**RESEARCH ARTICLE**

Post-processed modelled rainfall estimates represent better point-scale rainfall observations

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**Abstract.** Extreme rainfall events have become increasingly frequent and severe, with significant societal, environmental, and economic impacts. Accurate rainfall modelling is essential for predicting such events, yet current numerical weather prediction (NWP) models often exhibit limitations in their representation of localized extremes. This study evaluates the performance of four NWP-modelled rainfall datasets—ERA5’s Ensemble Data Assimilation (EDA), ERA5 short-range forecasts, ECMWF 46r1 reforecasts, and ERA5-ecPoint—by comparing them against rain gauge observations over a 20-year period. Two key research questions are addressed: how well the NWP rainfall distributions align with rain gauge observations and how accurately they capture the extremes in rainfall distributions. The empirical cumulative distribution functions (ECDFs) of the NWP datasets are analysed to assess their ability to represent observed rainfall patterns. Our results show that ERA5-ecPoint provides the most accurate depiction of point-scale rainfall, significantly improving the representation of extremes compared to the raw NWP models. These findings highlight the importance of post-processing techniques, such as ERA5-ecPoint, in improving NWP-modelled rainfall accuracy, particularly for extreme rainfall events, and have critical implications for disaster preparedness and urban planning.

**Keywords.** Extreme rainfall, reanalysis, reforecasts, ERA5, ERA5-EDA, ecPoint.

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# Introduction

Among extreme weather events, extreme rainfall has drawn particular attention in recent scientific literature (Schumacher 2017; Gimeno et al. 2022). Its impacts are increasingly recognised to be catastrophic for society, infrastructure, and the environment (IPCC, 2023; WMO, 2024). Extreme rainfall can lead to catastrophic flooding, which puts life, infrastructure, and food security at risk (Emrich et al. 2019; Suppasri et al. 2021). Among the most recent devastating flood events induced by extreme rainfall are Western Europe, Afghanistan, and China in 2021, including hurricane Ida affecting primarily the North-East coast of the USA (WMO 2021); Pakistan, Brazil in 2022, including hurricane Ian in Florida (USA) and Fiona in Dominican Republic and Puerto Rico (WMO 2022); in 2023, storm Daniel in the Mediterranean, Cyclone Freddy in Madagascar, Mozambique, and Malawi, Hurricane Otis in Mexico, and extensive flooding in the Horn of Africa (WMO 2024). At the time of writing, one of the most recent devastating events in 2024 include severe flooding due to persistent rainfall in Central Europe and Hurricane Helene in Florida (USA). Extreme rainfall events also have significant environmental consequences, leading to soil erosion, water quality degradation, and habitat destruction (Lugo 2018). Extreme rainfall can also have severe psychological effects on affected communities, leading to long-term anxiety and post-traumatic stress, hindering recovery efforts (Doocy et al. 2013). Finally, it has been shown that extreme rainfall reduces worldwide macroeconomic growth rates and slows global economic rise (Liang 2022). Extreme rainfall is expected to become more intense and frequent due to climate change (Fowler et al. 2021; Tabari 2020; Min et al. 2011), even in regions where the average rainfall has decreased (Asadieh and Krakauer 2015; Westra et al. 2014; Zittis et al. 2021). Hence, understanding extreme rainfall and analysing its past and future trends accurately can inform decision-making in disaster preparedness, agricultural management, and urban planning.

There exist different sources to obtain rainfall timeseries. Rain gauges are a primary source of ground truth providing direct rainfall measurements at specific locations. When properly maintained and calibrated, rain gauges provide highly accurate point-scale rainfall measurements (Lanza and Stagi 2008). Where high-density networks exist, they also offer a good spatial representation of localized extremes (Haiden and Duffy 2016). Moreover, many rain gauge stations have been in operation for decades, providing long-term historical records for trend analysis (Anand and Karunanidhi 2020; Tadeyo et al. 2020). Notably, rain gauge coverage is spatially and temporally uneven, leaving many regions uncovered (Kidd et al. 2017). In areas with complex topography or low-density networks, rain gauges may not adequately represent rainfall’s spatial variability (Di Curzio et al. 2022). Inadequate rain gauge maintenance can also cause instrument malfunctioning, leading to errors and missing data (Lanza and Stagi 2008). Satellite- and radar-derived rainfall gridded datasets offer broader spatial and temporal coverage, especially in ungauged areas(Herold et al. 2017). Their rainfall distributions may, however, differ significantly from the rain-gauge-derived rainfall distributions, and observed extremes may be severely underestimated (Ensor and Robeson 2008; Satgé et al. 2020; Gupta et al. 2020). Rainfall estimates from Numerical Weather Prediction (NWP) models, like reanalysis and reforecasts, offer spatially and temporally consistent datasets with global and multi-decadal coverage. Reanalyses, such as ERA5 and its Ensemble Data Assimilation (EDA) component (Hersbach et al. 2020) or NCEP/NCAR Reanalysis (Kalnay et al. 1996; Hamill et al. 2022), integrate historical weather observations with a state-of-the-art NWP model to produce a high-resolution rainfall dataset that is spatially and temporally consistent. Reforecasts, such as those produced for NCEP’s Global Ensemble Forecast System (Hamill et al. 2006) and ECMWF’s Integrated Forecast System (Richardson et al. 2014), consist in 20-30 years of retrospective forecasts generated with the current operational NWP model. Reforecasts may be used to bias-correct operational forecasts or develop compatible climatologies. Reanalyses tend to capture rainfall’s spatial patterns and temporal trends (Lavers et al. 2022). However, they tend to underestimate the intensity of extreme rainfall events, especially in regions with complex topography or sparse rain gauge measurements (Gomis-Cebolla et al. 2023; Espinosa et al. 2024; Alexandridis et al. 2023; Donat et al. 2016)[[1]](#footnote-2). Similar results are obtained for reforecasts (Hewson 2024). Statistical post-processing of reanalysis and/or reforecast can improve the local-scale representation of patterns and trends of extreme rainfall (Giorgos et al. 2024). The good performance of any post-processing depends on a good spatial/temporal coverage of rainfall observations (Vannitsem et al. 2021). ecPoint post-processing has shown to improve the spatial and temporal representation of NWP-modelled rainfall forecasts (Hewson and Pillosu 2021) and ERA5 (ERA5-ecPoint(Hewson et al. 2023), especially for extremes, including in areas with scarce observations or ungauged.

This study evaluates the strengths and weaknesses of four NWP-modelled, gridded rainfall datasets with different spatial resolutions against rain gauge observations: ERA5’s Ensemble Data Assimilation (EDA) at 62 km, ERA5’s short range forecasts at 31 km, ECMWF 46r1 reforecasts at 18km resolution, and ERA5-ecPoint at point-scale. Two research questions are examined in this study. How does the distribution of NWP-modelled rainfall realizations compare to that built with rain gauge observations (RQ1)? How does the wet tail of the NWP-modelled rainfall distribution compared to that built with rain gauge observations (RQ2)? The study is organized as follows. Section 2 describes the rain gauge observations, and the NWP-models used in this study. Section 3 describes the methods used to answer the research questions. Section 4 and 5 presents the results and discusses them, respectively. Final conclusions are drawn in section 6.

# Data

## Point-scale rain gauge rainfall observations

This study considered 24-hourly rainfall from surface synoptic observations (SYNOP) from the Global Telecommunication System (GTS) network and stored internally at ECMWF. SYNOP observations consist of standardized, historical and near-real time, meteorological reports that ensure consistency in data quality and format across diverse regions. High-density national rain gauge networks (primarily from European countries and available internally at ECMWF) were also integrated in the analysis (Haiden and Duffy 2016). The observations were manually quality-controlled to primarily eliminate erroneous high totals. If not corrected, they could have significantly distorted the upper tails of the observed rainfall distributions, leading to inaccurate results. The number of rain gauge of observations stored at ECMWF increased significantly since the 2000s. Thus, in this study we consider a 20-year verification period, between the 1st of January 2000 to the 31st of December 2019. Only observations ending at 00 UTC were considered, for a total of 7300 rainfall realizations within the 20-year verification period (Table 1, row no.1). Many rain gauge stations had missing data. TO ensure that the timeseries were representative of the considered 20-year period, only rain gauges with at least 75% of valid recordings were considered. Such condition reduced the number of rain gauges in the database from 28834 to 4546.

## Gridded NWP-modelled rainfall estimates

### ERA5 Reanalysis (ERA5) and ERA5 Ensemble Data Assimilation (ERA5-EDA):

ERA5 is the fifth generation of atmospheric reanalysis produced by the Copernicus Climate Change Service (C3S) run by ECMWF (Hersbach et al. 2020). Compared to its predecessor ERA-Interim, ERA5 offers high spatial (~31 km) and temporal (hourly) resolution, and extended temporal coverage from 1940 to near-real time. ERA5 assimilates a diverse range of observational data from satellites, weather balloons, aircraft, and ground stations, employing a 4D-Var assimilation system. This system not only improves the accuracy of the data by adjusting it in four dimensions (three spatial and one temporal) but also enhances the continuity and stability of the climatological records. No rainfall observations are assimilated into ERA5 (Hersbach et al. 2020).

The ERA5 Ensemble Data Assimilation (EDA) system enhances the robustness of the ERA5 reanalysis by generating multiple simulations with slightly varied initial conditions (Hersbach et al. 2020). Each ensemble member in ERA5 EDA provides an equally probable realization of the atmospheric state which estimates the most likely state of the atmosphere and quantifies the uncertainty associated with observational errors and limitations within the forecasting model itself. ERA5-EDA has 10 ensemble members, running at 62 km spatial resolution and at 3 hour temporal resolution.

To match the rain gauge observations, ERA5 and ERA5-EDA data between the 1st January 2000 to the 31st December 2019 was extracted, and only 24-hourly rainfall ending at 00 UTC was considered. Hence, ERA5 rainfall distribution was built with 7300 realizations while ERA5-EDA distribution, considering the 10 ensemble members as equally probable rainfall realizations, was built with 73000 realizations (Table 1, row no.2 and 3).

### ECMWF Reforecasts

Reforecasts are retrospective weather forecasts generated with a fixed NWP model. The reforecasts’ uniformity (i.e., with no discrepancies caused by historical changes in model configurations) ensures that differences in climatological patterns are attributable to actual atmospheric variations rather than artifacts of evolving model technologies. To match as closely as possible the temporal span of the rainfall observations, reforecasts from the ECMWF’s IFS 46r1[[2]](#footnote-3) cycle were considered. They span between 1st July 1999 to 30th June 2019 and are provided at 18 km spatial resolution. 46r1 reforecasts were produced on Mondays and Thursdays. ECMWF reforecasts consist in an ensemble of one control run and 10 perturbed members, produced at 00 UTC with a 6-hourly resolution up to t+1104 (day 46). The model configuration (e.g., resolution, parametrizations) of the control and the perturbed members is the same. However, the control run uses the best estimate of the initial conditions (i.e., the operational analysis), and it has been shown to have a different rainfall climatology than the perturbed members (personal communication with Frederic Vitart). Hence, in this study, only the control run was used. Since reforecasts have less realizations per year (as they are produced only on Mondays and Thursdays), we increased the rainfall realizations by considering lead times up to day 10 equally probable rainfall realizations (it was checked that there was no drift in the forecasts up to day 10, not shown). Hence, the rainfall distribution built with ECMWF reforecasts contain 20800 realizations (Table 1, row no.4).

## ERA5-ecPoint

Within the Highlander project, co‑financed by the EU and coordinated by Italy’s Cineca computing centre, ECMWF’s ecPoint post-processing technique was applied to the raw ERA5 ‘deterministic’ fields to address ERA5 limitations (Hewson et al. 2023). ecPoint aims to infer sub-grid variability and to correct biases (both according to ongoing weather and geographical scenarios). ERA5-ecPoint has so far been created for 1950 to near-real time. Among other variables, ERA5-ecPoint produces probabilistic point-scale 24-hourly rainfall ending at 00 UTC, with percentiles between 1 to 99. Currently, ERA5-ecPoint represent point-scale rainfall, but it is provided on its native (reduced Gaussian) grid at 31 km spatial resolution (TL639). The 99 percentiles can be considered as equally probable rainfall realizations, so that the rainfall distributions are built with 722700 realizations (Table 1, row no.5).

# Methods

## RQ1: comparison of distributions built with rain gauge observations and NWP-modelled rainfall realizations

Observed and NWP-modelled distributions have a different number of rainfall realizations (Table 1). To compare them, empirical cumulative distribution functions (ECDFs) for both distributions were sampled using 99 percentiles (1st to 99th). The difference between modelled (ECDF1) and observed (ECDF2) ECDFs was computed at corresponding xth percentiles to determine the average areal difference (ECDFdiff) between the two distributions (Figure 1):

|  |  |
| --- | --- |
| ECDFdiff = , with i = 1 to 99 | (1) |

The values of ECDFdiff were expressed as a percentage (in %) of the corresponding station’s mean observed rainfall. This was done to normalize ECDFdiff between different rainfall climatologies. Otherwise, ECDFdiff would have appeared consistently bigger in wetter climates. Maps plotting the values of ECDFdiff at different rain gauge locations are shown to compare the performance of the four analysed NWP models. ECDFdiff values have been divided in five coloured categories: ECDFdiff values below 10% are shown in black and indicate a close representation of observed point-rainfall distributions by the NWP-modelled estimates; ECDFdiff values between 10-30% in blue, 30-50% in green, and 50-100% in yellow indicate intermediate categories of representation. ECDFdiff values above 100% are represented in pink and indicate a very poor representation of the observed point-rainfall distributions by the NWP-modelled rainfall estimates. A selection of representative ECDFs for all four models against their correspondent observed point-scale rainfall distribution are also shown to understand where the differences lie between the observed and the NWP-modelled rainfall estimates.

## RQ2: comparison of the wet tail in the distributions built with NWP-modelled rainfall estimates and rain gauge observations

To compare the wet tails in the observed and NWP-modelled rainfall distributions, the rainfall maps for the 10-year return period were visually compared to assess geographical differences in the estimation of extreme rainfall. The 10-year return period was considered because it was the most extreme rainfall event that was possible to compute with the observational dataset in hand (Table 1, column 7 and 8, row 1), even though larger events could have been computed with the NWP-modelled rainfall estimates (Table 1, column 7 and 8, rows 2 to 5).

To complement the general global comparison between observed and NWP-modelled extreme rainfall, 24-hourly rainfall estimates from a case of widespread flash floods in Italy is presented. Italy was chosen because, out of all countries in our database, it has the rain gauge network with the highest spatial resolution. This is vital for case-study-based analysis, as it increases the chances to capture extreme localized rainfall.

# Results

## RQ1: comparison of distributions built with rain gauge observations and NWP-modelled rainfall realizations

Out of all NWP-modelled rainfall estimates, ERA5-ecPoint provides the best representation of observed point-rainfall distributions due to the larger number of black dots in Figure 2e compared to Figure 2b-d, where the number of coloured dots is larger. The global maps are divided in six domains (Figure 2a). The piecharts in Figure 2b-e summarize, for each domain, the percentage of ECDFdiff values that fall in the five colour categories. The piecharts are also expressed in numerical form in the tables appearing in Figure 2b-e. ERA-ecPoint increases the number of ECDFdiff values in the black category by a factor of ~10, 30, and 27 compared to the reforecasts, ERA5, and ERA5-EDA, respectively. In the raw NWP models (i.e., ERA5-EDA, ERA5, and ECMWF reforecasts), the percentage of black dots is consistently below 2% in all domains, apart from North-America in the reforecasts (4.26%). In South-America, there is 0% of black dots in all raw NWP models, while ERA5-ecPoint brings such percentage to 13.19%, and they are mainly located in the east coast of Brazil. ERA-ecPoint reduces the number of ECDFdiff values in the pink category of 60% compared to ERA5-EDA and 50% compared to ERA5 and reforecasts. The main reductions are focused on the Arabian Peninsula, Asia and North America. In a lesser extent, reforecasts also reduce the numbers of pink dots in these areas. However, it increases it in South-America of 2.42% and 5.55% compared to ERA5-EDA and ERA5, respectively, mainly over the Bolivian Amazon. ERA5-ecPoint reduces the number of pink dots in South America of 47.12%, 22.84%, and 9.96% compared to reforecast, ERA5, and ERA5-EDA. The reductions are observed mainly over the flatter Amazonian regions to the east of the Andean highlands, while in the latter and the thin desertic coastlines of Peru and Chile there remain a significant number of pink dots also in ERA5-ecPoint. For the intermediate ECDFdiff values (i.e., in blue, green, and pink), the piecharts show that ERA5-ecPoint reduces the values of ECDFdiff in all domains. Most values fall in the blue and the green categories instead of the yellow and pink as seen for the raw NWP models, especially in South America, Africa, Asia, and Oceania.

It is worth comparing the observed and the NWP-modelled ECDFs to gain insights into where the distributions differ. Each ECDF (in linear scale) has an insert with the ECDF’s x-axis represented in logarithmic scale to compress the small rainfall totals and expand the higher ones and see more clearly differences in the distributions. In flat areas (Figure 3a), ERA5-ecPoint (in coral) represents the distribution of point-scale rainfall observations better than the raw NWP-models: it captures very well the frequency of observed zero rainfall totals (see ECDF in log scale), the growth rate of the rainfall observations (see ECDF in log scale), and the length of the wet tail (see ECDFs in linear scale). There are no significant differences between the distributions from ERA5-EDA (in green), ERA5 (in brown), and reforecasts (in blue): they all underestimate similarly the frequency of observed zero rainfall totals and they have similar growth rates, which are greater to that in the observed distribution. They all underestimate the length of the wet tail but in different degrees: ERA5-EDA shows the biggest underestimation, reforecasts show the smallest, and ERA5 falls in between the two. ERA5-ecPoint behaves similarly in hilly/mountainous areas (Figure 3b). It represents well the frequency of observed zero rainfall totals and the growth rate of the rainfall observations. ERA5-ecPoint tends to, however, slightly overestimate the distribution’s wet tail of the observed ECDFs. Raw NWP models show a similar behaviour to what was observed for flat areas. The main difference lies in a progression in a better representation of the observed ECDF for NWP models with increasing spatial resolution. In very mountainous areas (Figure 3c), all NWP models fail to represent the observed ECDFs. First, they all underestimate the frequency of observed zero rainfall totals. ERA5-ecPoint tends to double such a frequency but it does not reach the values in the observed ECDFs. The ECDFs from raw NWP-models show a too large growth rate compared to that in the observed ECDFs while ERA5-ecPoint improves on that. Finally, while the raw NWP models tend to slightly underestimate the length of the observed ECDFs (with ERA5 providing the best representation out the three models), ERA5-ecPoint tends to significantly overestimate it. In desertic areas (Figure 3d), all NWP-models tend to represent well the observed ECDFs, apart from the wet tails that tend to all be overestimated. The overestimation reduces with the increase in the spatial resolution of the NWP models, with ERA5-ecPoint representing best the actual length of the wet tail.

## RQ2: comparison of the wet tail in the distributions built with NWP-modelled rainfall estimates and rain gauge observations

The rainfall maps for the 10-year return period show that ERA5-ecPoint provides an overall better representation than the raw NWP-models of the 10-year return period events in the observational datasets. In North America, the extremes in 24-hourly rainfall over the west coast of Alaska, Canada and North-West USA, which reach peaks up to 500 mm, are better represented in ERA5-ecPoint than in ERA5-EDA, ERA5, and reforecasts that tend to not exceed 125 mm. The peaks around the border between Canada and USA, the Gulf of Mexico and USA’s East coast are also better represented in ERA5-ecPoint. The extremes over the Rocky Mountains are better represented by the raw NWP models since ERA5-ecPoint overestimates them. However, the latter shows an overall closer representation of the observed ECDFs apart from the tail (not shown). ERA5-ecPoint improves greatly the rainfall peaks over Mexico and South America over the other three NWP models, apart from the Andean region and the desert in the west coast of Peru and Chile where ERA5-ecPoint overestimates the wet tails (as shown in section 4.1). It is worth noting that the ECMWF reforecasts from 46r1 halved the rainfall extremes over the Amazon compared to ERA5-EDA and ERA5. The extremes over Europe also verify better on ERA5-ecPoint than the three raw NWP models. The wetter climatology with peaks up to 300-500 mm around the Mediterranean catchment (including the African part), the Alps, the Atlantic coast of Spain and UK, and the Norwegian Fiords are better captured in ERA5-ecPoint than in the three raw NWP models. The higher spatial resolution in the reforecasts helps to increase the extremes compared to both reanalysis but they still do not exceed 100 mm in 24-hours. In Asia, there is a varied picture. The raw NWP models do a good job at highlighting the wetter climatologies of India (especially the North-East regions), East China, Japan, South-East Asia, and the Malay Archipelago. However, they do not reach the peaks of 300-500 mm/24h seen in the observations. ERA5-ecPoint represents better such peaks. However, the peaks greater than 500 mm/24h observed in the Malay Archipelago remain underestimated also in the post-processed ERA5. The overall overestimation in the mountainous regions of Western China have a similar flavour of the ones discussed over the Rocky Mountains in the USA: ERA5-ecPoint shows the best overall representation of the full observed ECDFs but tends to overestimate the wet tails. In the Arabian Peninsula, all models tend to represent well the overall observed ECDFs. As discussed in section 4.1 for desertic areas, such good representation origins from the high frequency of zero rainfall totals that are well estimated by all NWP models. The only exception consists in the south coast of the peninsula, where rainfall peaks can reach up to 200 mm/24h and raw NWP models estimate maximum peak only up to 80 mm/24h. ERA5-ecPoint increases them up to 150 mm/24h. In Oceania, all NWP-models show a good overall representation of the observed ECDFs with slight underestimations of the wet tails. The added value of ERA5-ecPoint in this region consists mainly in providing a better representations of the rainfall peaks. In Africa, there are not many observations, and nothing can be said about the model representation of rainfall extremes in the numerous ungauged areas of this continent. All NWP models represent well the wet climatology of West Africa, including its Atlantic coast. However, ERA5-ecPoint provides the best representation of the observed local peaks that vary between 100 and 500 mm/24h. It is worth noting that ECMWF 46r1 reforecasts degrade the representation of the extreme rainfall around the Gulf of Guinea by producing maximum peaks only up to 80-100 mm/24h. Similarly, out of all NWP models, ERA5-ecPoint best represents the varied rainfall peaks, between 80 and 500 mm/24h, in South Africa, where raw NWP models suggest extreme rainfall might not exceed 80 mm/24h. Also in East Africa, ERA5-ecPoint provides a more realistic representation of the extreme rainfall peaks (up to 500 mm/24h) than raw NWP models. The reforecasts again reduce significantly the rainfall in this area. The wet climatology of Madagascar is well represented in all NWP models, but ecPoint can increase the wet tail of ERA5 and provide extreme rainfall totals that are closer to those observed. Finally, the all NWP-models show an overall good representation of the observed rainfall distribution in the Sahara. This is due primarily to the high frequency of zero rainfall totals. However, the wet tails tend to be slightly overestimated (as discussed also in section 4.1).

We now examine the case of widespread (flash) flooding in Italy on the 28th of October 2018. This event belongs to a weather system that persisted over different parts of Italy between the end of October and the beginning of November 2018, called storm Vaia. In the observations, one can see extreme rainfall amounts between 300-400 mm/24h over Veneto (north-east), up to ~200 mm/24h over Lombardi (North) and Liguria (North-East), up to 240 mm/24h in Lazio (centre), up to 130 mm/24h in Puglia (Southwest), and up to 260 mm/24h in Calabria (Southeast). ERA5-EDA, ERA5, and reforecasts provide a good signal on which might be the wetter areas in Italy for that day, apart from the south of Italy that does not stand out as a possible area at risk of extreme rainfall. The rainfall peaks over the Italian Peninsula increase with the increasing spatial resolution of the NWP models, but they do not reach the observed extreme rainfall totals. ERA5-EDA estimated a maximum total of ~100 mm/24h and ERA5 pushed the estimated peaks to 150 mm/24h over Veneto. Reforecasts increased the rainfall peaks in Veneto and Lazio up to 200 mm/24h, but rainfall in Liguria, Puglia, and Calabria remain highly underestimated. ERA5-ecPoint instead, is able to represent much better the observed rainfall peaks.

# Discussions

The results of our study suggest that by post-processing ERA5 to better align with observed climatology, especially through enhancements in spatial resolution and region-specific model adjustments, we can significantly improve the representativeness of the climatological outputs. This alignment is crucial for the accurate prediction of localized weather patterns and can greatly enhance the capability of these models to issue timely and accurate warnings for extreme localized events. The analysis of the representativeness of various NWP-modelled climatologies against observed climatology, as demonstrated through the Anderson-Darling test at a 99.99% confidence level, reveals significant regional and model-specific variations. The ERA5-EDA (62 km) model shows high representativeness in North and South America, with over 95% of locations aligning with observed data, but less so in the Africa & Arabian Peninsula where only 87.2% of locations are representative. In contrast, the finer resolution ERA5 (31 km) model indicates improvements in most regions except Oceania, where the representativeness drops to 89.7%. The ECMWF Reforecasts (18 km) model further enhances fidelity, particularly in Asia and the Europe & Mediterranean regions, achieving over 99% representativeness in South America. However, challenges persist in the Africa & Arabian Peninsula, where only 66.6% of locations are representative in this model setup. Lastly, the ERA5-ePoint model, offering point-scale granularity, shows a notable improvement in North America, with a representativeness of 95.5%, but still struggles in Oceania and the Africa & Arabian Peninsula, with only 74.3% and 92.2% of locations found representative, respectively. This variability underscores the complexities in model performance across different spatial resolutions and geographic domains, highlighting the need for region-specific adjustments in NWP models to enhance their predictive accuracy globally.

The ability to establish a threshold for extreme rainfall predictions globally, independent of direct observational data, marks a significant advancement in meteorological science. This methodology leverages improved computational models that integrate historical data and predictive analytics, enabling the prediction of extreme weather events even in regions lacking physical measurement infrastructure. As a result, warnings for extreme rainfall can now be disseminated across ungauged areas, ensuring that all regions, regardless of their monitoring capabilities, are forewarned and can prepare adequately. This approach not only expands the coverage of weather warnings to a global scale but also enhances the resilience of vulnerable communities to the impacts of severe weather events.

The significant improvements in global weather models have facilitated a more accurate representation of climatic conditions worldwide, including extreme weather events. This enhanced modelling is pivotal for predicting phenomena such as severe storms, heatwaves, and intense precipitation with greater precision. By integrating advanced algorithms and extensive meteorological data, these models can now more reliably forecast the intensity and frequency of extreme conditions, providing crucial information for disaster preparedness and risk management. Such advancements not only aid in safeguarding lives and property by enabling more effective early warning systems but also support adaptive strategies in agriculture, infrastructure, and emergency planning across diverse geographic landscapes.

Utilizing ecPoint ERA5 for creating weather event thresholds requires careful calibration, particularly for Europe, to avoid setting thresholds that are too high, which could lead to underestimating or missing significant weather events. This model's high resolution can sometimes produce data that skew towards more extreme values, potentially setting the bar too high for triggering alerts. To prevent this, it is essential to rigorously validate the model against historical weather events across Europe, ensuring that the thresholds are adjusted to accurately reflect the frequency and intensity of occurrences. This approach will help maintain a balance, ensuring both the sensitivity and specificity of the model in predicting genuine weather threats without overlooking milder but still impactful events.

# Conclusions

The analysis conducted in this study highlights the effectiveness of refining NWP models to more closely align with observed climatology, particularly by improving spatial resolutions and making region-specific model adjustments. Such enhancements have significantly bolstered the representativeness of climatological outputs across various global regions, critical for the accurate forecasting of localized weather patterns and extreme events. Our findings, validated through the Anderson-Darling test at a 99.99% confidence level, demonstrate considerable variations in model performance by region and resolution. For instance, the ERA5-EDA (62 km) model exhibits high accuracy in North and South America, while the ERA5 (31 km) and ECMWF Reforecasts (18 km) models show substantial improvements in Europe, Asia, and South America. However, challenges remain in regions like Africa & the Arabian Peninsula and Oceania, underscoring the need for targeted adjustments to enhance model accuracy. Furthermore, our study underscores a significant advancement in meteorology with the ability to set thresholds for extreme weather predictions globally, independent of direct observational inputs. This advancement is crucial for issuing timely warnings, particularly in ungauged areas, thus expanding protective measures worldwide and enhancing community resilience against severe weather impacts. The integration of sophisticated algorithms and comprehensive data has also facilitated a more precise prediction of extreme weather phenomena, crucial for effective disaster preparedness and risk management. However, caution must be exercised, particularly with high-resolution models like ecPoint ERA5, to avoid setting overly high thresholds that may miss significant weather events in regions such as Europe. Rigorous validation against historical data is essential to ensure these models maintain a balance between sensitivity and specificity, providing reliable and actionable weather warnings. This holistic approach to improving NWP models not only helps in safeguarding lives and properties but also supports adaptive strategies across various sectors, thereby enhancing global readiness and response to climatic extremes.

# Tables

Table – Summary of the characteristics of the rainfall observations and NWP models considered in this study (rows 1 to 5). Description of the computed climatologies (row 6 to 8).

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **No.**  **Column** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| **No.**  **Row** | **Type of climatology** | **Dataset for computation of climatology** | **Dataset description** | **Spatial coverage & resolution at equator** | **Temporal coverage** | **No. of independent daily & total no. of realizations in the 20-year period (between 2000 and 2019)** | **Max return period that can be computed in the 20-year period**  **(Max return period computed)** | **Max percentile (%) computed**  100 – ( \* 100 ) |
| 1 | Observational,  for points | SYNOP observations + higher resolution national databases | Rain gauges | Global (patchy),  Point-scale | From 01/01/2000 to 31/12/2019 | 1 daily real.  -  1 real. x 365 days x 20 years = 7300 total real. | 7300 real. / 365 days / 2  (required a minimum of 50% of valid obs) =  1 in 10 year event  (1 in 10 year event) | 99.97260 |
| 2 | NWP-modelled, gridded | ERA5 - Ensemble Data Assimilation  (ERA5-EDA) | Analysis, probabilistic (10 ensemble members) | Global,  62 km | From 01/01/2000 to 31/12/2019 | 10 daily real.  (all ensemble members were used as daily independent realizations)  -  10 real. x 365 days x 20 years = 73000 total real. | 73000 real. / 365 days =  1 in 200 year event  (1 in 100 year event)\*  \*Some dates were not available, so only 66940 real. were available) | 99.99726 |
| 3 | NWP-modelled, gridded | ERA5 | Analysis, deterministic | Global,  31 km | From 01/01/2000 to 31/12/2019 | 1 daily real.  -  1 real. x 365 days x 20 years = 7300 total real. | 7300 real. / 365 day  1 in 20 year event  (1 in 20 year event) | 99.98630 |
| 4 | NWP-modelled, gridded | ECMWF Reforecasts for 46r1 | Forecasts, probabilistic (10 ensemble members, up to day 10). Used only control run. | Global,  18 km | Past 20 years for period between 01/07/2019 and 30/06/2020; forecast runs only on Mondays and Thursdays | 10 daily real.  (all lead times for 2 control runs a week were used as daily independent realizations)  -  10 real. x 2 runs x 52 weeks x 20 years = 20800 total real. | 20800 real. / 365 days =  1 in 56 year event  (1 in 50 year event) | 99.99452 |
| 5 | NWP-modelled, gridded | ERA5-ecPoint | Analysis, probabilistic (99 ensemble members) | Global,  point-scale but provided on ERA5’s grid (31 km) | From 01/01/2000 to 31/12/2019 | 99 daily real.  (all ensemble members were used as daily independent realizations)  -  99 real. x 365 days x 20 years = 722700 total real. | 722700 real. / 365 days =  1 in 1980 year event  (1 in 1000 year event) | 99.99972 |

# Figures

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Figure – Schematic representation of the calculation of the average areal difference (ECDFdiff) between two ECDFs.

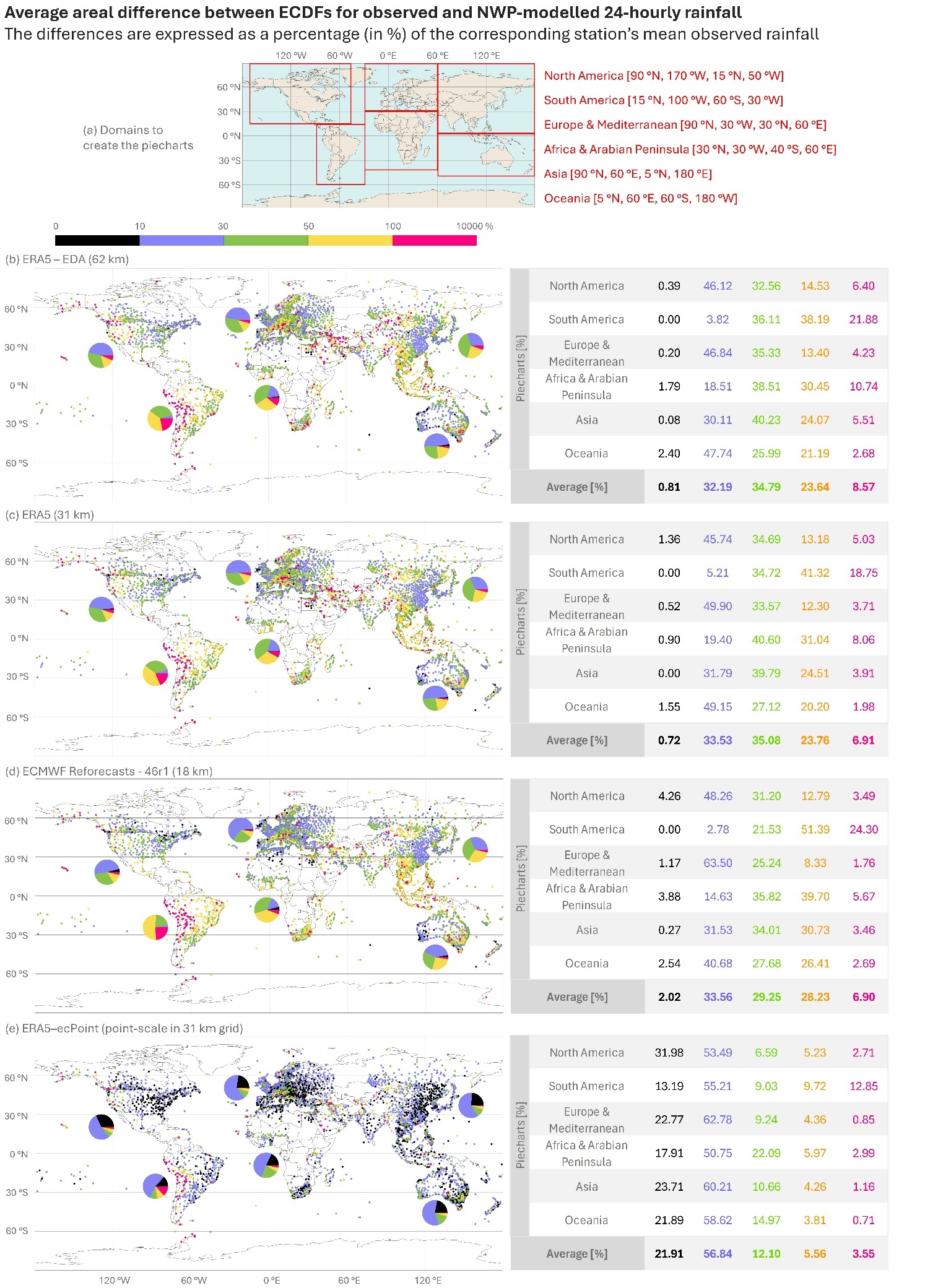


Figure – Average areal differences between Empirical Cumulative Distribution Functions (ECDFs) for observed and NWP-modelled 24-hourly rainfall. The differences, expressed as a percentage (in %) of the correspondent station’s mean observed rainfall, are summarized in piecharts for the domains defined in panel (a). Panels (b) to (e) show the average ECDFs’ areal differences for ERA5-EDA, ERA5, reforecasts, and ERA5-ecPoint, respectively. The tables on the right offer a numerical representation (in %) of the piecharts.

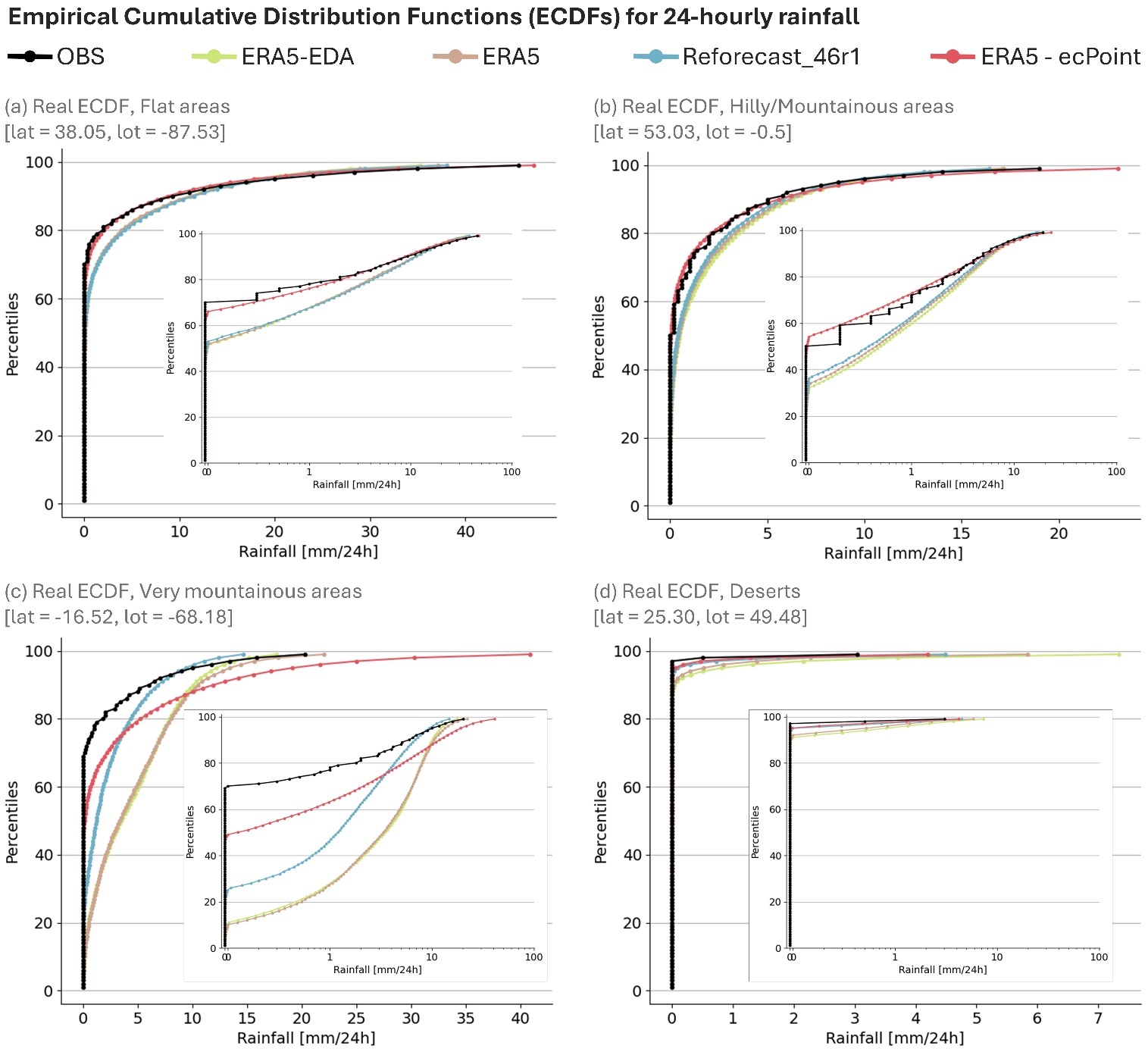


Figure – Empirical Cumulative Distribution Functions (ECDFs) for 24-hourly rainfall from rain gauge observations (OBS, in black) and the NWP models ERA5-EDA (green), ERA5 (brown), reforecasts (Reforecasts\_46r1, light blue), and ERA5-ecPoint (coral). Panels (a) to (d) show representative ECDFs, respectively, for flat areas, hilly/mountainous areas, very mountainous areas, and deserts. The inserts represent the same ECDFs but with the x-axis on a logarithmic scale (Log ECDF).

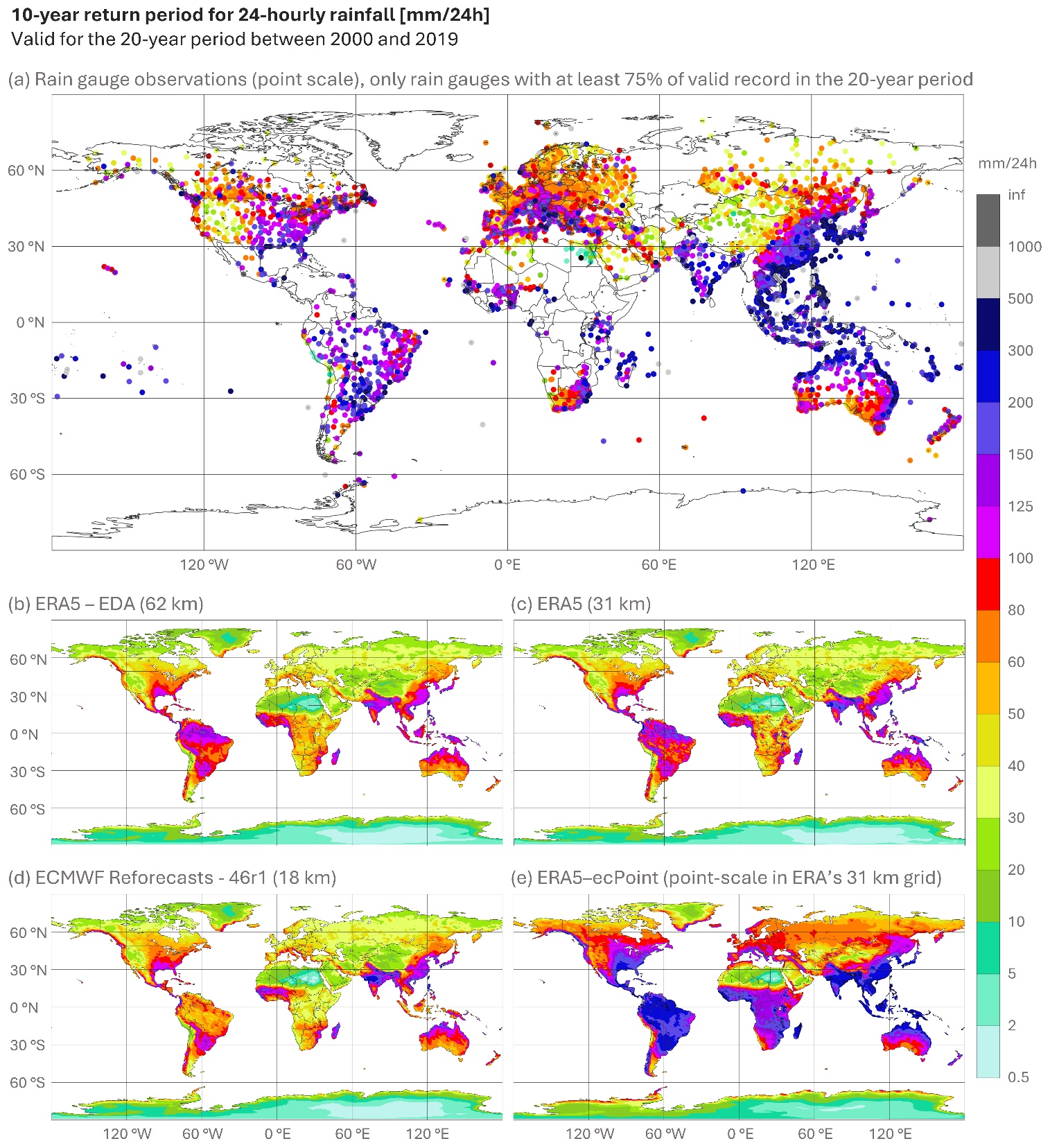


Figure – Panel (a) displays the 10-year return period for 24-hourly rainfall from rain gauge observations, calculated over the 20-year period between 2000 and 2019, and using only rain gauges with at least 75% of valid records. Panels (b) to (e) show the 10-year return period for NWP-modelled 24-hourly rainfall: ERA5-EDA (62 km), ERA5 (31 km), reforecasts (Reforecasts\_46r1, 18 km) and ERA5-ecPoint (point-scale, provided on ERA5 grid).

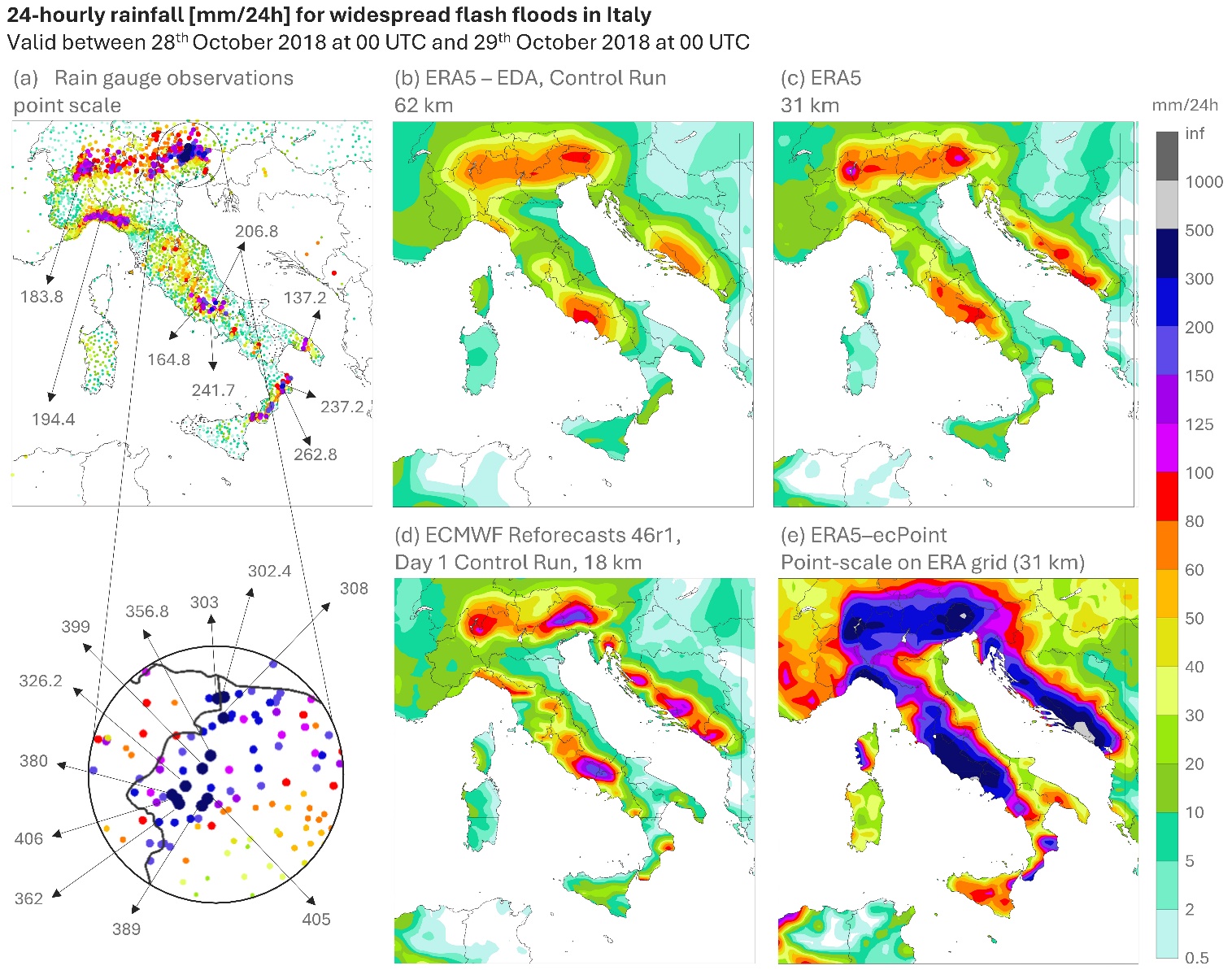


Figure – 24-hourly rainfall [mm/24h] for widespread flash floods in Italy on 28th October 2018. Panel (a) shows observations from rain gauges. Numbers in grey indicate peak rainfall totals in mm/24h. Panel (b) to (e) indicate rainfall totals from, respectively, control run for ERA\_EDA (62 km), ERA5 (31 km), day 1 control run ECMWF Reforecasts 46r1 (18 km), and 99th percentile for ERA5-ecPoint (point-scale, provided on ERA5 grid).

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1. Note that the studies comparing ERA5 and ERA5-Land against rain gauge observations are considered in this study only for their analysis of ERA5. The comparisons between ERA5 and ERA5-Land rainfall are faulty as ERA5-Land simply re-grids, without any statistical or dynamical downscaling, the rainfall in ERA5 onto ERA5-Land’s grid (Muñoz-Sabater et al. 2021). [↑](#footnote-ref-2)
2. https://confluence.ecmwf.int/display/FCST/Implementation+of+IFS+cycle+46r1 [↑](#footnote-ref-3)