Enhanced summer convection explains observed trends in extreme subdaily precipitation in the northeastern Italian Alps

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Key Points:

- We present a method for analyzing extreme precipitation trends based on the separation of storm intensity and occurrence frequency
- Our approach reproduces observed trends in annual maxima and allows to quantify trends on rare return levels
- Observed trends in the eastern Italian Alps are explained by an increased proportion of heavy convective storms in the summer

Abstract

Understanding past changes in precipitation extremes could help us predict their dynamics under future conditions. We present a novel approach for analyzing trends in extremes and attributing them to changes in the local precipitation regime. The approach relies on the separation between intensity distribution and occurrence frequency of storms. We examine the relevant case of the eastern Italian Alps, where significant trends in annual maximum precipitation over the past decades were observed. The model is able to reproduce observed trends at all durations between 15 minutes and 24 hours, and allows to quantify trends in extreme return levels. Despite the significant increase in storms occurrence and typical intensity, the observed trends can be only explained considering changes in the tail heaviness of the intensity distribution, that is the proportion between heavy and mild events. Our results suggest these are caused by an increased proportion of summer convective storms.

Plain Language Summary

Quantifying past trends in extreme rainfall is important because it can help us understand future changes caused by global warming. Climate scientists and hydrologists use specific statistical models to to do so, but interpreting the results is complicated because extremes are rare and the structure of the models is not linked to the local meteorology. We use a new statistical model that allows to better understand the mechanisms behind the trends we detect. We find that extreme rainfall in the easter Italian Alps increased over the past decades and we associate this change to an increased proportion of summer thunderstorms.

1 Introduction

Understanding past and future changes in extreme subdaily precipitation intensities is of enormous interest because they are responsible for flash floods, urban floods, landslides and debris flows, and cause numerous casualties and huge damages every year (Borga et al., 2014; Cristiano et al., 2017; Paprotny et al., 2018). Physical laws translate increasing atmospheric temperature into increasing water vapor holding capacity. Together with changes in the atmospheric dynamics, this is expected to drive future precipitation changes (Trenberth et al., 2003; Pendergrass et al., 2020; Fowler et al., 2021b). In general, larger reponses are expected for precipitation extremes because mean precipitation, on a global scale, is limited by energy constraints (Allan and Soden, 2008; Pendergrass & Hartmann, 2014). However, detecting changes in extreme precipitation is highly affected by the stochastic uncertainty characterizing the sampling of extremes. This uncertainty may mask the influence of climate forcing on the processes which locally control the extremes (Fatichi et al., 2016; Marra et al., 2019).

Statistically significant changes in the frequency of extreme precipitation in the past decades were reported, often with stronger trends in subdaily extremes, as opposed to daily (Guerreiro et al., 2018; Markonis et al., 2019; Papalexiou & Montanari, 2019). In some cases, opposing trends between short and long durations emerged, with complex implications for flood risk (Zheng et al., 2015). Available observations show different temporal trends for precipitation intensities associated to different exceedance probabilities (Schär et al., 2016; Pendergrass, 2018). In general, increasing trends are reported for rarer events (Myhre et al., 2019), but the specific differences depend on duration, season, and local conditions, such as the dominating meteorological features contributing extremes (Blanchet et al., 2021; Moustakis et al., 2021).

Extreme return levels characterized by different exceedance probabilities are thus changing at different rates (Myhre et al., 2019; Marra et al., 2021).

Nonstationary extreme value models could aid the detection and quantification of trends in extreme precipitation of different exceedance probability (e.g., Min et al. 2009). However, the information these models can provide is impacted by stochastic uncertainties (Serinaldi and Kilsby, 2015; Fatichi et al., 2016), and their flexibility is limited by the assumptions concerning high order statistical moments. In fact, due to intrinsic limitations in parameter estimation accuracy, the shape (and sometime also the scale) parameter of the extreme value distribution is assumed to be constant (Prosdocimi and Kjeldsen, 2021). Additionally, due to the structure of these statistical models, a link between the properties of the underlying process, such as precipitation occurrence frequency and intensity distribution, and extremes is difficult to establish (e.g. Marra et al., 2019). As such, the possibility to attribute the observed changes to specific physical and meteorological processes is hampered.

This background suggests that there is a need to move beyond traditional trend detection techniques applied to extremes only and develop novel methodologies. These methods should be able to detect general changes in extreme precipitation at multiple durations, quantify changes at different exceedance probabilities, and attribute these to changes in the underlying physical processes.

A recent methodology for extreme precipitation frequency analysis, termed Metastatical Extreme Value (MEV) (Marani and Ignaccolo, 2015), provides grounds for addressing these issues. The approach relies on the concept of *ordinary events*, that is all the independent realizations of a process of interest, and proved highly effective in reducing stochasting uncertainties (Zorzetto et al., 2016; Marra et al., 2018). As opposed to traditional methods, MEV assumes the distribution describing the ordinary events is known, and derives an extreme value distribution by explicitly considering (i) occurrence frequency of the ordinary events, and (ii) inter-annual variability of their intensity distribution and of their occurrence frequency. Multiple types of ordinary events and their temporal changes can be directly considered in the formalism (Marra et al., 2019). The parameters describing the ordinary events intensity distribution and their yearly number are thus treated separately, and are estimated on a yearly basis, providing great potential for trend detection and attribution studies (Miniussi and Marani, 2020; Marra et al., 2021).

Here, we combine a novel approach for ordinary-events-based precipitation frequency analyses across durations (Marra et al., 2020) with a regional trend detection technique to: (a) detect and quantify trends in sub-daily annual maxima and extreme return levels by independently considering the changes in statistical properties and occurrence frequency of storms, and (b) attribute the observed trends in extremes to specific changes in the local precipitation regime. We examine the relevant case of the eastern Italian Alps, where consistent significant changes in annual maximum precipitation intensities at subdaily and daily duration were reported (Libertino et al., 2019).

2 Data and methodology

2.1 Study area and data

We focus on Trentino, a 6000 km^2-wide mountainous area in the Eastern Italian Alps (**Figure 1**a) which experienced significant increases in extreme short-duration rain intensities over the last decades (Libertino et al., 2019). Mean annual precipitation varies from ~1300 mm yr^{-1} in the south-eastern portion of the area to lower amounts (~900 mm yr^{-1}) typical of the "inner alpine province" in the north (Borga et al., 2005). A dense network of more than one hundred rain gauges is present. From these, 33 stations (density ~1/190 km^{-2}) with at least 25 complete years (<10% missing data) of 5-minute resolution data in the period 1986-2019 are selected (**Figure 1**a; see Table S1 in the Supporting Information).

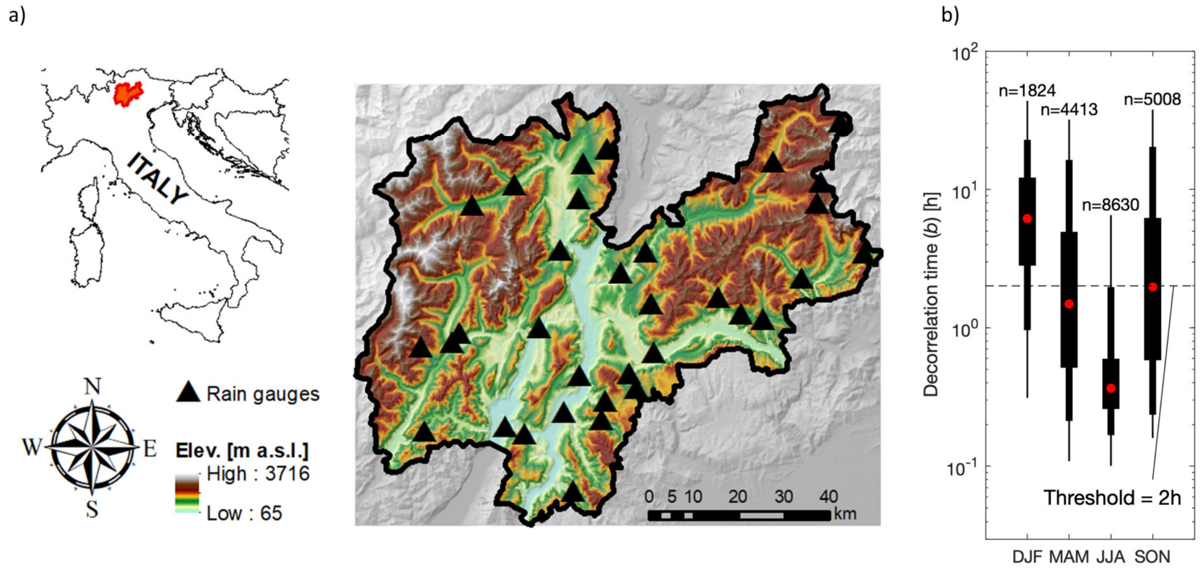

Figure 1. **a)** Location ad orographic structure of the study area and location of the rain gauges used in this study; b) Decorrelation time of the highest 25% ordinary events organized by season. The red dots indicate the median values; bars indicates percentiles: 25-75th, 5-95th, 1-99th. The number of storms occurred across the stations in each season is reported.

2.2 Methodology

The MEV approach expresses the cumulative distribution $\zeta(x)$ of extreme return levels x as a function of the yearly cumulative distributions of the ordinary events $F(\cdot)$ and their yearly number of occurrences (Marani and Ignaccolo, 2015; Zorzetto et al., 2016):

$\zeta(x) = \frac{1}{M}\sum_{j=1}^{M} F\left(x, \boldsymbol{\theta}_j\right)^{n_j}$, where $\boldsymbol{\theta}_j$ are the parameters describing the yearly distribution $F(\cdot)$ in the j-th year, n_j the corresponding number of ordinary events, and M is the number of years in the record. Indirectly, this formalism allows us to quantify return levels from individual years using the $\zeta_j(x) = F\left(x; \boldsymbol{\theta}_j\right)^{n_j}$, thus allowing to directly quantify trends in return levels themselves.

Previous studies show that subdaily precipitation intensities require three- (or more) parameters distributions to be fully described (Papalexiou et al., 2018). However, their right tails can be well approximated using a two-parameter distribution which, in many cases, is found to be a Weibull distribution (e.g., Zorzetto et al. 2016; Marra et al., 2020). This means that a portion of their distribution including the extremes can be approximated as $F(x, \lambda, \kappa) = 1 - e^{-\left(\frac{x}{\lambda}\right)^{\kappa}}$, where λ is a scale parameter and κ is a shape parameter which determines the tail heaviness:

higher shape parameters are associated to lighter tails, and vice versa (see Figure S1). In particular, the tail is sub-exponential for $\kappa > 1$, exponential for $\kappa=1$, and heavier than exponential for $\kappa < 1$. The number of yearly events modulates the tail of the extreme value distribution $\zeta(x)$.

The here presented analysis is based on the storm-based definition of ordinary events proposed by Marra et al. (2020). For each station, "storms" are defined as wet periods separated by dry hiatuses of predefined length. We define as wet all the 5 min time intervals reporting at least 0.1 mm of precipitation, and separate storms using 24 hr dry hiatuses. A minimum duration of 30 min for a single storm is set to avoid individual tips to be considered as storms. Ordinary events are then defined as the maximum intensities observed over the duration of interest in each storm (details in Marra et al., 2020). Durations between 15 min to 24 hr are explored. For each station and duration, we derive temporal series of ordinary events and, for each year, we estimate parameters of the Weibull distribution by left censoring the portion of data which is deemed not representative of the tail. We use the least-squares method in Weibull-transformed coordinates (Marani and Ignaccolo, 2015). The choice of the left-censoring threshold follows the test described in Marra et al. (2020): the distribution parameters are estimated for different thresholds by explicitly censoring the observed annual maxima; the maxima are then compared to the sampling confidence interval from the estimated distribution to assess whether they could be likely samples. Following the method suggested in Marra et al. (2019), we select the 75th percentile of the ordinary events for the left-censoring. This is in line with previous findings in different areas (Marra et al., 2019; Marra et al., 2020). It should be recalled that the selection method implies a low sensitivity of the results to this threshold. After left-censoring, an average of ~14 ordinary events per year are used for parameter estimation. Yearly return levels are obtained by inverting the equation for $\zeta_j(x)$ (Zorzetto et al., 2016). In this way, we obtain, for each station, yearly series of scale parameter, shape parameter, number of ordinary events, and return levels. Annual maxima (AM) series are also extracted.

We investigate the presence of monotonic trends in these quantities using the Regional Mann-Kendall test at the 0.05 significance level (Mann, 1945; Kendall, 1975; Helsel & Frans, 2006), and we quantify the average rate of change using the nonparametric Sen's slope estimator (Sen, 1968). Serial correlation in the series was tested and found negligible. In case trends within the region are heterogeneous, the slope and significance estimated by the Regional Mann-Kendall test could be misleading (Gilbert, 1987). We verify the homogeneity among the trends at the different sites in the area by applying the Van Belle and Hughes test (1984). We find that homogeneity is verified for all the investigated variables. As spatial correlation among nearby stations could decrease the power of regional test, we include the correction proposed by Hirsch and Slack (1984).

The null hypothesis of the Mann-Kendall test is true (i.e., no trend) when about half of the pair comparisons between ordered each data points is concordant and half discordant. Considering that 2 yr return levels correspond to the theoretical median of the AM, we consider the estimated trend on the 2 yr return levels as our model quantification of the trend in the AM.

The ability of our statistical model to reproduce observed trends in AM is verified by accounting for stochastic uncertainty in a Monte Carlo framework. For each station i, year j and duration d, n_{ijd} Weibull-distributed ordinary events are generated according to the distribution parameters λ_{ijd} and κ_{ijd}, and the AM are extracted. The procedure is iterated 1000 times (which was found to provide coherent estimates of the 90% confidence interval), to obtain 1000 synthetic regional sets of AM series for each duration. The Regional Mann-Kendall test is then performed on these sets to obtain 1000 slopes estimates for each duration, which provide a quantification of the stochastic uncertainty in the trends of the modelled AM.

A sensitivity analysis is performed for evaluating the relative impact of trends in the model parameters on the emerging trend in the modelled AM. For each station and duration, the trends on modelled AM are computed using different combinations in which inter-annual variability in the parameters is either considered or ignored. In the latter case, the median parameter is used. We thus obtain the following cases: one case with 3 time-varying parameters (real case), 3 combinations of 2 varying and 1 constant parameter, 3 combinations of 1 varying and 2 constant parameters, and one case of 3 constant parameters (no-change). Then the Regional Mann-Kendall test is applied to the resulting series.

Changes in the seasonal proportions between convective-like and other event types in different seasons are explored to investigate the seasonal and physical mechanisms underlying the observed trends. Events exceeding the left-censoring threshold at any of the durations are organized by seasons. The temporal decorrelation of the rain intensity timeseries is used as a proxy for broadly distinguishing between convective-like and other types of storms. The decorrelation time (**Figure 1**b) is taken equal to the scale parameter of the exponential fitting of the temporal autocorrelation. This is thus the time lag at which the temporal autocorrelation drops to e^{-1}. The average (across stations) number of storms belonging to the two groups is calculated for each season, and the significance and slope of their trend is estimated using the Mann-Kendall test ($p=0.05$) and the Sen's slope estimator. This shows if temporal changes in the proportion of different event types in the seasons emerged. A 2 hr threshold is found to optimally describe (that is, optimize the statistical significance) the temporal changes in our data and is therefore used as a proxy for distinguishing between convective-like (decorrelation time $\leq$ 2 hr) and other event types (> 2 hr). Qualitatively analogous outcomes are obtained with thresholds between 1 and 3 hr.

3 Results and discussion

3.1 Regional trends on multi-duration extremes

Slopes for the regional trends for the nine investigated durations are reported in **Figure 2**a. Hereinafter, slopes are normalized over the median value of each variable and expressed as percent change per year. As expected (Libertino et al., 2019), observed AM show positive trends at all durations. Statistically significant trends are observed for durations below 6 hours and stronger increases for hourly and sub-hourly durations. The slopes estimated using the MEV model ("modelled AM" in **Figure 2**) lie within the 90% confidence interval due to stochastic uncertainty (grey area), indicating that they are likely samples from our model. This means that the model well reproduces the trends in the observed AM.

The annual number of storms, uniquely defined for all durations (Marra et al., 2020), shows a significant increase (4% yr^{-1}) (**Figure 2**b). Trends in the scale parameter of the intensity distributions are always positive, indicating a general increase in the intensity of the largest 25% of the ordinary events, with larger and significant increases (up to 8-9% yr^{-1}) for multi-hour durations (**Figure 2**b). The shape parameter shows negative trends for sub-hourly durations and positive trends for longer durations (**Figure 2**b), indicating that the proportion between heavy and mild events changed in different ways for short and long durations: increased tail heaviness is reported for sub-hourly durations and decreased tail heaviness for multi-hour durations (see

Figure S1 for a visual interpretation of the effect of the shape parameter on tail-heaviness). At short durations the changes in the two parameters have a synergistic impact on extremes. Although the trend in individual parameters is not significant, observed and modelled AM experience stronger and significant changes. In contrast, at longer durations the changes in the parameters have opposing impact on extremes, and AM exhibit weaker increases, despite the significant increase of both scale parameter and yearly number of storms. In particular, where tail-heaviness has its strongest significant decrease (increase in the shape parameter), trends in extremes are at a minimum and are not significant.

These findings indicate that in the examined period (1986-2019) and area, AM exhibit significant changes, in particular for short-duration intensities, in agreement with previous studies (Libertino et al., 2019). Overall, our statistical model reproduces these trends accurately, and allows us to investigate the underlying statistical mechanisms. Changes in AM seem to be mostly influenced by changes in the tail-heaviness of the ordinary events, although trends in the shape parameter itself are not statistically significant.

3.2 Sensitivity of the changes in annual maxima to changes in intensity, occurrence frequency and tail heaviness of the ordinary events

We investigate the sensitivity of the trends in AM to trends in the individual model parameters (**Figure 2**c). The 'real' case in which all parameters change with time reproduces the trends in the modelled AM (line 1 in **Figure 2**c). The other lines are a combination of varying and constant (median) parameters. Notably, the significant increase (+4% yr^{-1}) in the number of yearly storms only has a marginal impact on the overall trends in extremes (same-color pairs of lines). Synergistic and opposing impacts of the other parameters are mostly evident by comparing the constant scale-parameter case (line 2) with the constant tail-heaviness case (line 3). When no changes in tail-heaviness are considered, AM show increasing trends whose magnitude can even increase with duration, instead of decreasing (lines 3, 7). This sensitivity analysis shows that little changes in the tail-heaviness (shape parameter) turn into large changes in extreme intensities, suggesting this is an important parameter explaining the observed AM trends in the region. Crucially, without considering changes in tail heaviness it is not possible to explain the large observed increase in short-duration AM, as well as the different response of short and long duration extremes. This has profound implications for change-permitting extreme value models in which tail heaviness is often assumed to remain constant.

3.3 Regional trends of extreme return levels

Our statistical model allows to directly quantify changes on specific rare return levels. In general, slopes are always significantly positive for sub-hourly durations and decrease with increasing duration until they lose significance for durations above 2-3 hr (**Figure 2**d). For higher return levels, this behavior is enhanced: higher positive slopes are estimated for subhourly durations and lower slopes for multi-hour durations, even approaching no-trend or negative-trend behaviours for 25 and 50 yr return levels and 12-24 hr duration. There is a duration interval between 1 and 2 hr where the trends don't depend on return period, closely following the change in regime in which the trend in the shape parameter crosses zero, that is no change in tail heaviness.

The here adopted statistical framework gives the opportunity to quantify and evaluate the statistical significance of trends in rare return levels of interest for hydrological design and risk management. It could be argued that estimating rare quantile on a yearly basis should lead to unberable uncertainties. We showed here that the statistical significance of trends in yearly-modelled return levels as high as the 50 yr events is comparable to the statistical significance of trends in AM, suggesting a similar signal to noise ratio. Trends on extreme return levels estimated on yearly basis from our model are thus characterized by stochastic uncertainties comparable to the ones of AM.

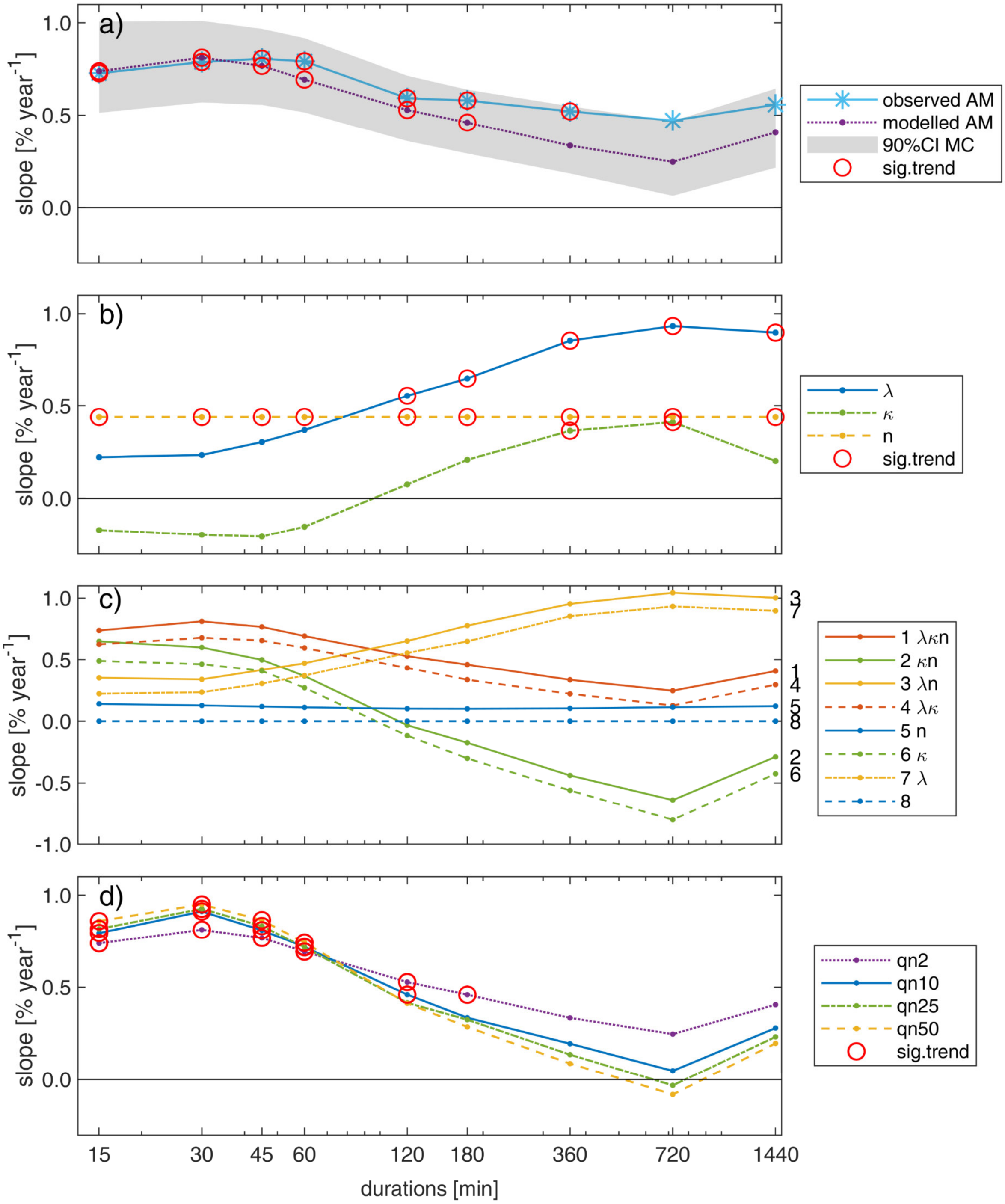

Figure 2. a) Slopes of the regional trends at different durations for observed and modelled AM; significant trends (p=0.05) are marked; stochastic uncertainty associated with the modelled AM (90% C.I. of the MonteCarlo simulation) is also reported. **b)** Slopes of the regional trends for the model parameters: scale parameter (λ), shape parameter (κ), and yearly number of storms (n); significant trends (p=0.05) are marked. **c)** Sensitivity of the modelled trends to combinations of changes and no-changes in the model parameters; series labels report the parameters which are allowed to change. **d)** Slopes of the regional trends for some estimated return levels (2, 10, 25, 50 yr); significant trends (p=0.05) are marked; note that the 2 yr return levels correspond to the modelled AM.

3.4 Changes in the proportion of convective-like events

The parametrization of our model allows us to formulate hypotheses about the physical processes underlying the detected changes. In particular, the observed changes could be explained by an increased number of intense convective events, which would mainly contribute to the short duration annual maxima. We analyze possible changes in the number of storms occurring in different seasons, and in the seasonal number of convective-like and other types of storms (**Figure 3**). The significant positive trend in the yearly number of storms reported above is fully explained by a significant increase in the number of storms in autumn (SON, **Figure 3**a) and a non-significant increase in winter (DJF). However, examining changes in the types composition shows no distinct increase in convective-like storms during these seasons (**Figure 3**b, c).

Conversely, although no trend emerges in the number of storms in summer (JJA), the number of summer convective-like storms in this season increased significantly, while the number of other storms decreased significantly (**Figure 3**b, c). This implies a significant increase in the proportion of summer convective-like events. Since convective-like storms are generally associated with heavy intensities at short durations, this change in composition could explain the observed increase in tail heaviness at short durations, and thus the observed trends on short-duration AM. This is confirmed when the parameters of the ordinary events distribution are examined considering spring-summer (MAMJJA) and autumn-winter (SONDJF) separately (Figure S2). These results suggest that the significant positive trends found for short-duration extremes are mostly related to changes in summer storms, and that these can be related to changes in the intensity distributions (increasing tail-heaviness) induced by an increasing proportion of heavy convective-like storms in the summer.

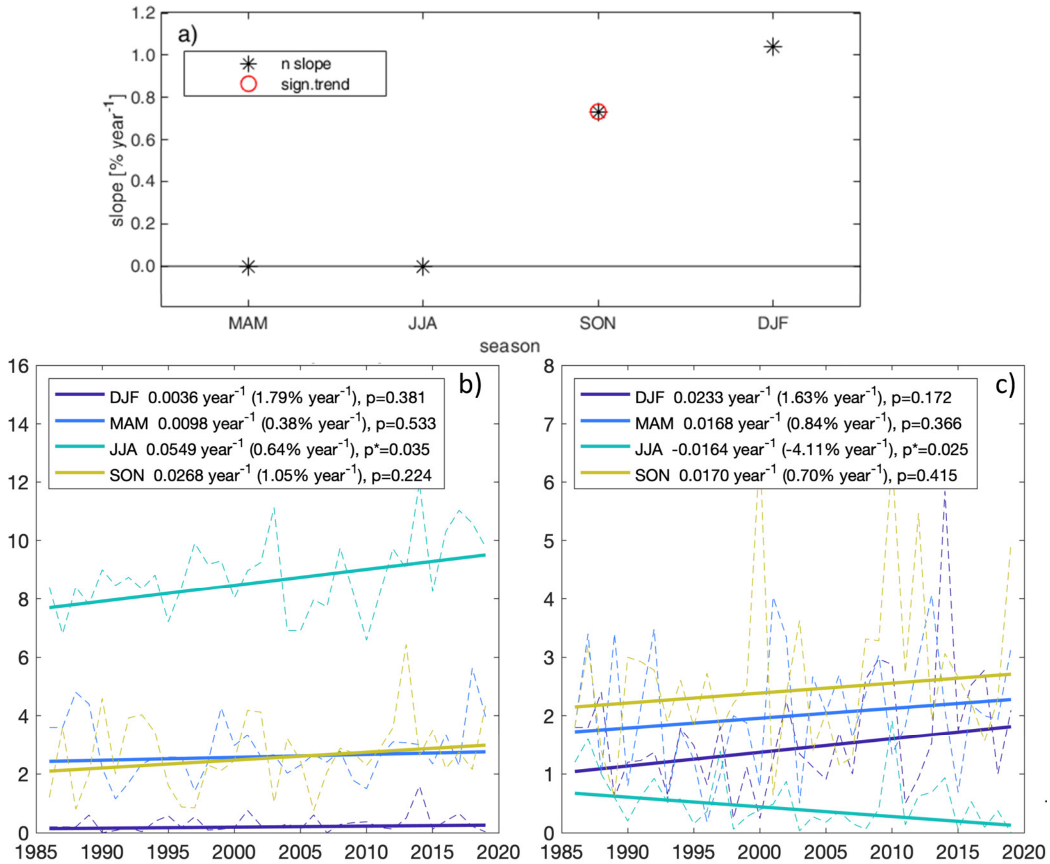

Figure 3. a) Slope of the regional trends for the number of seasonal storms; significant trends (p=0.05) are marked. **b)** Average (across stations) seasonal number of convective-like (decorrelation time < 2 hr) and **c)** other (decorrelation time > 2 hr) storms; the Sen's slope and the p-value of the Mann-Kendall test are reported; asterix (*) indicates significant trends (p=0.05).

5 Conclusions

We examine changes in extreme sub-daily precipitation intensities for the relevant case of the eastern Italian Alps, where consistent significant changes in annual maximum (AM) intensities were reported (Libertino et al., 2019). Specifically, we aim at detecting and quantifying trends in sub-daily AM and extreme return levels, and linking the observed trends in extremes to specific changes in the local precipitation regime. To do so, we adopt a novel unified framework for extreme value analyses based on ordinary events, and we quantify trends by means of the regional Mann-Kendall test. With respect to traditional change-permitting extreme value models, the here presented method provides a statistical tool for better quantifying changes in extremes in spite of the large stochastic uncertainties, and for better understanding the observed changes by separately considering multi-duration storm intensity distributions and storm occurrence frequency. The approach can be expanded to direcly consider different types of storm events (Marra et al., 2019).

Results confirm the presence of significant positive trends in the AM. Trends in the 2 yr return levels estimated yearly using our model are consistent with the observed trends in AM. These trends are more marked for 15 min to 1 hr durations and less marked for 3 hr to 24 hr durations. The model parametrization allows to conclude that these trends are likely due to a combination of (i) increasing number of storm events per year and increasing intensity of the storms, and (ii) changes in the tail properties of the storms. In particular, an increasing, albeit not-significant, trend in tail heaviness at short durations seems to mostly explain the changes in AM and return levels. A significant increase in the proportion of convective-like storms is detected during the summer (JJA). This could explain the observed trends in AM and return levels emerged at the short durations in the previous analyses, and is in agreement with results reported by Fowler et al. (2021a), who highlight that the stronger increases in short-duration extremes are related to feedbacks in convective clouds dynamics at the local scale.

The here-reported trends are derived from a relatively short data series and should be considered as representative of the examined period only (1985-2019). Due to decadal climate variability, they should not be considered as representative of climate change in general, nor extrapolated to predict future conditions (Iliopoulou and Koutsoyiannis, 2020). Nevertheless, considering the increasing attempts of the scientific community to quantify changes in hydrometeorological extremes with rare yearly exceedance probability, our model could provide insights for better describing local climatologies under change, and for extending our understanding of changes in the underlying physical processes. This information can be valuable for improving our ability to create and use process-based change-permitting statistical models for hydrometeorological extremes.

Data Availability Statement

Precipitation data was provided by the Provincia Autonoma di Trento and can be retrieved from https://www.meteotrentino.it (Accessed: October 2020). The codes used for the MEV analyses are available at https://doi.org/10.5281/zenodo.3971558. The executable for the Regional Mann-Kendall test (Helsel & Frans, 2006) was downloaded from https://pubs.usgs.gov/sir/2005/5275/downloads.

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