

Sub-daily magnification of extreme precipitation frequency trends over Europe

Matteo Borgnino

`matteo.borgnino@unimib.it`

University of Milano-Bicocca

Claudia Pasquero

University of Milano-Bicocca

Article

Keywords:

Posted Date: October 22nd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10437337/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Sub-daily magnification of extreme precipitation frequency trends over Europe

Matteo Borgnino^{*1} and Claudia Pasquero¹

¹Department of Earth and Environmental Sciences, University of Milano - Bicocca, Milano, Italy

Abstract

Anthropogenic climate change is driving unprecedented shifts in extreme precipitation, outpacing risk management. While rising daily rainfall extremes are well documented and reflect the larger atmospheric moisture content at higher temperatures, how global warming accelerates sub-daily rainfall remains elusive due to data scarcity and high natural variability. Here we provide multi-dataset evidence that extreme precipitation frequency has increased across Europe over the past two decades, with short duration extremes intensifying systematically faster than daily ones. Analyzing five high-resolution observational and model-based products, we demonstrate a statistically significant rise of 24% in sub-daily exceedance frequency, compared to a non-significant 15% rise in the daily signal. This amplification is robust across regional clusters and event rarity thresholds, consistent with a moisture-driven intensification that is further amplified by dynamical processes at sub-daily scales under a warming atmosphere. Our findings provide a clear observational fingerprint of warming-induced sub-daily extremes acceleration, revealing that short-duration events are already emerging as a distinct and intensifying climate hazard across Europe.

Introduction

There is increasing scientific, societal, and economic concern about the rising frequency and intensity of extreme weather events and their links to anthropogenic climate change. Among these, extreme precipitation events are particularly impactful due to their role in triggering floods, landslides, and other hydrological hazards [1, 2]. Observational evidence and climate model projections consistently show that many regions worldwide are experiencing, or are expected to experience, a significant increase in extreme precipitation as a consequence of global warming [3–8]. This trend has critical implications for infrastructure, water management, and disaster preparedness, especially in densely populated and vulnerable areas. Numerous processes operating across a wide range of scales shape the global water cycle, making the response of precipitation to climate change more complex than the simple “wet gets wetter, dry gets drier” paradigm. On average, the atmospheric moisture content increases by 6–7% per degree Celsius of global warming, consistent with thermodynamic expectations based on the Clausius–Clapeyron relationship and constant relative humidity. The intensity of daily precipitation events globally follows the same scaling, as they feed

^{*}Corresponding author: matteo.borgnino@unimib.it

on atmospheric moisture in the atmosphere at their onset [9–12, 5]. Such a relationship reflects a mere amplification of rainfall associated with moisture availability, neglecting the possible role of dynamical changes. Indeed, it holds at the global scale, but not locally, where other factors come into play [13]. In the midlatitudes, part of the discrepancy is driven by differential warming between land and sea, which causes a divergent anomaly of moisture flux, and thus a net drying, on the windward part of the continents [14]. Indeed, regional responses can diverge markedly from the global-scale estimates due to the influence of atmospheric dynamics [15–21].

The increase of occurrence of daily heavy precipitation over the European region has been documented by several studies [22, 7, 4, 23] that also showed a more pronounced intensification for the most extreme events and distinct spatial patterns and regimes of mean and extreme precipitation change [24]. In addition, the frequency of daily extremes has been shown to be notably higher in urban areas [23], a phenomenon possibly associated with the urban amplification of convective activity.

Convective precipitation is considered to scale with temperature at a higher rate than what predicted by Clausius-Clapeyron relationship, possibly due to dynamical changes triggered by latent heat released within storms that invigorates vertical motion [25, 26]. Indeed, when the temperature dependence of short duration heavy precipitation events - which are typically convective events [27] - is analyzed, stronger sensitivity than for daily rainfall is found [28, 25]. Other studies also document a nonlinear relation between extreme short duration rainfall and temperature [e.g. 29–31]. The cited studies however investigate the *apparent scaling* emerging from day-to-day rainfall variability rather than the *climatic scaling* associated with global warming. Based on theoretical considerations and on modeling studies that show a climatic scaling larger than the apparent one [32], [26] conclude that at present it is unclear how the two are related and advocate for more investigations. The question is not only academic but it has direct socioeconomic implications, as sub-daily extreme precipitation is a key driver of urban flooding, flash floods in small catchments, and landslides.

The direct estimate of sub-daily heavy precipitation dependence on global warming is, however, severely hampered by data scarcity and the masking effect of natural variability [33]. Recent studies have confirmed that both frequency and intensity increase more strongly at sub-daily than daily timescales in Australia [34], and have documented distinct regional changes across multiple global datasets [31], yet the evidence base remains limited and further work is needed.

In this study, we quantify how the frequency of extreme precipitation events has changed over Europe in recent times, with the aim of documenting whether different trends emerge for daily and for sub-daily events. To this end, we combine multiple high-resolution datasets, including satellite-based precipitation estimates (IMERG, GSMaP, CMORPH-CDR), a merged product integrating rain gauge measurements, satellite retrievals and reanalysis (MSWEP), and a high-resolution convection-permitting dynamical downscaling of reanalysis (CHAPTER); details on the dataset are provided in the Methods section). This work provides an extensive and in-depth assessment of how the frequency of extreme precipitation events has evolved over the past two decades.

Results

Climatological context of European precipitation

Before documenting changes in the frequency of extreme precipitation events over the past two decades, we first establish the spatial baseline by presenting the multi-dataset mean annual cumulative precipitation (Figure 1). This climatological overview visually introduces the domain of interest and clearly illustrates well known regional features, including the arid regimes of the Iberian Peninsula, the wet regions across the United Kingdom and the orographic rainfall over major European mountain ranges. Given that our framework incorporates datasets of different origins, satellite based, reanalyses downscaling, and merged products, certain notable discrepancies in annual accumulation emerge among individual datasets (Supplementary Figure S1). Systematic biases are evident: while CHAPTER, IMERG and MSWEP show broadly consistent values, domain-wide mean precipitation is significantly lower for GSMaP and higher for CMORPH. Despite those differences, all evaluated datasets exhibit positive trends over the analyzed two decades period; however, these trends differ in magnitude and are generally not statistically significant, given their large interannual variability (Table 1 and Supplementary Figure S2).

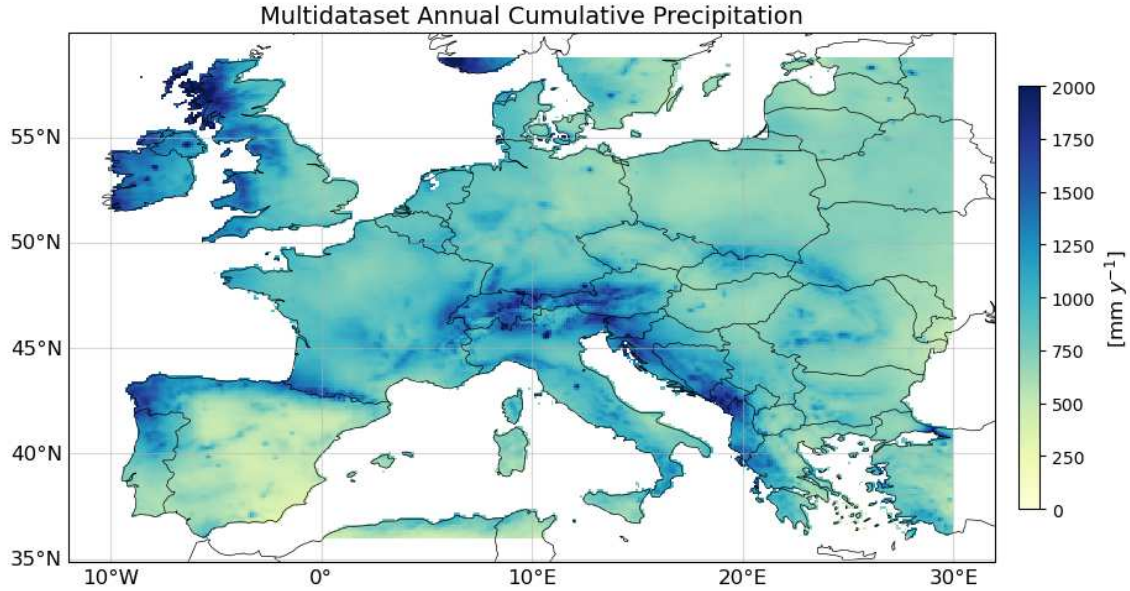


Figure 1

Spatial and temporal characterization of extreme precipitation

With the aim of selecting extreme rainfall events, to ensure comparability across datasets we use the approach proposed by [7]: rather than applying a fixed precipitation threshold, which would select a different number of events from each dataset depending on their climatological biases, we select the strongest N events in each dataset and at each location (see Methods for details). This guarantees

Dataset	Mean Annual Precip [mm]	Trend [mm yr ⁻¹]	p-value	Relative Trend [% yr ⁻¹]
CHAPTER	925.7	0.6	0.76	0.06
IMERG	825.0	2.5	0.03	0.30
MSWEP	783.9	0.6	0.26	0.08
GSMaP	645.2	1.8	0.79	0.28
CMORPH	1194.7	9.5	0.22	0.79
MDM	874.9	3.0	0.17	0.34

Table 1: Linear trend and associated p-value for annual cumulative precipitation across the analyzed datasets and multi-dataset mean (MDM), computed over the 2000–2020 period.

that the number of extreme events is the same across all datasets, making their multi-dataset mean physically meaningful. The method is applied both on the daily cumulated precipitation and on the 3-hr precipitation, to obtain both a daily and a sub-daily extreme events dataset. In addition, for the sub-daily timescale, no more than one event per day is selected. This prevents counting multiple occurrences during the same day and ensures that the sub-daily and daily results remain directly comparable in terms of event rarity. Results shown below refer to the case $N=21$, i.e. an average of one event per year, unless otherwise specified. It should be noted that the daily and sub-daily extreme event datasets are not completely distinct: on average, in about half the cases (48%) a daily extreme event happens on the same calendar day of a 3-hr extreme event at the same location (Figure S3). The selected events exhibit a pronounced seasonality: the majority occur in summer (JJA) and autumn (SON) (Figure 2). This pattern holds for both daily and sub-daily cases and across all datasets (see Supplementary Figure S4), with the only notable difference being a decrease in JJA events and a corresponding increase in SON events when transitioning from sub-daily to daily scales (see Supplementary Figure S5). This behavior is not unexpected and reflects the predominance of short-duration events typical of the warm season, whereas broader atmospheric patterns, more prominent in Fall, become more relevant when integrating over daily timescales. A latitudinal dependence also emerges from the spatial distribution of selected events: Central and Northeastern Europe are predominantly affected by JJA events, whereas the Mediterranean region is characterized by SON events, likely driven by land–sea interactions. This spatial pattern is consistent across both temporal scales.

Systematic magnification of short-duration extreme frequency

We then construct a time series with the domain averaged number of events occurring every year, in each individual dataset and separately for daily and sub-daily events. For IMERG and GSMaP datasets the time series construction includes a correction to account for the presence of gaps in the data (see Methods for details). The multi-dataset mean time series exhibit substantial interannual variability (Figure 3a-b); a 3-year running mean is also shown to aid visualization. Over the past two decades, both daily and sub-daily cases show an increase in the frequency of extreme events, which we quantify through the Exceedance Frequency Change (EFC), defined as the percentage change in event frequency over the study period (see Methods). We find that the sub-daily EFC is notably larger than its daily counterpart (+24% vs. +15%), and the 3 hourly extreme precipitation trend is statistically significant while for the daily events the null hypothesis of stationarity cannot be rejected at the 95% confidence level, given the (natural) interannual

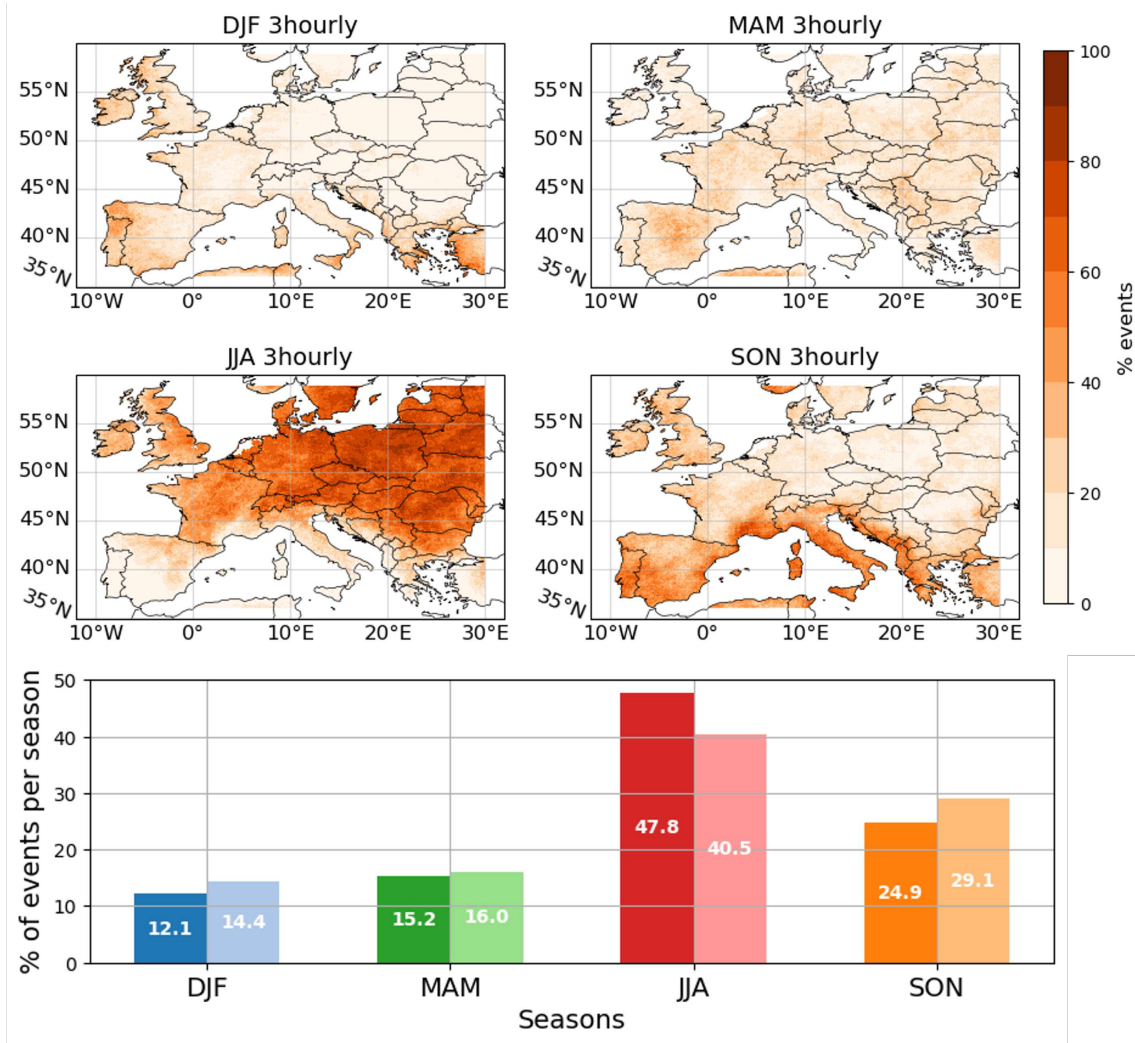


Figure 2

variability of the signal. To further assess whether the 48% overlap between daily and sub-daily extreme events (i.e. cases where a daily and a sub-daily extreme occur on the same day at the same grid point) could affect the results, we have computed the EFC separately for overlapping and non-overlapping events (Supplementary Table S1). This analysis confirms that the sub-daily amplification is not an artifact of the overlap: non-overlapping sub-daily events, which are extreme at the 3-hr timescale but don't last long enough to generate a daily extreme, show the largest EFC (+26%), while non-overlapping daily events show the smallest (+10%), further reinforcing the robustness of our central finding. Overlapping events, characterized by a +22% in the EFC, effectively dampen the overall amplification signal. This decomposition confirms that the sub-daily magnification is primarily driven by short-lived precipitation extremes and that the overlap between the two event datasets, rather than inflating the signal, actually moderates it.

Disaggregating the analysis across the individual datasets we find that all datasets exhibit an increase in the frequency of extreme precipitation events at 3hr larger than at daily time scale, even though the magnitude of the change widely differs among datasets and not in all cases it is statistically significant (Figure 3c). Considering that datasets differ in spatial resolution, mean precipitation, and temporal behavior, we also tested whether the multi-dataset mean was dominated by single products. To this aim, we performed a leave-one-dataset-out analysis, computing the multi-dataset mean EFC after sequentially removing each of the five datasets (Supplementary Figure S6). The central finding, that sub-daily EFC exceeds its daily counterpart, holds in all cases. Furthermore, the EFC values obtained in each leave-one-out configuration fall within the uncertainty range of the complete multi-dataset mean, confirming that the MDM EFC is stable and not overly sensitive to the inclusion or exclusion of any individual dataset.

The robustness of the results is further confirmed by a different statistical approach: while the results presented here refer to linear regressions computed with the Ordinary Least Square method, Theil-Sen's slope estimator and the Mann-Kendall test consistently indicate a larger increase at sub-daily than at daily timescales (Supplementary Figures S7). While the exact magnitude of the EFC and the statistical significance of individual dataset trends slightly vary across methods, the central finding, i.e. sub-daily extreme precipitation frequency has increased faster than its daily counterpart, remains consistent across all approaches.

These changes have been computed on the average number of events per year across the entire land region, providing a domain-wide perspective on changes in extremes, as proposed by [22] who used spatial aggregation at continental scales to identify a clearer signal in extreme rainfall. When the change in extreme precipitation occurrence is instead investigated at the local scale, very different trends, both positive and negative, are obtained (Figure S8), with a significant spatial correlation between daily and sub-daily changes (Pearson correlation coefficient 0.71 in the multi-dataset mean, varying from 0.44 to 0.74 in individual datasets, Table S2). To preserve spatial aggregation while retaining some local-scale information, we count on how many points the sub-daily trend is larger than the daily trend, and viceversa, and finally we take the ratio of the two. This metric, referred to as the ratio in the following, indicates a domain in which sub-daily extrema increase at a faster pace than daily ones when its value exceeds 1. This is indeed the case, both for the multi-dataset record and for each individual dataset (Figure 3d). The full distribution of the pointwise difference $k_s - k_d$ (Supplementary Figure S9) confirms that such a difference is predominantly positive across the domain, providing a quantitative complement to the sign-based ratio metric.

We thus conclude that the frequency of short-duration extreme precipitation events has increased faster than that of daily extremes. Given the known predominance of convective processes at sub-

daily timescales, this result is consistent with, though does not directly demonstrate, a preferential intensification of convective precipitation over Europe.

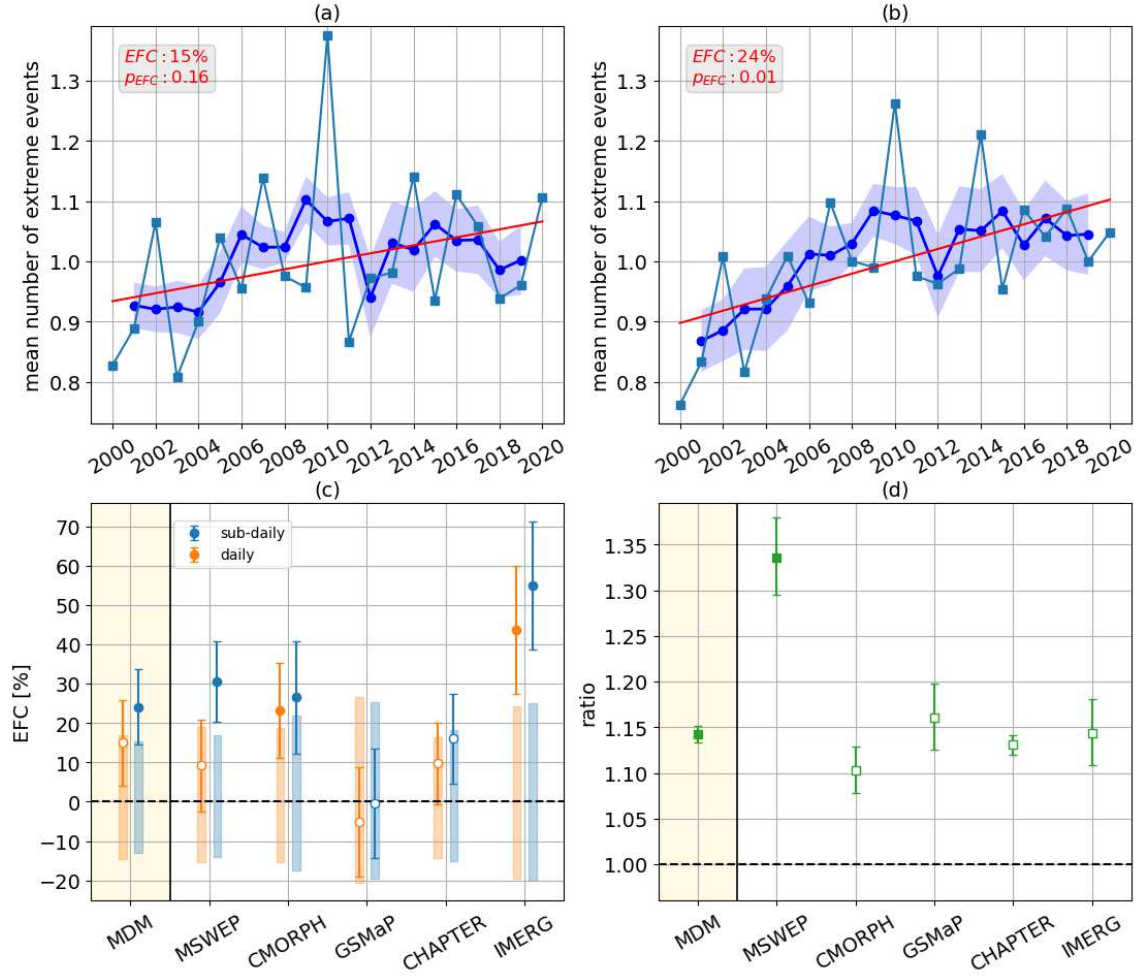


Figure 3

Regional robustness and event rarity

We now adopt a finer-scale analysis, grouping together different European regions based on shared characteristics.

To do this, we employ a clustering algorithm based on k -means to define data-driven regions. Using the multi-dataset mean of the total annual precipitation, we have identified five distinct clusters (Figure 4a) with different annual precipitation variability (Supplementary Figure S10). This choice was twofold: it ensures that regionalization accounts for more than 70% of the explained variance (Figure S11) and it maintains consistency with the Köppen-Geiger climate classification

[35] (Supplementary Figure S12). Indeed, the five identified clusters are closely related to the five main Köppen-Geiger regions in the study domain: the arid zone (cluster 0), temperate with dry summer (1), temperate with no dry season (2), cold (3) and polar (4) (Figure S13a).

This regional clustering confirms that sub-daily extreme trends are consistently larger than their daily counterparts across all clusters (Figure 4c). Regions such as the Atlantic coastlines, mountain and foothill areas (represented by clusters 1 and 4) exhibit the most substantial increases in extreme precipitation frequency over the last two decades.

The sub-daily minus daily ratio yields values consistently around 1.0 and 1.3 in all clusters (Figure 4d). This indicates that the clustering does not introduce a significant imbalance in the number of grid points showing magnified sub-daily trends. The regional distribution of the pointwise difference $k_s - k_d$ for each cluster further confirms this result: the median of $k_s - k_d$ (Supplementary Figure S14) is positive in all clusters and is negligible in only one case, providing a quantitative complement to the ratio metric. As for the domain-wide analysis, the regional results are robust to the choice of statistical method: Theil-Sen's slope and the Mann-Kendall test confirm the results across all clusters (Supplementary Figures S15), with only minor differences in the magnitude of the EFC and in the statistical significance of individual cluster trends.

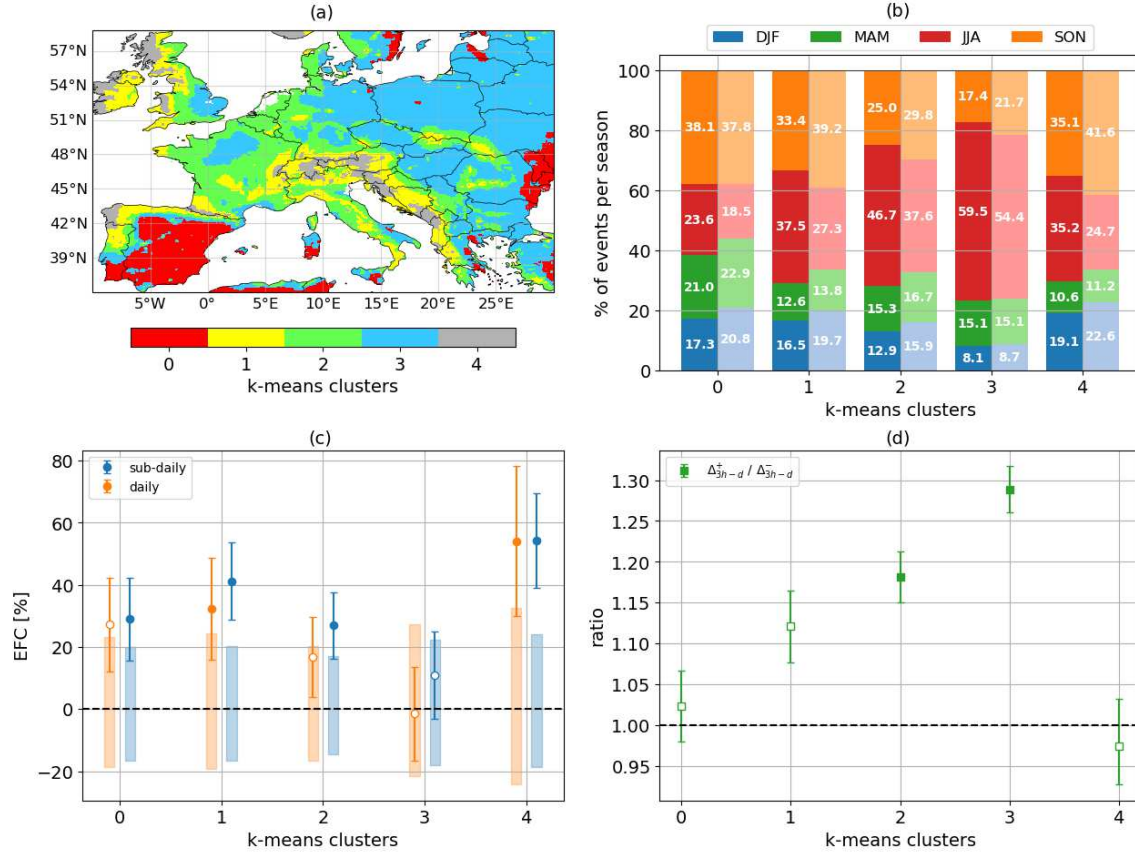


Figure 4

To test whether the results previously presented depend on the rareness of the selected events, a sensitivity analysis was conducted by varying the number of events used to define the extreme precipitations. Instead of selecting the 21 most intense precipitation events (daily and sub-daily) over the 21 year period analyzed, a wider range of events was considered. Specifically, for both the sub-daily and the daily timescale between 10 and 336 events were selected; these correspond to percentile thresholds ranging from the 95.6th to the 99.86th (Figure 5).

This analysis shows that, across all considered percentiles, the frequency of intense precipitation events over Europe has increased over the first two decades of the XXI Century at both daily and sub-daily timescales. Moreover, the increase over the study period is more pronounced for the most extreme events; in other words, the more extreme the event, the greater the observed increase. This finding not only aligns with [22] for the daily scale but extends the result to the sub-daily scale, where not only is the increase confirmed, but it is also consistently larger across all percentiles. In fact, the ratio between sub-daily and daily trends remains approximately constant around 1.6 across all considered percentiles, indicating that the sub-daily amplification is independent of event rarity and that the frequency of short-duration extreme precipitations has increased at roughly one and a half times that of daily extremes.

Theil-Sen's slope estimator confirms the sub-daily amplification across all percentile thresholds (Supplementary Figure S16).

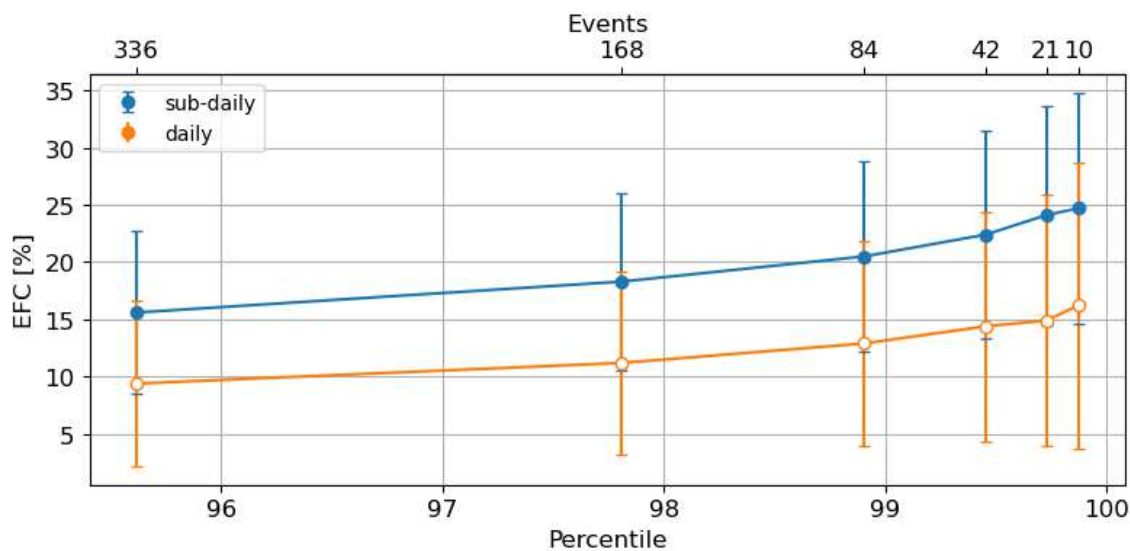


Figure 5

Discussion

While the findings presented here are supported by a robust statistical framework, they should be interpreted taking into account certain limitations regarding the resolution of the datasets and the methodological approach employed. Primarily, the relatively short temporal span of the study

period of two decades may limit the ability to isolate long-term signals, thus precluding any definitive attribution of these trends to climate change. The selection of this 21-year window is strictly dictated by the current availability of the employed high resolution sub-daily precipitation records, which, in most cases, do not yet offer the multi-decadal coverage required for long-term climatological trend analysis. Nevertheless, our results provide a critical snapshot of recent intensification that remains remarkably consistent across the diverse range of datasets used, from purely observational products to model-based reanalyses. Although the datasets are not fully independent, as merged products incorporate overlapping data sources, this cross-dataset consistency strengthens the robustness of our findings, highlighting that the sub-daily signal manifests as a clear magnification of the daily trends.

This outcome has been confirmed in an analysis of the CHAPTER dataset, available over the period of 1981-2022: even over this 42 years long interval, the sub-daily trend of intense precipitation occurrence has been larger than the daily one, with an exceedance frequency change of +26% at the sub-daily scale, significant at the 95% confidence level, versus a +19% at the daily timescale (see Supplementary Figure S17).

The observed preferential intensification at the sub-daily scale is physically consistent with a progressive shift toward more frequent short-duration precipitation extremes over Europe. While a direct mapping of extreme 3-hourly accumulations onto intense convective events and of extreme daily accumulations onto synoptic-scale events would require dedicated process-level diagnostics, sub-daily extremes are nonetheless generally associated with convective activity, whereas daily extremes more typically reflect synoptic-scale forcing. [36, 27]. Growing observational and modeling evidence suggests that short-duration precipitation may respond to warming at rates exceeding those of longer-duration events [25, 34]. A plausible driver consistent with our findings is the increase in the Convective Available Potential Energy (CAPE), a measure of atmospheric instability that directly controls the vigor of convective updrafts and thus convective precipitation. Under global warming, increasing surface temperatures and enhanced lower-tropospheric moisture are expected to increase CAPE [37, 38], thus creating more favorable conditions for the initiation and intensification of deep convection. Consistently, increasing CAPE has been documented over the past decades in the European region [39–41]. Although a formal attribution of our results to CAPE changes lies beyond the scope of this study, the consistent sub-daily magnification observed across the different regions and datasets, suggests that the increasing short precipitation occurrence may partially reflect a progressive destabilization of the atmosphere over Europe. This interpretation is further supported by the dominant summer and fall seasonality of the selected extreme events (Figure 2), both seasons being typically associated with convective precipitation regimes.

In this context, future work explicitly linking sub-daily frequency trends to changes in convective environments, for instance through analysis of associated CAPE, convective inhibition, or storm tracking, would be a valuable step toward a more mechanistic understanding of the observed changes.

An additional aspect of our analysis, representing both a challenge and a strength, concerns the regionalization of the trends. To investigate the spatial heterogeneity of the observed trends without relying on rigid, predefined geographical boundaries, we employed a k -means clustering approach based on total annual precipitation. This data-driven partitioning successfully identified regions characterized by distinct precipitation regimes. However, a key caveat emerges regarding the high-precipitation cluster that encompasses much of the Alpine arc and other high-elevation areas of Europe, where observational precipitation products notoriously suffer from lower reliability. Factors such as gauge undercatch of solid precipitation, low station density and the limited ability

of gridded products to resolve localized convective cells and fine-scale topographic effects, suggest that the observed trends within these mountainous regions must be interpreted with additional caution.

Furthermore, despite the clear macro-regional distinctions provided by the clustering framework, a substantial degree of inter-class variability persists within individual clusters, reflecting the inherent heterogeneity of precipitation regimes across Europe (Figure S10-S12). This inherent sub-regional heterogeneity indicates that cluster-level trends should be regarded as indicative of large-scale tendencies rather than spatially homogeneous responses.

Crucially, the independent k -means partitioning shows a strong spatial convergence with the traditional Köppen–Geiger climate zones, effectively recovering the transition from arid to alpine regimes on purely data-driven grounds. This high degree of alignment provides a robust cross-validation of our spatial patterns and confirms that the identified sub-daily magnification is a structurally consistent feature of the European climate, remaining independent of whether a statistical or a classical climatological framework is employed.

In conclusion, we highlight that, regardless of the physical interpretation, the finding reported here is robust and carries direct societal relevance. The systematic increase in the frequency of short-duration extreme precipitation events over Europe, consistently detected across five observational and model-based datasets, multiple statistical methods, climate regions and event rarity thresholds, implies a growing exposure to flash floods and related hydrological hazards. We note, however, that this study does not directly analyze flood events or their impacts; rather, this inference is based on precipitation frequency changes, which represent a critical driver of changing hydrological risk. This enhanced sensitivity of short-duration extremes to global mean temperature is consistent with the superposition of a thermodynamic contribution (associated with increased atmospheric moisture content at warmer temperatures) and a dynamical contribution, possibly linked to enhanced static instability in the atmospheric column. As the length of available sub-daily observational records increases, future studies will be able to further consolidate and extend these findings. Nevertheless, the detection of a significant and consistent sub-daily amplification signal within only two decades of data already represents a relevant signal, with implications for flood risk assessment and climate adaptation policy across Europe.

Methods

Precipitation Datasets

In this study, daily and sub-daily precipitation data were analyzed from five different datasets, encompassing a range of data sources and spatial resolutions. This approach allows for both comparative evaluation and the exploitation of the distinct characteristics of each dataset. The datasets include a high-resolution dynamically downscaled dataset (CHAPTER), three satellite-based products (CMORPH, GSMaP, and IMERG) and a merged product combining gauge observations, satellite estimates and reanalysis data (MSWEP). The version, native resolution, and full temporal coverage of each dataset are summarized in Supplementary Table S3. A common 21 year period from 2000 to 2020 was selected across all datasets to ensure consistency. The spatial domain covers a large portion of Europe (10°W–30°E; 32°N–58.8°N). The hourly or sub-hourly precipitation offered by certain datasets has been aggregated to both the three-hourly and daily scales in order to be consistent among all available datasets. For the purposes of this study, hereafter, sub-daily refers to three-hourly precipitation data.

MSWEP

The Multi-Source Weighted-Ensemble Precipitation V2.8 (MSWEP) dataset is a global precipitation product that provides three-hourly estimates at 0.1° spatial resolution, available from 1979 to near real-time [42, 43]. MSWEP is distinctive in that it combines gauge observations, satellite-based retrievals, and reanalysis data to generate high-quality precipitation estimates across a broad range of spatial and temporal scales. A key strength of MSWEP lies in its integration of daily gauge measurements with careful consideration of reporting times, thereby minimizing temporal mismatches with satellite and reanalysis inputs. This blended approach improves the consistency and accuracy of precipitation estimates, particularly in both well-gauged and data-sparse regions. Although MSWEP is available from 1979, data prior to 2000 are not used in this study for trend analysis, as [43] note that MSWEP V2 trends are subject to greater uncertainty before 2000 due to changes in the observing system and the limited availability of passive microwave-based precipitation datasets.

CMORPH-CDR

The bias-corrected Climate Data Record (CDR) version 1 of the Climate Prediction Center (CPC) Morphing Technique (MORPH) provides high resolution global satellite-based precipitation estimates at 30-minute temporal resolution and 8 km spatial resolution, available from January 1998 onward [44, 45]. CMORPH employs a two-step methodology: it first generates global fields of instantaneous precipitation rates by integrating Level 2 passive microwave retrievals from multiple low Earth orbiting satellites and then these satellite-only estimates are systematically bias corrected. Bias correction is performed by comparing satellite-derived precipitation with the CPC daily gauge analysis over land, and with the Global Precipitation Climatology Project merged precipitation estimates over the oceans. This correction ensures improved consistency with in situ and long-term climatological data. The final product spans the global domain between 60°S and 60°N .

GSMaP

The Global Satellite Mapping of Precipitation (GSMaP Gauge RNL v5) dataset provides global, gauge-adjusted precipitation estimates at an hourly temporal resolution and 0.1° spatial resolution. GSMaP leverages multi-band passive microwave and infrared observations from the GPM Core Observatory, supplemented by data from a constellation of additional satellites. Precipitation retrievals in GSMaP are based on a radiative transfer model, which enables the estimation of precipitation rates from satellite radiometer observations. To improve accuracy, especially over land, the hourly precipitation estimates are bias-corrected using daily gauge measurements from NOAA/CPC, through an optimization process that adjusts the 24-hour accumulation of satellite-derived rainfall to match ground-based observations. To assess the reliability of the precipitation estimates, GSMaP provides a quality flag ranging from 1 (lowest reliability) to 10 (highest). This quality indicator accounts for three key factors affecting retrieval accuracy: surface type (with generally higher reliability over oceans than land), surface temperature (with lower reliability in cold conditions), and the time elapsed since the last satellite overpass. To ensure high-quality input, only precipitation data with a quality flag greater than 4 were retained for analysis in this study [46].

IMERG

The Integrated Multi-satellitE Retrievals for GPM (IMERG v7) dataset [47], developed by NASA, provides high-resolution, half-hourly global precipitation estimates by combining data from the constellation of satellites within the Global Precipitation Measurement (GPM) mission. IMERG is especially valuable for monitoring precipitation over regions lacking ground-based measurements. IMERG integrates observations from both the Tropical Rainfall Measuring Mission (TRMM; 1998–2015) and the GPM mission (2014–present), resulting in a continuous precipitation dataset spanning more than two decades. The algorithm intercalibrates and merges passive microwave observations from multiple satellites, infrared-based precipitation estimates, and in situ gauge analyses, producing a consistent, high-frequency record of global precipitation that supports a wide range of hydrological, meteorological, and climate applications. In this study, we use the IMERG Final Run product, which incorporates monthly gauge-based corrections, due to its enhanced temporal consistency and accuracy, particularly in long-term and extreme event analyses. To determine the reliability of rainfall data, IMERG provides a half-hourly quality index, which represents a measure of the relative skill that might be expected from the fluctuating mix of different passive microwave and infrared-based precipitation estimates. In this work analyzes only estimates with quality index above 0.4 which is the threshold to consider the data as "fair" [48].

CHAPTER

The Computational Hydrometeorology with Advanced Performance to Enhance Realism (CHAPTER) dataset [49] provides high-resolution, convection-permitting regional climate simulations obtained through dynamical downscaling of the ERA5 global reanalysis from the European Centre for Medium-Range Weather Forecasts (ECMWF). CHAPTER is produced using the Weather Research and Forecasting (WRF) [50] model, configured on a $3\text{ km} \times 3\text{ km}$ grid nested within a larger domain driven by hourly ERA5 boundary conditions. To generate the daily hindcasts, the WRF model is initialized each day at 18:00 UTC and run for 30 hours. The initial 6 hours are treated as spin-up and discarded, yielding a 24-hour forecast window that maintains close alignment with large-scale atmospheric conditions in ERA5. This daily reinitialization strategy minimizes long-term drift and removes the need for spectral nudging. Further details on the CHAPTER dataset and its validation are available in [51].

Extreme Events Identification and Frequency Metrics

The selection of extreme precipitation events follows the methodology proposed by [7]. For each grid point within the study domain, the N_{ev} most intense 3-hourly or daily precipitation events were identified during the analysis period 2000–2020 ($N_y = 21$). Unless otherwise specified (as in the sensitivity analysis shown in Figure 5), the number of selected events was fixed at $N_{\text{ev}} = 21$, which, under the stationary hypothesis, corresponds to one extreme event per year. To ensure the independence of sub-daily events and avoid counting multiple 3-hourly intervals from the same precipitation system as separate events, no more than one 3-hourly event per day was retained at each grid point; specifically, the maximum 3-hourly accumulation within each day was considered as a candidate extreme event. This declustering criterion guarantees that daily and sub-daily extreme events are drawn from samples of comparable size and that selected 3-hourly events are independent. This selection procedure enables the construction of annual time series of extreme event frequency, either at individual grid point or aggregated over the entire domain or sub-regions.

In the latter case, the regional frequency is defined as the mean number of selected events per year in the region. Trends are estimated by applying ordinary least squares (OLS) linear regression directly to the annual time series, which provides the trend k , representing the annual rate of change in the number of extreme events, its standard error and the associated p-value. The latter is used to assess the statistical significance of the trends and is reported in Figures 3a-b, represented by filled and empty markers in Figures 3c, 4c and 5. As additional robustness checks, Theil-Sen’s slope estimator and the Mann-Kendall test are also applied to the annual time series; these non-parametric methods are particularly suitable given the limited number of data available. The Mann-Kendall p-value is used to assess the statistical significance in Supplementary Figures S7a-b and represented by filled and empty markers in Figures S7c, S15c and S16.

Throughout the study, we quantify the non-stationarity of the time series using the Exceedance Frequency Change (EFC), defined as the relative change in the frequency of extreme events between the beginning and the end of the N_y -year period, based on the regression line. Specifically, given the linear trend k estimated by the regression, the expected number of extreme events per year at the midpoint of the record is $\bar{N} = N_{ev}/N_y$, so that the estimated number of events per year at the start and end of the period are $N_{start} = \bar{N} - 0.5 * k * N_y$ and $N_{end} = \bar{N} + 0.5 * k * N_y$, respectively. The EFC is then computed as the relative change between these two values:

$$EFC = \frac{N_{end} - N_{start}}{N_{start}} \times 100 = \frac{k \cdot N_y}{\bar{N} - 0.5 \cdot k \cdot N_y} \times 100 \quad (1)$$

The standard error of the slope given by the OLS is then propagated to estimate the error on the relative trend (Figure 3c). For the Theil-Sen estimator, the standard error is derived via bootstrap resampling as the standard deviation of the slope distribution obtained across 10,000 iterations (Supplementary Figure S7).

To enable comparison between the different datasets and to communicate a unified message, we adopt the so called multi-dataset mean. This involves the construction of a single time series across all datasets, referred to as the multi-dataset time series. Specifically, for each year, we compute the mean number of extreme precipitation events across all datasets, thereby obtaining a domain-wide time series (Figure 3a-b). Similarly, the multi-dataset standard deviation refers to the standard deviation computed across the average number of events reported by the individual datasets for each year. Once we have the multi-datasets time series, we use the same approach explained above for single dataset (rolling mean, OLS and error’s propagation) to estimate the relative trends.

This approach is also applied in the regional analysis based on the k -means clustering or Köppen-Geiger climate classification. Since the classification is provided at a spatial resolution of 0.1° , all datasets were first upscaled to this common resolution. Subsequently, the multi-dataset mean was computed within each region, resulting in a single time series and, consequently, one relative trend value per region that synthesizes the information across all datasets. As in the domain-wide analysis, uncertainties and statistical significance are derived from the ordinary least squares (OLS) linear regression described above.

To assess whether the estimated trends are physically robust or merely artifacts of interannual internal variability, a Monte Carlo bootstrapping approach was implemented to test the significance of the slopes. For each original time series (at single-dataset, multi-dataset mean or regional scales), the original N_y data points were randomly resampled with replacement to construct 10,000 synthetic time series of identical length. This shuffling procedure disrupts any coherent temporal structure and long-term trend while preserving the underlying interannual variability. For each bootstrap iteration, the linear slope of the synthetic time series was estimated directly via OLS

regression, thereby generating an empirical null distribution of slopes driven solely by random interannual fluctuations. The 5th and 95th percentiles of this distribution were calculated to establish a two-tailed confidence interval, shown as transparent shaded boxes in Figures 3c-4c and Supplementary Figure S7c-S15c. An observed trend is deemed robust against natural interannual variability if its slope falls outside this bootstrap-derived interval.

An additional metric used in this study is the ratio, which quantifies the proportion of the domain where the sub-daily trend exceeds the daily trend. Specifically, the ratio is defined as the number of grid points where the difference in trend magnitudes ($k_s - k_d$) is positive (i.e., sub-daily trend > daily trend), divided by the number of points where the difference is negative.

$$\text{ratio} = \frac{\Delta^+}{\Delta^-} = \frac{\Delta_{s-d}^+}{\Delta_{s-d}^-} = \frac{\sum_i (k_s - k_d)_i > 0}{\sum_i (k_s - k_d)_i < 0} \quad (2)$$

This ratio is computed at the grid-point level in the entire domain for each dataset (Figure 3d) and within individual Köppen-Geiger climate zones (Figure S13d). In the regional case, the ratio is calculated as the total number of grid points with a positive difference (Δ^+), summed across all datasets, divided by the number with a negative difference (Δ^-) in each climate region. In both cases, statistical significance is assessed using a binomial test. To account for spatial autocorrelation, the data are subsampled using 100×100 km grid cells. Uncertainty is expressed as the 5th and 95th percentiles of the ratio distribution, obtained via a Monte Carlo approach. Specifically, one fifth of the available grid points are randomly drawn – either from a single dataset, from all datasets pooled together in the multi-dataset case, from the grid points belonging to a given Köppen region, or from those within a given cluster | and the corresponding ratio is computed on this subsample. Repeating this procedure 10,000 times yields an empirical distribution of the ratio, from which the confidence bounds are derived.

Quality-based time series correction

As noted in the dataset descriptions above, GSMaP and IMERG provide quality indices alongside precipitation estimates, and only data exceeding a minimum quality threshold are retained (flag >4 for GSMaP; quality index >0.4 for IMERG). While this filtering ensures data reliability, it may introduce time-varying gaps in the record that vary across grid points, seasons, and years, potentially generating artificial frequency trends. To address this concern, following the approach of [34], we introduce an annual correction factor that accounts for the spatially and temporally varying fraction of valid data.

Given the pronounced seasonality of extreme events (Figure 2), the correction factor is computed by weighting the seasonal valid data fraction by the seasonal distribution of selected extreme events. A seasonal decomposition is further motivated by the fact that the fraction of valid observations itself exhibits a marked seasonality: satellite-based retrievals are known to suffer from reduced reliability in cold conditions, particularly over snow-covered surfaces, leading to a lower fraction of valid data in winter (Supplementary Figure S18). Crucially, however, DJF is also the season in which the fewest extreme events are selected, so that the impact of reduced winter data availability on the corrected event counts is minimized. The correction factor for year y , timescale s (sub-daily) or d (daily), at each grid point, is defined as:

$$\text{cf}(y)^{s,d} = f_{\text{DJF}}^{s,d} \cdot \frac{N_{\text{valid}}^{\text{DJF}}}{N_{\text{tot}}^{\text{DJF}}}(y) + f_{\text{MAM}}^{s,d} \cdot \frac{N_{\text{valid}}^{\text{MAM}}}{N_{\text{tot}}^{\text{MAM}}}(y) + f_{\text{JJA}}^{s,d} \cdot \frac{N_{\text{valid}}^{\text{JJA}}}{N_{\text{tot}}^{\text{JJA}}}(y) + f_{\text{SON}}^{s,d} \cdot \frac{N_{\text{valid}}^{\text{SON}}}{N_{\text{tot}}^{\text{SON}}}(y) \quad (3)$$

where $f_{\text{season}}^{s,d}$ is the fraction of selected extreme sub-daily/daily events occurring in each season (Figure 2), $N_{\text{valid}}^{\text{season}}$ is the number of days with valid quality-filtered data in that season of year y and $N_{\text{tot}}^{\text{season}}$ is the total number of days in the season. All quantities cf , f , $N_{\text{valid}}/N_{\text{tot}}$ are computed at each grid point.

To preserve consistency with the percentile threshold used for the other datasets, the number of events selected at each grid point is adjusted prior to applying the correction. Specifically, the mean correction factor is first estimated as $\langle \text{cf} \rangle = \frac{1}{N} \sum_y \text{cf}(y)$, and $N_{\text{ev}} \cdot \langle \text{cf} \rangle \leq N_{\text{ev}}$ events are selected at each grid point instead of N_{ev} . The spatial distribution of the number of selected events is shown in the Supplementary Figure S19. The corrected annual event count is then obtained as $n_{\text{corr}}(y) = n_{\text{raw}}(y)/\text{cf}(y)$, where $n_{\text{raw}}(y)$ is the count of selected extreme events in year y after the adjusted selection. This procedure ensures that the total number of corrected events at each grid point remains close to N_{ev} , although not necessarily exactly equal to it. Finally, the corrected time series is rescaled by a multiplicative factor $\frac{N/N_{\text{ev}}}{\langle n \rangle}$ so that its mean is restored to the expected value N_{ev}/N_y , ensuring that each dataset contributes equally to the multi-dataset mean. This final step, being a multiplicative factor homogeneously applied to the time series, does not affect the value of its EFC. The domain averaged time series is then used in all the analyses, including OLS trend estimation, EFC and ratios computation described above.

Regionalization through k -means clustering

To identify specific precipitation regions, we applied a k -means clustering algorithm to the multi-dataset-mean annual precipitation. The input feature space was constructed by flattening the multi-dataset mean precipitation into a two-dimensional matrix ($N_{\text{points}} \times N_{\text{datasets}}$), where N_{points} represents the total number of spatial grid cells in the domain. We utilized Euclidean distance as the similarity metric to partition these grid cells into k distinct clusters. To determine the optimal number of clusters, we performed an elbow analysis by evaluating the Sum of Squared Errors (SSE), also named as cluster inertia, for k values ranging from 1 to 10. The selection of $k = 5$ was identified as the elbow point accounting for over 70% of the total variance (figure S11).

Data availability

The Multi-Source Weighted-Ensemble Precipitation V2 (MSWEP) dataset can be downloaded from <https://www.gloh2o.org/>. Information about how to get the CMORPH Climate Data Record by NOAA can be found at https://www.cpc.ncep.noaa.gov/products/janowiak/cmorph_description.html. The Global Satellite Mapping of Precipitation (GSMaP) developed by the JST/CREST research project can be downloaded through the G-Portal at <https://gportal.jaxa.jp/gpr/index/index>. The Integrated Multi-satellite Retrievals for GPM (IMERG) dataset provided by NASA, can be found at <https://gpm.nasa.gov/data/directory>. Direct link to the dataset on GLOBUS: CHAPTER public folder on the LRZ DSA Container PN29CO-DSS-0000.

Code availability

The analysis was performed using Python (version 3.9). The regionalization was implemented using the k -means clustering algorithm from the scikit-learn library (v0.24.2). Custom scripts used for data preprocessing, analysis, calculating the elbow method and generating the precipitation cluster,

seasonality and trends maps are available from the corresponding author at [52]. All the details, parameters and variables used are described in the Methods section.

Acknowledgments

This work is an outcome of Progetto Dipartimenti di Eccellenza 2023 - 2027, funded by MIUR. M.B. has been supported by the European Union - Next Generation EU, Mission 4 Component 1 CUP H53D23011300001, project LocCLIMA and by OGS and CINECA under HPC-TRES program.

Author Contributions

M.B. acquired and curated the datasets, developed the analysis code, performed the formal analysis, prepared the figures, and wrote the initial draft of the manuscript. C.P. conceived the project, supervised the research, and revised the manuscript. Both authors contributed to the interpretation of the results and approved the final version of the manuscript. M.B. will act as the corresponding author and will handle post-publication correspondence and material requests.

Competing Interests

The authors declare no competing interests.

References

- [1] Liu, B., Peng, S., Liao, Y. & Wang, H. The characteristics and causes of increasingly severe saltwater intrusion in pearl river estuary. *Estuarine, Coastal and Shelf Science* **220**, 54–63 (2019).
- [2] Mondal, S. K. *et al.* Projected urban exposure to extreme precipitation over south asia. *Science of the Total Environment* **822** (2022).
- [3] Westra, S. *et al.* Future changes to the intensity and frequency of short-duration extreme rainfall (2014).
- [4] Myhre, G. *et al.* Frequency of extreme precipitation increases extensively with event rareness under global warming. *Scientific Reports* **9** (2019).
- [5] Westra, S., Alexander, L. V. & Zwiers, F. W. Global increasing trends in annual maximum daily precipitation. *Journal of Climate* **26**, 3904–3918 (2013).
- [6] Donat, M. G., Lowry, A. L., Alexander, L. V., O’Gorman, P. A. & Maher, N. More extreme precipitation in the world’s dry and wet regions. *Nature Climate Change* **6**, 508–513 (2016).
- [7] Papalexiou, S. M. & Montanari, A. Global and regional increase of precipitation extremes under global warming. *Water Resources Research* **55**, 4901–4914 (2019).
- [8] Ciarlo’, J. & Giorgi, F. An increase in global daily precipitation records in response to global warming based on reanalysis and observations. *Open Research Europe* **4** (2024).

- [9] Allen, M. R. & Ingram, W. J. Constraints on future changes in climate and the hydrologic cycle. *Nature* **419**, 224–232 (2002).
- [10] Held, I. M. & Soden, B. J. Robust responses of the hydrological cycle to global warming. *Journal of climate* **19**, 5686–5699 (2006).
- [11] Trenberth, K. E. Conceptual framework for changes of extremes of the hydrological cycle with climate change. *Climatic change* **42**, 327–339 (1999).
- [12] on Climate Change (IPCC), I. P. *Future Global Climate: Scenario-based Projections and Near-term Information*, 553–672 (Cambridge University Press, 2023).
- [13] Roderick, M. L., Sun, F., Lim, W. H. & Farquhar, G. D. A general framework for understanding the response of the water cycle to global warming over land and ocean. *Hydrology and Earth System Sciences* **18**, 1575–1589 (2014).
- [14] Byrne, M. P. & O’Gorman, P. A. The response of precipitation minus evapotranspiration to climate warming: Why the “wet-get-wetter, dry-get-drier” scaling does not hold over land. *Journal of Climate* **28**, 8078–8092 (2015).
- [15] Fischer, E. M., Beyerle, U. & Knutti, R. Robust spatially aggregated projections of climate extremes. *Nature Climate Change* **3**, 1033–1038 (2013).
- [16] Fischer, E. M. & Knutti, R. Detection of spatially aggregated changes in temperature and precipitation extremes. *Geophysical Research Letters* **41**, 547–554 (2014).
- [17] Pendergrass, A. G. & Hartmann, D. L. The atmospheric energy constraint on global-mean precipitation change. *Journal of climate* **27**, 757–768 (2014).
- [18] Pfahl, S., O’Gorman, P. A. & Fischer, E. M. Understanding the regional pattern of projected future changes in extreme precipitation. *Nature Climate Change* **7**, 423–427 (2017).
- [19] Asadieh, B. & Krakauer, N. Y. Global trends in extreme precipitation: Climate models versus observations. *Hydrology and Earth System Sciences* **19**, 877–891 (2015).
- [20] Zuo, D. *et al.* Spatial patterns of short-term extreme precipitation and their causes. *Hydrological Processes* **38** (2024).
- [21] Wang, X. *et al.* Spatiotemporal evolution patterns of contiguous extreme precipitation events across china from a 3d perspective. *Geophysical Research Letters* **49** (2022).
- [22] Fischer, E. M. & Knutti, R. Observed heavy precipitation increase confirms theory and early models. *Nature Climate Change* **6**, 986–991 (2016).
- [23] Guccione, A. *et al.* Extreme precipitation changes in relation to urbanization. *npj Natural Hazards* **3**, 10 (2026).
- [24] André, J., D’Andrea, F., Drobinski, P. & Muller, C. Regimes of precipitation change over europe and the mediterranean. *Journal of Geophysical Research: Atmospheres* **129** (2024).
- [25] Berg, P., Moseley, C. & Haerter, J. O. Strong increase in convective precipitation in response to higher temperatures. *Nature Geoscience* **6**, 181–185 (2013).

- [26] Fowler, H. J. *et al.* Anthropogenic intensification of short-duration rainfall extremes. *Nature Reviews Earth & Environment* **2**, 107–122 (2021).
- [27] Hand, W. H., Fox, N. I. & Collier, C. G. A study of twentieth-century extreme rainfall events in the united kingdom with implications for forecasting. *Meteorological Applications* **11**, 15–31 (2004).
- [28] Lenderink, G. & Van Meijgaard, E. Increase in hourly precipitation extremes beyond expectations from temperature changes. *Nature Geoscience* **1**, 511–514 (2008).
- [29] Hardwick Jones, R., Westra, S. & Sharma, A. Observed relationships between extreme sub-daily precipitation, surface temperature, and relative humidity. *Geophysical Research Letters* **37** (2010).
- [30] Drobinski, P., Alonzo, B., Bastin, S., Silva, N. D. & Muller, C. Scaling of precipitation extremes with temperature in the french mediterranean region: What explains the hook shape? *Journal of Geophysical Research: Atmospheres* **121**, 3100–3119 (2016).
- [31] Zhang, Y. & Wu, X. Global space-time patterns of sub-daily extreme precipitation and its relationship with temperature and wind speed. *Environmental Research Letters* **20** (2025).
- [32] Bao, J., Sherwood, S. C., Alexander, L. V. & Evans, J. P. Future increases in extreme precipitation exceed observed scaling rates. *Nature Climate Change* **7**, 128–132 (2017).
- [33] Kendon, E. J., Blenkinsop, S. & Fowler, H. J. When will we detect changes in short-duration precipitation extremes? *Journal of Climate* **31**, 2945–2964 (2018).
- [34] Guerreiro, S. B. *et al.* Detection of continental-scale intensification of hourly rainfall extremes. *Nature Climate Change* **8**, 803–807 (2018).
- [35] Kottke, M., Grieser, J., Beck, C., Rudolf, B. & Rubel, F. World map of the köppen-geiger climate classification updated (2006).
- [36] Scoccimarro, E. *et al.* Projected changes in intense precipitation over europe at the daily and subdaily time scales. *Journal of Climate* **28**, 6193–6203 (2015).
- [37] Chen, J., Dai, A., Zhang, Y. & Rasmussen, K. L. Changes in convective available potential energy and convective inhibition under global warming. *Journal of Climate* **33**, 2025–2050 (2020).
- [38] Taszarek, M., Allen, J. T., Marchio, M. & Brooks, H. E. Global climatology and trends in convective environments from era5 and rawinsonde data. *NPJ climate and atmospheric science* **4**, 35 (2021).
- [39] Taszarek, M., Allen, J. T., Brooks, H. E., Pilguy, N. & Czernecki, B. Differing trends in united states and european severe thunderstorm environments in a warming climate. *Bulletin of the American Meteorological society* **102**, E296–E322 (2021).
- [40] Pilguy, N., Taszarek, M., Allen, J. T. & Hoogewind, K. A. Are trends in convective parameters over the united states and europe consistent between reanalyses and observations? *Journal of Climate* **35**, 3605–3626 (2022).

- [41] Laviola, S., Monte, G., Cattani, E. & Levizzani, V. How hail hazards are changing around the mediter-ranean (2023).
- [42] Beck, H. E. *et al.* Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrology and Earth System Sciences* **21**, 6201–6217 (2017).
- [43] Beck, H. E. *et al.* Mswep v2 global 3-hourly 0.1 precipitation: methodology and quantitative assessment. *Bulletin of the American Meteorological Society* **100**, 473–500 (2019).
- [44] Xie, P. *et al.* Reprocessed, bias-corrected cmorph global high-resolution precipitation estimates from 1998. *Journal of Hydrometeorology* **18**, 1617–1641 (2017).
- [45] Xie, P. *et al.* Noaa climate data record (cdr) of cpc morphing technique (cmorph) high resolution global precipitation estimates, version 1 (2019). URL <https://doi.org/10.25921/w9va-q159>. NOAA CDR Program.
- [46] Japan Aerospace Exploration Agency (JAXA), Earth Observation Research Center (EORC). Data Format Description for Global Satellite Mapping of Precipitation Microwave-IR Combined Product (GSMaP_MVK) and Gauge-calibrated Rainfall Product (GSMaP_Gauge), Reanalysis Products (GSMaP_RNL), and Gauge-calibrated Reanalysis Product (GSMaP_Gauge_RNL) Version 6. Technical Report, JAXA Earth Observation Research Center (2015). URL https://sharaku.eorc.jaxa.jp/GSMaP/document/new/DataFormatDescription_MVK_RNL_v6.5133.pdf.
- [47] Huffman, G. J., Stocker, E. F., Bolvin, D. T., Nelkin, E. J. & Tan, J. GPM IMERG Late Precipitation L3 Half Hourly 0.1 degree x 0.1 degree V07 (2024). URL <https://doi.org/10.5067/GPM/IMERG/3B-HH-L/07>. Accessed: [Data Access Date].
- [48] NASA Global Precipitation Measurement (GPM) Mission. IMERG V07 Technical Documentation. Tech. Rep. (2023). URL https://gpm.nasa.gov/sites/default/files/2023-07/IMERG_TechnicalDocumentation_final_230713.pdf. Date Last Updated: July 13, 2023.
- [49] Tartaglione, N., Parodi, A., Bernini, L., Hachinger, S. & Kranzlmüller, D. Chapter: 3x3 km meteorological data 1981-2022 for europe: 2d extracted fields.[data set] (2024). URL <https://doi.org/10.25927/0ppk7-znk14>.
- [50] Skamarock, W. C. *et al.* A description of the advanced research wrf version 4. *NCAR tech. note ncar/tn-556+ str* **145** (2019).
- [51] Bernini, L. *et al.* Convection-permitting dynamical downscaling of era5 for europe and the mediterranean basin. *Quarterly Journal of the Royal Meteorological Society* e5014 (2025).
- [52] Borgnino M. Sub-daily and daily scripts (2026). URL <https://doi.org/10.5281/zenodo.21161794>.

Figure Legends

Figure 1. multi-dataset mean annual cumulative precipitation over the study domain, averaged over the 2000–2020 period.

Figure 2. Top maps: multi-datasets mean of percentage of selected independent sub-daily extreme events per season (daily cases show in figure S5). Bottom panel: multi-dataset percentage of selected extreme events per season. Solid color and transparent color represent the sub-daily and daily cases, respectively.

Figure 3. Multi-dataset timeseries of the frequency of extreme events (light blue) and its 3-years running mean (blue) for daily (a) and sub-daily (b) cases. Shadowed area represents the multi-dataset standard deviation. Red line is the linear regression fitted directly to the raw annual timeseries. Exceedance Frequency Change (EFC) of sub-daily (blue) and daily (orange) extreme precipitation events (c) and ratios of number of points with sub-daily trends larger than daily trends to number of points with sub-daily trends smaller than daily trends (d) for each dataset. Empty points in panel (c) indicate that the null hypothesis of stationarity in the occurrence of extreme precipitation events cannot be rejected at the 95% confidence level; error bars on relative trends are the propagated standard error of the slope; shaded bars around the zero lines indicate the 95% confidence band of changes expected from internal variability alone, obtained applying a bootstrap technique using a Monte Carlo algorithm. In panel (d) statistical significant results, based on binomial test, are denoted by filled points and the error bars represent the 5th and 95th percentile of ratio distribution built through a Monte Carlo method.

Figure 4. (a) Map of k -means clusters. (b) Percentage of selected events per season (different colors) for each cluster; solid and transparent color represent the sub-daily and daily cases, respectively. Summary of multi-dataset EFC (Exceedance Frequency Change) (c) and ratios (d) for each cluster. Empty points are not statistically significant. Shaded bars around the zero lines (c) indicate the 95% confidence band of changes expected from internal variability alone, obtained applying a bootstrap technique using a Monte Carlo algorithm.

Figure 5. Multi-dataset sensitivity to threshold percentile used to define extreme events at the daily (orange) and sub-daily (blue) timescales. The top x-axis indicates the corresponding number of events.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [supplementaryREV2.pdf](#)