**RESEARCH ARTICLE**

Post-processed modelled rainfall climatology represents better observational point-rainfall climatologies

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**Abstract.**

**Keywords.**

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# Introduction

Society has a great interest in understanding extreme rainfall events due to its severe impacts on human life, infrastructure, and the environment (Gimeno et al., 2022; Lugo, 2018; McPhillips et al., 2018, Schumacher et al., 2017). The cascading impacts of multi-hazard types have been described for historical catastrophic events such as the impact of Hurricane Irma on the Caribbean and the southeast of United States (Emrich et al., 2019) or the 2004 Indian Ocean Tsunami and 2011 great East Japan earthquake and tsunami (Suppasri et al., 2021). Extreme rainfall can lead to catastrophic flooding, which poses risks to life and property, disrupts transportation networks, and damages critical infrastructure (Ward et al., 2013; Rosenzweig et al., 2018). Extreme rainfall events also have significant environmental consequences, leading to soil erosion, water quality degradation, and habitat destruction, thereby affecting biodiversity and ecosystem services (Gimeno et al., 2022; Rosenzweig et al., 2018). Moreover, the psychological and social dimensions of extreme rainfall events cannot be overlooked, with communities experiencing after flooding long-term psychological impacts, including anxiety and post-traumatic stress, which can hinder recovery efforts (Doocy et al., 2013). Moreover, a recent study also confirmed that extreme rainfall reduces worldwide macroeconomic growth rates and slows the global economy rise (Liang, 2022).

There is growing evidence that anthropogenic activity affects the climate in numerous ways, and the effects of extreme conditions are likely to become stronger due to changes in their intensity and frequency. In particular, the intensity of extreme rainfall is expected to increase in regions with high moisture availability, particularly in wet moths. This will cause more frequent and severe flooding under global warming (e.g., Min et al., 2011; Tabari, 2020). Despite the current observational uncertainties of extreme rainfall (Herold et al., 2017), increasingly extreme rainfall has been reported in a large number of locations, even in regions where the average rainfall has decreased (e.g., Asadieh & Krakauer, 2015; Kharin et al., 2013). The precipitation budget will be therefore affected, becoming a challenge to water resources management (Zittis et al., 2021). It is therefore of great interest to understand the changing characteristics and impacts of extreme precipitation events as part of attempts to design adaptation and mitigation policies that could allow improvements to be made in terms of the ability of society to adapt to potential changes caused by global warming (IPCC, 2021).

Different type of datasets are used to understand past trends in extreme rainfall and contextualizing current extreme events. Long observational datasets, in particular long rain gauge records play a crucial role in examining various aspects of extreme rainfall events. However, their coverage if small and not consistent in time (Kidd et al., 2017). Reanalysis and reforecast datasets play a crucial role, including their historical ranking, associated circulation features, provide a consistent and comprehensive picture of historical weather patterns, allowing researchers to analyse long-term trends and variability in extreme precipitation. Reanalysis products, such as those used by the National Centers for Environmental Prediction (Kalnay et al., 1996) and the 5th generation of reanalysis from ECMWF (Hersbach et al., 2020), combine observational data with numerical weather prediction models to create a coherent dataset spanning several decades. Reforecast data, like that generated by the Global Ensemble Forecast System version 12 (Hammil et al., 2006) or by ECMWF (Richardson et al., 2014), offer a consistent set of hindcasts that can be used to calibrate and improve current forecasting models. By comparing reanalysis and reforecast data with current observations, scientists can better understand how extreme rainfall events are changing in frequency and intensity over time to assess possible shifts in precipitation patterns and assess the potential impacts of global warming on extreme weather events. Modelling precipitation and detecting extreme events is challenging due to the use of different schemes for parameterizing processes at the sub-grid scale (Madakumbura et al., 2021). Uncertainties also arise regarding the behaviour of the major mechanisms of atmospheric moisture transport and their role in the occurrence of extreme precipitation events under global warming (Westra et al., 2014; Gimeno et al., 2016, Davies et al., 2024). Most of the studies that analyse and contextualize extreme rainfall events uses reanalysis such as ERA5 and NOAA NCEP/NCAR Reanalysis 1. Two common findings emerge when compared to ground rainfall observations. First, reanalysis products generally capture the spatial patterns and temporal trends of extreme rainfall events, but often show biases in intensity, particularly underestimating the magnitude of extreme events in many regions. Second, the performance of reanalysis datasets varies significantly across different geographical regions and climatic zones, with better results typically observed in areas with dense observational networks and more challenging performance in regions with complex topography or sparse ground-based measurements. Similar results are obtained when analysing extreme rainfall patterns and trends using reforecasts (Hewson, 2024).

While global reanalyses like ERA5 generally provide good overall representation of large-scale precipitation patterns, regional reanalyses tend to show reduced biases and better accuracy in representing the intensity and frequency of extreme rainfall events, especially in regions where the global models struggle to capture local meteorological processes. Regional reanalyses still exhibit biases and limitations in precisely representing localized extreme rainfall when compared to rain gauge data. For instance, the SPHERA study showed seasonal biases ranging from wet in summer to dry in winter for the 95th percentile of spatial rainfall distributions, indicating that while improved, the representation of extreme events is not perfect. Statistical downscaling of ERA5 generally improves the representation of extreme rainfall patterns and trends, particularly in regions with complex topography or varied climate regimes. This is evidenced by the study focused on Greece (Giorgos t al., 2024), which showed that the downscaling algorithm achieved better R² and RMSE scores compared to the standalone ERA5 dataset, especially in estimating wet days and precipitation over 10 and 20 mm. The downscaling process tends to address some of ERA5's limitations in capturing local-scale extreme events, reducing biases in intensity and frequency of extreme rainfall. For instance, the Greek study demonstrated significant improvements in areas where ERA5 tended to overestimate wet days and underestimate heavy precipitation events, particularly in island regions where ERA5 performed poorly in simulating precipitation intensity. Statistical downscaling of ERA5 typically enhances its ability to represent extreme rainfall patterns and trends, offering more accurate local-scale information. However, it's important to note that the effectiveness of downscaling can vary depending on establishing statistical relationships between large-scale predictors (from reanalysis or global models) and local-scale observations; they require a dense network of high-quality, long-term observational data at the locations of interest, performance can vary significantly based on the spatial and temporal coverage of available observations; and they may not perform well in areas with sparse or no observational data.

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# Data

## Point-scale observational climatology

The point-scale observational rainfall climatologies were computed using 24-hourly rainfall from surface synoptic observations (SYNOP) from the Global Telecommunication System (GTS) network and stored internally at ECMWF. SYNOP data consists of standardized meteorological reports, historical and near-real time, that ensure consistency in data quality and format across diverse regions. To enhance the spatial coverage of rain gauges used to compute the rainfall climatologies, high-density national rain gauge networks available internally at ECMWF, primarily from European countries (Haiden & Duffy, 2016), were also integrated into the analysis. The observations were manually quality-controlled to remove erroneous values. Focus was given to eliminating erroneous high totals, which, if not corrected, could have significantly distorted the upper tails of the climatological distribution, leading to inaccurate results. Given the increased number of SYNOP observations at ECMWF from the 2000s, the analysis focused on the 20-year period between 1 January 2000 to 31 December 2019. For each location, the rainfall climatology was computed when at least 50% of the days within this period had valid observations, ensuring a reliable and comprehensive representation of the rainfall distribution.

## NWP-modelled climatologies

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

ERA5 is the fifth generation of atmospheric reanalysis produced at ECMWF (Hersbach et al., 2020). Compared to its predecessor ERA-Interim, ERA5 offers higher spatial (~31 km) and temporal resolution (hourly), providing more detailed insights into global atmospheric processes. The ERA5 dataset 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. The data spans from 1940 to the present, allowing for long-term climate variability and trend analysis. It also allows to validate the performance of weather prediction models against observed atmospheric conditions. Providing a single realization per day, the maximum rainfall totals that can be computed in the ERA5-derived climatology corresponds to the 20-year return period.

The ERA5 Ensemble Data Assimilation (EDA) system enhances the robustness of the ERA5 reanalysis by incorporating ensemble forecasting techniques, which generate multiple simulations with slightly varied initial conditions. This approach not only estimates the most likely state of the atmosphere but also quantifies the uncertainty associated with observational errors and limitations within the forecasting model itself. Each ensemble member of the ERA5 EDA provides a possible realization of the atmospheric state, which, when aggregated, offers a probabilistic forecast that is crucial for risk assessment and decision-making processes in climate studies. ERA5-EDA has 10 ensemble members, running at 62 km spatial resolution and at 3 hour temporal resolution. Figure 3b shows the rainfall values (in mm/24h) corresponding to the 10-year return period in ERA5. Since the 10 ensemble members of ERA5-EDA were used to compute independent realizations of 24-hourly rainfall totals per day, , the maximum rainfall total that can be computed corresponds to the 20-year return period (Table 1, row 3).

### ECMWF Reforecasts

Reforecasts are created by retrospectively applying the latest operational model settings to past weather events, creating a historical dataset with no discrepancies caused by historical changes in model configurations. Hence, reforecasts provide a consistent basis for evaluating accuracy and bias of weather prediction models, and developing adjustments that correct systematic model biases. The uniformity of reforecasts is crucial for this analysis, as it ensures that differences in climatological patterns are attributable to actual atmospheric variations rather than artifacts of evolving model technologies. In this study, the 46r1 model cycle was considered as it was produced for over a year and, hence, we can use only one model cycle, and it runs over a similar period of interest (1st July 1999 to 30th June 2019).

### ERA5-ecPoint

Observation-based climatologies help detect trends and patterns in the climate over a long period of time and can contextualise extreme, high-impact weather events. However, observations can be inaccurate and are unevenly distributed in space and time. The ERA5 reanalysis, which is produced by the Copernicus Climate Change Service (C3S) run by ECMWF and is based on state‑of‑the‑art data assimilation and numerical weather prediction (NWP), provides an alternative: an accurate, temporally consistent, gridded estimate of the past state of the Earth system worldwide. However, this does not satisfy all needs due to ERA5’s relatively coarse model resolution, which precludes representation of localised extremes, and because of some intrinsic biases. 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 raw ERA5 ‘deterministic’ fields to address ERA5 limitations (Hewson et al., 2023). ecPoint is formulated for independent application to any single model realisation and aims to infer sub-grid variability and to correct biases (both according to ongoing weather and geographical scenarios). So, in this way we create much more reliable (probabilistic) point-scale climatologies. ERA5\_ecPoint has so far been created for 1950 to near-real time, for 24- and 12‑hourly rainfall, and 24 h minimum, maximum, and mean 2m temperature. Two product classes were developed: grid-scale bias-corrected (‘deterministic’) and point-scale (probabilistic; percentiles 1 to 99). Currently, ERA5-ecPoint is provided on its native (reduced Gaussian) grid, with a spatial resolution of approximately 31 km (TL639).

# Methods

## Computation of the rainfall climatologies

The 24-hourly rainfall realizations ending at 00 UTC were computed for each day in the analysis period (01/01/2000 to 31/12/2019) from the rain gauge observations and the reanalysis/reforecast datasets. According to the considered dataset, a different number of daily realizations can be computed (Table 1, column 6). The total number of realizations in the 20-year analysis period (Table 1, column 6) were aggregated and ranked to compute a percentile-based climatology. Since the 1 in 10 year event (= 99.97260th percentile) was the maximum rainfall event that could be computed in the observational climatologies (Table 1, column 7 and 8, row 1), the comparison between the latter and the NWP-modelled climatologies used events up to a 10-year return period even though larger events could have been computed (Table 1, column 7 and 8, rows 2 to 5). Figure 3 shows the rainfall values (in mm/24h) corresponding to the 10-year return period for the observational (Figure 3) and NWP-modelled climatologies (Figure 3b-e).

## Statistical test to assess representativeness of NWP-modelled climatologies of the observational ones: k-sample Anderson-Darling test

In the k-sample Anderson-Darling (AD) test, the null hypothesis states that all samples are drawn from the same underlying distribution. Rejecting the null hypothesis indicates that there is sufficient evidence to conclude that at least one of the samples comes from a different distribution, suggesting significant differences between the samples. The critical values in this test increase with higher confidence levels, as more stringent thresholds are required to reject the null hypothesis when higher confidence is sought. For instance, at a 99% confidence level, the critical value is larger, meaning stronger evidence (i.e., a larger test statistic) is necessary to reject the null hypothesis compared to a 90% confidence level. This adjustment reduces the likelihood of making a Type I error—incorrectly rejecting the null hypothesis—at higher confidence levels. As a result, the test becomes more conservative, demanding more extreme evidence to detect distributional differences between the samples as statistical significance is evaluated with increasing rigor.

The non-parametric k-sample Anderson-Darling test is used to assess whether NWP-modelled rainfall climatologies are representative of observational climatologies. This non-parametric test is a good choice because it assesses whether the empirical cumulative distribution functions (ECDFs) of the two considered datasets have the same underlying distribution without having to specify the distribution function of that population. The test gives emphasis not only to differences in the centre of the distributions (like other tests such as Kolmogorov-Smirnov), but it also gives emphasis to differences in the tails. This makes the Anderson-Darling test highly effective for detecting departures in the extreme values in distributions with significant skew or kurtosis, e.g. rainfall distributions (Scholz & Stephens, 1987).

The test statistic Ak is calculated by integrating the squared difference between the two ECDFs, weighted by the variance function of the combined sample. A higher value of the Anderson-Darling statistic indicates a greater discrepancy between the two samples, suggesting that they may come from different distributions. The Ak values are compared to critical values of the test statistic, Acrit, to make inferential judgments about the homogeneity of the populations under study. Acrit is determined, at a certain confidence level (CL), via Monte Carlo simulations due to the complexity of the test’s distribution under the null hypothesis:

* **Ak <= Acrit(99.99% CL)**, the NWP-modelled rainfall climatology **is representative** of the observational climatology.
* **Ak > Acrit(99.99% CL)**, the NWP-modelled rainfall climatology **is not representative** of the observational climatology.

Such a binary decision was considered not appropriate for our case because the critical values were the same for all the NWP models.

The Anderson-Darling test is designed to compare distributions using all available data points, regardless of the difference in sample sizes, allowing for a more precise comparison of differences in the tails of the distribution (Baumgartner & Kolassa, 2021). This is particularly useful in our case where the NWP-modelled distributions can have 10 times more data points than the distribution from observations (see Table 1, column 6). However, it's important to note that very large differences in sample sizes (such as in the case of the distribution from ERA5-ecPoint that is 99 times bigger than the one from observations) may affect the test's sensitivity and introduce biases (Makarov & Simonova, 2017). Specifically, the larger sample may dominate the test statistic, potentially masking meaningful differences in the smaller sample or exaggerating minor deviations in the larger one. This imbalance can lead to either Type II errors (failing to detect true differences) or Type I errors (detecting differences that are not meaningful). Resampling techniques, such as bootstrapping, can help reduce this bias, but caution is needed if the focus is on differences in the tails of the distributions (as it is in this study), as resampling can sometimes obscure tail behaviour due to random sampling variability. Permutation methods, on the other hand, are a robust alternative because they preserve the structure of the original data, making them particularly effective when analysing differences in the tails. The permutation method tests the null hypothesis by randomly shuffling the group labels between samples, simulating a scenario where there is no true difference between the groups. By recalculating the test after each shuffle and repeating this process many times, the method generates a distribution of test statistics under the null hypothesis. If the original test statistic, calculated from the unshuffled data, falls in the extreme tail of this distribution, it suggests that the observed difference between the groups is unlikely to have occurred by chance, providing strong evidence to reject the null hypothesis. This approach ensures that any detected differences are meaningful and not simply due to random variation. Differences in the computed p-values reduced drastically after 100 permutations (not shown), so such value was considered as the best compromise between accuracy in the computation of the p-values and reducing code runtime.

As the sample size of your data increases, your chances of discovering non-normality increase. Small sample sizes may give you a false reading of normality. If you are using a probability plot, don’t be deceived by the impact of the sample size. Let your decision be guided by the p-value. The p-value of your AD test will indicate, with your desired level of risk, whether you can reject your null hypothesis.

# Results

Out of all NWP-modelled rainfall climatologies, ERA5-ecPoint provides the best representation of observational point-rainfall climatologies. This overall better representation can be seen by a much wider extension of blue dots (i.e., locations where NWP-modelled climatologies are representative of observational point-rainfall climatologies) in Figure 2e compared to Figure2b-d, where there is a much more significant number of pink dots (i.e., locations where NWP-modelled climatologies are not representative of observational point-rainfall climatologies). ERA5-ecPoint represents observational climatologies in more than 90% of locations in all six considered domains (whose definitions are provided in Figure 2a), except for South America, where it reaches only 74.3%. The best representation is reached in the Oceania and Europe & Mediterranean region, where the representativeness reaches 98.3% and 98.8% of locations. The lower resolution NWP-modelled climatologies, i.e. ERA5\_EDA (Figure 2a), ERA5 (Figure 2b), and reforecast\_46r1 (Figure 2c) are representative of observational climatologies in a much smaller number of locations, with performances that, on average, increase with the resolution (ERA5\_EDA < ERA5 < Reforecast\_46r1). The performance of ERA5-EDA and ERA5 climatologies is mostly comparable, with the worst representation in South America (less than 1% of locations with representative climatologies) and relatively poor representation over North America, Europe & Mediterranean, and Asia (less than 6%). Both NWP-modelled climatologies in Africa & Arabian Peninsula and Oceania reach at least 10% of locations that represent observational climatologies. However, it is worth noting that those points (blue dots in Figure 2b-c) are mainly located over the Sahara Desert in Africa and the arid regions of Australia. Overall, the climatologies from reforecasts provide a larger number of locations where they are presentative of observational climatologies, with improvements compared to ERA5-EDA and ERA5 that exceed 15% in Oceania, Asia, Africa & Arabian Peninsula, and 10% in Europe & Mediterranean and North America. Climatologies from reforecasts do not improve the representation of observational climatologies in South America, where they remain below 1%.

It is worth comparing the observational and the NWP-modelled climatologies to gain insights into where and why the climatological distributions differ. The climatologies are displayed with the x-axis in a logarithmic scale to compress the small rainfall totals and expand the higher ones. Compared to a graph with x-axis in linear scale, the logarithmic scale makes it easier to compare the climatologies on a single graph. In flat (Figure 2a) and orographic areas (Figure 2b), all NWP-model climatologies, with the exception of ERA5-ecPoint, are not able to represent the growth rate that observational climatologies have between 0.1 to 10, the frequency of zero rainfall totals, and the long wet tails in the observational climatology. In the flat areas, there is a progressive better representation of the observational climatology with increasing spatial resolutions. In orographic areas, ERA5-EDA and ERA5 perform very similarly for small rainfall totals, with ERA5 performing better in the representation of the wet tail. Reforecasts perform better than ERA5-EDA and ERA5. In very complex orographic areas such as the Andean region (Figure 2c), also ERA5-ecPoint fails to represent the growth rate that observational climatologies have between 0.1 to 10 and the frequency of zero rainfall totals, while still providing a better representation of the wet tail compared to the other NWP-modelled climatologies. As highlighted above, the AD test highlights that ERA5-ecPoint is indeed not representative of the observational climatology in the Andean region (Figure 1e). In desertic areas (Figure 2d), all NWP-modelled climatologies represent well the observational climatology, a part from the tail of the observational climatology.

# 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 1 – 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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Description automatically generated with medium confidence

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

A screenshot of a computer screen

Description automatically generated

Figure 2 – 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.

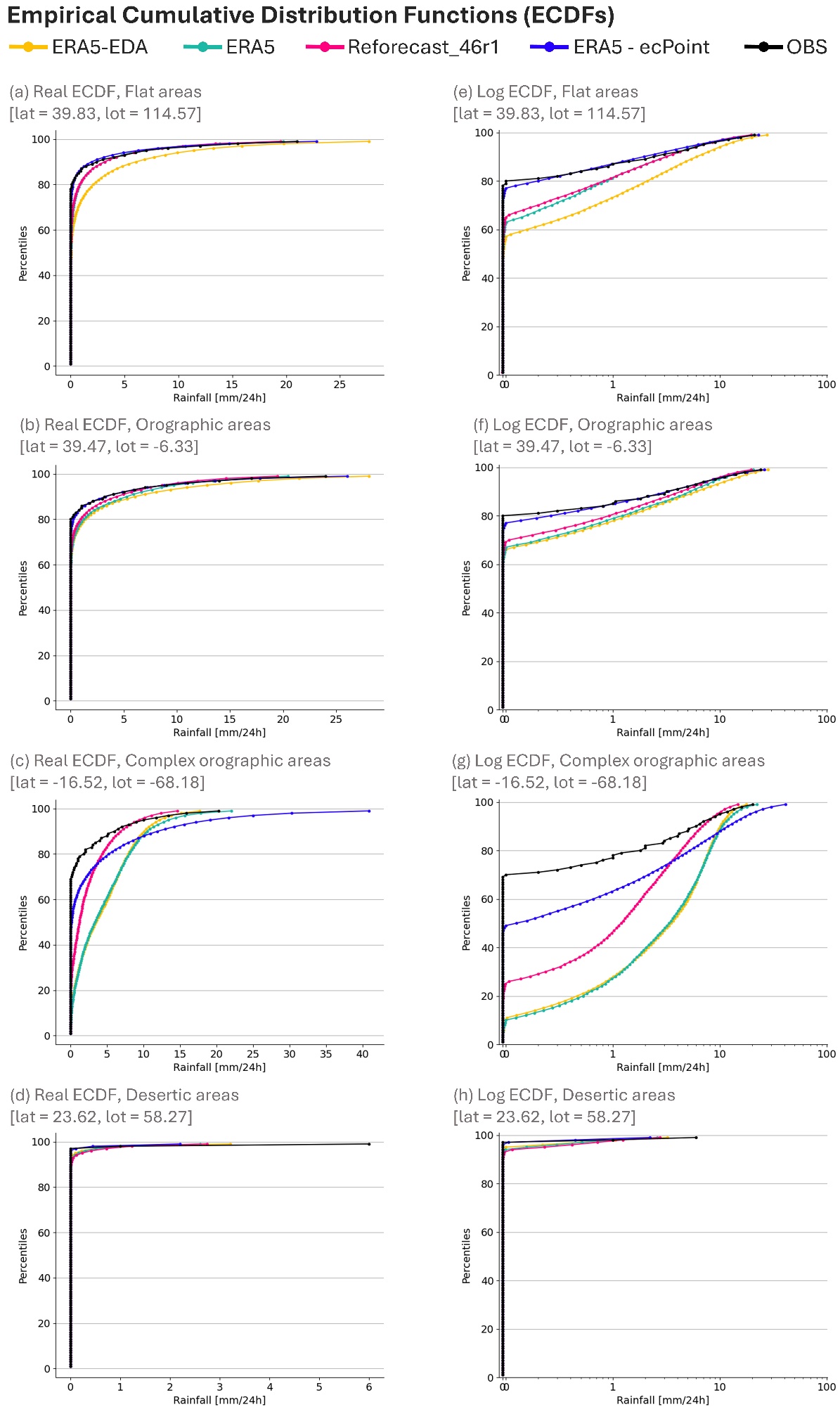


Figure 3 – Empirical Cumulative Distribution Functions (ECDFs) for 24-hourly rainfall from rain gauge observations (OBS, in black) and the NWP models ERA5-EDA (yellow), ERA5 (turquoise), reforecasts (Reforecasts\_46r1, pink), and ERA5-ecPoint (in blue). Panels (a) to (d) show the ECDFs, respectively, 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).

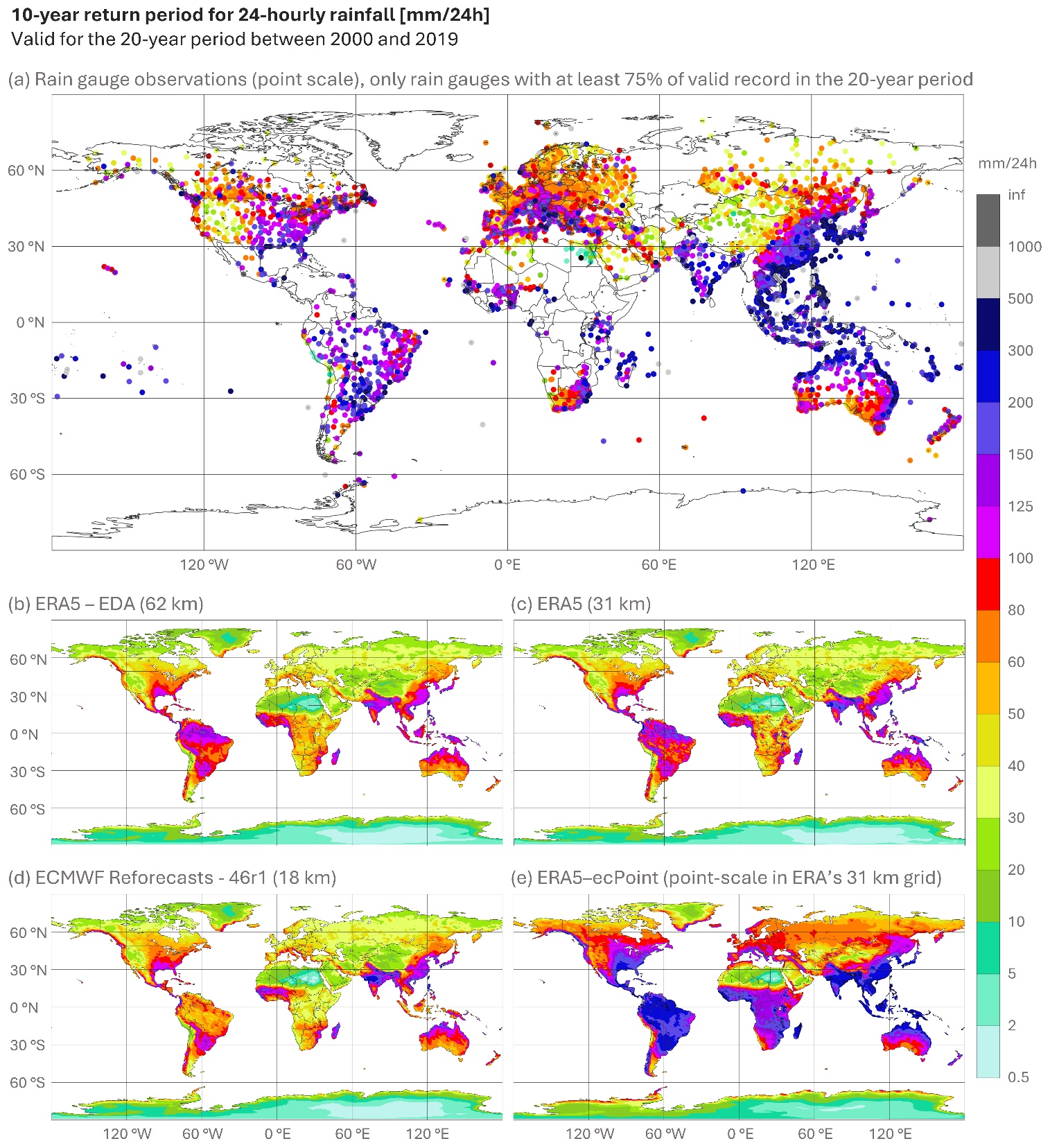


Figure – Panel (a) displays the 10-year return period for 24-hourly rainfall from rain gauge observations, calculated over the 20-year period between 2000 and 2019, and using only rain gauges with at least 75% of valid records. Panels (b) to (e) show the 10-year return period for NWP-modelled 24-hourly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

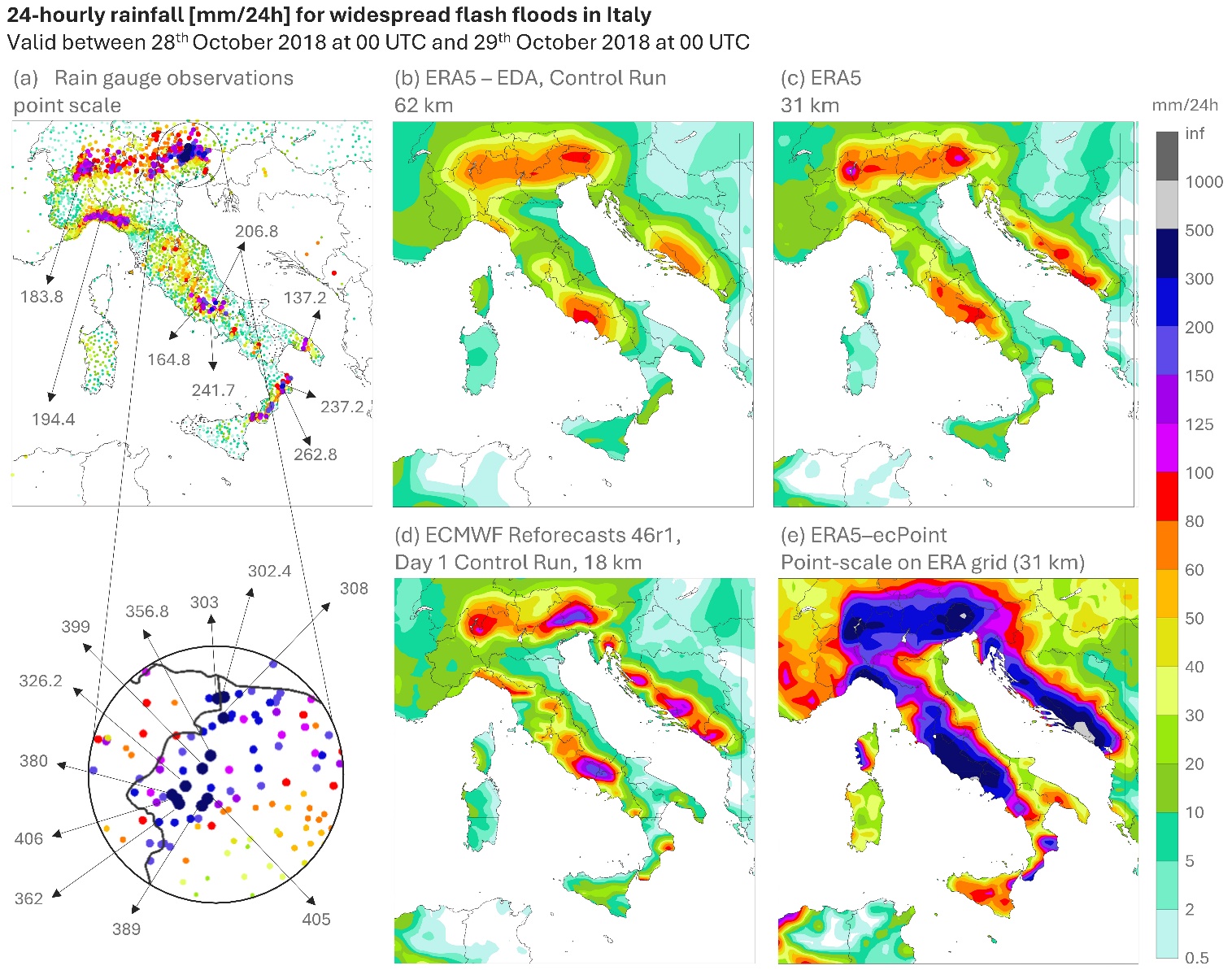


Figure 5 – 24-hourly rainfall [mm/24h] for widespread flash floods in Italy on 28th October 2018. Panel (a) shows observations from rain gauges. Numbers in grey indicate peak rainfall totals in mm/24h. Panel (b) to (e) indicate rainfall totals from, respectively, control run for ERA\_EDA (62 km), ERA5 (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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