We thank the Reviewer for the comments. Our detailed replies are in blue below.

RC1: 'Comment on essd-2025-554', Anonymous Referee #1, 02 Oct 2025

The author developed a High-resolution Dataset of Extreme Orographic QPE by closing the water budget using stream gauge measurements. This is a novel method and will be of great value if further validated. Therefore, I recommend a major revision, as some clarification is needed, and more dataset evaluation may be beneficial.

Major comments:

1. I would recommend that the authors mention ICC as well in the abstract, as it is also one step in the precipitation data generation.

Thank you. The abstract is now revised with information regarding the ICC. (Lines 24-25)

2. I recommend that the author provide a brief code to show how to read the data. The current format and structure of the data are unclear. It will be helpful for readers to try the data.
A simple Matlab script to read the QPE data and soil moisture data is provided in the same Zenodo repository as along with the data.

3. Are the ICC and IRC corrections implemented simultaneously in windows 2 and 5? Intuitively, overestimated rainfall values can compensate for an underestimated initial soil moisture condition. I am curious whether this compensation causes some difficulties in determining precipitation.

ICC and IRC are implemented in windows 2 and 5 in sequence. It is assumed that rainfall uncertainty dominates uncertainties in windows 3 and 4 (flood high flows), while initial soil moisture is assumed to dominate hydrologic uncertainties in windows 2 and 5. To reflect the priority of ICC in these two windows (2 and 5), soil moisture correction is carried out first, and then the remaining hydrologic residuals are attributed to rainfall uncertainty as documented in Liao and Barros in detail (2025, JHRS).

4. In the inverse correction process, there are likely more unknowns (precipitation at each pixel) than the knowns (observed discharge). Is it possible to obtain two different precipitation fields that can generate very similar discharge? How can you guarantee that you can get the "optimal" precipitation fields compared to other possible realizations? Is it reasonable to obtain an ensemble precipitation dataset to account for this variability?

Thank you for the insightful comments. The inverse correction process itself is a deterministic process for a given original precipitation in this case StageIV. However, the fractal downscaling method used to bring precipitation from the original StageIV resolution (4km) to the resolution of the precipitation product in this work (250 m), is statistical in nature and it implies generating an ensemble of downscaled precipitation fields (Bindlish and Barros, 2000; Tao and Barros, 2010; Nogueira and Barros, 2015). In the current implementation of the IRC-ICC, we generate an ensemble of 50 downscaled precipitation fields, and then use the mean of the 50-member ensemble as the precipitation forcing as the original field to be corrected. Please see detailed description in Section 2.3.2. Norte that we use 50 members in our applications following previous work, but the number N of ensemble members could be larger or smaller.

Instead of applying the IRC to the ensemble mean, it is possible and trivial from a methodological perspective to repeat the IRC for each ensemble mean and then calculate the ensemble mean of the 50-member IRC corrected QPE. The reason to use the ensemble mean is the computational challenge that for each ensemble member, it is necessary to calculate the distribution of travel times and associated trajectories for Lagrangian backtracking of the error followed by the iterative IRC. That is: deriving travel distributions for each ensemble member, for each storm, and for each watershed, and then repeat the IRC for each case. Indeed, this field-by-field approach would be preferable as it can provide a quantitative assessment of uncertainty. However, the time and computational resources to implement the methodology in this manner for many watersheds and storms are prohibitive and out of the scope of this work. In Liao and Barros (WRR,2023), we demonstrated an alternative approach to estimate uncertainty and generalize the IRC using Machine Learning.

Nevertheless, because of the very small area of headwater basins, the differences among ensemble members are expected to be small (see also references above) and thus the variance among ensemble members is small as shown also in Tao and Barros (2010). As we apply the IRC-ICC to larger river basins, this question should be considered more carefully. A statement to this effect was added to the manuscript. (Lines 728-739)

5. Why did the authors select Stage IV as the primary precipitation source? In the first step, the authors downscale the precipitation field from 4km to 1km. Other available precipitation datasets, such as MRMS and AORC, provide precipitation estimates at a 1km resolution. If the authors use these 1km datasets, the downscale step can be removed.

The authors selected StageIV as the basis because StageIV is widely considered the best long-term gridded precipitation dataset for the U.S., as we have flood events in this study dated back to 2008 and thus the length of the record is critical. In addition, products like MRMS suffer from the same spatial biases and gaps in the mountains as does StageIV. The authors used MRMS (1 km resolution) as a ‘reference’ dataset for evaluation purposes, as shown in Figure 13. The AORC is a gridded reanalysis dataset a the same resolution of StageIV that merges different data sources, which makes it hard to interpret rainfall estimation errors for specific extreme events at the event scale.

6. L201-204, what does "self-similar statistics" mean? In L213, what does "the same rainfall statistics" mean here? I am curious which type of rainfall statistics is preserved in the downscaling process.

The self-similar statistics specifically refer to the power-law-like behavior of rainfall fields with scale (Nogueira and Barros, 2015, Eq. 5). This results in the linear dependence of the power spectra of rainfall fields with wavelength in Log-Log plots. This scaling behavior (i.e., described by the slope of the power spectrum, the beta value in Eq. 5) is the key rainfall statistic that is preserved in upscaling and downscaling applications.

7. What is the size of the rainfall field in Ordinary Kriging? Is it a basin-based rrection? Ordinary Kriging has the assumption of geostationary, which may not perform optimally when applied to a large complex region.

The Reviewer’s point is well taken. The Kriging approach was applied over a 1-degree x 1-degree box that contains the raingauge network in the inner region of the Southern Appalachians. This area is small, and we expect the impact of rainfall heterogeneity to be acceptable when using Kriging.

8. L505-L508, the authors mentioned that "The climatologically corrected STIV_DBKC fields have a significantly accurate diurnal cycle compared to only event-scale bias-corrected STIV_DBK." But in Figure 5, I did not see many differences between the blue and green lines. And should not the "STIV_DBK" here be "STIV_DB"?

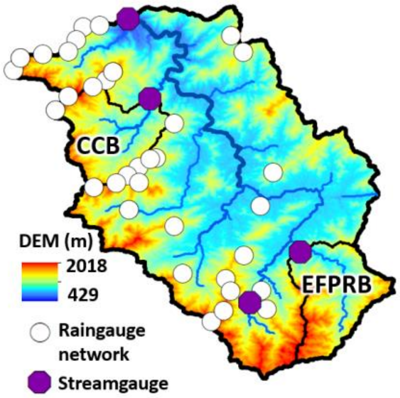
Thank you for pointing out this mistake. The legend was wrong. The blue is the rain gauge the green is STIV_DBKC, and the black is the STIV_DBK. It is now fixed. Here in Figure 5, we exclude the potential impact of Kriging, the focus is on the impact of climatology corrections, and that’s why we are comparing STIV_DBK against STIV_DBKC. This figure shows that STIV_DBK consistently underestimates rainfall (by 0.5mm-1mm/hr) for a 10-year study period, and Kriging alone could not resolve this underestimation.

9. L610, the authors mentioned that "IRC-ICC" is the recommended dataset. In Section 5, the author provides the citation for "IRC". Why don't the authors publish IRC-ICC?

Thank you. The dataset we published is IRC-ICC, and we added this information in the abstract following our Reply to Major Comment #1. In general, the improvement in hydrographs from IRC-only to IRC-ICC is relatively small compared to the improvement from original rainfall to IRC-only because rainfall uncertainties dominate over initial soil moisture uncertainties for these extreme storms leading to significant flood events (Figure 5, in Liao and Barros, JHRS 2025), This also implies smaller rainfall changes from IRC-only rainfall to IRC-ICC rainfall. In summary, ICC is only one component of the IRC framework aimed at reducing the impact of initial soil moisture uncertainty in the time to rise of the hydrograph and the hydrograph recession. Other modeling developments that have improved the results from the IRC framework since it was first published (Lao and Barros, RSE, 2022) such as the improved routing scheme and land surface parameterizations are described in (Liao and Barros, WRR 2025). Because the IRC framework implemented in this manuscript encompasses all these elements, we refer to the final product as StageIV-IRC. We added an explanation statement to the manuscript to make clear that IRC includes ICC. (Lines 612-614)

10. I recommend that the authors provide the results of STIV_IRC_ICC in Figures 5, 6, and 7. I understand that the lack of rainfall ground truth makes the evaluation of precipitation data a little bit hard. The better discharge estimates from your methods cannot reflect the absolute accuracy of precipitation data, as the discharge is your objective function. I would recommend more evaluation of the precipitation data itself. Alternatively, you can use STIV_IRC_ICC to drive another hydrologic model to evaluate whether you can also have a better discharge prediction than Stage IV. Model calibration can also be implemented, as hydrologists usually do so with a precipitation dataset.

Figures 5, 6, and 7 are climatology results, and the IRC-ICC dataset is implemented at flood-event scales. In principle, IRC-ICC can be applied to the entire record of radar rainfall estimation, but it is not computationally feasible for us. We do have some verification against other precipitation data sources using the IRC-only approach (e.g., Figure 9 in Liao and Barros, 2022, *RSE*) and the IRC-ICC approach (Liao and Barros, 2025b, *JHRS*). It is worth noting that, apart from the scarcity of rain gauges in this region, and in mountainous regions generally, in this particular study almost all rain gauges are located at the ridges (i.e., along the borders of the basins, see the zoom-in figure below for Basin05 or CCB as an example), which makes it challenging for a fair rainfall comparison for the IRC framework because IRC is based on travel time theory and rainfall at the basin borders can take days to reach the basin outlet even for flood-producing events. Therefore, a long continuous simulation would be required to derive the IRC climatology(e.g. 10 year period), which is beyond the scope of the current study and would require dedicated computational resources. Furthermore, rainfall comparison at point scales (e.g., raingauges) requires much finer spatial resolution of the IRC-ICC, as rainfall heterogeneity is significant in this region. Nevertheless, we show comparison of IRC results against rain gauges within the same pixel with very good agreement in Liao and Barros (2022).



The reason that calibration is not involved in our study is that parameter calibration often compensates for precipitation uncertainties. Lots of studies deterioration of model performance when evaluated outside the calibration period, and flood peaks are often poorly captured by calibrated models. We propose this is due to the lack of a proper reduction in precipitation uncertainty, which is important for high-flow floods.

In terms of using IRC-ICC products to drive another model, we should like to see this done by the community members who may be interested in assessing their models, or even using these datasets for calibration, which is why we are releasing the data. This dataset is specifically developed for extreme flood events in complex terrain. Different hydrological models have different strengths. Therefore, many aspects of a hydrological model can impact the performance. For example, if a hydrological model has a routing module specifically built for steep-slope terrain, the results will reflect that. We would recommend that our proposed XY routing scheme (Liao and Barros, 2025a), which is trivial to implement, be adopted by high-resolution hydrology models in steep terrain. The DCHM used in this study has developed and evolved starting the mid-90s, with a particular focus on complex terrain.

Minor comments:

1. I recommend that the authors clarify the terminology usage. In Figure 2, the event scale

bias correction is noted as STIV_BD. But in some places of the figure and the article, STIV_DBK is used.

STIV_DBK was also created (not shown in Figure 2) for the purpose of illustrating the importance of climatological adjustments by comparing STIV_DBK against STIV_DBKC. Otherwise, it is not fair to compare STIV_DB against STIV_DBKC for climatological evaluations.

2. L690. The resolution of StageIV_D is "1km, hourly" in Figure 1, but you mention " the same resolution as StageIV_D datasets (250m, 5min)".

In lines 541-542, we explained that for hydrological simulation, StageIV_D is further downscaled to 250m resolution. This is to capture the fast response in flash floods. Following this comment, we recognized that this is confusing and added clarification at Line 690.

3. Provide the legend in Figure A3, Figure 8,9, 11, 12
Thank you. Done.
4. Provide the unit in Figure 10
Thank you. Done.
5. Provide the y-axis in Figure 11

Thank you. The figures are revised according to the three comments above.

We thank the Reviewer for the comments. Our detailed replies are in blue below.

RC2: 'Comment on essd-2025-554', Anonymous Referee #2, 21 Nov 2025

Excellent work! My only concern is regarding the Inverse Correction process. What is the solution process given that there is more precipitation data than observed discharge? is there an averaging process of the rainfall in the basin ? I think this is a similar question to comment 4 by reviewer 1. Thanks !

Thank you for the positive feedback. Regarding the question on the inverse rainfall correction: there is more precipitation information than discharge information in the sense that the rainfall fields are discretized at 250m resolution and at the model time-step, whereas the streamflow is measured at the basin outlet. The first step of the IRC is to derive the runoff travel time distributions, that is the trajectories that will be followed by runoff produced at each pixel as they move through the watershed and reach the outlet. During the forward simulation of the event, the runoff is integrated in space and time until it reaches the basin outlet. In the second step, the differences between the model simulated discharge and the observed discharge are distributed by all the convergent runoff trajectories that reach the outlet at the same time proportional to the rainfall intensity in the source area and transported backward to the runoff source pixels and applied to the local rainfall. This is akin of saying that if basin discharge went through the de-convolution process, the water budget residual errors at the outlet would be revealed as precipitation uncertainties. In the current version of the inverse rainfall correction, water budget residual errors are distributed in a deterministic way, and it is based on precipitation magnitude at described above, at the location mapped by the Lagrangian backward tracking. Therefore, there is no averaging process in the approach beyond that implicit in the numerical solution and discretization of the domain, and every pixel gets different corrections based on the rainfall intensity at their location.