



The missing precipitation extremes in the world's mountains

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Abstract. Precipitation estimation in mountainous regions is heavily reliant on remote sensing observations and analysis. We demonstrate that the most advanced global precipitation products underestimate extreme rainfall in mountainous regions. A study comprising over 10 000 flood-producing extreme rainfall events worldwide over the past 52 years (1973–2024) shows median underestimations of 100 mm and 225 mm for the top 5 % and 1 % extreme rainfall events, respectively. The spatial variability of rainfall is also significantly underestimated by a factor of 3 in the world's mountains. These findings confirm the limited ability to monitor and quantify extreme rainfall in complex terrain. This work provides a novel path to systematically enhance precipitation estimates globally using a general hybrid physics–AI framework, even for the top 1 % of extreme events.

1 Introduction

15 Extreme rainfall is one of the deadliest natural disasters. Over the past few decades, extreme rainfall has become an important research topic due to its social, economic, and environmental impacts (Westra et al., 2014; Wernberg et al., 2013). An increase in the frequency and intensity of extreme rainfall events has been observed in Europe, America, and other parts of the world over the last century (Sun et al., 2021; Milly et al., 2002), often resulting in severe floods and flash floods in mountainous regions due to steep slopes (Schumacher, 2017; Borga et al., 2014). Floods were also among the most expensive and deadliest natural disasters in the 20th century (Willner et al., 2018; Perry, 2000), with more than 94 million people affected worldwide each year since 2000 (Wu et al., 2020). The average annual economic loss from freshwater flooding in the United States alone exceeds USD 8 billion (Wing et al., 2018).

Measuring extreme rainfall has remained a challenging task for decades, particularly in mountainous regions (Barros et al., 2000; Wilson and Barros, 2014; Duan and Barros, 2017; Arulraj and Barros, 2017; Barros and Lettenmaier, 1993; Buytaert et al., 2006). Rain gauges, arguably the most accurate method for measuring rainfall at small scales, are scarce in mountainous regions due to topographic constraints and the high cost and operational challenges of deploying and maintaining dense networks, particularly in developing countries. For better spatial coverage, satellites and weather radars have become viable options for estimating rainfall over the past 2–3 decades. Research shows that these remote sensing products underestimate extreme rainfall in the mountains because of the missed detection of highly localized orographic enhancement (Sun and Barros, 2010; Barros and Tao, 2008). Similarly, weather prediction models that rely on the



assimilation of remotely sensed information to produce rainfall forecasts are also plagued with severe underestimation errors when it comes to forecasting extreme rainfall events (Jiang et al., 2021; Lavers et al., 2022), with cascading effects impacting downstream applications: flood simulation (Wang et al., 2017), flood forecasting (Shrestha et al., 2013; Yucel et al., 2015), landslide forecasting (Canli et al., 2018), etc. However, it cannot be overemphasized that the spatial coverage of rain gauge networks is extremely limited in the world's mountains. For reference, the total surface area of the world's rain gauges' orifices combined is less than a soccer pitch or an American football field, with most rain gauges located in the plains. Notably, a large percentage of rain gauges do not provide rainfall measurements regularly (Kidd et al., 2017). Therefore, the quality of remote sensing-based rainfall estimation and analysis remains largely unknown in the vast regions of the world's mountains, particularly during extreme events, because such events are relatively rare.

In this study, we investigate a current state-of-the-art high-resolution global precipitation reanalysis dataset (i.e., the land component of the fifth generation of European Reanalysis (Muñoz-Sabater et al., 2021), abbreviated as ERA5-Land or ERA5L), using a sample of over 10 000 extreme rainfall events in the mountains worldwide over the past 52 years. We then estimate rainfall errors using a physics-based Lagrangian framework (Liao and Barros, 2022, 2023, 2025) and demonstrate that most extreme events exhibit severe and systematic underestimation of rainfall magnitude. These underestimation errors show an increase with elevation up to 900–2000 m above sea level (a.s.l.), thus along the altitudinal range of orographic rainfall maxima. Furthermore, our results demonstrate a drastic underestimation of rainfall spatial variability by a factor of 3 worldwide. Underestimation also exists in various advanced satellite-based precipitation estimation datasets (e.g., Integrated Multi-satellite Retrievals for the Global Precipitation Measurement (IMERG, version 07B) of the National Aeronautics and Space Administration (NASA), and Climate Prediction Center MORPHing (CPC MORPHing or CMORPH, version 1.0) of the National Oceanic and Atmospheric Administration (NOAA)). Finally, this work establishes a generalizable and reliable physics-based correction framework that significantly alleviates orographic rainfall underestimation. We show satisfactory improvements in independent water-prediction applications, using flood simulation as an example.

2 Data and methods

2.1 Study regions and event selection

First, mountain ranges worldwide that experience frequent flash floods are selected. Then, watersheds with drainage areas up to 2500 km² are identified, encompassing a wide range of mountain terrains. Larger watersheds are outside the scope of this work because they have more expansive areas of smooth topography at lower elevations rather than hillslopes, and small mountainous basins are generally more vulnerable to extreme rainfall events than larger downstream basins (Borga et al., 2014). The locations of the selected watersheds are shown in Fig. A1, with each region labeled for discussion. Next, extreme rainfall events are selected based on the flood volume they generated at gauged watershed outlets. Daily streamflow data are downloaded from the Global Runoff Data Centre (GRDC), which has been operating under the auspices of the World Meteorological Organization (WMO) since 1988. Streamflow peaks exceeding the 97.5th percentile of the streamflow record



for the study period (1973–2024) are identified as potential extreme precipitation events. To isolate rainfall-driven events, only events for which the watershed-averaged temperature before (15 days ahead) and during the potential event is consistently greater than 0 °C are included in this study. The rainfall and temperature data are downloaded from ERA5L, the current state-of-the-art high-resolution global reanalysis dataset. This current state-of-the-art high-resolution global reanalysis dataset incorporates data from multiple sources, including satellites, weather stations, aircraft data, and radiosondes. Subsequently, errors in ERA5L are estimated using a previously published physics-based framework to correct precipitation (the Inverse Rainfall Correction, or IRC; see details in Sect. 2.2). The Quantitative Precipitation Estimates (QPE) of total rainfall amount per extreme event are calculated for both the original ERA5L and post-IRC ERA5L, and the QPE error is expressed as ΔQPE (i.e., $\Delta QPE = \frac{QPE_{IRC} - QPE}{QPE}$), which is shown in Fig. 1. The term QPE refers to the product of original ERA5L unless otherwise specified in this work. The methodology applied here is general and can be used with any precipitation data set.

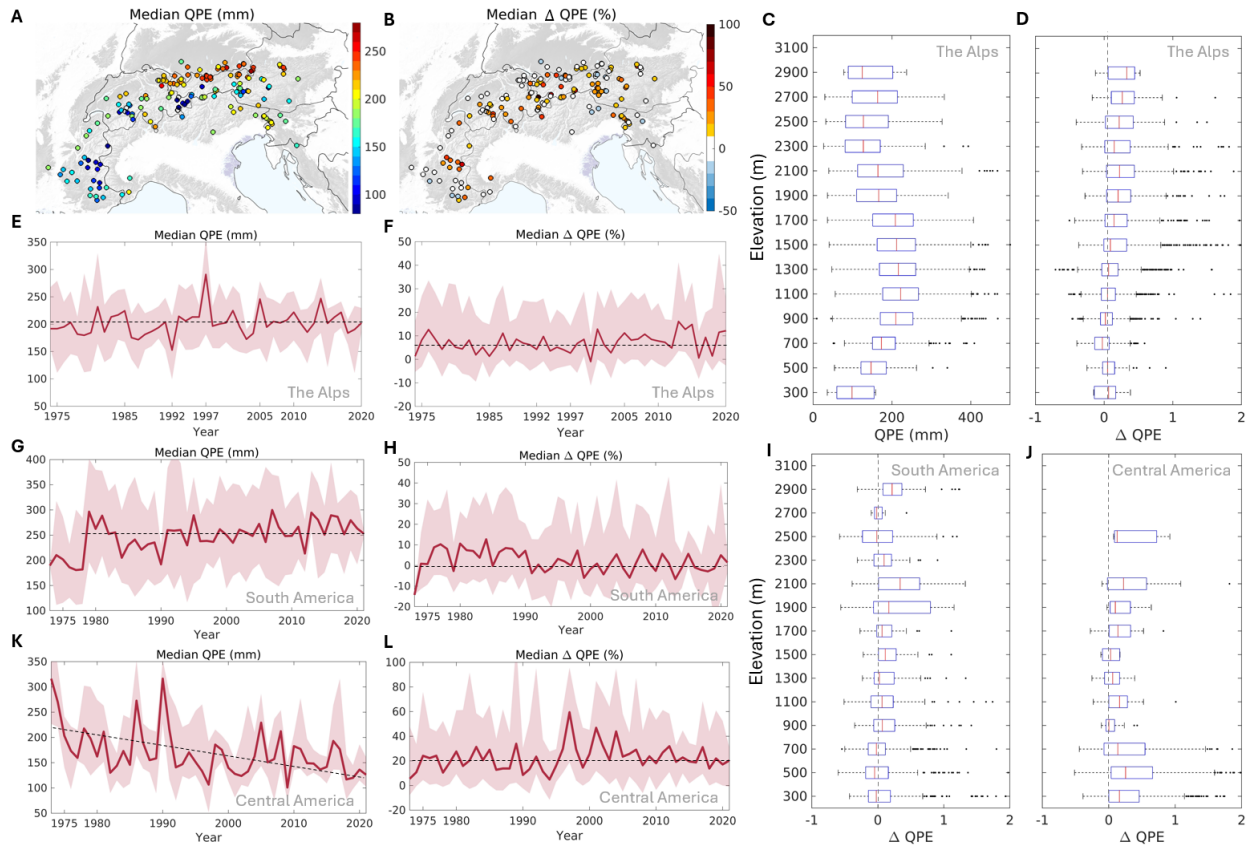


Figure 1. Extreme rainfall magnitude underestimation. (a) Spatial distributions of event-total amount in the Alps for all events (the median value displayed at each basin) and its dependence on elevation (c). The rainfall data used in this study are retrieved from ERA5-Land (1973–2024) at 9 km resolution. Elevations below 500 m (above sea level, a.s.l.) are masked out. (b) Spatial distribution of relative rainfall errors ΔQPE in the Alps for all events (with the median value displayed at each basin). Positive ΔQPE values indicate an underestimation of ERA5L, and a negative ΔQPE value indicates overestimation of ERA5L. Time series of the median QPE for all events are shown across the Alps (e), South America (g), and Central America (k), grouped by year, with the red uncertainty envelope bounded by the 25th and



75th percentiles. Time series of the median Δ QPEs of all events are shown across the Alps (f), South America (h), and Central America (l), grouped by year, and the red uncertainty envelope is bounded by the 25th and 75th percentiles. The elevation dependence of the Δ QPE distribution by elevation band is shown for the Alps (d), South America (i), and Central America (j).

The principle of event selection is based on the impact of rainfall on the corresponding drainage watersheds, specifically on streamflow magnitudes at watershed outlets. For each watershed, the Duke Coupled Hydrology Model (DCHM; see Sect. 2.4) follows a traditional spin-up approach to warm up. Specifically, the first year (September to April) is used as a spin-up period, after which the DCHM is run continuously for the remaining years at each basin. If a streamflow peak exceeds 97.5 % of available streamflow records, then that event is selected as a potential extreme rainfall event. In addition to this condition, the air temperature must be consistently higher than 0 °C during and before the event for at least 15 days for the potential event to be categorized as an extreme rainfall event. In the mountains, extreme rainfall produces extremely fast floods on the scale of a few hours to a few days, which are usually referred to as flash floods. Therefore, to eliminate any “slow” floods caused by slow snowmelt processes during spring and early summer, we limited the flood response time (i.e., the duration from the flood rising point to the flood peak at the basin outlet) to a maximum of 7 days. Note that slow-responding events are usually less dangerous, as they give people more time to respond.

2.2 Calculation of rainfall uncertainty

Given the lack of point-scale rain gauges and their limited representativeness of rainfall spatial distribution in the mountains (Michelon et al., 2021), we used the same framework developed by the same authors previously (Liao and Barros, 2022, 2023, 2025) to quantify rainfall uncertainties across each basin. This framework, named IRC (i.e., Inverse Rainfall Correction), produces improved rainfall estimates that are constrained by water budget closure at the basin scale using Lagrangian particle tracking coupled with a hydrological model. These improved rainfall estimates are used to quantify rainfall uncertainty in the original rainfall estimates. The hydrological model is a fully physics-based, distributed model, specifically the DCHM, which was developed in the 1990s and has evolved since then (Barros, 1995; Devonec and Barros, 2002; Garcia-Quijano and Barros, 2005; Yildiz and Barros, 2007; Tao and Barros, 2013, 2014). The spatial and temporal resolutions of the Lagrangian tracking are 900 m and 5 min, respectively. The DCHM spatial and temporal resolutions are 900 m and 1 h, respectively. Note that no parameters are calibrated for any watersheds or any events. Instead, parameters are determined using publicly available databases and literature (Tao and Barros, 2013, 2014). During a rainfall event, if any forcing data or streamflow data are missing, that event is discarded for quality control. The total events studied amount to 10 971, and data outputs are approximately 186 TB.

The validation of this IRC method is provided here: post-IRC rainfall (i.e., ERA5L-IRC) is evaluated against publicly available rain gauge-only gridded QPE datasets at the basin scale. The results are shown in Fig. 2. Specifically, rain gauge-only gridded QPE data at 5 km resolution are extracted from the Alpine Precipitation Grid Dataset (APGD; Isotta et al., 2014) from 1971 to 2019. Note that for basins in other mountain ranges (i.e., non-Alps basins), due to much lower spatial coverage of rain gauges, particularly in developing countries, rain gauge-only gridded QPE data at high resolutions are not



available for comparison. Most of the gridded QPE datasets outside the Alps are created by merging rain gauge
115 measurements with coarse-resolution satellite precipitation data (10–25 km resolution). Therefore, the validation of the IRC
products in the non-Alps mountains is not done in this work.

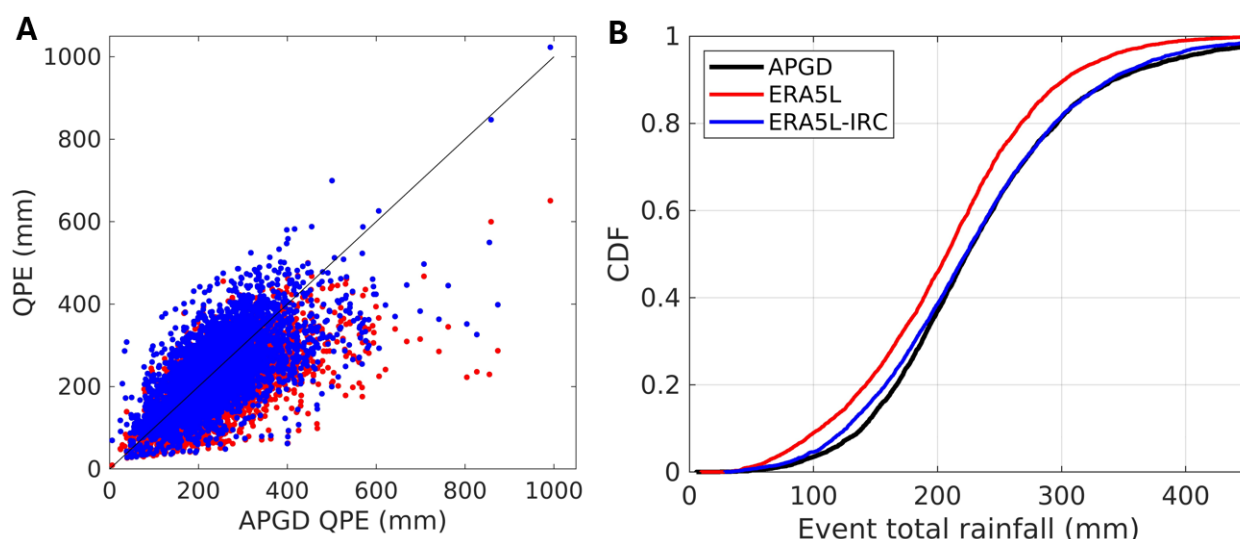


Figure 2. (a) Event total rainfall comparison against rain gauge-only QPE (APGD) of basin-averaged rainfall amounts. (b) Basin-averaged event total rainfall distributions expressed as the cumulative distribution function.

120 It is demonstrated that the original QPE data (i.e., ERA5L) severely underestimate rainfall (see Fig. A2 for other QPE
datasets) and that the IRC provides improvements in rainfall estimation both at the pixel scale against rain gauge-only QPE
and at the basin scale constrained to close the water budget at the basin outlet (Liao and Barros, 2022, 2023). It is worth
noting that even at sub-km resolution, as in this study, rainfall can still vary drastically in the mountains from ridges to
valleys. This has been a challenge in atmospheric science and hydrology for decades. The IRC approach bridges the scale
125 gap to improve rainfall estimation across scales.

Experiments with a smaller sample size of basins and events were carried out at much finer scales (i.e., 250 m and sub-100
m resolution) previously, with excellent performance of the IRC for the Appalachian Mountains in the United States (Liao
and Barros, 2022, 2023, 2025). However, it is not practical to conduct a complete experiment of more than 10 000 events
worldwide at these spatial scales with current computing infrastructure. The projected data storage would exceed 200
130 petabytes. We argue that the major limitation of the IRC is the computational time required to deconvolve the complex
rainfall–runoff relationship using physics-based methods in this work. Nevertheless, the advantage of using the IRC for
rainfall uncertainty quantification is clear: improved rainfall from the IRC is characterized by significantly enhanced rainfall
at high elevations, which is commonly observed in mountainous regions. The boxy patterns in the original rainfall are
improved to patterns aligned with the topography, as shown in previous studies (Liao and Barros, 2022, 2023, 2025) and in
135 Fig. 3. In addition, Fig. 3 highlights a common issue in the field of rainfall estimation: an overreliance on rain gauges when
developing gridded rainfall estimation datasets. For instance, the rain gauge-only gridded APGD agrees well with the rain



gauge data, as expected (Fig. 3f). However, flood simulations using APGD exhibit excessively large peak flows with errors greater than 140 % (Fig. 3e). This is because of the large spatial variability of rainfall in complex terrain, which changes regionally with landform and synoptic-scale weather patterns. It is therefore challenging to extrapolate rainfall measurements from a 0.04 m² area (i.e., a rain gauge's collection area) to the pixel scale (e.g., 1 km², Fig. 2a) and to the regional scale (50–1000 km², Fig. 2b) using statistical methods without physical constraints.

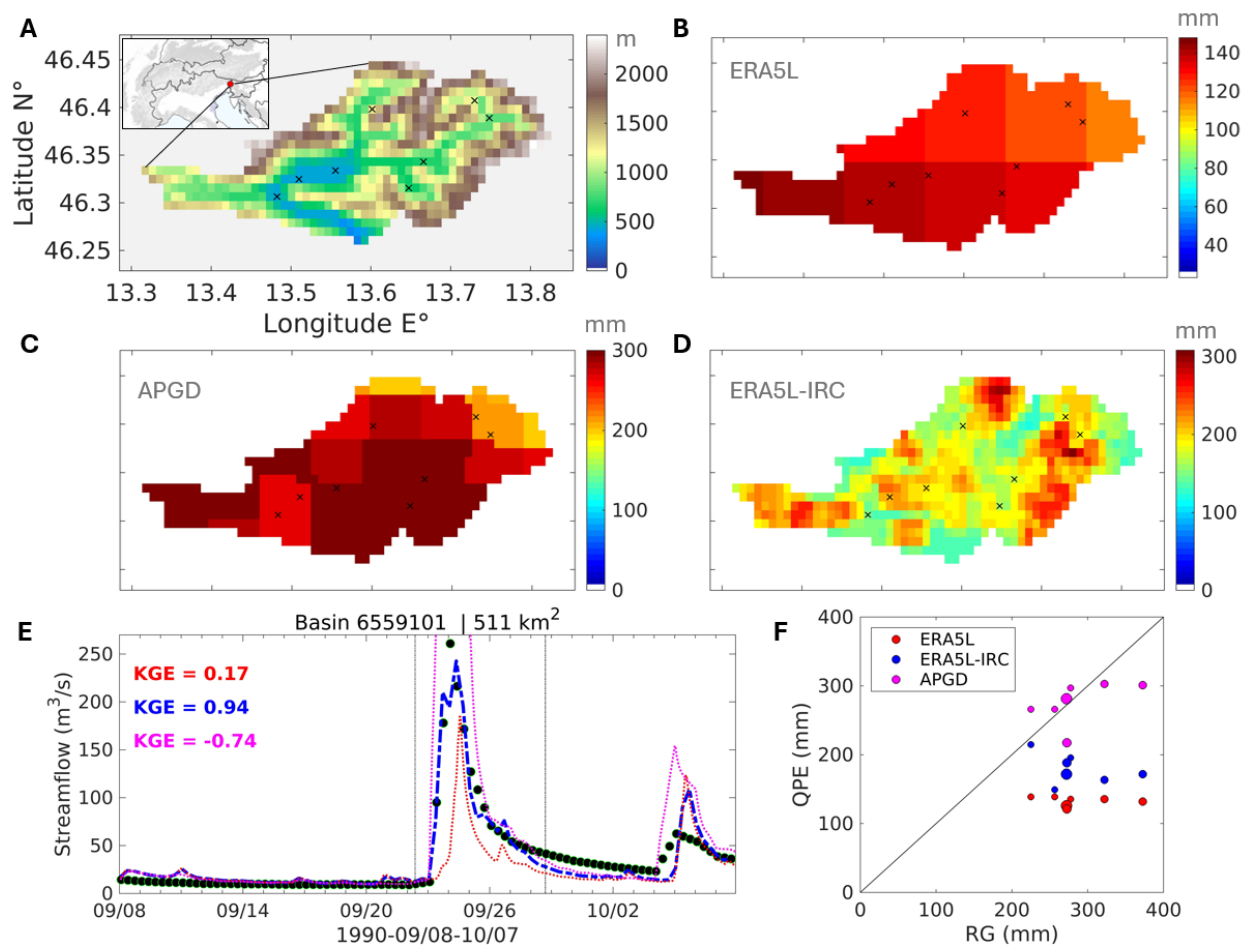


Figure 3. An example event to show the impact of the IRC on improving ERA5L and the corresponding flood simulation. (a) The location of the watershed in the Alps, with rain gauges marked by black crosses. Event total precipitation using different products: ERA5L (b), APGD (c), and ERA5L-IRC (d). (e) The flood hydrographs using different products: ERA5L (red), ERA5L-IRC (blue), and APGD (pink). (f) Precipitation comparison at rain gauge locations for the same products.

2.3 Data for hydrological simulations

- Forcing data: 2 m air temperature, 2 m air pressure, specific humidity, downward shortwave radiation, downward longwave radiation, 10 m wind, and total precipitation. These data are derived from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5-Land reanalysis at hourly resolution.



- Land cover data: leaf area index, emissivity, coverage of vegetation, and albedo. These data come from the MODIS dataset linearly interpolated to hourly resolution.
- Soil properties data: porosity, field capacity, wilting point, and hydraulic conductivity. These data are from a high-resolution global soil dataset (Zhang et al., 2018).
- Streamflow data are obtained from the Global Runoff Data Centre (GRDC) at daily scales.

Forcing data and land cover data are bilinearly interpolated in space to each basin for each event. If any data are missing during an event, that event is discarded from this work. The total number of studied basins and events is 423 and 10 791, respectively.

2.4 Duke Coupled Hydrology Model (DCHM)

The DCHM is a physics-based distributed hydrology model with its first version (Barros, 1995) published in 1995. It has been extensively used in the mountains since the early 2000s (Barros, 1995; Devonec and Barros, 2002; Garcia-Quijano and Barros, 2005; Yildiz and Barros, 2007; Tao and Barros, 2013, 2014). Model parameters are chosen based on the literature, rather than through parameter calibration, consistent with previous research works (Liao and Barros, 2022; Yildiz and Barros, 2007). It is worth noting that this model is not calibrated for any basins or events to achieve the “best” results when compared to observations (in terms of rainfall amounts or flood responses), as this is not the focus of the paper. The focus of this paper is to demonstrate the underestimation of extreme rainfall in remote sensing products and show its impact on downstream tasks.

2.5 Cross-regional model validation

An artificial intelligence (AI) model based on random forest regression is developed to assess the general applicability of the technical advance presented in this paper. This technical advance specifically refers to the improvement in reducing underestimation errors in extreme-rainfall estimates. This AI model employs a traditional 5-fold cross-validation scheme for all events in the Alps at hourly temporal resolution, given the rich data records. The AI predictors or inputs include precipitation and topography characteristics at each basin at hourly time intervals during each rainfall event:

1. Basin drainage area in km².
2. Basin-averaged slope by averaging the slope of each basin pixel at 900 m resolution.
3. Basin-averaged rain rate in mm h⁻¹ for each hour during an event.
4. Rainfall distance relative to the basin outlet (ranging from 0 to 1) at the hour t (Eq. 1):

$$do(t) = \frac{\sum_y \sum_x P(x, y, t) do(x, y)}{\sum_y \sum_x P(x, y, t)} \quad (1)$$

where $do(x, y)$ is the distance from a basin pixel (x, y) to the basin outlet normalized by the maximum do in the basin, P is the rain rate at that basin pixel, and t represents time at hourly intervals.



180 5. Rainfall distance relative to the nearest streams (ranging from 0 to 1) at the hour t (Eq. 2):

$$ds(t) = \frac{\sum_y \sum_x P(x, y, t) ds(x, y)}{\sum_y \sum_x P(x, y, t)} \quad (2)$$

where $ds(x, y)$ is the distance from a pixel (x, y) to the nearest stream, normalized by the maximum ds in the basin, and P and t follow the same definitions as above.

6. Simulated flood $Q(t)$ at the basin outlet at the hour t using the DCHM.

7. Coefficient of variation of the simulated flood time series of an event using the DCHM.

185 The specifics of the random forest regression AI model are as follows:

1. Number of trees: 30.

2. Minimum leaf size (data points) to avoid overfitting: 10.

3. 5-fold cross-validation using Alps events.

The target of the AI model is the hourly basin-averaged rainfall uncertainty derived from the IRC method (i.e., the difference
190 between basin-averaged ERA5L-IRC and ERA5L). The trained AI model is subsequently applied to other mountainous
basins in the Andes, the Brazilian Highlands, the Himalayas, and the Southeast Asian mountain ranges at hourly time scales.
The event selection criterion and AI model inputs in these regions are the same as in the Alps. In total, the number of events
for testing purposes outside the Alps is close to 4500. It is worth noting that a simple random forest regressor is used in this
study to provide proof of concept for testing the generality of the technical advance in this work, instead of achieving the
195 absolute “best” results. Moreover, results using neural networks were also generated, but they are overall inferior to those
from the random forest regressor and much more sensitive to initial weights (not shown). To achieve even better results, data
and models at higher spatial and temporal resolutions are needed, and implementing other AI tools with more predictors may
lead to improved results, as shown by the same authors (Liao and Barros, 2022, 2023, 2025). However, it is not
computationally feasible for us to run sub-100 m scale simulations for such an extensive study as presented in this work. The
200 projected storage size would exceed 200 petabytes if simulations were carried out at the 100 m scale. We encourage readers
to utilize other machine learning tools and AI architectures, combined with additional domain knowledge, to further enhance
the performance of this generalizable AI tool to facilitate regional studies.

3 Results

3.1 Extreme rainfall underestimation

205 Rainfall is much more extreme in the Eastern Alps than in the Western Alps (Fig. 1a). Our results do not suggest a noticeable
trend in extreme rainfall magnitudes (Fig. 1e), nor a noticeable change in extreme rainfall detection skill (Fig. 1f) in the
broad Alps region from 1973 to 2024, which is consistent with the findings from previous precipitation research of the
greater Mediterranean region (Vicente-Serrano et al., 2025). The years 1992 and 1997 are highlighted on the x axis as the



lowest and highest median QPE years for the Alps across the half-century, respectively. Rainfall uncertainty analysis suggests severe underestimation (i.e., large positive Δ QPE), with a median Δ QPE of 25 % or more underestimation in many places for the top 25 % events (Fig. 1b and f). Figure 1e and f suggest a consistent underestimation of 20 mm for a median-magnitude extreme rainfall event in the Alps, which approximately produces 206 mm of rainfall, thus roughly 10 %. This underestimation phenomenon also occurs in other study regions with different severity. It is worth noting that trend analyses of QPE and Δ QPE are not performed in Southeast Asia and the Himalayas due to the limited number of events and short records, which preclude meaningful analyses. For the United States, the Rocky Mountains have much lower annual mean precipitation and maximum daily precipitation compared to the Appalachian Mountains (Asadieh and Krakauer, 2015; Donat et al., 2016), with few extreme events (Saharia et al., 2017; e.g., their Fig. 4). IRC results at very high spatial resolution (250 m) to simulate flash floods in the Appalachian Mountains were published previously (Liao and Barros, 2022, 2023, 2025, 2026); therefore, results for the United States are not included in this manuscript.

Results reveal that rainfall underestimation (Fig. 1c, d, i, and j) depends on elevation. For example, a large deviation of Δ QPE starting from 900–1100 m in the Alps indicates that extreme rainfall above this elevation is severely underestimated by ERA5L, illustrating the difficulties involved in capturing orographic enhancement on mountain slopes occurring at spatial scales that are much smaller than the ERA5L resolution (9 km) and other rainfall data sets, including satellite products (Barros and Arulraj, 2020). It is clearly shown that some events are underestimated by 60 % or more (corresponding to Δ QPE greater than 1.5) when the basin elevation is higher than 1100–1300 m a.s.l. in the Alps. These events are the most severe historical events in the past 50 years for each study region. In addition to errors in basin-averaged QPE, the spatial variability of extreme rainfall is much higher than what can be detected with current remote sensing and data assimilation techniques constrained by the underpinning models and observing systems. The standard deviation of rainfall estimation within each basin for each event is calculated for both the original QPE (ERA5L) and error-reduced QPE (ERA5L-IRC).

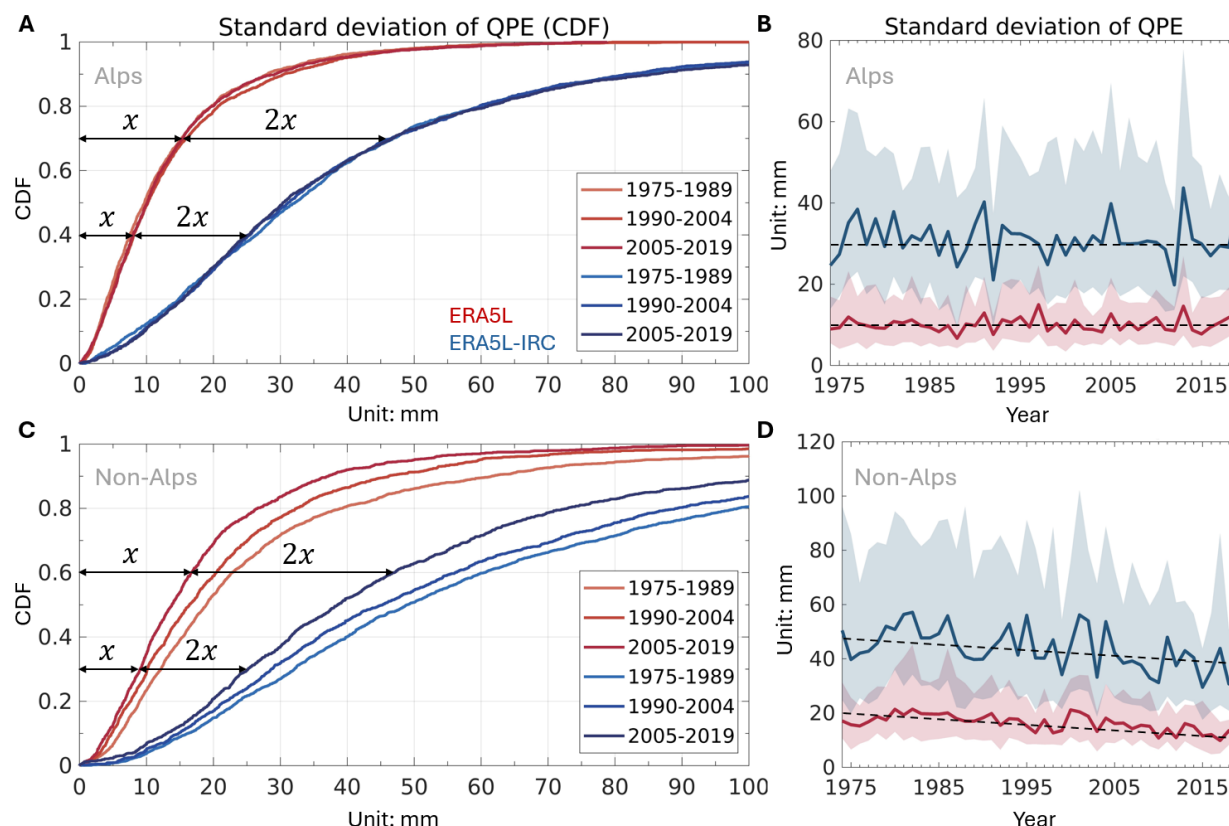


Figure 4. Extreme rainfall spatial variability underestimation. Cumulative distribution function (CDF) of the basin-wide standard deviation of event-total rainfall estimates for ERA5L (red) and ERA5L-IRC (blue) for three 15-year intervals in the Alps (a) and elsewhere (non-Alps, c). Standard deviation envelopes are calculated for every year using all events in the Alps (b) and non-Alps (d) regions. Solid lines represent the median, and shaded boundaries represent the 25th and 75th percentiles. The x and $2x$ annotations highlight a roughly 2-fold difference in rainfall spatial variability between the original ERA5L and ERA5L-IRC.

Results show that the standard deviation is three times larger for ERA5L-IRC (Fig. 4a and c). This demonstrates the lack of small-scale variability in orographic rainfall in ERA5L. Temporally, spatial variability remains roughly stationary in the Alps region (Fig. 4b) and exhibits a decreasing trend in other areas (Fig. 4d) over the past half-century, indicating a somewhat more uniform distribution of extreme rainfall at the watershed scale outside the Alps. We find that the stationarity or non-stationarity of extreme rainfall spatial variability is highly region-specific, reflecting geographical differences in weather regimes. It is worth noting that the Alps already have the densest network of rain gauges among the world's mountains, with each station spaced 10–20 km apart (Isotta et al., 2014). Based on our findings on rainfall spatial variability and previous studies using very dense rain gauge networks in small research watersheds (Villarini et al., 2008; Pedersen et al., 2010), we estimate that it would require 13.6–54.4 million rain gauges in the Alps alone to capture or represent the heterogeneity of extreme rainfall, compared to its current number of roughly 8500. This is neither practical nor affordable in the foreseeable future (e.g., the 21st century).



3.2 Implications for flood simulations

Quality rainfall measurements and estimates are essential for water cycle studies in Earth science and applications. To illustrate the impact of rainfall estimation errors, systematic hydrological simulations of floods produced by these extreme rainfall events are conducted using the DCHM (Sect. 2.4) at a spatial and temporal resolution of 900 m and 1 h, respectively. The hydrograph metric KGE (i.e., Kling–Gupta efficiency; Gupta et al., 2009) is used to assess agreement between observed and simulated stream discharge at gauged locations, with $KGE = 1$ indicating perfect agreement and $KGE = 0.7$ considered a quality value. Figure 5 shows KGE results for all flood events in data-rich regions, conditional on basin elevation (Fig. 5a, d, and e), rainfall magnitude percentile group (Fig. 5b), and cumulative distribution functions (Fig. 5c). Note that Fig. 5b and c are representative of results for other regions. The number of KGE outliers with large negative values is indicative of large errors in ERA5L precipitation that require corrections at higher spatial and temporal resolution (Liao and Barros, 2022, 2025). A key implication of this study is the need to improve ERA5L rainfall in mountainous regions to redress the rainfall deficit.

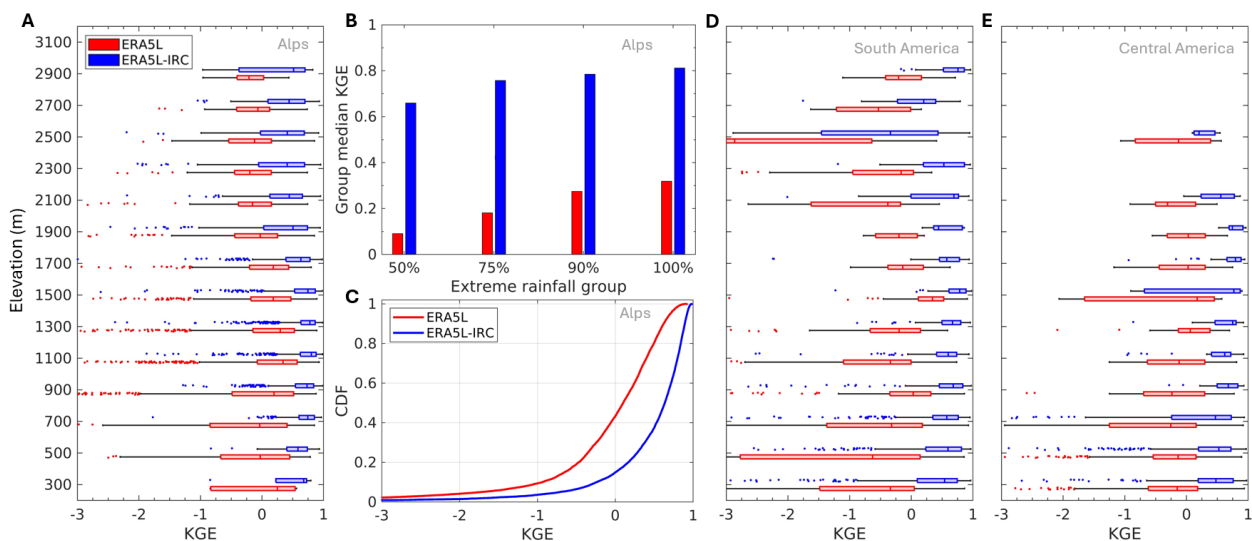


Figure 5. Flood simulations. Simulated flood KGE values conditional on elevation using the original QPE (ERA5L) and error-reduced QPE (ERA5L-IRC) for the Alps (a), South America (d), and Central America (e). (b) The median KGE of simulated floods in the Alps generated by rainfall events in each rainfall percentile category is calculated using ERA5L (0 %–50 %, 50 %–75 %, 75 %–90 %, 90 %–100 %), with the x-axis label denoted by the group upper boundary. (c) Cumulative distributions of KGE for all events in the Alps.

Precipitation errors are directly transmitted to the generation and propagation of flash floods because rainfall–runoff processes in the mountains are controlled by rainfall distribution and local topography, particularly for extreme rainfall events. Results suggest that the original ERA5L produces significantly worse results, as it underestimates orographic enhancement, as illustrated in Figs. 1 and 4. The improved QPE (i.e., ERA5L-IRC) yields a better flood response, with KGE values closer to 1, even for the most severe events selected with peak streamflow above 97.5 % of the historical flow records from 1973 to 2024. An example illustrating the IRC improvement on rainfall estimation is shown in Fig. 3, where rainfall



270 uncertainties are approximately aligned with basin topography, and the corrected rainfall patterns are modified to capture
topographic modulation of precipitation processes at small scales. These results (e.g., Figs. 1, 3, and 5) indicate that ERA5L
rainfall errors share similar characteristics across geographic locations, suggesting the transferability of orographic
precipitation errors derived using IRC in observation-rich regions such as the Alps to other mountain regions around the
world. Next, the generalizability and predictability of ERA5L rainfall errors are demonstrated in the following experiment
275 using a cross-regional validation technique.

3.3 Generalizability of extreme rainfall estimation errors

Rainfall error models are often developed using empirical statistics, with rain gauge measurements as the sole reference,
frequently at coarse resolution to average information from multiple rain gauges (Kirstetter et al., 2010; Maggioni et al.,
2014; Wright et al., 2017). Due to the lack of physical constraints for extrapolating from the point scale of rain gauges to
280 larger scales (e.g., watersheds), these rainfall error models are not generalizable. In this cross-regional validation experiment,
an AI model to predict orographic rainfall corrections using random forest regression was developed in the data-rich Alps.
The AI predictors or inputs include ERA5L rainfall characteristics and topography characteristics, which are detailed in Sect.
2.5. The targets are spatiotemporal rainfall errors derived from the IRC approach. The AI-improved rainfall is denoted as
ERA5L-AI. The KGE values for floods simulated using ERA5L-AI are compared against KGE values using the original
285 ERA5L, and 5-fold cross-validation performances are plotted in Fig. 6a. Subsequently, the trained rainfall error model
derived from the Alps is directly applied to other locations worldwide (i.e., cross-regional validation), as shown in Fig. 6b
and c. The maps show the percentage of events where ERA5L-AI produces better flood simulations than the original ERA5L
for each basin.

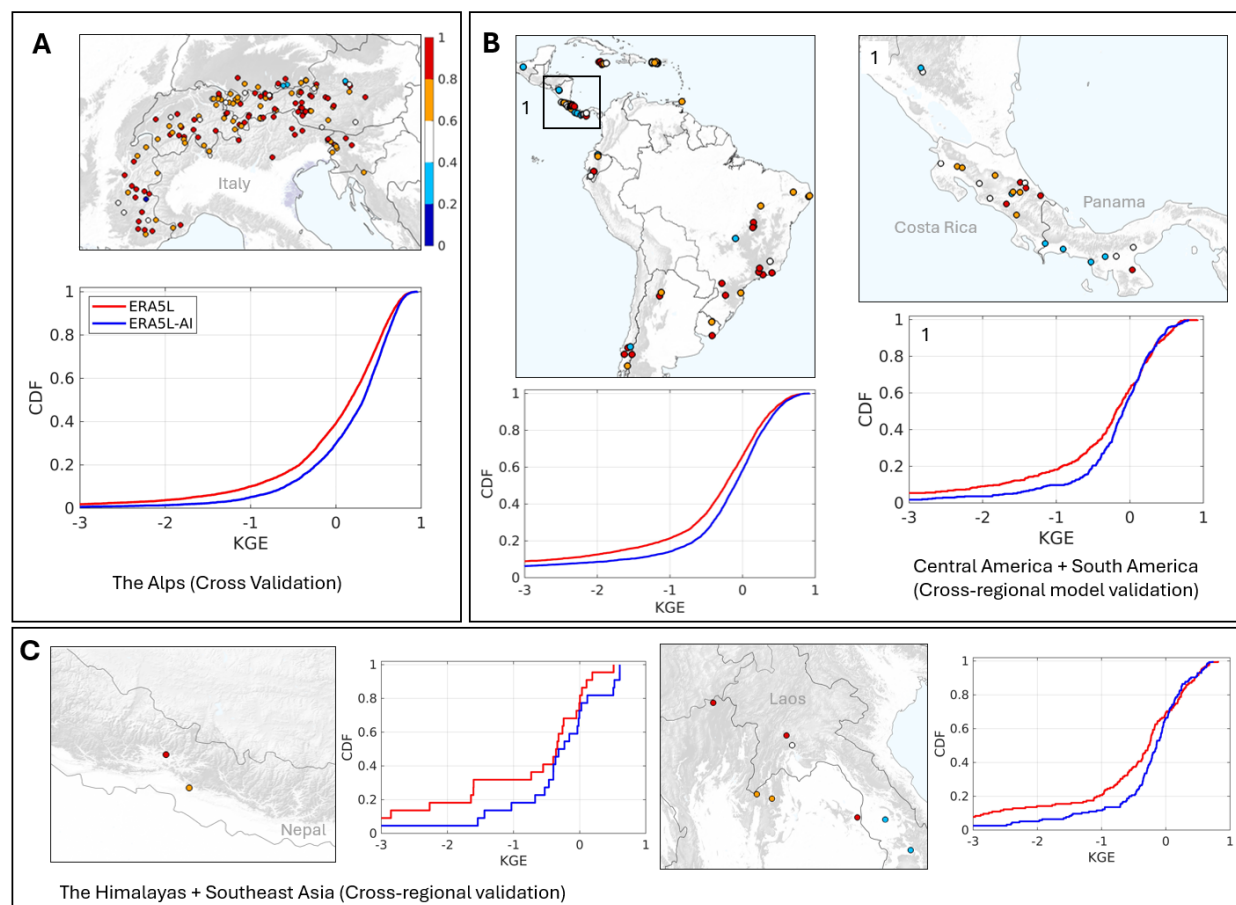


Figure 6. Cross-regional validation. (a) Top panel: fraction of flood events that show higher KGE using AI-enhanced precipitation (during validation) compared to using the original ERA5L for each basin in the Alps (red: 0.8–1; blue: 0–0.2); bottom panel: CDF of KGE for all events. (b) Cross-regional validation results for Central and South America, with an inset graph for better visualization and discussion. (c) Cross-regional validation results for the Himalayas and Southeast Asia.

Figure 6a shows that over 80 % of extreme events yield better flood simulations with AI-enhanced ERA5L, due to reduced rainfall uncertainty across the Alps. Cross-regional validation with ~4500 events strongly supports that the spatiotemporal structure of orographic rainfall errors in ERA5L can be generalized and predicted using only seven physics-based predictors related to local topography and rainfall characteristics, making it easily interpretable. There are overall improvements in regions where this AI model was not trained. The performance is robust, as shown by the warm-colored circles marking basin outlets in Fig. 6. Nevertheless, there are regional differences, such as in the case of Central America, with very different outcomes in mountain basins mostly on the Atlantic side of the Talamanca Cordillera in Costa Rica, in contrast with basins on the Pacific side at lower elevations in Panama. In addition to differences in basin shape and topography, this behavior can reflect differences in ERA5L's ability to capture regional hydrometeorology (Liao and Barros, 2023, 2025). The cross-regional validation demonstrates that 35 % of studied events show significantly improved rainfall estimation after AI corrections, measured by a higher flood KGE by at least 0.2; 58 % of studied events show similar KGE values (ranging



305 from -0.2 to 0.2) after AI corrections, and 7 % of the events show worse KGE values (with differences more negative than -0.2). The successful cross-regional validation demonstrates that the AI rainfall error prediction model is general and transferable and, along with the IRC approach, provides significant insights into ERA5L rainfall errors in complex terrain worldwide. Even better performance would be expected if large enough data sets were available to enable training the AI rainfall error model conditional on specific weather regimes (Liao and Barros, 2023). Similar results should be expected for
310 any rainfall products other than ERA5L (Liao and Barros, 2025). More importantly, this study outlines a straightforward strategy to improve precipitation estimates in mountainous regions by systematically reanalyzing ERA5L and other rainfall products.

4 Outlook

The consistent underestimation of rainfall associated with orographic enhancement of extreme rainfall has cascading effects
315 across closely related applications, such as flood simulation (Kirchner, 2006). Using flood simulation KGE thresholds of 0 (useful) and 0.7 (quality) at daily timescales as metrics of flood simulation skill, only 45 % (83 %) and 3.5 % (37 %) of extreme events studied are above the thresholds when using ERA5L compared to error-reduced ERA5L (numbers in parentheses), respectively. These statistics suggest a path to improving rainfall estimation by leveraging streamflow measurements, especially as we move towards hyper-resolution in Earth system modeling (Kelley et al., 2021), given that
320 the results are derived from a physics-based approach that can be applied to any precipitation data at any resolution. However, incorporating flood information into rainfall estimation at these small scales (i.e., sub-km for extreme events) has never been done before in atmospheric science and hydrometeorology.

5 Conclusions

This work originates from a very different perspective than most rainfall research, and we believe it provides valuable
325 insights from a fundamental physics point of view (i.e., water mass balance) into rainfall estimation, supported by analysis of more than 10 000 extreme events. We strongly recommend improving existing precipitation products (e.g., ERA5L, IMERG, CMORPH, etc.; see Figs. A2 and A3) to redress the missing precipitation challenge in the world's mountains.

Although much remains to be learned about rainfall estimation errors in general, this work focuses on extreme rainfall events that pose significant threats to hundreds of millions of people living in mountainous regions worldwide (Immerzeel et al.,
330 2010). This paper sets a milestone in advancing optimal rainfall estimation in complex terrain and establishes a foundation for achieving high-quality rainfall forecasts, which in turn underpin closely related downstream hazard modeling and engineering applications (e.g., flood simulation, flood forecasting, landslide prediction, flood inundation, reservoir design, etc.). The reason is simple: errors in model input inevitably propagate to errors in model output.

Appendix A: Additional figures

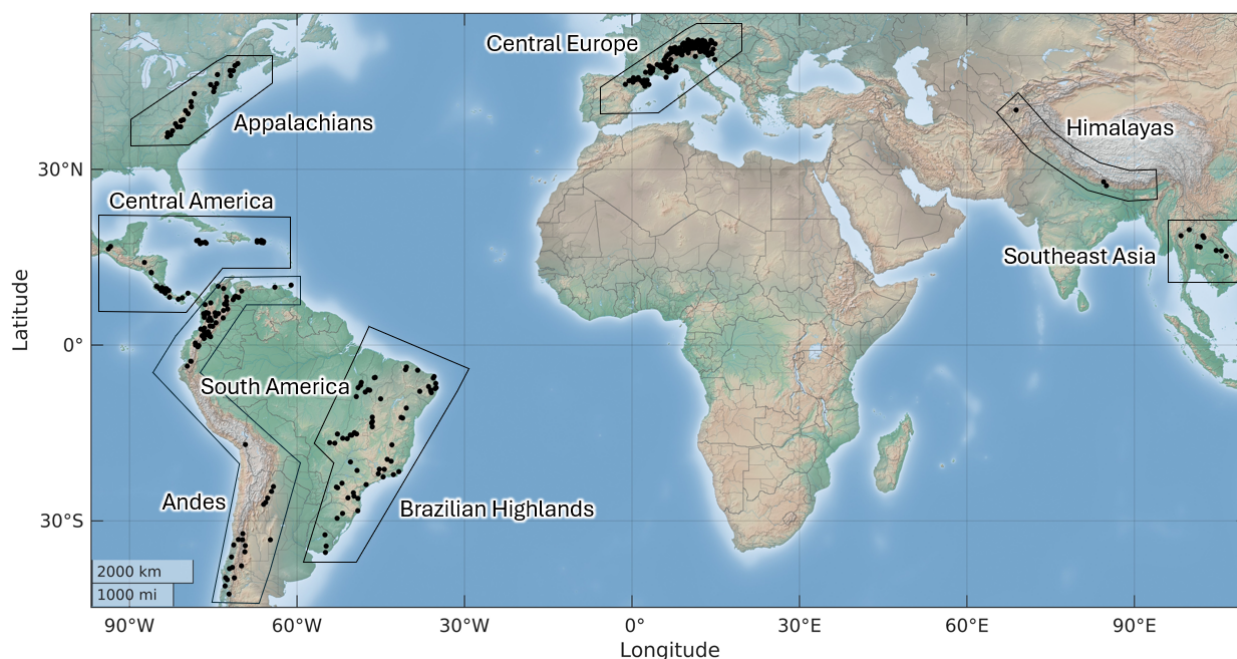


Figure A1. Locations of mountainous watersheds prone to frequent floods worldwide, with each region labeled only for discussion purposes in this work.

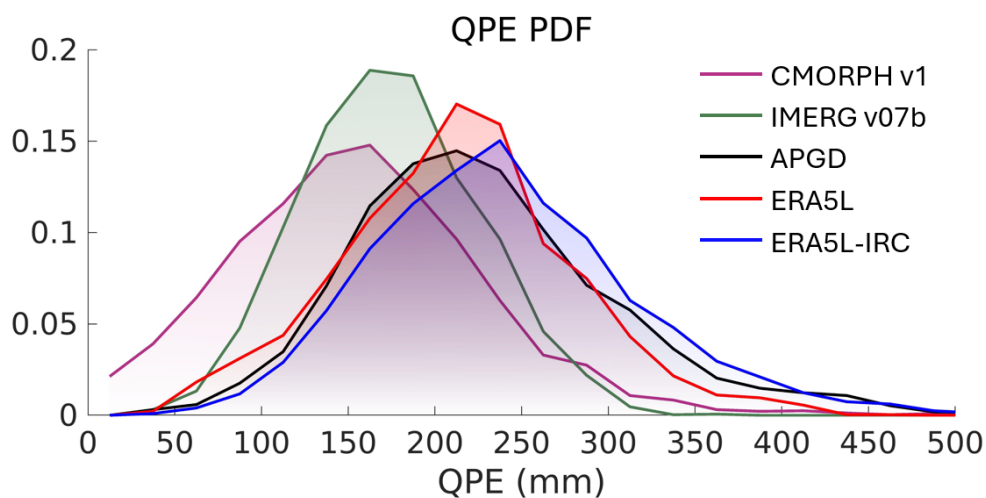


Figure A2. The distributions of event total QPE for various QPE datasets.

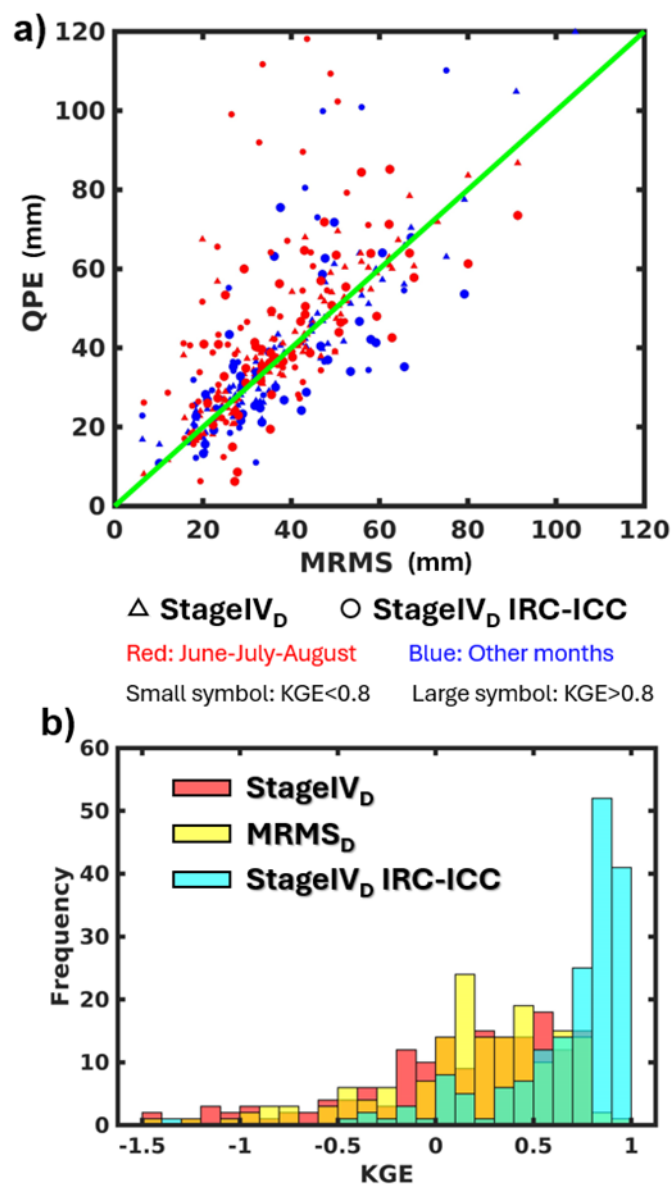


Figure A3. (a) Event total QPE plots for various QPE datasets conditional on seasons and KGE values (the Multi-Radar Multi-Sensor (MRMS) product is used as reference); (b) KGE distributions across events using different QPE datasets. This figure is adapted from Liao and Barros (2026).

Code and data availability

The ERA5-Land dataset is available for download from the Climate Data Store (CDS) of the Copernicus Climate Change Service (<https://cds.climate.copernicus.eu>). The soil data used in this work for hydrological simulations can be downloaded from the Harvard Dataverse repository



(<https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/UI5LCE>). The land use and land cover data from MODIS can be downloaded from <https://modis.gsfc.nasa.gov/data/>. The river flow records from GRDC were
350 downloaded from https://grdc.bafg.de/data/data_portal/. The 5 km rain gauge-based QPE reference dataset (APGD) can be requested and downloaded through the Swiss Federal Authorities via this link:
<https://www.meteoswiss.admin.ch/climate/the-climate-of-switzerland/spatial-climate-analyses/alpine-precipitation.html>.
Datasets used for comparison purposes include the NOAA CPC Morphing Technique (CMORPH, Version 1) Global
Precipitation Analyses, which can be downloaded from [https://noaa-cdr-precip-cmorph-](https://noaa-cdr-precip-cmorph-pds.s3.amazonaws.com/index.html#data/30min/8km/)
355 [pds.s3.amazonaws.com/index.html#data/30min/8km/](https://noaa-cdr-precip-cmorph-pds.s3.amazonaws.com/index.html#data/30min/8km/), and the NASA Integrated Multi-satellitE Retrievals for GPM (IMERG, Version 07B Final Run), which can be downloaded using the following link:
https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGHH_07/summary.
Code is available as part of the GitHub repository made available here:
https://github.com/liaomochi/orographic_enhancement_paper. This repository also includes scripts to plot the results
360 presented in this work.

Author contributions

Conceptualization: ML and APB. Methodology: ML and APB. Investigation: ML. Visualization: ML. Funding acquisition: APB. Project administration: APB. Supervision: APB. Writing – original draft: ML. Writing – review and editing: ML and APB.

365 Competing interests

The authors declare that they have no conflict of interest.

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