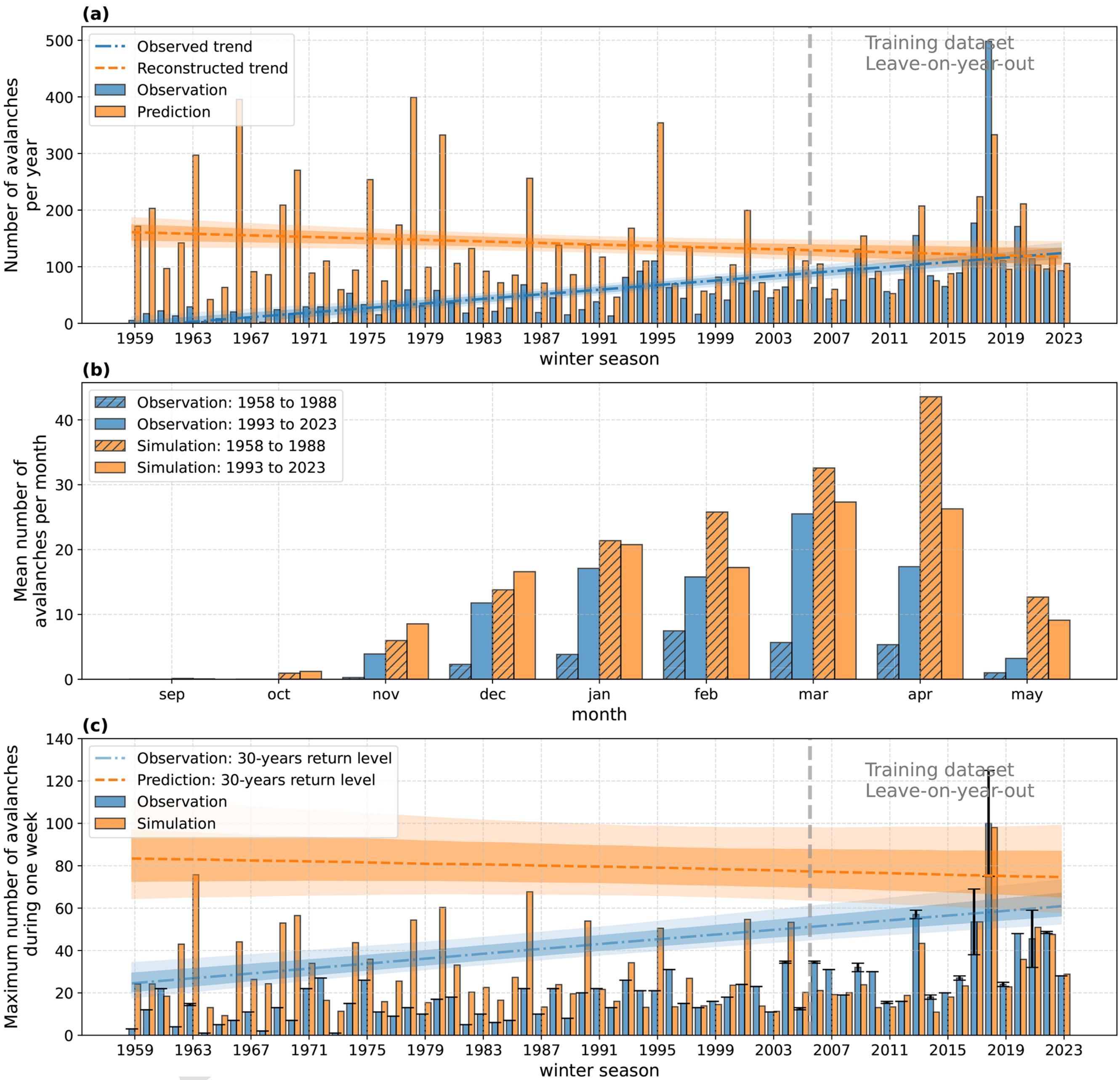

Figure 6. Past avalanche activity: **(a)** annual number of avalanches, **(b)** mean number of avalanches per month, **(c)** maximum number of avalanches per week. The model predictions are shown in orange. The raw observations are shown in blue. For panels **(a)** and **(c)**, linear trends are represented with their 10, 25, 50, 75, 90th percentiles.

lower rate for RCP4.5 and a higher rate for RCP8.5 (Fig. 7c). Yet, considering the credible intervals, for the near future (2020–2050) or under the RCP4.5 scenario at all temporal horizons, large avalanche events with intensities comparable to those observed during the 1975–2005 reference period remain possible with a similar probability. Indeed, the 30-year return levels show respective trends of −2.2 % per decade and ~~−5.1~~ % per decade for the RCP4.5 and RCP8.5 scenarios relative to the mean return levels computed from the historical runs between winters from 1975 to 2005. In other words, the 30-year avalanche cycle is expected to be composed of approximately 15 % (resp. 35 %) fewer avalanches in 2100 compared to the 1975–2005 reference period in the RCP4.5 scenario (resp. RCP8.5).

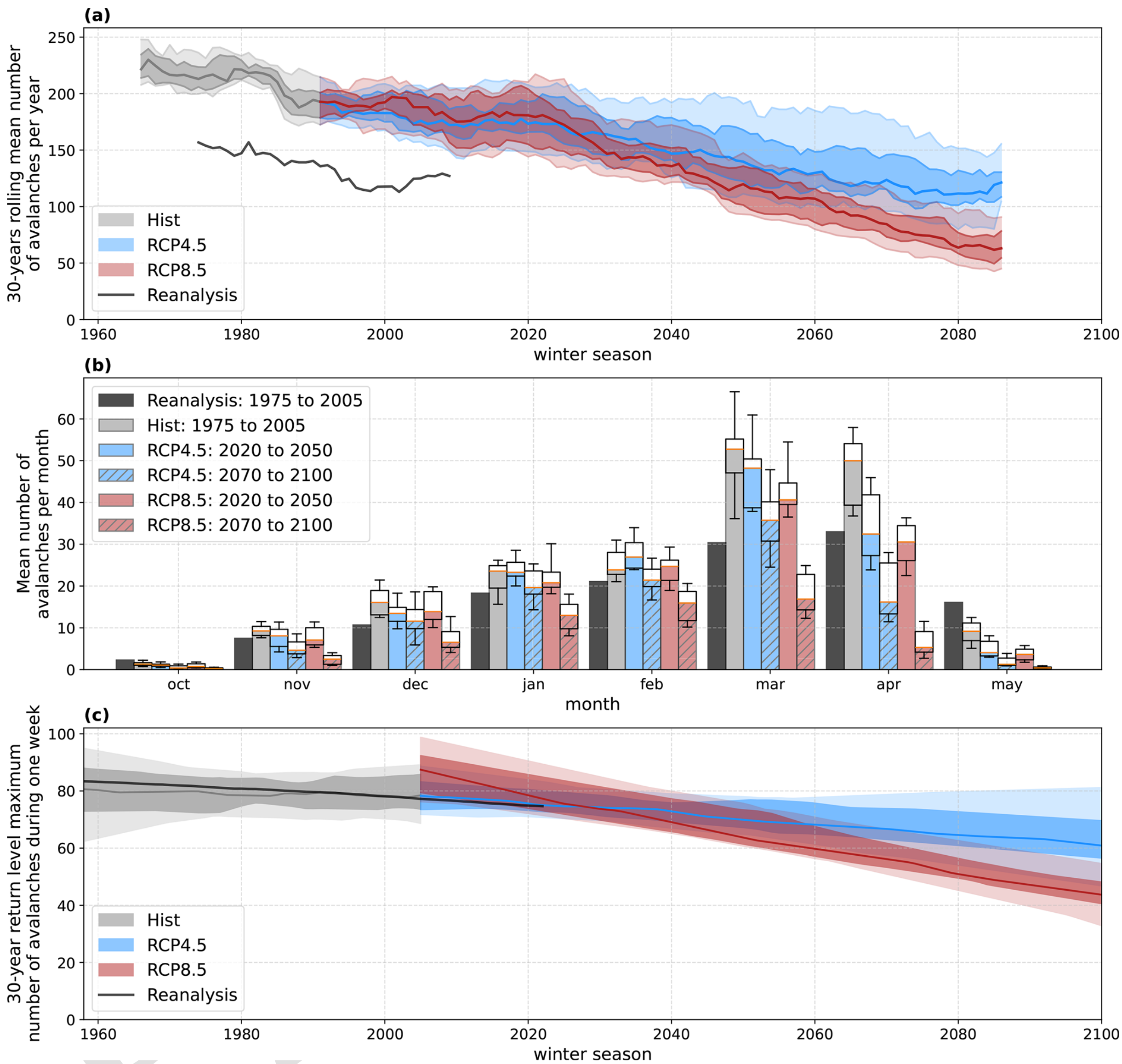

Figure 7. Climate simulations of avalanche activity: **(a)** 30-year running mean of the annual number of avalanches, **(b)** mean number of avalanches per month over different periods and **(c)** 30-year return level of the maximum number of avalanches per week.

Table 4. Median values and 10th–90th percentile posterior credible interval associated with the slope of the avalanche activity indicators in the future in % per decade with respect to the 1975–2005 period. The associated ensemble distributions are represented in Appendix Fig. A1.

	RCP4.5: 2005–2100 (% per decade)	RCP8.5: 2005–2100 (% per decade)
Annual number of avalanches	−4.6 [−8.7, −0.9]	−8.8 [~~−12.4~~, −5.5]
Number of avalanches in DJF	−3.1 [−8.0, 1.3]	−6.9 [−11.6, −1.8]
Number of avalanches in MAM	−5.4 [−10.8, −1.7]	−10.0 [~~−14.0~~, −7.0]
30-year return level of the maximum number of avalanches during 1 week	−2.2 [~~−5.9~~, 1.7]	−5.5 [~~−9.0~~, −2.3]

rather than absolute values, which are more prone to systematic biases. Moreover, Cannon et al. (2015) analyzed the impact of bias correction via quantile mapping on extreme precipitation and concluded that quantile mapping can inflate the magnitude of relative trends in precipitation extremes with respect to the raw dataset. A specific treatment of extreme values is used in ADAMONT: for RCM values greater than the 99.5 % quantile, the quantile mapping method is not applied and a constant adjustment is applied to allow for new extremes (Verfaillie et al., 2017). This treatment of the extreme values might be better than a simple quantile mapping method, but may be insufficient to capture the correct trends in the extreme values. Future work should therefore focus on more advanced extreme-value frameworks to better constrain the upper tail and assess the robustness of the projected changes in the extreme events.

4.3 Climate trends in avalanche activity

The past trend in avalanche activity based on the S2M reanalysis (1958–2023) shows a decrease in the mean annual number of avalanches between 1958 and 2023, at a rate of approximately ~~6~~ % per decade. Based on the S2M reanalysis and the raw EPA dataset without any prior statistical pre-processing, Castebrunet et al. (2012) found no significant trend in avalanche occurrences at the scale of the Northern French Alps between 1958 and 2009. Using a more advanced statistical treatment of the EPA dataset, Eckert et al. (2013) found a decrease of 19 % in the mean number of avalanches per winter between 1980 and 2009 in the entire French Alps, which corresponds to approximately 6 % per decade, in line with our result. We also showed that the decrease in avalanche activity is more pronounced during spring, which is consistent with Reuter et al. (2025) who reported an advancement of about 3 weeks of the onset date of wet-snow activity from 1958 to 2020. Moreover, we found that the magnitude of large avalanche cycles, quantified by the maximum number of avalanches during 1 week, decreased by around ~~2.2~~ % per decade, at a lower rate compared to the annual number of avalanches. Peitzsch et al. (2021) used dendrochronology analysis in the Rocky Mountains and demonstrated that the probability of large avalanche occurrence decreased by approximately 2 % per decade from 1950 to 2017. Although this metric is not directly comparable to our results, since we analyze avalanche counts during one week rather than the occurrence of large avalanches, both metrics address changes in the frequency of large avalanche cycles over time.

Regarding future climate simulations, our results are in agreement with the small number of existing studies that provide quantitative assessments, which consistently report a marked decrease in the mean annual avalanche occurrence. Mayer et al. (2024) reported a decrease in the number of avalanche days between the periods 1990–2020 and ~~2969~~–2999, with the magnitude of the decrease depending on station elevation. At the station with the lowest elevation (1824 m, similar to the Haute-Maurienne valley floor), the number of avalanche days declined by approximately 30 % under the RCP4.5 scenario and by about 60 % under the RCP8.5 scenario. At higher altitudes, between 2300 and 2800 m, this decline is less pronounced, reaching around 10 % in the RCP4.5 scenario and 20 % to 30 % in the RCP8.5 scenario. Mayer et al. (2024) also showed that seasonality in dry-snow avalanche activity (characterized by peaks in January and February) remains mostly unchanged while the wet snow avalanches are expected to appear earlier in the season and decrease in number in April and May. Taking into account all avalanche problems, it leads to a significant reduction in spring avalanches. Similarly, in the Rocky Mountains, the wet avalanches are expected to start earlier than historical averages (around 40 to 45 d earlier in the high emission scenario) (Lazar and Williams, 2008). This is consistent with our findings which indicate a drop in the number of avalanches in April and May, especially in the RCP8.5 scenario. More generally, the observed decrease in the annual number of avalanches appears to be largely associated with the shortening of the avalanche season, as discussed in Kruyt et al. (2023). We also found that the return levels of large avalanche cycles are expected to decrease, but at a slower rate than the mean avalanche activity. This is consistent with the results of Ortner et al. (2025), which show that despite climate change, some locations continue to be at high risk of avalanches. Furthermore, Bonsoms et al. (2025) demonstrated that the mean daily snowfall in the Pyrenees at 2500–3000 m will decline significantly and emphasize that extreme snowfall events will change only slightly. Similarly, Le Roux et al. (2023) demonstrated that the expected decrease in the 100-year return level of daily snowfall is slower than the expected decrease in the mean annual maximum value. This illustrates that a decrease in mean conditions does not necessarily imply a proportional decrease in extreme values.

The snowpack conditions in the Haute-Maurienne valley are rather specific: a relatively high valley floor compared to typical alpine valleys and substantial precipitation associated with eastern flows. Therefore, the spatial generalization of these results should be addressed in future work. In particular, future analyses should explicitly account for the influence of elevation on avalanche activity, given its major role in modulating the impacts of climate change on snowpack conditions (Dumont et al., 2025) and extreme snowfall events (Le Roux et al., 2023). Based on documented changes at low elevations (Giacona et al., 2021) and high elevations (Ballesteros-Cánovas et al., 2018), a conceptual framework describing elevation-dependent avalanche activity has been proposed by Eckert et al. (2024). However, further investigations are required to provide quantitative assessments of these elevation-dependent effects.

5 Conclusions

This study aims to better understand the impact of climate change on avalanche activity in the European Alps using an exemplary alpine valley. This study brings methodological improvements and provides quantified trends for several indicators of avalanche activity.

This study focuses on the upper part of the Haute-Maurienne valley in the French Alps, a region offering several advantages for the analysis of avalanche activity. In particular, it benefits from a long-term avalanche observation dataset documenting numerous events on well-identified avalanche paths over several decades, collected using a methodology that is as homogeneous as possible over time. To model avalanche activity, we combined meteorological and snowpack modeling, using the SAFRAN reanalysis for past conditions and an ensemble of climate simulations for future projections, together with the Crocus snowpack model. This framework provides consistent meteorological and snowpack variables at the massif scale, which are used as predictors of avalanche activity.

This study introduces a machine learning regressor to predict the daily number of avalanches, going beyond previous works based on binary classification. Unlike classifiers, it provides insight into the magnitude of avalanche activity and enables the use of quantitative indicators for trend analysis. The model was trained only on post-2006 data to avoid biases from inconsistent historical observation records, and the training step accounts for uncertainties in the reported avalanche release date, which significantly reduces prediction biases and errors. The proposed chain model is generic and can be transferred to other regions where simulated meteorological and snowpack data, together with systematic avalanche observations, are available.

This study shows a clear long-term decline in avalanche activity linked to climate warming. In the past, both reanalysis and historical climate simulations indicate a clear downward trend in the annual number of avalanches. The reanalysis exhibited a trend of ~~−4.7~~ % per decade over the 1958–2023 period (relative to the 1975–2005 baseline). In the historical climate simulations (1950–2005), the median trend is estimated at −5.9 % per decade. This decline is seasonally heterogeneous, mainly driven by a sharp reduction in spring avalanches (March–May), while winter activity (December–February) remains relatively stable. The 30-year return level of the weekly maximum number of avalanches shows a decline of ~~−1.7~~ % per decade for the reanalysis from winter seasons 1959 to 2023. This suggests a moderate decrease in extreme avalanche events, although less pronounced than the decline in total avalanche numbers.

For the future, we used an ensemble of 18 GCM/RCM couples for the RCP4.5 and 8.5 emission scenarios. The projected evolution of avalanche activity over the historical period (1950–2005) is consistent with the decline observed between 1958 and 2005. Under RCP4.5 and RCP8.5 scenarios, the annual number of avalanches is expected to decrease by 4.6 % per decade and 8.8 % per decade, respectively (relative to the 1975–2005 baseline). By the end of the century, this corresponds to a 37 % reduction under RCP4.5 and 65 % under RCP8.5 compared to 2025. Again, while winter activity remains relatively stable, spring avalanches (March–May) are projected to nearly disappear, leading to a substantial shortening of the avalanche season. Extreme events are also expected to decrease, but at more moderate rates, with return levels expected to decrease by 2.2 % per decade and 5.5 % per decade under RCP4.5 and RCP8.5 scenarios relatively to the 1975–2005 winter seasons.

Our results show a marked decrease in avalanche activity in the Haute-Maurienne valley, both in terms of frequency and intensity, particularly driven by a sharp reduction in spring avalanches. However, unlike lower-elevation ranges such as the Vosges (Giacona et al., 2017) where avalanche activity has nearly disappeared in the 20th century due to natural and anthropogenic warming, avalanches remain a frequent and significant phenomenon in the Haute-Maurienne. This highlights the persistence of avalanche risk in high alpine environments, even under ongoing climate change. Future work should explore how evolving snow and weather regimes may continue to reshape the spatial and temporal patterns of avalanche activity in mountainous regions.

Appendix A: Hyper-parameters

The gradient boosting model's optimal hyper-parameters depend on its predictors. The choice of hyper-parameters was informed by expert knowledge. For instance, the maximum depth of the trees was set to 6, the default value that prevents overfitting while maintaining sufficient model complexity. The *subsample* and *colsample by tree* parameters have been set to 0.7 and 0.8 respectively, to prevent overfitting. Regularization tends to reduce the predicted probability of rare events. Setting *lambda* to zero allows the model to predict rare events. They are summarized in Table A1. Furthermore, the results show that the scores (defined in Sect. 2.4.4) are not greatly affected by the chosen hyper-parameters, demonstrating that the model is robust.

Table A1. Hyper-parameters values chosen in the machine learning model.

Hyper-parameter	Selected value
max depth	6
eta	0.1
subsample	0.7
colsample by tree	0.8
alpha	0
lambda	0