



Climatology and trends of extreme precipitation in France: evaluation of an explicit-convection regional climate model

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Abstract. Climate change is intensifying the global water cycle, with extreme precipitation events increasing in frequency and intensity at the global scale. While trends in daily precipitation extremes are well-documented, sub-daily extremes—critical for flash flood risk—remain poorly characterized, due to limited long-term sub-daily observations. Convection-permitting models explicitly resolve deep convection and therefore offer the potential for a substantially improved representation of convective processes and short-duration precipitation extremes. This study evaluates the ability of the convection-permitting regional climate model AROME (2.5 km resolution, 1959–2022), forced by ERA5 reanalysis, to reproduce precipitation extremes and their trends, at daily and hourly scales, using a dense network of Météo-France stations.

Using extreme value theory (GEV modeling), we analyze trends in 10-year return levels for both daily (1959–2022) and hourly (1990–2022) extremes. At the daily scale, AROME reproduces observed positive trends in southeastern France, consistent with previous studies. Hourly trends are more heterogeneous and less robust, with high spatial variability and low model-observation correlation. Overall, the results highlight the added value of the explicit-convection model for extreme precipitation studies while underscoring its limitations for convective extremes.

1 Introduction and context

Climate change is driving a warming of the planet’s surface air, with a more pronounced increase over land than over oceans (IPCC, 2021). Global warming has reached +1.1°C worldwide, +1.7°C in metropolitan France, and +2°C in the French Alps compared to the pre-industrial era. Furthermore, the Clausius-Clapeyron relationship indicates that warmer air can hold more moisture (+7% per °C) (Clapeyron, 1834). Due to buoyancy (Archimedes’ principle), warm air surrounded by cooler air tends to rise. As warm air ascends in the atmosphere, it undergoes adiabatic cooling, leading to the condensation of water vapor and the formation of precipitation (Lin et al., 2022). However, under calm conditions, the central portion of the precipitation distribution does not fully capitalize on this excess moisture. Energetic constraints (radiative balance, evaporation, ocean-air exchanges) and dynamic constraints (subsidence, synoptic winds) limit the increase in mean precipitation to only 1–3% per °C (IPCC,



2021). In contrast, during intense convective events (thunderstorms, rapid cyclogenesis), rapid ascent condenses nearly all of this surplus, causing short-duration extreme rainfall to increase by 5–8% per °C—almost matching the theoretical potential. Extreme precipitation closely follows the Clausius-Clapeyron scaling, whereas mean rainfall remains influenced by numerous other energetic and dynamic factors (O’Gorman, 2015). Thus, climate warming theoretically leads to an increase in extreme precipitation, though this increase varies with changes in atmospheric circulation and can be locally amplified (Blanchet et al., 2021).

Extreme precipitation events are defined as events belonging to the upper tail of the precipitation intensity distribution. There is no consensus on what constitutes an extreme event. Some authors study precipitation intensities above the 99th percentile or seasonal/annual maxima, while others define extreme precipitation as events rarely or never encountered in a human lifetime (e.g., precipitation levels expected once every 50, 100 or 1,000 years). Extreme events are at the heart of climate and societal concerns, as they are responsible for numerous casualties and economic costs associated with flooding, landslides, and infrastructure failures (IPCC, 2022). In 2024, numerous such events made headlines, including in Nepal, Afghanistan, Central Europe, eastern Spain, and France (World Meteorological Organization (WMO), 2025). Notably, in France in June 2024, intense high-altitude rainfall contributed to major flooding in the Écrins massif (Blanc et al., 2024); in October 2024, over 600 mm of rain in 48 hours caused widespread flooding in the western slopes of the Massif Central (Météo-France, 2024a); and in May 2025, extremely intense but short-lived thunderstorms (locally exceeding 120 mm/h) caused extensive damage in the central Mediterranean region (Météo-France, 2025a).

Daily extremes have increased in intensity and frequency across more than half of the world’s land regions, at a rate close to +7% per °C of warming (IPCC, 2021). Some regional studies suggest similar trends in a significant proportion of land areas (Donat et al., 2016). In France, however, signals are far more heterogeneous, with strong regional variations. In most regions, trends remain weak or non-significant, and only in certain areas—particularly the southeast—are signals detected. In southeastern France, no significant trend in annual maxima of daily precipitation was detected before the early 1990s (Blanchet and Creutin, 2022). Since then, studies report increases on the order of 20% (with estimates reaching up to +40% depending on the metric and uncertainty range) (Ribes et al., 2019; Blanchet et al., 2018; Blanchet and Creutin, 2022). In the southeastern Alps, the increase in 20-year return level daily precipitation in autumn reaches up to +100% between 1958 and 2017 (Blanchet et al., 2021).

Hourly extremes are essential for characterizing intense convective phenomena (thunderstorm downpours, stationary thunderstorms) often responsible for flash floods. Due to the lack of long, spatially dense time series, there is no systematic global analysis of sub-daily trends; available data are often sparse, short, and non-significant. Nevertheless, several regional studies detect an intensification of hourly extremes across nearly all continents, though global confidence in an overall increase remains very low (IPCC, 2021). Increases in extreme rainfall have been observed in the United States, China (summer), Australia (annually), South Africa (summer), India, Malaysia, and Italy (IPCC, 2021). Depending on the method and region, studies highlight sensitivities ranging from +7% to +13% per °C—up to twice the Clausius-Clapeyron rate (Molnar et al., 2015). In France, few regional studies explicitly characterize trends in hourly extremes. Observed maximum 1-hour values now reach



40–60 mm during major Mediterranean events, compared to 30–40 mm in the 1980s–1990s (Météo-France, 2024b). Only the study by Berghald et al. (2025) quantifies trends in hourly extremes in the French Alps. However, trends in hourly return levels remain weak to non-significant, with no clear spatial or seasonal coherence, contrasting with the robust signals observed at daily time scales (Soubeyroux et al., 2015). This suggests that hourly extremes do not yet show a clear climate signal, possibly because the signal is still emerging but cannot be robustly detected given the short length of available series and the high year-to-year variability.

In France, a nationwide network of daily precipitation with good spatial coverage became available from the 1950-1960s, while most hourly records only began in the 1990-2000s (Météo-France, 2024b). In parallel, regional climate models (RCMs, about 12 km resolution for EURO-CORDEX) forced by reanalyses provide complementary advantages of: 1) precipitation series that potentially go back further in time than raingauge records; and 2) spatially complete and physically consistent fields, particularly useful in poorly instrumented areas. Although RCMs are useful for studying daily extremes (Dierickx et al., 2025; Steensen et al., 2025), they are not suitable for studying convective extremes, as convection is parameterized, leading to over-smoothed and poorly located hourly precipitation at 12 km resolution (Schär et al., 2020). The emergence of RCMs at kilometer-scale resolution allowing the explicit resolution of deep convection offers a unique opportunity, as they realistically simulate the dynamics of intense precipitation at fine spatial and temporal scales over long periods. Recent multi-model convection-permitting ensembles have been shown to better represent heavy precipitation compared to 12km resolution RCMs, in particular at hourly scale (Ban et al., 2021; Pichelli et al., 2021; Berthou et al., 2020). Such simulations also provide more certain projections of local changes in extreme rainfall, by substantially reducing model-related uncertainty compared to coarser-resolution RCMs (Fosser et al., 2024). The convection-permitting RCM model developed by CNRM (CNRM-AROME model, 2.5 km) forced by the global reanalysis ERA-Interim (80 km) has been evaluated by Caillaud et al. (2021) over the Pan-Alpine domain (1981-2018) and by Cortés-Hernández et al. (2024) over Corsica island (2000-2018). Caillaud et al. (2021) show a generally good representation of heavy precipitation events, but the model tends to underestimate the highest values (>200 mm/d and >40 mm/h).

Recently, a new hindcast simulation using the latest version of the CNRM-AROME model and forced by the most recent global reanalysis, ERA5 (25-31km), has been performed, covering the period from 1959 to 2022. This provides a unique dataset with sufficiently long series (63 years) to study precipitation extremes in France and their trends. However, the validity of the extremes simulated by this model has never been evaluated. Our study aims at addressing this gap. In addition to evaluating new simulations, our study shows two added-values compared to Caillaud et al. (2021), Ban et al. (2021) or Pichelli et al. (2021). First, we focus here on extremes, i.e. precipitation amounts observed only a few times in a lifetime (e.g. the 10-year return level, which is the level exceeded on average once every ten years), rather than heavy precipitation corresponding to high but non-extreme quantiles (e.g. the 99th percentile of daily precipitation considered in Ban et al. (2021) is exceeded on average 3.65 times a year, while the 99.9th percentile of hourly precipitation is exceeded on average once in 40 days). Second, we evaluate trends in extreme precipitation, whereas Caillaud et al. (2021), Ban et al. (2021) or Pichelli et al. (2021) looked at the climatology. Based on non-stationary Extreme Value Theory, our analysis is able to evaluate trends in 10-year return level in CNRM-AROME at both daily and hourly scale in France.



90 2 Data used

2.1 Stations

In order to evaluate the CNRM-AROME model, this study uses precipitation data from Météo-France stations (Météo-France, 2024b) at daily (1959–2022) and hourly (1990–2022) time steps. There is a strong contrast between daily and hourly observational records available in France. Daily stations provide long, dense time series: more than half of the 8,198 daily records have over
95 40 years of data with limited missing values, and several exceed 60 years. In contrast, hourly stations remain much shorter: most of the 2,315 hourly stations offer only 15–30 years of data, reflecting the later deployment of automatic networks. This disparity underscores why long-term trends in sub-daily extremes have been little studied in France so far.

Station selection is based on two criteria: at each station, we compute the proportion of missing data for each year/season/month. A year/season/month is considered as missing if it contains more than 10% of missing values. Then only the stations with at
100 least the required number of nonmissing years/seasons/months are retained: 50 years for the daily station (1959–2022) and 25 years for the hourly stations (1990–2022). Subsequent analyses are restricted to this subset of stations and years/seasons/months. These criteria, applied over the complete hydrological reference period, lead us to select 1,583 daily stations and 574 hourly stations.

2.2 CNRM-AROME model

105 CNRM-AROME model (hereafter referred to as AROME) is the Convection-Permitting Regional Climate Model (CP-RCM) developed at CNRM (Centre National de Recherches Météorologiques). Based on the limited-area mesoscale AROME model (Seity et al., 2011) used for National Weather Prediction at Météo-France since 2008, AROME is also used in climate mode since 2014 (Caillaud et al., 2021; Lucas-Picher et al., 2024a). AROME combines the non-hydrostatic dynamical ALADIN bi-spectral core and physical parameterisations coming from the research model Meso-NH. At the kilometer-scale resolution,
110 deep convection is no longer a sub-grid process but shallow convection still need to be parametrised. A new version of AROME is used in this study, with improvements mainly concerning surface schemes. Over the nature tiles, the soil is modelled by 14 soil layers instead of 3 in the previous version and 3 vegetation types are now taken into account, whereas only one was chosen previously, allowing a better representation of sub-grid heterogeneities. A new version of the snow model enables 12 snow layers (instead of one in the previous version). Over town, the existing Town Energy Balance (TEB) (Masson, 2000) now allows
115 for gardens within the urban canyon and is complemented by a building energy module that takes heating and air conditioning into account.

The studied simulation is a 63-year AROME evaluation simulation from 1959 to 2022 directly driven by the ERA5 global reanalysis (Hersbach et al., 2020) at 2.5 km resolution. This simulation is performed over the domain ALPX-3, covering extended metropolitan France (cf. Figure 1). The domain includes 687×847 grid-points, approximately $1,700 \text{ km} \times 2,100$

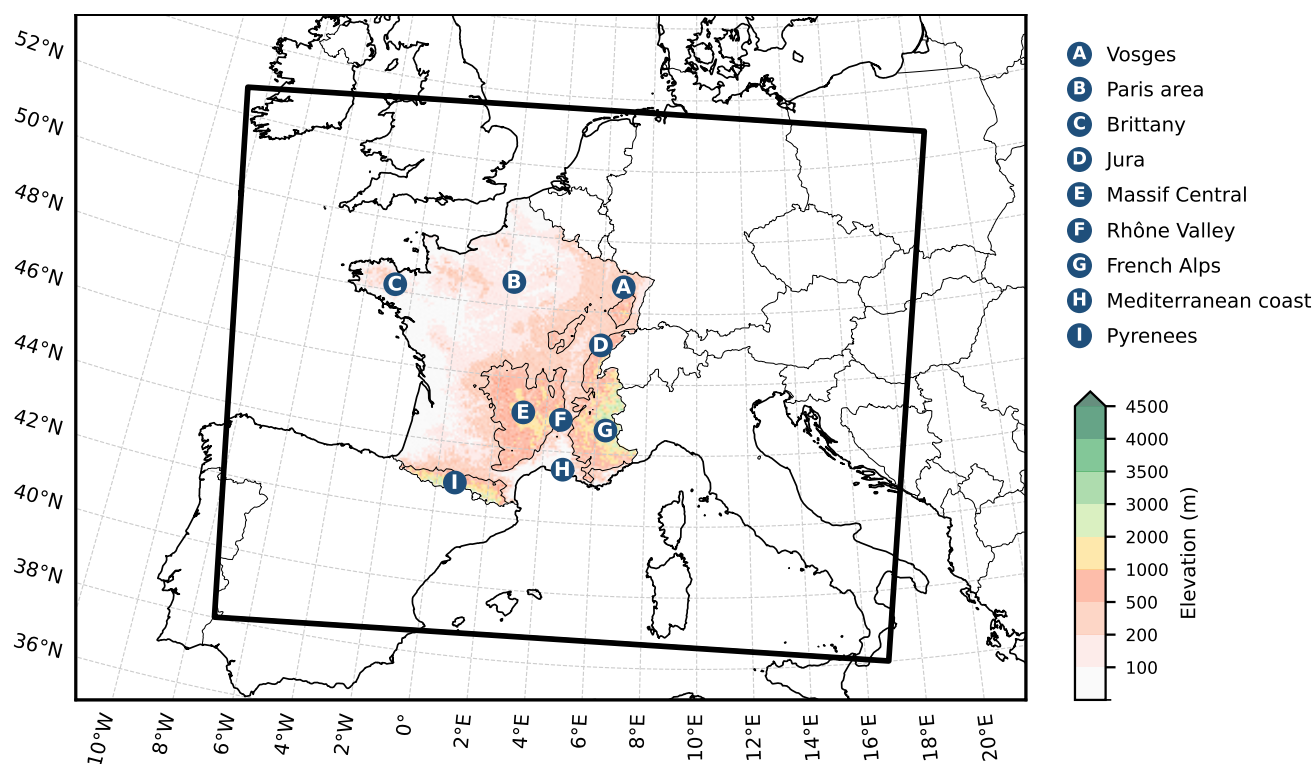


Figure 1. Map showing the computational domain of the AROME model. Shading shows topography at 2.5 km resolution and thin lines indicate the 400 m elevation contour. The letters show the geographical zones cited in the article.

120 km, with 87,536 regularly spaced grid cells over metropolitan France. The evaluation simulation is directly driven at the domain boundaries by the ERA5 reanalysis at 50 km every hour. The sea surface temperatures (SSTs) are also given by the ERA5 reanalysis at 30 km resolution. Aerosols are monthly evolving and come from the ALDERA reanalysis, a CNRM-ALADIN simulation at 12 km driven by ERA5 with an interactive aerosol scheme (Nabat et al., 2020). Green House Gases are evolving annually.

125 More information on the model version and the evaluation simulation can be found in the technical note of Caillaud et al. (2026).

It should be noted that temperature trends (cf. Figure 2) with the AROME model forced by ERA5 are about one-third weaker than observed trends. This implies a dampening of the Clausius-Clapeyron-related component of extreme precipitation trends, which is expected to influence the magnitude of the trends we can detect.

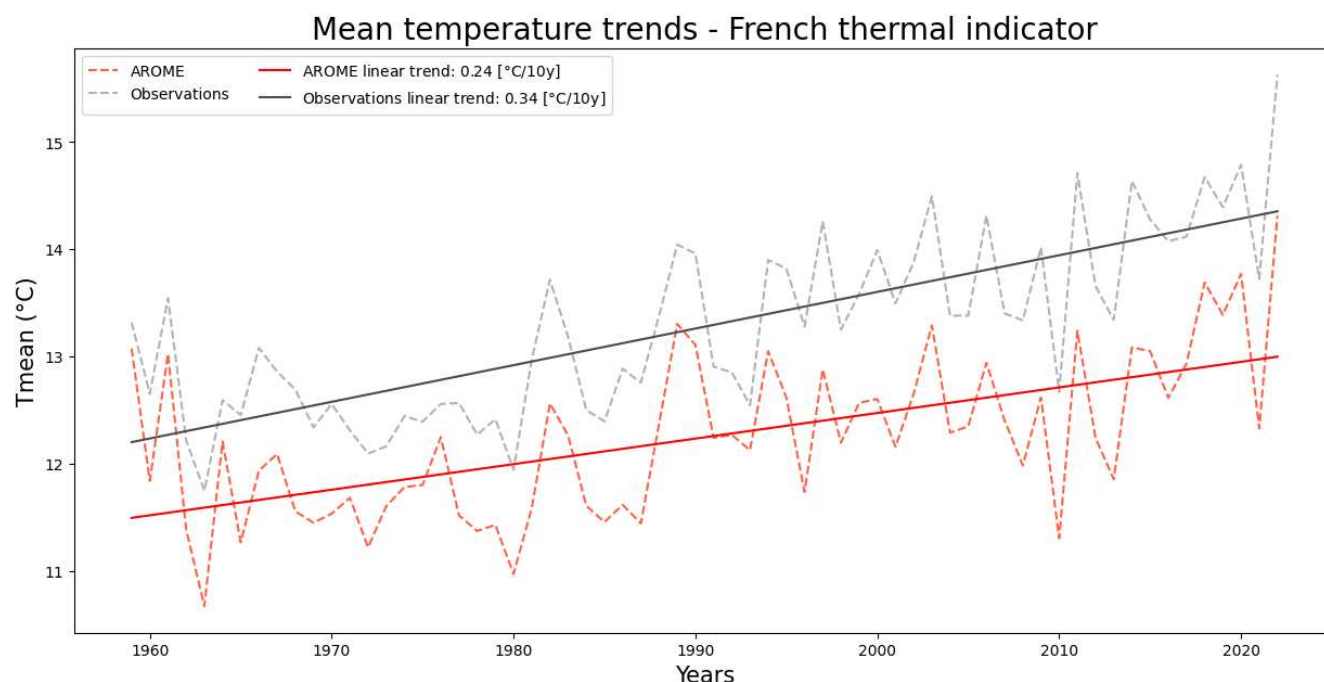


Figure 2. Temporal evolution of the annual mean temperature between 1959 and 2022. For the observations, the time-series are computed from the French thermal indicator, i.e. the mean of a given set of 30 stations with homogenised data, which are the reference temperature stations in France (Gibelin et al., 2014). For the model, the time-series are computed over the mean of the 30 grid-points that are the closest to the stations. For each time-series, the trend is computed using a linear regression.

3 Methodology

130 The primary objective of this study is to validate the AROME model (grid points) against stations over metropolitan France. This is first conducted under stationary conditions to focus on the climatology (Section 3.1), then in a non-stationary context to assess the variability and trends in extremes (Section 3.2).

Evaluation is made per year and season. Seasons are defined as follows: **OND**: October (OCT), November (NOV), December (DEC), **JFM**: January (JAN), February (FEB), March (MAR), **AMJ**: April (APR), May (MAY), June (JUN), **JAS**: July (JUL),
 135 August (AUG), September (SEP). The hydrological year (**YEAR**) is defined as the period from 1 September of year N to 31 August of year N+1.



3.1 Climatology of extremes

While descriptive statistics such as mean precipitation or wet day frequency provide useful summaries for overall precipitation, they cannot assess quality of rare occurrence, e.g. of 10 year return events that are exceeded on average only once every 10 years. To address this limitation, we apply extreme value theory (EVT) (Coles, 2001). This states that, under general conditions, the cumulative distribution function (CDF) of block maxima - e.g. annual maxima - can be approximated by the Generalized Extreme Value (GEV) distribution.

The GEV distribution is a continuous probability distribution parameterized by the triplet $\theta = (\mu, \sigma, \xi)$ — respectively the location, scale (strictly positive), and shape—with the following cumulative distribution function:

$$F(x; \mu, \sigma, \xi) = \exp \left\{ - \left[1 + \xi \frac{x - \mu}{\sigma} \right]^{-1/\xi} \right\}, \quad 1 + \xi \frac{x - \mu}{\sigma} > 0$$

It unifies the three classical distributions Gumbel ($\xi \rightarrow 0$), Fréchet ($\xi > 0$) and Weibull ($\xi < 0$) where the shape parameter ξ determines the tail behavior.

The return level (or quantile of order $1 - \frac{1}{T}$) of the GEV distribution corresponds to the threshold value exceeded, on average, once every T years. Denoting by F^{-1} the quantile function of the GEV, it is given by:

$$RL_T = F^{-1} \left(1 - \frac{1}{T} \right) = \mu + \frac{\sigma}{\xi} \left[\left(-\log \left(1 - \frac{1}{T} \right) \right)^{-\xi} - 1 \right]. \quad (1)$$

The GEV parameters (μ, σ, ξ) are estimated by maximum likelihood method for each spatial location separately, considering the block maxima at a given location to be independent. This gives a set of parameters μ, σ, ξ and thus return level estimates from Eq. 1.

3.2 Trends in extremes

3.2.1 Non-stationary GEV models

To consider trends in extremes, the GEV distribution can be made non-stationary by allowing at least one GEV parameter to vary with time: $\mu(t)$, $\sigma(t)$ and/or $\xi(t)$. Owing to the difficulty of estimating the tail parameter ξ , it is assumed stationary, i.e. $\xi(t) = \xi_0$. Three non-stationary models are considered:



$$\begin{array}{ccc}
 M_1(\theta_1) & M_2(\theta_2) & M_3(\theta_3) \\
 \theta_1 = (\mu_0, \mu_1, \sigma_0, \xi_0) & \theta_2 = (\mu_0, \sigma_0, \sigma_1, \xi_0) & \theta_3 = (\mu_0, \mu_1, \sigma_0, \sigma_1, \xi_0) \\
 \begin{cases} \mu(t) = \mu_0 + \mu_1 t \\ \sigma(t) = \sigma_0 \\ \xi_0 \end{cases} & \begin{cases} \mu(t) = \mu_0 \\ \sigma(t) = \sigma_0 + \sigma_1 t \\ \xi_0 \end{cases} & \begin{cases} \mu(t) = \mu_0 + \mu_1 t \\ \sigma(t) = \sigma_0 + \sigma_1 t \\ \xi_0 \end{cases}
 \end{array}$$

160 Furthermore, based on previous studies that showed trends in extremes in France emerging in the mid-80s (Blanchet et al., 2018; Ribes et al., 2019; Blanchet and Creutin, 2022), we consider the case of a trend starting at year $t_+ = 1985$, leading to the three models M_1^* , M_2^* , and M_3^* . For example, in M_1^* :

$$\mu(t) = \begin{cases} \mu_0 & \text{if } t \leq 1985, \\ \mu_0 + \mu_1(t - 1985) & \text{if } t \geq 1985. \end{cases}$$

165 Figure 3 illustrates the case of a non stationary GEV with trends in μ and σ starting in 1985 (corresponding to M_3^*), with the corresponding GEV densities and associated return level plots for several years.

This gives in total six non-stationary models, in addition to the stationary model denoted (M_0), which corresponds to $\mu(t) = \mu_0$, $\sigma(t) = \sigma_0$, and $\xi(t) = \xi_0$. Although the starting year $t_+ = 1985$ will be hold fixed below, considering starting year a few years before or after does not change the main results of this study (not shown).

3.2.2 Model selection

170 For each model, the GEV parameters θ are estimated by maximum likelihood method for each spatial location separately. At each spatial point, we thus have seven estimated models $M_0, M_1, M_2, M_3, M_1^*, M_2^*$, and M_3^* that we temporarily rename M_0 to M_6 . We apply for each non-stationary model M_j , $j \geq 1$, a likelihood ratio test to compare the goodness of fit of M_j to that of the stationary model M_0 , accounting for their respective number of parameters to avoid overfitting. The test is based on computing the statistics $\Lambda_j = 2(\ell_j - \ell_0)$, where ℓ are the maximum likelihood values. Under the null hypothesis that the
175 maxima are stationary, the statistics Λ_j follows a χ^2 with k degree of freedom, with k equal the difference in the number of parameters between M_j and M_0 .

Let p_j be the corresponding p -value. If $p_j \leq 10\%$, the model M_j is considered to perform better than M_0 , otherwise M_0 is selected. If several models M_j are preferred to M_0 , we apply the following procedure: 1) if either M_3 or M_3^* are preferred to M_0 , we select among these two models that with the smallest p -value among p_3 and p_3^* ; 2) otherwise, we select among M_1, M_1^* ,
180 M_2, M_2^* that with the smallest p -value among p_1, p_1^*, p_2, p_2^* .

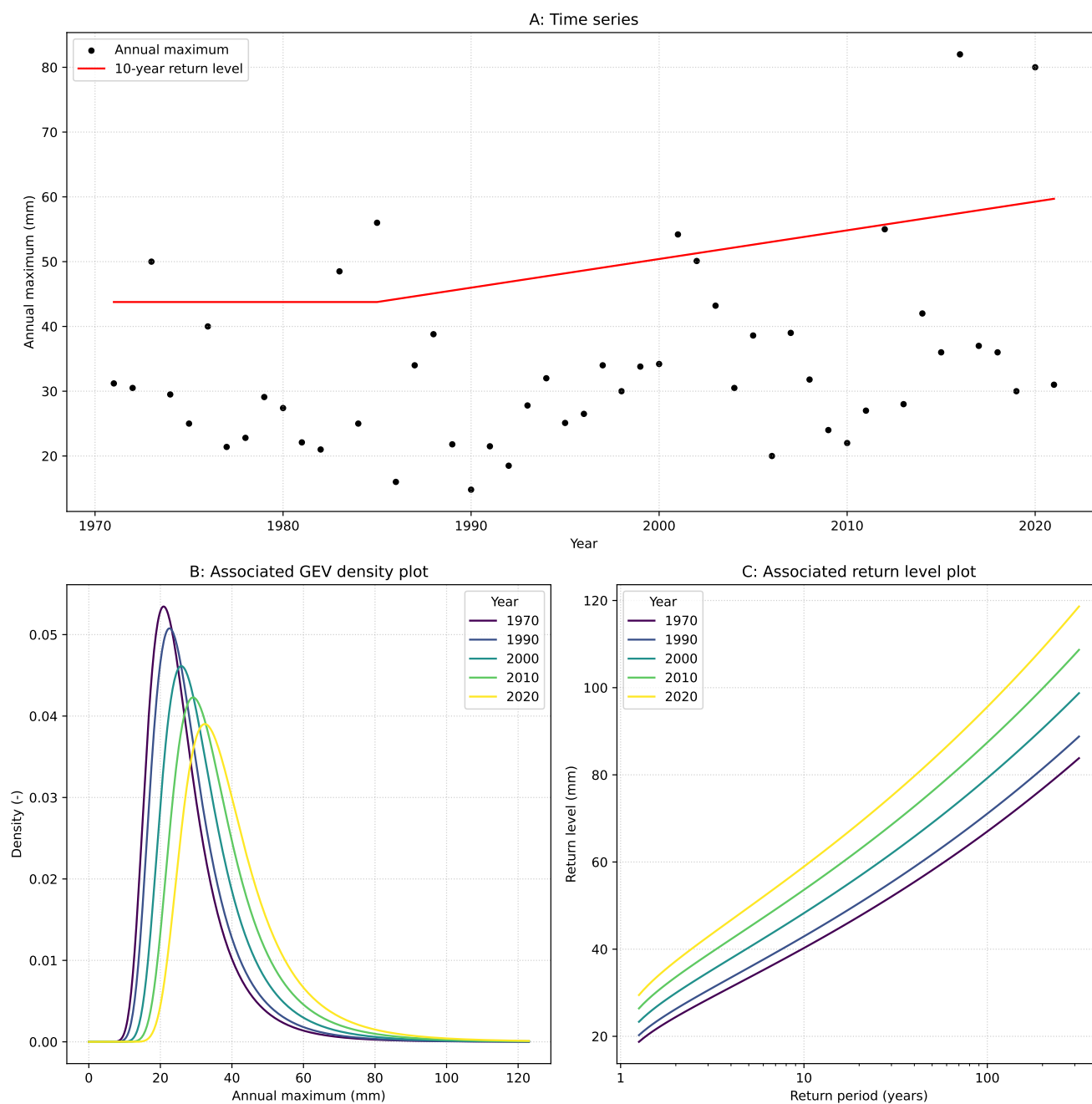


Figure 3. Influence of a trend in the μ and σ parameters for a time series of annual maxima (Example: Station 45330001 located at 48.09° N, 1.94° E). (a) Time series (black dots) with the 10-year return level (red line); (b) GEV densities for selected years between 1970 (purple) and 2020 (yellow); (c) Associated return level curves.



This two-step process prioritizes models with simultaneous temporal effects on μ and σ when statistically justified, ensuring complexity is introduced only when it provides plus-value. In the rest of the article, only the selected model is considered at each location (grid point or station). However, for the evaluation of 10-year return levels as a climatological metric, we consistently rely on the stationary model (M_0).

185 3.2.3 Trend in return level

For a non-stationary GEV with parameters $\mu(t)$, $\sigma(t)$ and ξ_0 , the T -year return level is still given by Eq. 1 but it is now a function $RL_T(t)$ of the year t .

Owing to the linear form of $\mu(t)$ and $\sigma(t)$ in the considered non-stationary models, return levels are linear functions of time in models M_1 , M_2 , and M_3 , and linear only after 1985 in the breakpoint models M_1^* , M_2^* , and M_3^* . In the stationary model M_0 ,
190 return levels are of course constant over time. For the non-stationary models, the relative trend in the T -year return level (%) over the most recent 30-year period (between 1992 and 2022) is computed as

$$\text{RelTrend} = \frac{RL_T(2022) - RL_T(1992)}{RL_T(1992)}.$$

It is obviously 0 if the stationary model has been selected.

3.2.4 Confidence intervals for the return levels

195 Noting that the T -year return level function can be written as $RL_T(t) = RL_{T,0} + RL_{T,1}t$ for models M_1 , M_2 , M_3 and as

$$RL_T(t) = \begin{cases} RL_{T,0} & \text{if } t \leq 1985, \\ RL_{T,0} + RL_{T,1}(t - 1985) & \text{if } t > 1985, \end{cases}$$

for models M_1^* , M_2^* , M_3^* , confidence intervals for the trend coefficient $RL_{T,1}$ are obtained by profiling the likelihood with respect to $RL_{T,1}$ (Coles, 2001). If the 90% confidence interval of $RL_{T,1}$ does not contain 0, the T -year return level trend is significant at level 10%.

200 4 Results

We begin by evaluating, grid point by grid point, the ability of AROME to reproduce the precipitation regime observed by Météo-France stations. This initial stationary evaluation allows assessing the quality of the extreme-value climatology before examining return-level trends.



4.1 Evaluation of the precipitation climatology of AROME

205 Figure 4 provides a spatial comparison of the precipitation climatology between AROME and Météo-France stations. In addition to the 10-year return level assessing quality of extremes, we show two descriptive statistics assessing the overall climatology of precipitation: the mean number of wet days per year (precipitation exceeding 1 mm) and the mean annual total precipitation. Across all indicators, AROME reproduces the large-scale spatial structures with high spatial correlations: matching the station locations to their closest grid points, Pearson correlation $r = 0.95$ for the annual frequency of precipitation days, $r = 0.94$ for
210 annual cumulative precipitation, $r = 0.95$ for the daily 10-year return level, and a lower correlation of $r = 0.78$ for the hourly 10-year return level. The model correctly captures the main climatic gradients of France: dryness of the Rhône valley and the Mediterranean coast (50-70 wet days per year, annual totals no more than 550 mm per year) contrasting with the wetness of the mountain ranges (Alps, Pyrenees, Massif Central, Vosges, Jura; 140-160 wet days per year, annual totals up to more than 1800 mm per year). The model also reproduces the localization of the largest extremes along the Massif Central ridge and to a lesser
215 extent in the Rhône valley and along the Mediterranean coast at both daily and hourly scales.

Despite this overall agreement, the difference maps reveal structured regional biases. For precipitation frequency, AROME shows little mean bias (+6 days/year) but local excesses above +30 days/year in the Massif Central and Pyrenees, while negative biases (-10 to -30 days/year) appear in the Northern Alps, Brittany, and the Vosges. For annual cumulative precipitation, the mean bias is very small (+11 mm/year) but regional discrepancies reach more than +300 mm per year along the Pyrenean ridge
220 and Northern Alps, and -100 to -400 mm per year from the Northern Pré-Alps to the Vosges. For daily 10-year return level, AROME shows almost no mean bias (-2 mm) but it spreads the extremes too widely around the Massif Central ridge, giving local deficits of -10 to -20 mm along the ridge where the station extremes are the largest and +10 to +30 mm over the Massif Central Plateau. Overestimation is also visible in the Northern Alps and the Pyrenees. At the hourly scale, AROME strongly underestimates the 10-year return levels (-6.37 mm, -23.30 %), with widespread deficits of -5 to -20 mm over most of
225 France, especially in the southern Massif Central and the Rhône Valley.

The good performance of AROME for the frequency of wet days, the annual precipitation and the daily extremes is found across all seasons (see Figure 5 for an overall view and Figures A1 and A2 for seasonal maps of extremes), despite a slight loss in performance in spring and summer for the extremes (AMJ to JAS, correlation around 0.9). Performance is lower for hourly extremes across all seasons and particularly in spring where correlation drops to 0.38.

230 In summary, AROME shows a good representation of the climatology of precipitation extremes that encourages us to continue evaluation on trends, keeping however in mind that hourly extremes are poorly represented in spring.

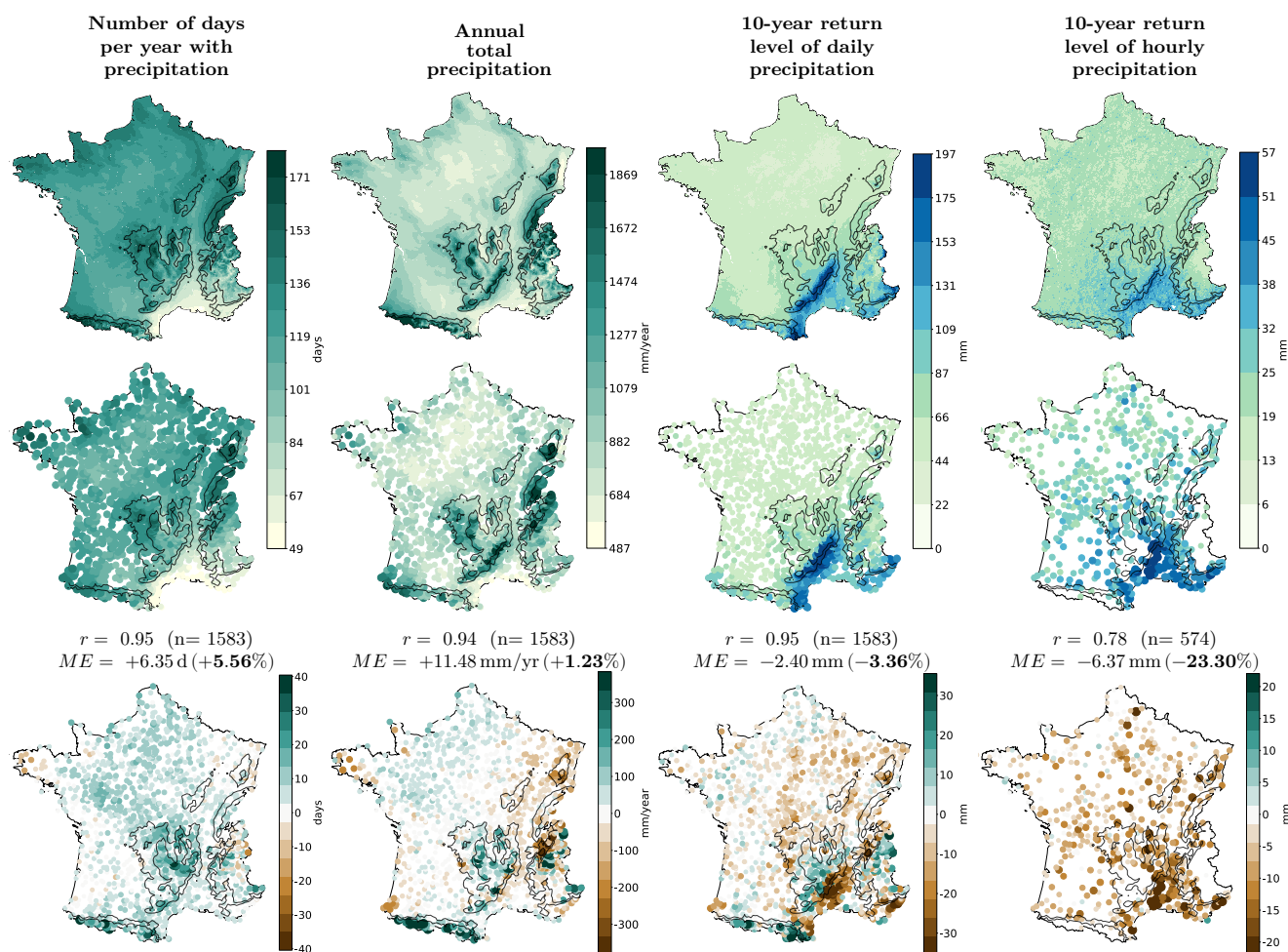


Figure 4. Climatology of the AROME model (first row), Météo-France stations (second row), and the AROMEstation difference (third row), with the spatial correlation between the stations and their closest grid points (r), the bias (ME) and the number of stations compared (n). The statistics of the three first columns are derived from daily data from 1959 to 2022. The last columns uses hourly data from 1990 to 2022. The contour lines show the 400 and 800 m isolines. To ease visualization, colour scales are symmetrically saturated above the 99.9th percentile for the number of days and the 99th percentile for annual and 10-year return level precipitation).

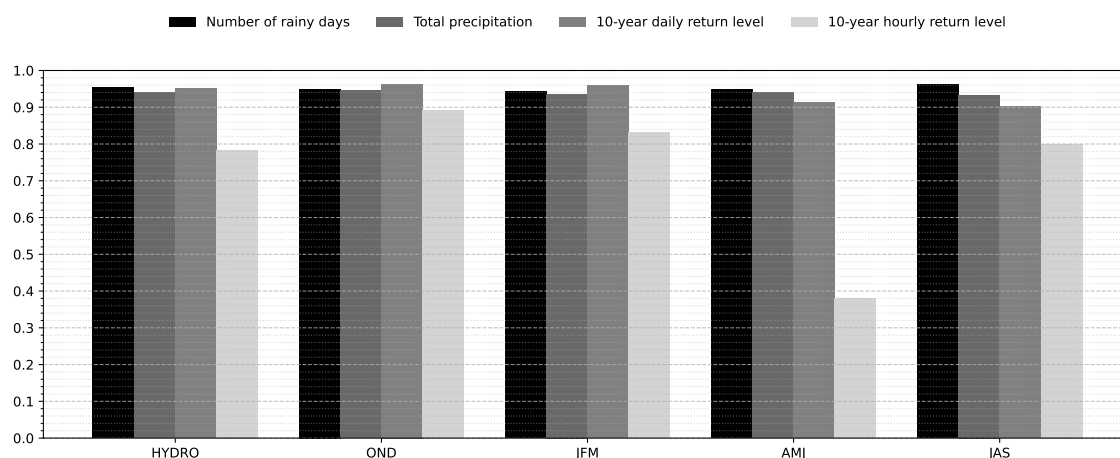


Figure 5. Spatial correlations of climatological indices between the AROME model and Météo-France stations at daily and hourly scales depending on the season.

4.2 Evaluation of extreme precipitation trends

4.2.1 Daily

At the daily scale, station-based trends in the 10-year return level (Figure 6) show spatially coherent but region-dependent signals across France over 1959–2022. For the hydrological year (YEAR), we see a clear reinforcement along the Rhône Valley (+5% to > +30%) and in the southern Alps (+20% to +30%). Elsewhere, trends are weak, of mixed sign, and often not significant, supporting a seasonal breakdown. Autumn (OND) shows a similar pattern in trends as the annual scale, with the exception of the Paris area that shows a decrease (-5 to -20%). In winter (JFM), France is cut in three with a diagonal of decrease from the Mediterranean coast to the Atlantic coast (-10 to -40%) and mainly increases elsewhere. Spring (AMJ) is characterized by a more spatially uniform positive trend over much of the country, with local increases exceeding +35%. Summer (JAS), shows predominantly negative trends in the southern half of France, apart in the Rhône valley, with an accentuated decrease along the Mediterranean coast (up to -40%) and mainly positive trends in the northern half.

AROME reproduces the broad spatial organization of these daily-scale patterns but generally underestimates their amplitudes (negative bias). For the hydrological year, the model partly captures the significant increase in the Southern Alps, albeit with weaker intensities, and does not reproduce the Rhône Valley reinforcement observed in the stations. Autumn is the season when trend patterns are best represented ($r = 0.40$). AROME correctly identifies the positive signal in the Rhône valley and the negative trends in the Paris area, although it barely sees the decrease in the northern Alps. In winter, the model barely retrieves the diagonal of decrease from the Mediterranean to the Atlantic coast and it misses the decrease over the Alps. All the largest trends are anyway less marked. In spring, AROME produces weak and poorly organized signals and fails to reproduce the



250 widespread positive trends measured by the stations. In summer, the model correctly identifies a general negative tendency over the southern half of France but does not see the increase over the Rhône valley and the northern half of France. Overall, AROME captures the large-scale signs and structure of daily return-level trends but tends to underestimate both their intensity and spatial coherence.

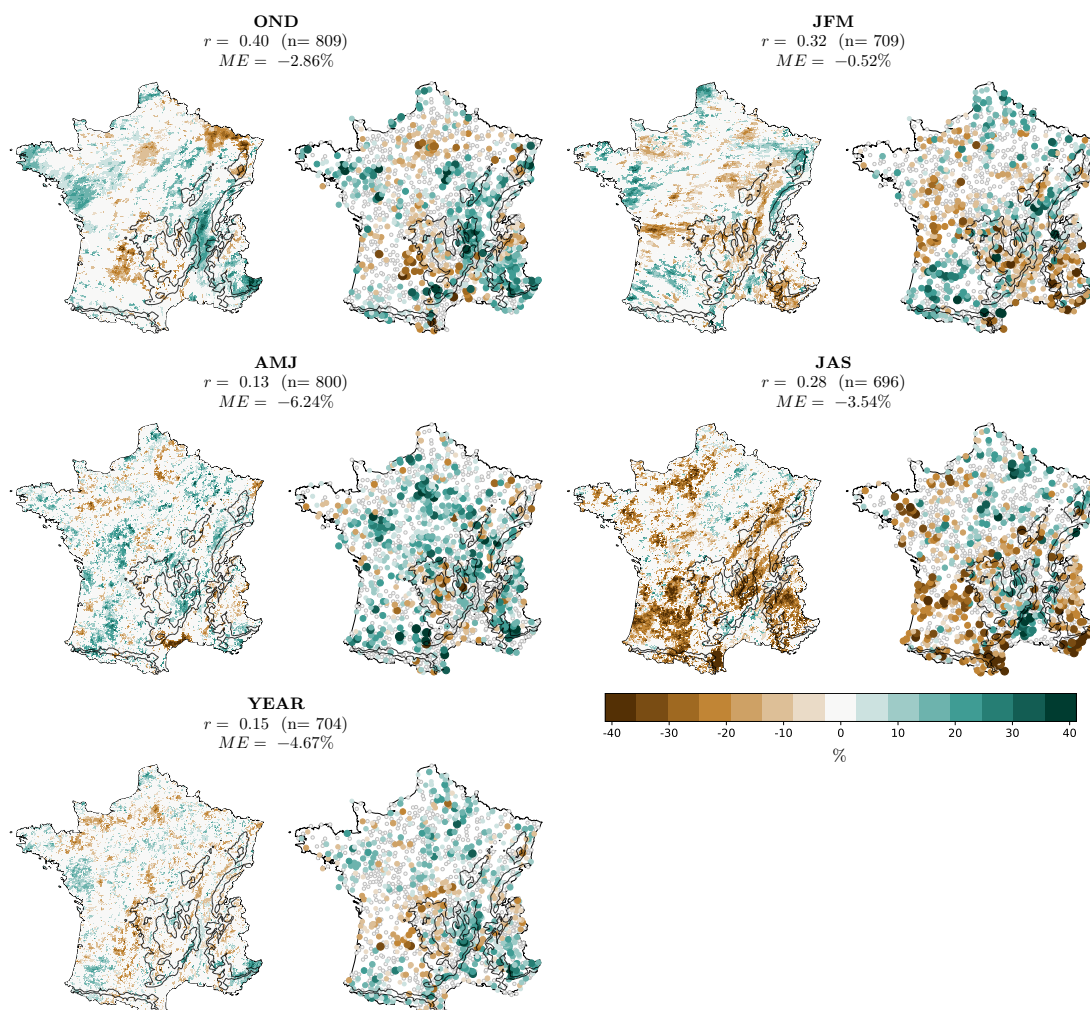


Figure 6. Relative trends over the last thirty years ending in 2022 (%) in the 10-year return level of daily precipitation for AROME (left) and Météo-France stations (right). The correlation (r), the number of stations compared (n), and the bias (ME) are computed on the stations with significant trends. These results are derived by fitting, at each location, the selected GEV model to daily precipitation maxima from 1959 to 2022. The contour lines show the 400 and 800 m isolines. To ease visualization, colour scales are symmetrically saturated using a 99% threshold. All maps are clipped to this common percentile range. Only statistically significant trends are shown, non-significant trends are set to zero.



4.2.2 Hourly

255 At the hourly scale (Figure 7), station-based trends in the 10-year return level over 1990–2022 are markedly more heterogeneous, noisy, and locally more extreme than their daily counterparts (Figure 6), with significant trends ranging $[-50\%, +100\%]$ versus $[-30\%, +30\%]$ at the daily scale. Most of the significant trends are highly positive. Though noisier than at daily scale, these trends are robust in the sense that they are not produced by a single year. Removing the overall maxima of each station and fitting the GEV distributions on these new series gives slightly lower trends for the positive trends and slightly larger trends
260 for the negative ones (Figure B1) - which was expected since the largest value is omitted - but the magnitudes and patterns remain close. Over the hydrological year, almost no trend is found apart in few isolated stations where trends reach $\pm 50\%$ and occasionally exceed $+100\%$. Seasonally, the signals remain highly contrasted. In autumn, a pronounced positive pattern emerges along the Mediterranean coast, locally approaching $+100\%$. In winter, no trend is found apart at some isolated stations spread over western France, the eastern Pyrenees and the Rhône valley, where strong increases of up to $+100\%$ are found. Spring is the
265 only season when a quite coherent pattern is found. Stations exhibit widespread and very strong increases across much of the country, frequently above $+60\%$ and locally approaching $+100\%$. In summer, spatial variability reaches its maximum, with trends spanning the full range from -100% to $+100\%$, particularly in the Rhône Valley. These patterns reflect both the strong local variability of convective extremes and the limited length of the hourly record, which jointly hinder the emergence of a clear regional-scale climate signal.

270 AROME only partially reproduces these hourly-scale patterns. Across all seasons, the model simulates weak and spatially inconsistent signals and fails to capture the most pronounced positive trends seen in the station data. For the hydrological year, spatial correlation between AROME and stations remains low ($r \approx 0.12$), and seasonal correlations are close to zero for several seasons. Mean biases are substantial and of varying sign, with values reaching $ME = +84.7\%$ in spring and $ME = -28.4\%$ in summer. While AROME occasionally recovers the sign of the observed trends in some regions, it generally does not reproduce
275 their fine-scale spatial organization or amplitude.

The monthly analysis (Figure 8) further highlights the specificity of convective regimes and the strong temporal concentration of some signals. Station data show that hourly 10-year return level trends are not uniformly distributed throughout the year but cluster in a few key months. In late winter, strong increases emerge over the Rhône Valley and the Mediterranean coast in February, while March extends these trends all along the western Mediterranean arc. In late autumn, November exhibits
280 substantial increases on the eastern Mediterranean coast (Azur region). In early summer, June displays the clearest signal with widespread positive trends over almost all of France, with local values exceeding $+150\%$.

AROME reproduces partly the enhanced activity of some months but it underestimates their magnitude. The model reproduces the existence of positive signals in February, March, November, and June, consistent with the station-based identification of convectively active months. However, the simulated trends are often weaker by a factor of two and display inconsistent spatial
285 localization compared to observations, as reflected by the very low spatial correlations for some months (e.g. $r = 0.08$ in June).

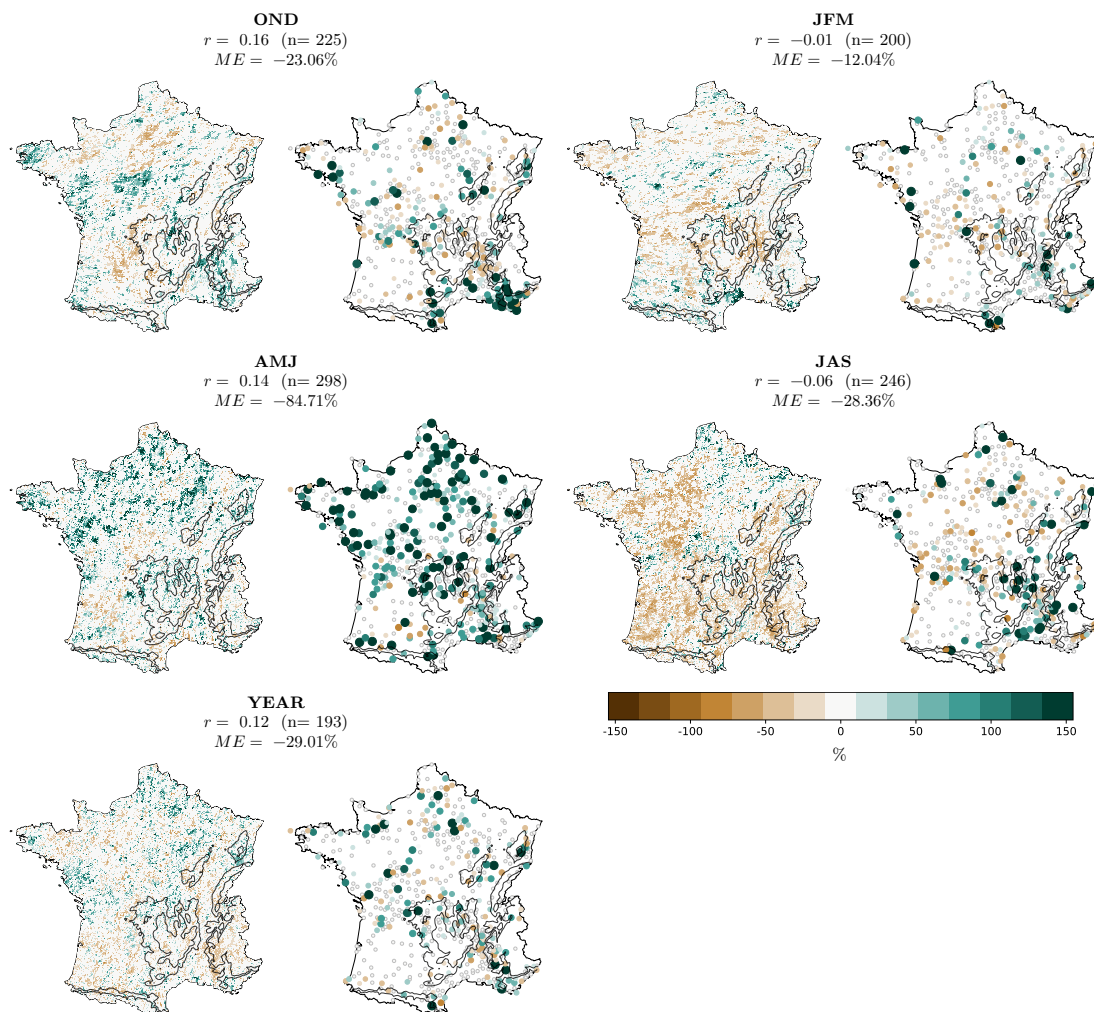


Figure 7. Relative trends over the last thirty years ending in 2022 (%) in the 10-year return level of hourly precipitation for AROME (left) and Météo-France stations (right), with the correlation (r), the number of stations compared (n), and the bias (ME), filtering on the stations with significant trends. These results are derived by fitting, at each location, the selected GEV model to hourly precipitation maxima from 1990 to 2022. The contour lines show the 400 and 800 m isolines. To ease visualization, colour scales are symmetrically saturated using a 90% threshold. All maps are clipped to this common percentile range. Only statistically significant trends are shown, non-significant trends are set to zero.

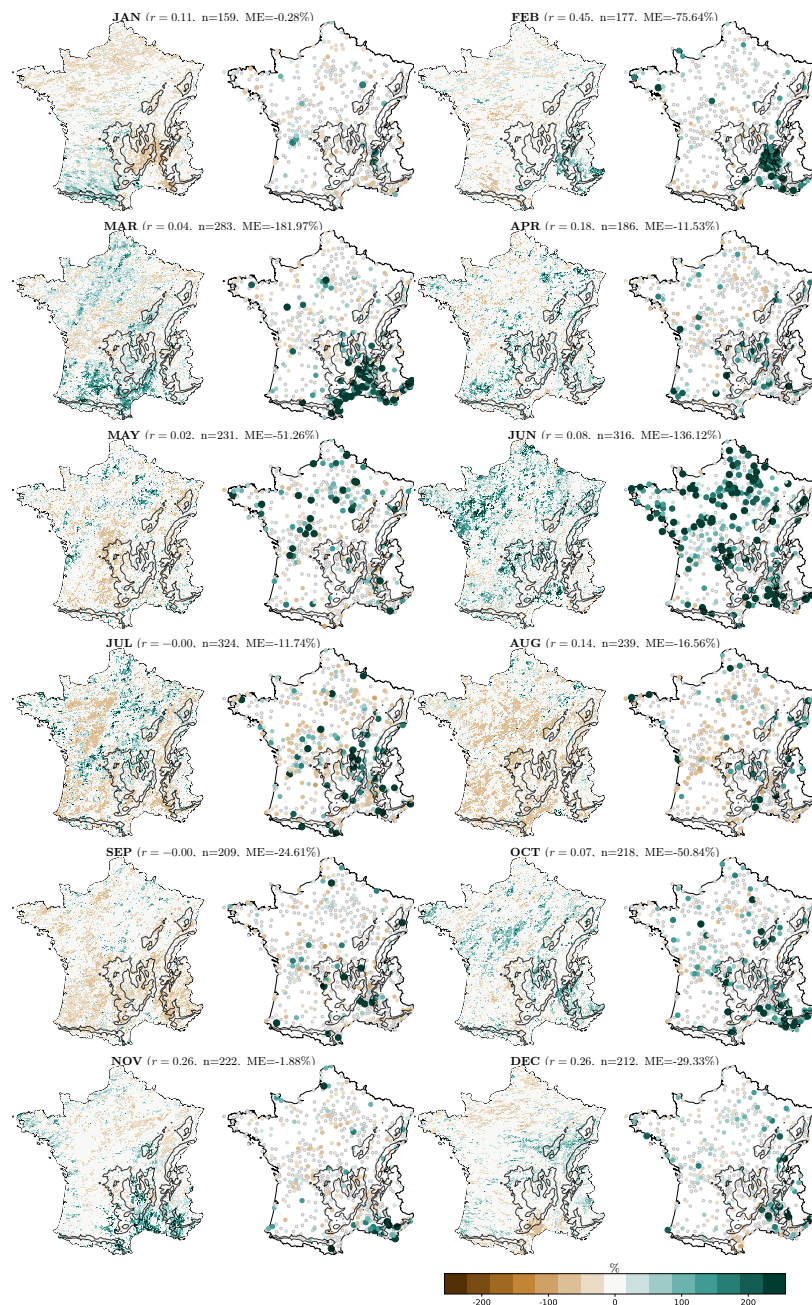


Figure 8. Relative trends over the last thirty years ending in 2022 (%) in the 10-year return level of hourly precipitation for AROME (left) and Météo-France stations (right), with the correlation (r), the number of stations compared (n), and the bias (ME). These results are derived by fitting, at each location, the selected GEV model to daily precipitation maxima from 1990 to 2022. The contour lines show the 400 and 800 m isolines. To ease visualization, colour scales are symmetrically saturated using a 90% threshold. All maps are clipped to this common percentile range. Only statistically significant trends are shown, non-significant trends are set to zero.



Figure 9 summarizes the spatial correlations between AROME and station-based monthly trends, confirming an overall better representation at the daily than at the hourly scale, with strong month-to-month variability. At the daily scale (1959-2022), correlations span from 0.07 to 0.62 depending on the month, peaking in early winter (November, December and January) and remaining high in late summer (August) and early spring (March). Agreement weakens markedly in spring and early summer.

Hourly trends (1990-2022) are generally lower and less consistent, ranging from 0.004 to 0.445. February is the only month when correlation exceeds 0.4, while correlations are almost null in March, May and September. Overall, these results indicate that AROME captures part of the large-scale structure of monthly trend patterns at daily scale, whereas its representation at the hourly scale remains limited, consistent with the stronger local and convective variability affecting sub-daily extremes.

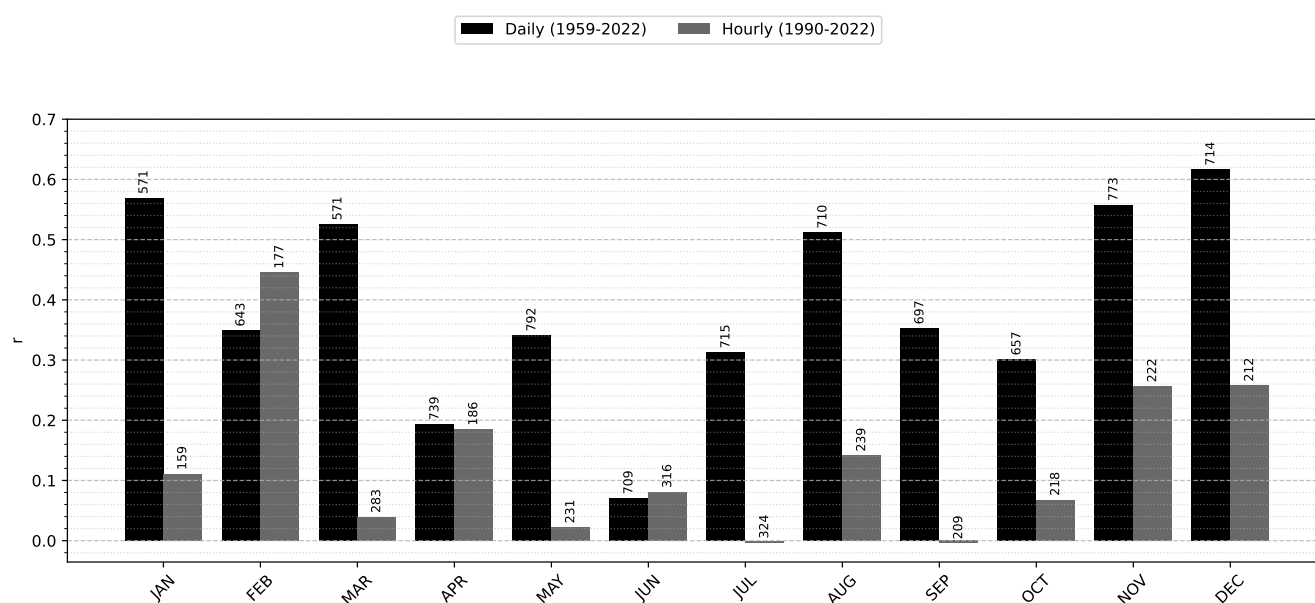


Figure 9. Correlations of relative significant trends between AROME and Météo-France stations, by month. Values above each bar indicate the number of stations used in the calculation.

5 Discussion

5.1 Limitations of the study

This study provides the first evaluation of AROME model for reproducing trends in extremes in France. The evaluation is based on a comparison with rain gauge data, considered here as the reference, which induces some limitations that we list below.



First, station precipitation measurements are frequently affected by undercatch errors, which are particularly pronounced in cold and mountainous regions with strong winds. They can also show heterogeneity, although the data used here have been quality-controlled by Météo-France.

Second, raingauges provide measurement over short periods, particularly the hourly data that are available since the 1990s only. This is particularly problematic when studying extremes within a GEV framework, as only one value (the maximum value) is used per year. In some cases, isolated outliers can significantly influence estimates of the return level (Zeder and Fischer, 2024). For example, in Figure 7, some individual points stand out from their surroundings, which is probably due to sampling bias and not to differences in climate. To make the estimation more robust, other solutions include taking into account threshold exceedances within a generalized Pareto distribution (GPD) framework, or using a distribution modeling all precipitation values, such as the recent extended generalized Pareto distribution (Haruna et al., 2025), or using a neighborhood or region-of-influence approach (Blanchet et al., 2021) to reduce sampling bias by using more data. All these methods have their advantages and disadvantages. Our general advice is not to interpret trends at an individual point, but to look for consistent trends across regions, to avoid over-interpretation.

Third, the stations are not evenly distributed across the country. In particular, hourly stations are lacking in the Alps, the Pyrenees and, to a lesser extent, the Massif Central. This naturally has an impact on our evaluation measures (correlation and bias) and prevents us from fully evaluating AROME in mountainous regions.

Finally, a limitation of the evaluation is that it compares point-scale raingauge measurements with $2.5 \text{ km} \times 2.5 \text{ km}$ AROME grid-box averages. This mismatch in spatial support is relatively modest for daily accumulations, but it becomes a major limitation at the hourly scale: a single convective core may affect only part of a grid cell, so that local station extremes can be much higher (or lower) than the corresponding AROME value even when the event is realistically simulated at the grid-box scale. A high-resolution gridded observational product would therefore be better suited to evaluating hourly extremes than individual stations. In this respect, Météo-France COMEPHORE product – a 1 km, hourly radar-gauge precipitation reanalysis over metropolitan France – would be particularly valuable (Météo-France, 2025b). It would have been interesting to include COMEPHORE in this study, but the reanalyses only begin in 1997 and the method for calculating the rainfall fields changed in 2007, which could affect trend estimation.

Another limitation stems from the modeling framework. We have applied a non-stationary GEV framework to estimate trends in extremes. This requires more parameters to be estimated and additional assumptions to be made about the shape of the trends. Here, we have assumed that the distribution of parameters, and therefore return levels, evolve linearly over time. This is obviously a simplification, as i) there is no physical reason for the evolution to be linear, ii) there is no direct physical dependence between return levels and time. The linearity assumption could be relaxed by considering non-linear transfer functions (e.g. power functions), with the risk of over-fitting and increased uncertainty if more parameters have to be estimated. Here, as in many other studies based on GEV distributions, we prefer to use a rigid (linear) relationship to increase robustness. Previous studies analyzing the relationship between temperature and precipitation (Da Silva and Haerter, 2025) lead us to believe that



temperature might be a more appropriate covariate. However, which temperature to choose and at which scale (e.g. local temperature at the time of the event, annual region-mean temperature, sea-surface temperature) is a matter of debate in itself (Schröer and Kirchengast, 2018; Dash and Maity, 2023; Zeder and Fischer, 2020), which is why we chose to keep time as the simplest covariate. Temperature change over the recent past is anyway close to linear in time, so we believe that the magnitude of the trends would be barely affected.

5.2 Climatology: consistencies and divergence

The results confirm that AROME correctly reproduces the main rainfall regimes over metropolitan France, as supported by the literature (Fumière et al., 2020; Caillaud et al., 2021; Dura et al., 2024; Lucas-Picher et al., 2024b; Cortés-Hernández et al., 2024). It is able to reproduce the climatological orographic intensification of precipitation over the Alps, the Pyrenees, and the Massif Central, a pronounced transition from Atlantic to continental climatic influence in the west, and the dryness of the Mediterranean basin. This consistency with the stations indicates a satisfactory representation of the dynamical forcings (moisture transport by westerly flows, orographic uplift, low-level circulation in the Mediterranean).

AROME's ability to reproduce the frequency and quantity of precipitation and the 10-year return level of daily precipitation is maintained throughout the year. Performance declines for the 10-year return level hourly precipitation specially in spring ($r = 0.38$). Studies with the previous version of the model show that AROME underestimates high-intensity precipitation (> 40 mm/h) (Caillaud et al., 2021; Poncet et al., 2024). Summer convection remains partially under-resolved despite the 2.5 km spatial resolution. Running AROME at finer resolution might improve this, as it was shown that a 1.3 km resolution results in a better representation of maximum intensities (Brousseau et al., 2016). A separate analysis (not shown) shows that correlation increases (+30%) for 6- and 9-hour precipitation. One can hypothesize that AROME spreads convective precipitation too widely in time and in space over nearby grid points, giving underestimated local peak precipitation. Unfortunately this hypothesis cannot be fully evaluated given the sparse station network.

5.3 Trends in precipitation extremes: consistencies and divergence

5.3.1 Daily data: confirmation of known patterns and modelobservation consistencies

The daily trends derived from Météo-France stations confirm and refine previously documented spatial structures of extreme-precipitation evolution in France. The significant increases in the Rhône Valley and the southern Alps (+5 to +30%) are fully consistent with earlier regional analyses reporting an intensification of daily extremes in southeastern France (Blanchet et al., 2018, 2021; Ribes et al., 2019). The marked increases detected in northern France (locally up to +35%) also agree with national-scale projections indicating a northward-shifted reinforcement of daily extremes under strong warming scenarios (Soubeyroux et al., 2025). The weak or non-significant trends observed across large parts of western and central France likewise corroborate the high spatial variability highlighted in the IPCC report (IPCC, 2021).



Overall, AROME reproduces the main spatial structures and magnitudes reasonably well when compared with the station-based climatology. The model correctly identifies regions of positive change (southern Alps, Rhône Valley, parts of northern France) and regions with weak or negative signals (western France, the Paris area), indicating an overall ability to capture the pattern of daily return-level evolution. However, AROME systematically underestimates the amplitude of the trends. This reduced
365 magnitude is consistent with the underestimation of temperature trends in AROME that is about one-third weaker than observed trends (Figure 2), and with the smoothing inherent to 2.5 km grid-box values.

5.3.2 Hourly data: new national-scale findings and limited model-observation consistency

Unlike the daily scale, no national mapping of hourly 10-year return-level trends has previously been available for France. The present work therefore provides the first nationwide characterization of hourly extreme-precipitation trends, offering new insight
370 into their spatial organisation.

Over 1990-2022, trend magnitudes in hourly extremes frequently reach $\pm 50\%$ and can exceed $+100\%$, with strong seasonal dependence. Coherent monthly signals emerge nonetheless: February trends in the Rhône Valley, March trends along the western Mediterranean arc, November increases in the eastern Mediterranean arc, and widespread June increases across most of France. These patterns, though noisier than daily trends, are robust in the sense that they are not produced by a single year (Figure B1).
375 This indicates the start of an emerging trend in hourly extremes even within the constraints of a relatively short observational period.

AROME reproduces part of the structure of these hourly signals – particularly it concords in the months associated with enhanced extreme activity- but does not capture their spatial organization nor magnitude. Model-observation correlations remain low or near zero for most seasons and months, and the model substantially underestimates the amplitude of station-based
380 trends. Even where stations show widespread enhancements (e.g. February, March, June), AROME simulates much weaker and spatially inconsistent changes. Part of this was expected: the trend magnitude underestimation is consistent with the strong underestimation of temperature trends in AROME. It is also partly due to the mismatch between point-scale raingauge measurements and 2.5 x 2.5 km AROME grid box averages. Inconsistencies in the trend spatial localization were also expected since AROME runs freely on the domain without data assimilation. Thus, depending on the weather situations - and particularly
385 for the convective months - precipitation zones can be shifted.

Overall, the hourly results highlight two major conclusions: i) the station-derived hourly trends presented in this study constitute a new contribution to the climatology of French precipitation extremes, revealing structured yet highly localized patterns; ii) AROME currently shows limited skill in representing both the magnitude and spatial heterogeneity of hourly return-level trends, even when significant signals are isolated, underscoring the challenges of simulating sub-daily extremes.



390 6 Conclusion

This study evaluated the ability of the convection-permitting regional climate model AROME (2.5 km), forced by ERA5 over 1959–2022, to reproduce the climatology and the recent evolution of extreme precipitation in metropolitan France, using Météo-France rain-gauge observations at daily (1959–2022) and hourly (1990–2022) time scales. Extremes were characterized using GEV models (stationary and non-stationary), and trends were quantified through changes in 10-year return levels.

395 Overall, the AROME model provides clear added value for the climatology and the spatial organization of daily extremes, and it can support national-scale analyses of daily extreme-precipitation changes, provided that trend magnitudes are interpreted cautiously. In contrast, the evaluation indicates that hourly return levels and especially their trends are less well reproduced, with hourly trends almost inexistent in AROME. However our evaluation shows limitation at hourly scale due to spatial support mismatch between stations and grid points, and short observational record length of stations that prevented us from making the
400 comparison over the full 1959–2022 simulation period. Future work should rely on high-resolution gridded reference datasets (e.g. radar–gauge reanalyses) to reduce representativeness errors and investigate the sensitivity of results to temporal and spatial aggregation (multi-hour maxima, intensity-duration-area-frequency curves, Haruna et al. (2024)). These steps are necessary to assess the reliability of the AROME model’s representation of extremes, and to pave the way for its use in studying extremes in climate projections.

405 Code availability

The source code for the ExtremePrecipit analysis is available on GitHub (<https://github.com/NCSdecoopman/ExtremePrecipit>) and is archived on Zenodo (Decoopman, 2026). The DOI is: 10.5281/zenodo.18788767.

Data availability

The precipitation datasets used in this study, including the AROME model outputs and processed station data (totaling several
410 hundred gigabytes), are hosted on Hugging Face at https://huggingface.co/datasets/ncsdecoopman/ExtremePrecipit_sauv. The AROME simulations will be available on the ESGF (<https://esgf.github.io/>) in 2026. Summary statistics and key indicators are included in the code repository archived on Zenodo (DOI: 10.5281/zenodo.18788767).

Author contribution

ND: Conceptualization, Methodology, Validation, Formal Analysis, Visualization, Writing - Original Draft, Writing - Review &
415 Editing. **JB:** Conceptualization, Methodology, Validation, Writing - Review & Editing, Supervision. **AB:** Conceptualization,



Methodology, Validation, Writing - Review & Editing, Supervision. CC: Data Curation, Resources, Methodology, Writing - Review & Editing

Competing interests

The authors declare that they have no conflict of interest.

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Appendix A: 10-year return level of precipitation

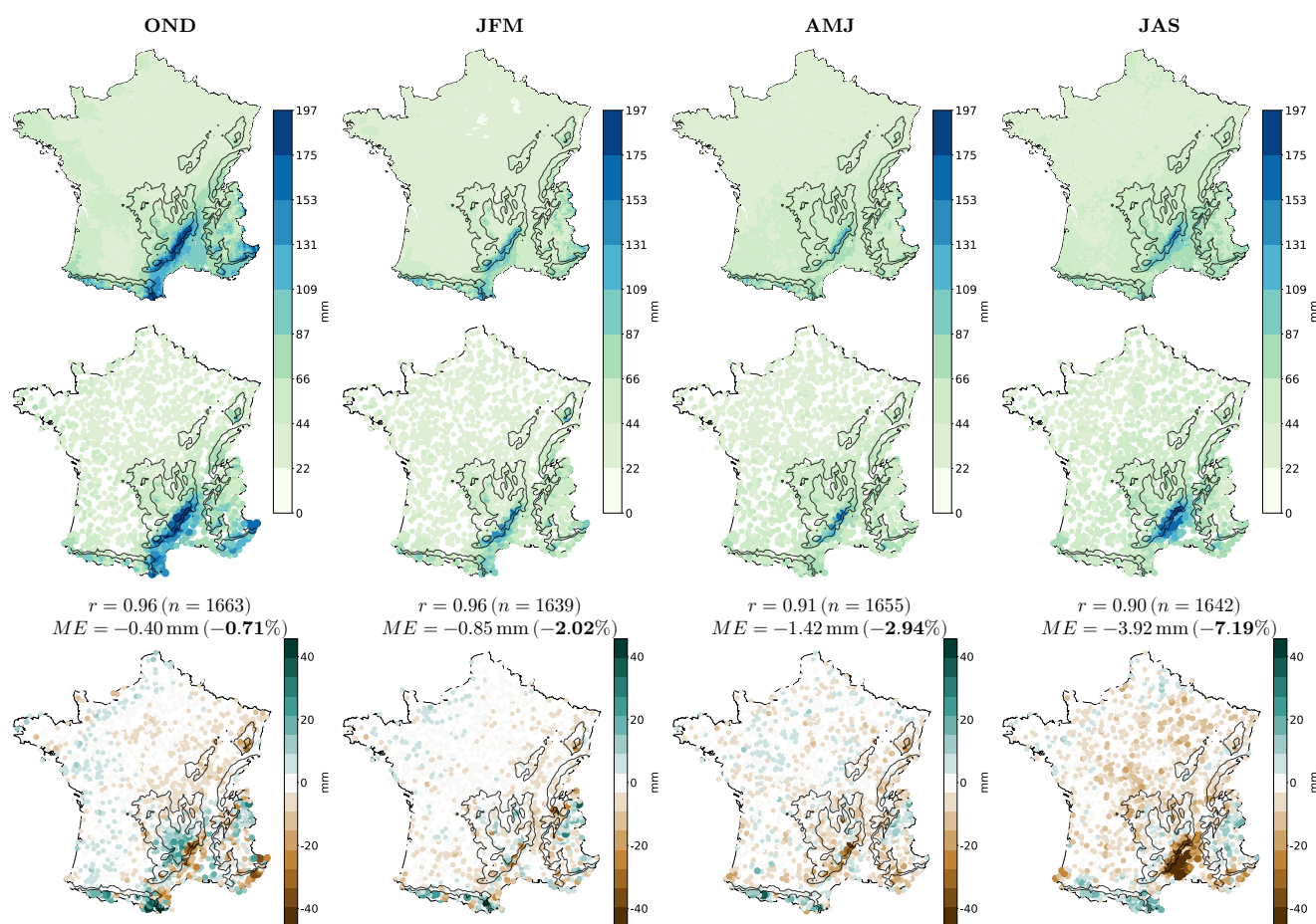


Figure A1. 10-year return level of daily precipitation of the AROME model (first row), Météo-France stations (second row), and the AROMEstation difference (third row), with the spatial correlation between the stations and their closest grid points (r), the bias (ME) and the number of stations compared (n). The statistics are derived from daily data from 1959 to 2022. The contour lines show the 400 and 800 m isolines. To ease visualization, colour scales are symmetrically saturated above the 99th percentile.

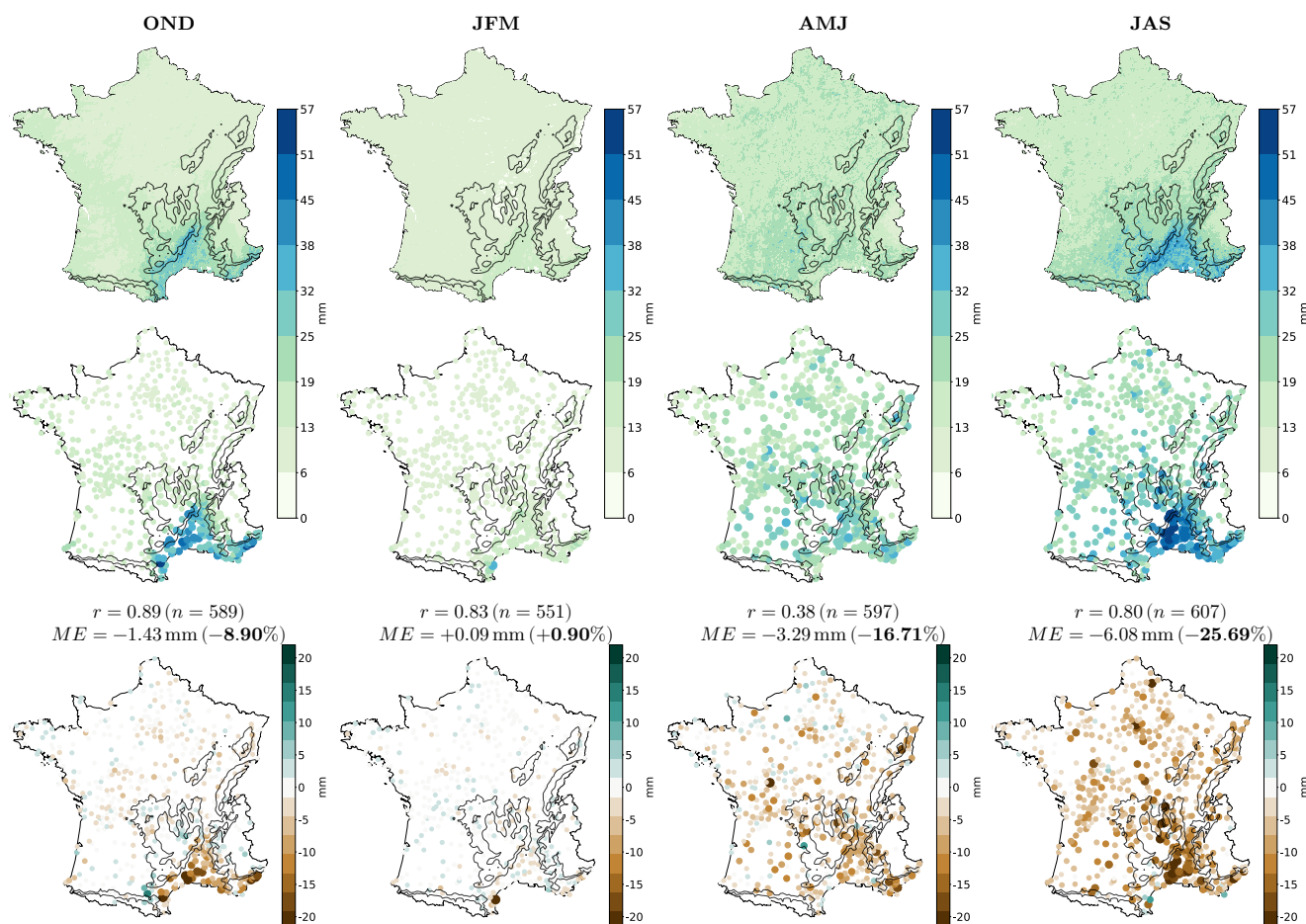


Figure A2. 10-year return level of hourly precipitation of the AROME model (first row), Météo-France stations (second row), and the AROMEStation difference (third row), with the spatial correlation between the stations and their closest grid points (r), the bias (ME) and the number of stations compared (n). The statistics are derived from daily data from 1990 to 2022. The contour lines show the 400 and 800 m isolines. To ease visualization, colour scales are symmetrically saturated above the 99th percentile.

Appendix B: Robustness of trends when discarding the overall maxima

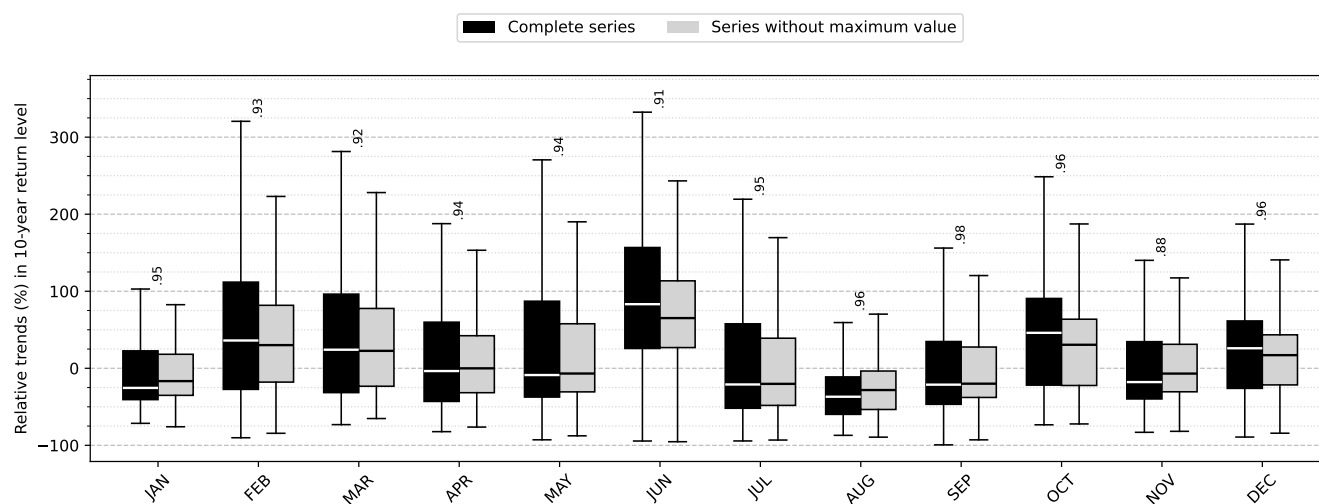


Figure B1. Relative trends over the last thirty years ending in 2022 (%) in the 10year return level of hourly precipitation for MétéoFrance stations when considering the complete series (left) and when discarding the overall maximum (right). Only the the stations with significant trends (for the complete series) are used. The numbers written above each month indicate the Pearson correlation (r) between trends of the complete series and trends of the series without the overall maximum.