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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

Supporting Information:

Supporting Information may be found in the online version of this article.

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Enhanced Summer Convection Explains Observed Trends in Extreme Subdaily Precipitation in the Eastern Italian Alps

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Abstract Understanding past changes in precipitation extremes could help us predict their future dynamics. 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 and occurrence of storms. We examine the relevant case of the Eastern Italian Alps, where significant trends in extreme precipitation were reported. The model is able to reproduce the observed trends at all durations between 15 min and 24 hr, and allows us to quantify trends in extreme return levels. Despite the significant increase in storm 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 that the observed changes 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 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 rainfall extremes in the Eastern 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 (Pendergrass, 2020; Fowler et al., 2021a; Trenberth et al., 2003). In general, larger responses are expected for extreme precipitation because mean precipitation, on a global scale, is limited by energy constraints (Allan & Soden, 2008; Pendergrass & Hartman, 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 trends for precipitation intensities associated to different exceedance probabilities (Pendergrass, 2018; Schär et al., 2016). 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 to extremes (Blanchet et al., 2021; Moustakis et al., 2021). Extreme return levels characterized by different exceedance probabilities are thus changing at different rates (Marra et al., 2021; Myhre et al., 2019).

We define as *ordinary events* all the independent realizations of a process of interest (Marani & Ignaccolo, 2015)–for the case of precipitation, independent storms. Extremes emerge as the largest values sampled from these ordinary events. Traditional extreme-value approaches assume the ordinary events distribution is unknown and derive a cumulative distribution function which optimally fits the observed extremes (either the maximum values

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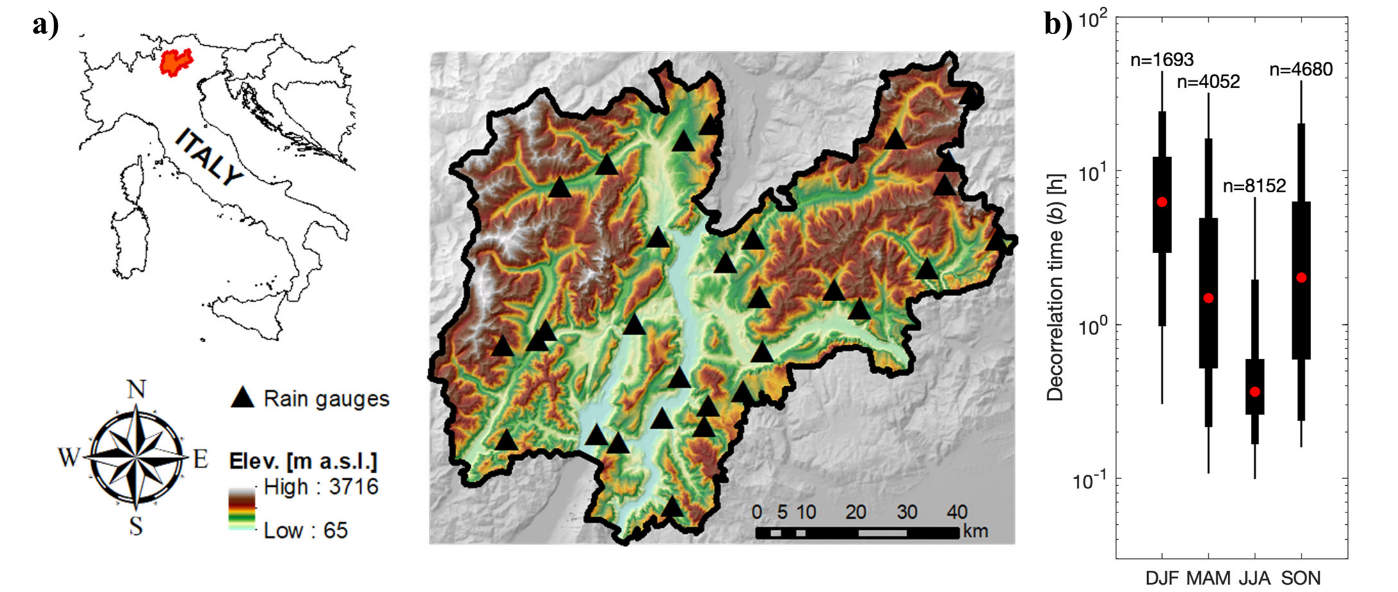

Figure 1. (a) Location and orography of the study area and location of the rain gauges used in this study; (b) Decorrelation time of the highest 25% ordinary events organized by season. The red dots indicate the median values; bars indicates percentiles: 25–75th, 5–95th, and –99th. The number of storms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

observed in each year or the values exceeding a high threshold; Coles, 2001). This approach is robust in that it does not require prior knowledge on the distribution of the ordinary events, but comes with two important shortcomings. First, extremes are rare: only a small part of the available information is used. This leads to important stochastic uncertainties, which make the use of these models under changing conditions challenging (e.g., Prosdocimi & Kjeldsen, 2021; Serinaldi & Kilsby, 2015). Second, only a finite number of storms occur every year: due to their structure, these models merge the information on the distribution of the ordinary events and on their yearly number. A link between the extremes and the properties of the underlying ordinary events (that is, the processes) is thus difficult to establish (e.g., Marra et al., 2019). The possibility to attribute observed changes to specific changes in the physical and/or meteorological processes is hampered. For example, Libertino et al. (2019) reported significant changes in the magnitude of precipitation annual maxima (AM) at local scales in Italy, but no hyphotesis could be formulated on the reasons behind these changes.

This background suggests that there is a need to move beyond traditional methods based on extremes only and develop novel methodologies able to tackle the two above shortcomings. Miniussi and Marani (2020) provided an application of a method able to leverage information from the ordinary events: extreme return levels could be computed over moving time windows with reduced stochastic uncertainties with respect to traditional methods. Conversely, the separation between storm frequency and intensity is still a key open question, and so is the identification of relations between changes in extremes and changes in the underlying storm properties.

In this paper, we present a novel approach to quantify and attribute changes in precipitation extremes which addresses both the need for reduced uncertainty and for separation of intensity and frequency. 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) analyze the changes in properties and occurrence frequency of storms, (b) detect and quantify trends in sub-daily AM and extreme return levels, (c) 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 subdaily and daily AM were reported (Libertino et al., 2019).

2. Data and Methodology

2.1. Study Area and Data

We focus on a 6,000 km^2-wide mountainous area in the Eastern Italian Alps (Figure 1a). Mean annual precipitation varies from ~1,300 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, 30 stations (density ∼1/200 km^{-2}) with at least 27 complete years (<10% missing data) of 5-min resolution data in the period 1991–2020 are selected (Figure 1a; Table S1 in Supporting Information S1).

2.2. Definition of the Ordinary Events

Ordinary events are all the independent realizations of a process of interest, in our case precipitation intensities at multiple durations. Our analysis is based on the storm-based identification of ordinary events proposed by Marra et al. (2020), in which "storms" are defined as independent meteorological objects, and "ordinary events" of given duration are extracted from the storms. 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 isolated tips to be considered as storms. This ensures accuracy in the model application with minimum data loss: in our study, at most one storm in the tail is missed every 6–7 years on average. 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 and 24 hr are explored: 15, 30, and 45 min, 1, 2, 3, 6, 12, and 24 hr.

2.3. Tail of the Ordinary Events Distribution

Previous studies show that subdaily precipitation intensities require three- (or more) parameter distributions (Papalexiou et al., 2018). However, their extremes can be well approximated using a two-parameter distribution. Thermodynamical reasoning (Wilson & Toumi, 2005) suggests that the extremes of the precipitation intensity distribution can be represented using a Weibull distribution (stretched-exponential). Numerous recent studies confirmed the suitability of this model for subdaily to daily precipitation intensities (e.g., Papalexiou et al., 2018; Marra et al., 2020; Zorzetto et al., 2016). This means that a portion of their distribution including the extremes, which is here termed "tail," 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. Larger shape parameters are associated to lighter tails, and vice versa (Figure S1 in Supporting Information S1). In particular, the tail is sub-exponential for $\kappa > 1$, exponential for $\kappa = 1$, and heavier than exponential for $\kappa < 1$.

The identification of the tail follows the test described in Marra et al. (2020), which we run for all the stations and durations. The distribution parameters are estimated from the whole record by censoring the values below different left-censoring thresholds as well as the observed AM. 10^3 synthetic samples of M years each one of n events (where M is the record length in years and n the average number of storms per year) are then extracted from the fitted distribution. The observed AM are then compared to the sampling confidence interval from these samples, 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 to define the tail. This is in line with previous findings in areas dominated by convective processes (Marra et al., 2019, 2020). It should be recalled that the selection method implies a low sensitivity of the results to this threshold, and that the test is rather strict: in the examined conditions (record length, yearly events number, 75th percentile as threshold) the probability of not-rejecting a Weibull tail in presence of power-type tail is close to zero, while the probability of rejecting a real Weibull tail is about 10%.

2.4. Extreme Value Model

The cumulative distribution $\zeta(x)$ of extreme return levels x emerging from the underlying distribution of ordinary events with tail $F(x;\lambda,\kappa)$ can be written as $\zeta(x) = F(x;\lambda,\kappa)^n$ (Marra et al., 2019; Serinaldi et al., 2020). When one considers the jth year of data, this formalism allows us to quantify return levels from individual years by inverting $\zeta_j(x) = F(x;\lambda_j,\kappa_j)^{n_j}$, where λ_j and κ_j are the parameters describing the ordinary events tail at the jth year and n_j is the number of ordinary events in the year.

The parameters describing the ordinary events distribution tail are computed at each station, duration and year by left-censoring the lowest 75% of the ordinary events and using the least squares method in Weibull-transformed coordinates (Marani & Ignaccolo, 2015). After left-censoring, an average of ∼14 ordinary events per year (including AM) are used for parameter estimation. Yearly return levels are obtained by inverting the equation for

$\zeta_j(x)$. In this way, we obtain yearly series of scale parameter, shape parameter, number of ordinary events and return levels for each station. AM series are also extracted.

2.5. Temporal Trends Analysis

We investigate the presence of monotonic trends in these quantities using the Regional Mann-Kendall test at the 0.05 significance level (Helsel & Frans, 2006; Kendall, 1975; Mann, 1945), 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). By applying the van Belle and Hughes test (van Belle & Hughes, 1984), we find that the homogeneity of the trends at the different sites in the area 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).

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

2.6. Validation of the Statistical Model

The ability of our statistical model to reproduce observed trends in AM is verified in a Monte Carlo framework, in order to account for stochastic uncertainty. For each station i, year j and duration d, n_{ij} 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 10^3 times (which was found to provide coherent estimates of the 90% confidence interval), to obtain 10^3 synthetic regional sets of AM series for each duration. The Regional Mann-Kendall test is then performed on these sets to obtain 10^3 slopes estimates for each duration, which provide a quantification of the stochastic uncertainty in the trends of the modeled AM. It is worth noting that this confidence interval is obtained by neglecting spatial correlation in the local exceedance probability of the events, and it is thus a lower limit to the true confidence interval. In fact, such a correlation would cause a loss of information in the regional pooling of the trend test, inflating the stochastic uncertainty in the outcome.

2.7. Differential Impact of Ordinary Events Change on Annual Maxima Changes

The relative impact of trends in the ordinary events properties on the emerging trend in the AM is evaluated. For each station and duration, the trends on modeled AM are computed using different combinations in which interannual 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.

2.8. Changes in the Proportion of Convective-Like and Other Types of Storms

Changes in the seasonal proportions between convective-like and other event types in different seasons are explored to investigate the seasonal processes underlying the observed trends. Events exceeding the left-censoring threshold at any of the durations are organized by seasons. The temporal decorrelation b of the rain intensity time series is used as a proxy for broadly distinguishing between convective-like and other types of storms. The decorrelation time (Figure 1b) is taken equal to the scale parameter of the exponential model fitting the temporal autocorrelation. This is the time lag at which the temporal autocorrelation drops to e^{-1}. For each station and season, the yearly number of storms belonging to the two groups is calculated, and the significance and slope of the regional trend is estimated using the Regional 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 1 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 ($b \leq 1$ hr) and other event types ($b > 1$ hr).

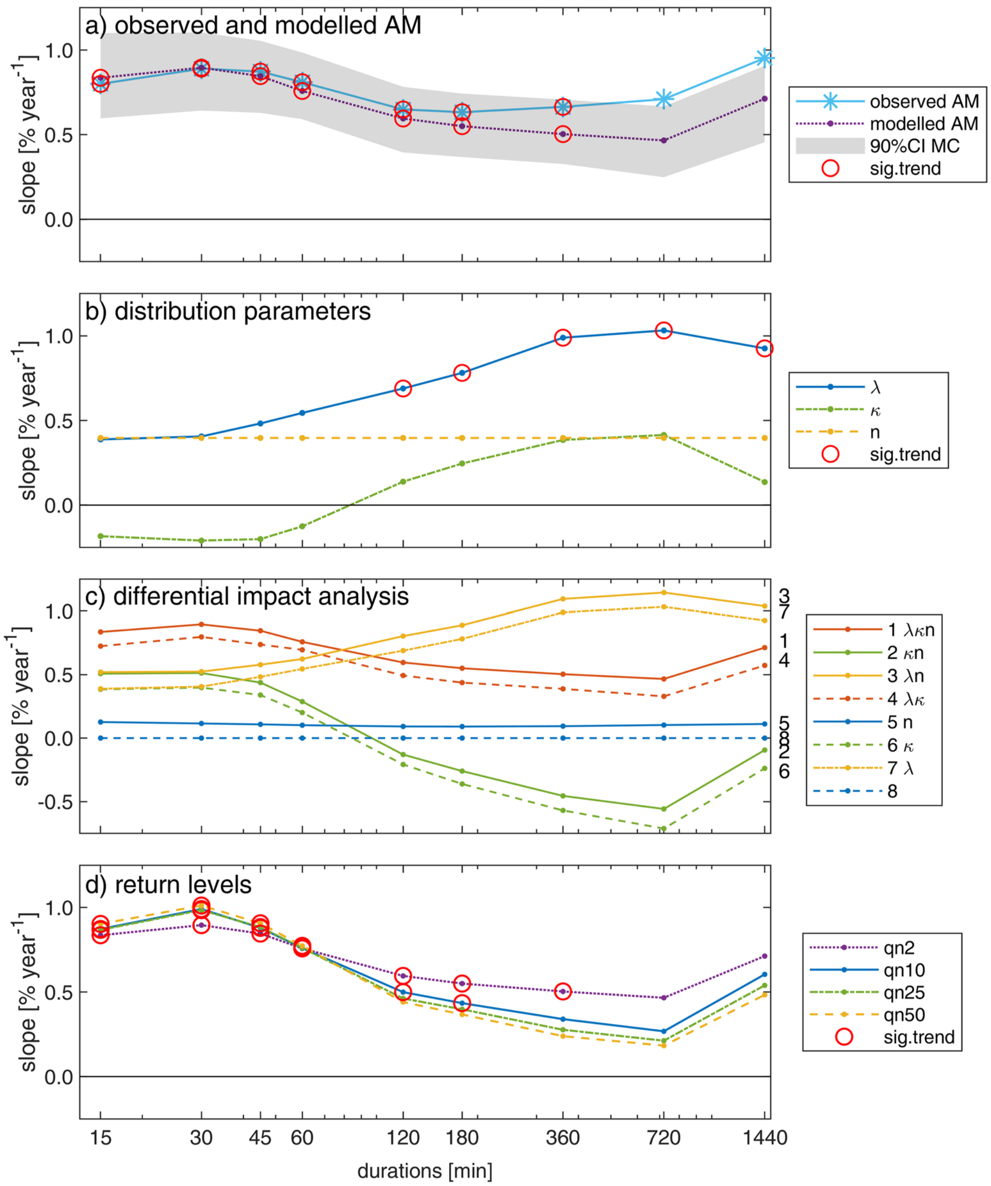

Figure 2. (a) Slopes of the regional trends at different durations for observed and modeled annual maxima (AM); significant trends (α-level = 0.05) are marked; stochastic uncertainty associated with the modeled AM (90% C. I. of the Monte Carlo simulation) is also reported. (b) Slopes of the regional trends for the model parameters: scale parameter (λ), shape parameter (κ), and yearly number of storms (n); significant trends (α-level = 0.05) are marked. (c) Differential impact on the modeled trends of 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, and 50 years); significant trends (α-level = 0.05) are marked; note that the 2 years return levels correspond to the modeled AM.

3. Results and Discussion

3.1. Regional Trends on Multiduration Extremes

Slopes for the regional trends for the nine investigated durations are reported in Figure 2a. 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 up to 6 hr and stronger increases for hourly and sub-hourly durations. The slopes estimated using the model ("modeled AM" in Figure 2) lie within the 90% confidence interval due to stochastic uncertainty (gray area), with the exception of the longest durations (12 and 24 hr). At longer durations, the confidence interval is likely underestimated due to a larger correlation in the exceedance probability of the ordinary events. This indicates that the observations are likely samples from our model, and 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 an increase (0.4% yr^{-1}) (Figure 2b). 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 1.0% yr^{-1}) for multi-hour durations (Figure 2b). The shape parameter shows negative trends for sub-hourly durations and positive trends for longer durations (Figure 2b), 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 in Supporting Information 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, modeled AM experience stronger and significant changes, which match the observed AM. In contrast, at longer durations the changes in the parameters have opposing impact on extremes, and AM exhibit weaker increases, despite the increase of both scale parameter (significant) and yearly number of storms. In particular, where tail-heaviness has its strongest decrease (increase in the shape parameter), trends in extremes are at a minimum and not significant.

These findings indicate that in the examined period (1991–2020) 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. Differential Impact of Ordinary Events Change on Annual Maxima Changes

We investigate the impact of the trends in the individual model parameters on the trends in AM (Figure 2c). The "real" case in which all parameters change with time reproduces the trends in the modeled AM (line 1 in Figure 2c). The other lines are a combination of varying and constant (median) parameters. Notably, the increase (+0.4% yr^{-1}) in the yearly number of storms 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 (lines 3, 7). This analysis shows that little changes in the tail-heaviness (shape parameter) of the ordinary events distribution 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 us to directly quantify changes on specific rare return levels. In general, slopes are significantly positive for sub-hourly durations and decrease with increasing duration until they lose significance for durations above 2–3 hr (Figure 2d). For higher return levels, this behavior is enhanced: higher positive slopes are estimated for subhourly durations and lower not significant slopes for multihour durations. In the duration interval between 1 and 2 hr 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 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 return levels on a yearly basis should lead to unbearable uncertainties. We showed here that the statistical significance of trends in yearly modeled return levels as high as the 50-year events is comparable to the statistical significance of trends in AM, suggesting a similar signal-to-noise ratio. Trends on extreme return

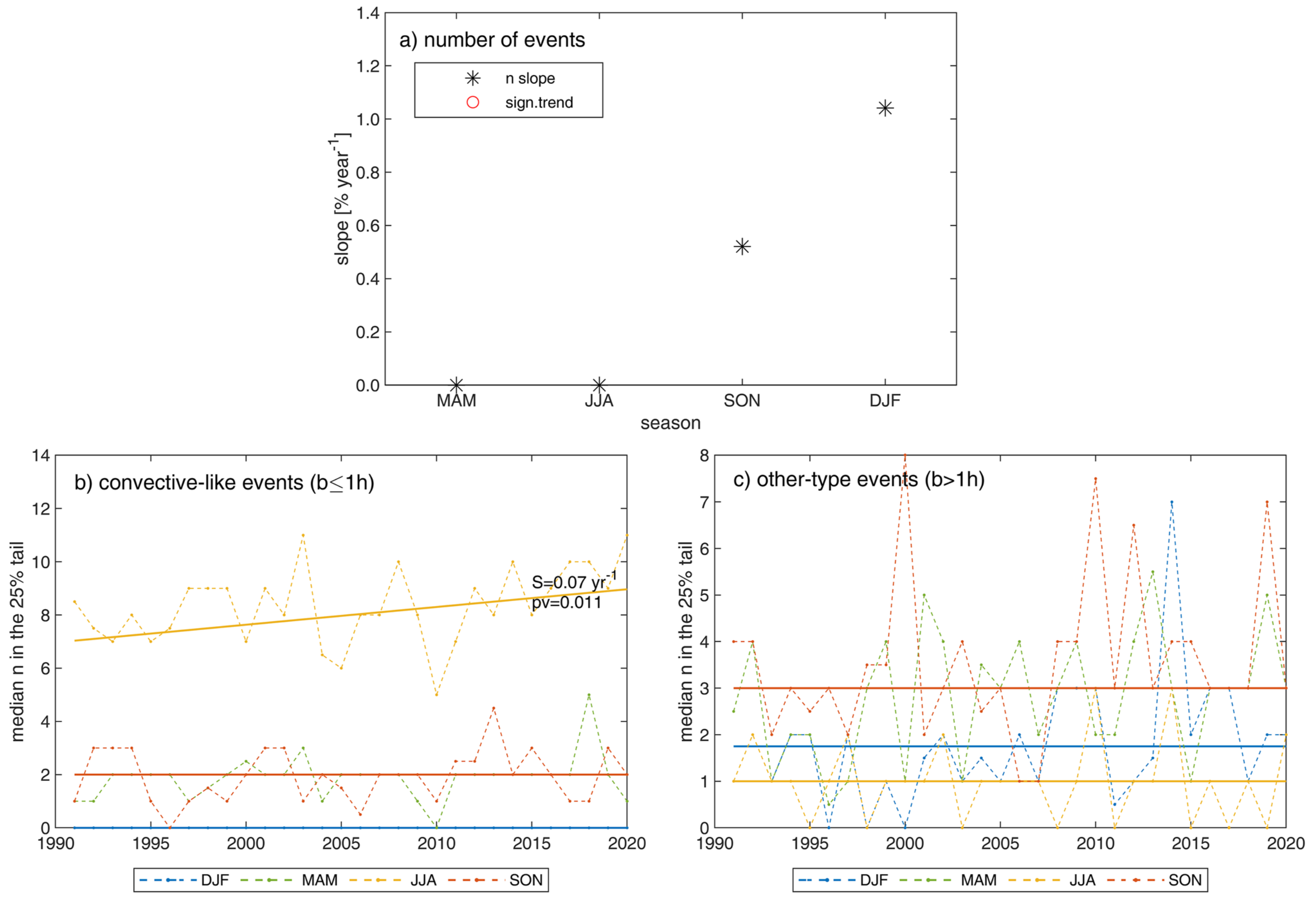

Figure 3. (a) Slope of the regional trends for the number of seasonal storms; significant trends (α-level = 0.05) are marked. (b) Median (across stations) seasonal number of convective-like ($b \leq 1$ hr) and (c) other ($b > 1$ hr) storms in the 25% tail; the Sen's slope (S) and the p-value (pv) of the Regional Mann-Kendall test are reported in case of significant trends (α-level = 0.05).

levels estimated on yearly basis from our model are thus characterized by stochastic uncertainties comparable to the ones of AM.

3.4. Changes in the Proportion of Convective-Like Events

The parametrization of our model allows us to formulate hypotheses about the 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 AM. 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 positive trend in the yearly number of storms reported above is fully explained by the increases in the number of storms in autumn (SON) (Figure 3a) and in winter (DJF). However, examining changes in the storm types composition shows no distinct increase in convective-like storms during these seasons (Figures 3b and 3c).

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 shows no trend (Figures 3b and 3c). 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 event distribution are examined considering spring-summer (MAMJJA) and autumn-winter (SONDJF) separately (Figure S2 in Supporting Information S1). 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.

4. Conclusions

We examine changes in extreme subdaily precipitation intensities for the relevant case of the Eastern Italian Alps, where consistent significant changes in annual maximum intensities were previously reported. 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 non-asymptotic framework for extreme value analyses based on ordinary events, which permits to separately examine trend in frequencies and intensities of the storms, and we quantify trends using a regional Mann-Kendall test. With respect to traditional change-permitting extreme value models, our method provides a statistical tool for quantifying changes in extremes in spite of the large stochastic uncertainties, and for understanding the observed changes by separately considering multi-duration storm intensity distributions and storm occurrence frequency.

Results confirm the presence of significant positive trends in the AM. Trends in the 2 years 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 3–24 hr durations. The model parametrization allows us to conclude that these trends are likely due to a combination of (a) increasing number of storms per year and increasing intensity of the storms, and (b) 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. Fowler et al. (2021b) highlighted that in some regions the intensification in short-duration extremes is related to feedbacks in convective clouds dynamics at the local scale. Further analysis considering air temperature and dew-point temperature, could help investigating the physical drivers behind the changes we observe, and could directly address the changes in storm properties, such as duration and total storm amount. In the study area, a recent work by Formetta et al. (2022) shows evidence of extremes dependence on elevation. Temporal changes of this dependence are however still unexplored, mostly because of a lack of stations at high altitudes. This could be subject of future studies, provided that larger samples of long-recording high-resolution stations at higher elevations are made available.

Our results come with some caveats. First, our statistical model is as good as its underlying assumption, that is the tail of the ordinary events distribution is stretched-exponential. We ensured the validity of this assumption for all stations and durations, and selected a left-censoring threshold in order to optimize its validity. Second, the trends in this study are derived from a relatively short data series and should be considered as representative of the examined period only (1991–2020). Due to decadal climate variability, they should not be considered as representative of climate change in general, nor extrapolated to predict future conditions (Iliopoulou & Koutsoyiannis, 2020). Last, our definition of convective-like events is based on a threshold on the temporal autocorrelation of the time series. Using physics-based definitions to label the storms could lead to more robust relations between the statistical model and the underlying physical processes. Additionally, it could help expanding our approach to directly consider different types of storms (Marra et al., 2019), as previously done in the Two-component Extreme value distribution (Rossi et al., 1984) or the mixed Gumbel (Kjeldsen et al., 2018). This information can prove valuable for improving our ability to create and use process-based change-permitting statistical models for hydrometeorological extremes.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Precipitation data was provided by the Provincia Autonoma di Trento (raw data can be retrieved in Italian only from https://www.meteotrentino.it/#!/content?menuItemDesktop=143, last accessed: September 2021). The quality-controlled data used for our research are publicly available in Dallan and Marra (2022) with the Creative Commons Attribution 4.0 International. The codes used for the statistical model are available in Marra (2020).

The Regional Mann-Kendall trend test was performed based on the functions by J. Burkey, downloaded from https://it.mathworks.com/matlabcentral/fileexchange/22389-seasonal-kendall-test-with-slope-for-serial-dependent-data (retrieved July 2021). The codes developed in the study and the elaborated data for reproducing the results of the paper are publicly available in Dallan and Marra (2022) with the Creative Commons Attribution 4.0 International.

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