Revision Note 2

This report addresses the comments from the reviewer on our submission HESS-2024-228, "Very high spatial and temporal resolution rainfall data for accurate flood inundation modelling"

This is a well-structured and straightforward paper. I have no doubt that the authors' results are likely to be very useful to flood-risk and flood-disaster managers. If I understand correctly, the authors derive a new 15-year high-res spatiotemporal precip. dataset from existing rain gauge and reanalysis data in an Australian location which is prone to short timescale flooding and hence where good hydrological precipitation/flood modelling is highly desirable. The authors compare the resulting product with existing alternatives and find that it is superior when their specific metrics are used. I do not disagree in principle with the authors conclusions, nor do I find fault with the methodology used to produce the CHRain dataset or used to compare the CHRain dataset with BARRA-SY, ANUClimate, and AGCD.

My sole reservation is with this study's contribution to the current state-of-the-art. The datasets used are all well-established. The interpolation is done via an off-the-shelf software tool. The temporal downscaling is done "*using the hourly distribution pattern from the nearest hourly station*" and applying some reasonable quality control which is not an innovation.

The authors are correct in that: "The proposed method opens an opportunity to develop high resolution spatiotemporal rainfall datasets for other regions" which are essential for developing "detailed flood modelling". However, I find this paper to be more a successful, and very useful, application of an established methodology that a progression beyond the state of the art.

Thank you for your evaluation.

This paper aims to develop a methodology to generate a 1km hourly rainfall dataset for the Richmond River catchment in Australia, which can be applied to other areas. Since the catchment has a coarse distribution of hourly rain gauges, we have to disaggregate daily data at some daily stations to hourly. Unfortunately, improving the disaggregation method or the quality control process is not within the scope of this paper, but we suggest including better approaches where they are doable.

Even though the study applied the thin-plate spline method, which has been previously used for spatial interpolation of climatic variables, this paper is the first to test the ability of the ANUSPLIN program to generate 1km hourly rainfall surfaces. Moreover, the revised version of the paper has incorporated two key methodological advancements. Firstly, the paper now describes the joint optimisation of the supporting DEM resolution and elevation scaling, now assessed to be 5km and 4,000 respectively. Secondly, the paper has now implemented a robust process to automatically detect false zero data values by analysing the hourly occurrence data. False zeroes are a very common problem with rainfall observations. They are hard to detect by applying simple thresholds. The automated occurrence analysis detected and removed 42,913 false zeroes from 157,378,817 observations (around 0.26%). This led to a significant improvement in the accuracy of the analysis shown in Figure 6.

We edited sub-section **2.6 Generate hourly splines using ANUSPLIN** in the revised manuscript as:

> The hourly rainfall splines were generated using ANUSPLIN version 4.4 (Hutchinson and Xu, 2004). There are four main steps to generate daily and hourly splines, including preparing the input data (.dat) files and preparing the command (.cmt) files, running the spline program to generate interpolating parameters and flagging bad zero values, rerunning the spline program with the flag file results from the first fit using spline program, and running the lapgrd program to generate rainfall surfaces. For the hourly rainfall surfaces, we ran the ANUSPLIN program daily (24 splines per day) from 30/01/2007 to 31/12/2022.
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> The details of the setup are:
>
> 1. The independent variables include the longitudes, latitudes, and DEM values of the hourly stations. The dependent variables are the measured rainfall values at the hourly stations.
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> 2. For the spline commands, the numbers of knots were set as 90% of the total number of stations, as read from the input data files. The dependent variable transformation was set as the square root of the data surface to comply with the positive skew of the rainfall values, often including many zeroes, and to ensure that the fitted values are always non-negative Hutchinson et al. (2009).
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> 3. Since the hourly data contain a significantly higher number of zeros and some of the zeros values are artifacts (bad zeros), the flag file resulted from the first fit using the spline program was fed into a second spline fit, where the flagged bad zeros could be removed automatically. There were 42,193 bad zeroes out of 15,737,817 data values in our hourly dataset, amounting to 0.26% of the data values.
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> 4. The optimised parameters from the spline program and the 1 km smoothed DEM were input into the lapgrd program to generate the rainfall grids.

We added sub-section 2.5 in the section 2 Data and methods in the revised manuscript as:

> ***2.5 Calibrate the DEM smoothing scale and the elevation transformation parameter***
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> The 5 m resampled to 1 km averaged LiDAR Digital Elevation Model (DEM) from Geosciences Australia was used to define the boundary of the rainfall surfaces in the ANUSPLIN package (https://ecat.ga.gov.au/geonetwork/srv/eng/catalog.search#/metadata/89644). A set of 1 km resolution smoothed DEMs was prepared by calculating the focal mean with distances from 2 to 10 km to investigate the impacts of topographic scale on the rainfall surfaces. The focal mean at each 1 km pixel is calculated as the mean of a square window with a specified distance around that pixel.
>
> In the ANUSPLIN program, the independent variable transformation for the DEM is *h/a*, where *h* [m] is the elevation value and *a* is the transformation parameter. The usual recommended a value for interpolating monthly and daily data is 1000 (Hutchinson, 1995; Hutchinson et al., 2009). In this study for hourly splines, a was calibrated in the range from 1000 to 10,000. We also tested the performance of the interpolation model

using bivariate (without the elevation variable) and trivariate (with the elevation variable) analyses.

The days of hourly rainfall data were categorised into two groups to analyse the impact of topography on spatial rainfall patterns. Days with average hourly rainfall between 0 and 1 mmh-1 were considered as light rain days, and days with average hourly rainfall exceeding 1 mmh-1 were considered medium to high rainfall days. There were 3379 light rainfall days and 111 medium to high rainfall days. There were 246 days with zero rainfall across the whole data network. These days were omitted from the calibration. The focal mean distance and the elevation scaling parameter a were jointly optimised to minimise the average of the generalised cross validation of the fitted splines over all medium to high rainfall days.

The performances of the different spline models were compared using the Mean Absolute Predictive Error (MAPE) and the Mean Absolute Residual (MAR) provided by the spline interpolation model. The MAPE is calculated from the individual cross validation residuals as afforded by the “leaving out one lemma” described in Wahba (1990).

We added sub-section 3.2 in the section 3 Results in the revised manuscript as:

3.2 Impacts of topography on the spatial interpolation of hourly rainfall splines
Table 3 and Table 4 show the Square Root of the average Generalised Cross Validation (RTGCV) of the trivariate spline model for light rainfall days and medium to high rainfall days as a function of DEM focal distance and elevation scaling. The light rainfall days indicate a very broad dependence on the topographic parameters with an optimum DEM focal distance around 10 km or possibly larger. On the other hand, the medium to high rainfall days indicate a clear optimum DEM focal distance of 5 km and an optimum elevation scaling of 4000. This suggests that topography plays an important role in interpolating larger rainfalls while the response of smaller rainfalls to topography is fairly flat. The daily average 1 mmh-1 threshold appears to be an effective discriminator of light and medium to high rainfall days. Setting a lower threshold gave rise to multiple local minima in the RTGCV patterns for days with average hourly rainfall greater than 0.5 mmh^{-1}. The optimal DEM focal distance is in agreement with the analysis of Sharples et al. (2005), who showed that similarly averaged DEMs with focal distances from 5 to 10 km performed best in interpolating monthly rainfall across Australia.

Table 3. Performance of the interpolation model with different elevation transformation parameters and elevation smoothing scales for light rain days (0-1 mmh^{-1}). The minimum values of the RTGCV are shown in bold.

a	1 km	2 km	3 km	4 km	5 km	6 km	7 km	8 km	9 km	10 km
1000	0.2003	0.2005	0.1993	0.1984	0.1981	0.1980	0.1978	0.1978	0.1976	0.1978
2000	0.1983	0.1978	0.1981	0.1976	0.1976	0.1973	0.1970	0.1969	0.1969	**0.1968**
3000	0.1975	0.1978	0.1976	0.1974	0.1973	0.1973	0.1973	0.1972	0.1971	0.1967
4000	0.1975	0.1976	0.1975	0.1973	0.1972	0.1974	0.1973	0.1970	0.1971	0.1971
5000	0.1976	0.1974	0.1973	0.1972	0.1972	0.1972	0.1971	0.1970	0.1971	**0.1969**
6000	0.1975	0.1973	0.1973	0.1972	0.1972	0.1972	0.1970	0.1970	**0.1969**	**0.1969**
7000	0.1975	0.1973	0.1973	0.1972	0.1972	0.1971	0.1970	0.1970	**0.1969**	**0.1969**
8000	0.1974	0.1973	0.1972	0.1973	0.1972	0.1971	0.1970	0.1970	**0.1969**	0.1970
9000	0.1975	0.1972	0.1974	0.1972	0.1972	0.1971	0.1970	0.1970	**0.1969**	0.1970
10,000	0.1974	0.1972	0.1973	0.1972	0.1972	0.1971	0.1970	0.1970	**0.1969**	0.1970

Table 4. Performance of the interpolation model with different elevation transformation parameters and elevation smoothing scales for medium to high rain days (> 1 mmh^{-1}). The minimum value of the RTGCV is shown in bold.

a	1 km	2 km	3 km	4 km	5 km	6 km	7 km	8 km	9 km	10 km
1000	0.5536	0.5518	0.5485	0.5449	0.5427	0.5438	0.5431	0.5436	0.5423	0.5442
2000	0.5429	0.5408	0.5411	0.5385	0.5372	0.5362	0.5374	0.5374	0.5366	0.5403
3000	0.5387	0.5393	0.5377	0.5364	0.5359	0.5352	0.5370	0.5370	0.5376	0.5366
4000	0.5387	0.5372	0.5366	0.5357	**0.5348**	0.5359	0.5363	0.5361	0.5369	0.5362
5000	0.5369	0.5366	0.5362	0.5351	0.5356	0.5357	0.5362	0.5464	0.5367	0.5359
6000	0.5368	0.5356	0.5351	0.5349	0.5359	0.5364	0.5363	0.5465	0.5363	0.5361
7000	0.5358	0.5355	0.5351	0.5350	0.5359	0.5364	0.5363	0.5366	0.5362	0.5360
8000	0.5356	0.5354	0.5352	0.5354	0.5362	0.5363	0.5363	0.5366	0.5363	0.5360
9000	0.5354	0.5354	0.5356	0.5364	0.5367	0.5464	0.5363	0.5365	0.5358	0.5359
10,000	0.5354	0.5353	0.5361	0.5364	0.5365	0.5461	0.5366	0.5366	0.5359	0.5359

The analysis on the impact of including the DEM as an independent variable also supports the previous conclusion. Table 5 shows that the optimal trivariate analysis reduced the MAPE by about 2%, during both light, medium, and heavy hourly rainfalls. When the elevation was included in the interpolation, the MAR decreased by 15% and 18% during the light and medium to heavy rainfalls, respectively. The transformation parameter of 4000 and the optimal DEM focal distance of 5 km were used in the ANUSPLIN program to generate the CHRain surfaces for further analysis.

Table 5. Comparison between bivariate and optimal trivariate analyses on light (0-1 mmh-1) and medium to high rainfalls (>1 mmh-1).

	Bivariate		Trivariate	
	MAPE	MAR	MAPE	MAR
0-1 mmh^{-1}	0.2008	0.0548	0.1972	0.047
> 1 mmh^{-1}	0.5441	0.5394	0.5348	0.4432

We also added in lines 393-404 in the Discussion in the revised manuscript as:

"Compared to daily or monthly data, the hourly data contains significantly more zero values, which can increase the instability of the interpolation model. This paper is the first to test the ability of the ANUSPLIN program to generate hourly rainfall surfaces. It has also incorporated a robust automated process to remove false zeroes from the data. False zeroes are a very common problem with rainfall observations. They are hard to detect by applying simple thresholds. The method proposed in this study has been successfully applied to generate a 1 km hourly gridded rainfall dataset for a larger area. Hourly rainfall data are essential for many hydrological, ecological, and meteorological applications (Lewis et al., 2018; Hatono et al., 2022).

Including elevation data enhances the performance of the thin-spline interpolation model in generating hourly rainfall surfaces, more significantly during larger rainfalls. While the response of the splines to the topography during light rain days is quite broad, the elevation data has greater impacts during larger rain days and results in the clear optimal values for the DEM transformation parameter and the smoothing distance. There are higher resolution DEMs than the 1 km used in the analysis in this paper.

However, the result suggests including finer topographic data does not result in better rainfall surfaces at higher spatial resolution. For our study area, the optimal values for the elevation transformation parameter and the DEM focal distance are 4000 and 5 km, respectively."

Minor comments and typos:

Line 31) "Observation" should be "observations"

33) "... more than 20 years" should be "... more than 20 years long"

65) "showed to improve" should be "appeared to improve"

84) "An accurate high resolution spatial and temporal resolution rainfall" should be "An accurate high spatial and temporal resolution rainfall"

104) spurious comma after "especially".

132) in "an" area...

176) "Disaggregate daily rainfall data to hourly" should be "Disaggregation of daily rainfall to hourly" or something similar...

189) "After cleaning, disaggregating, and detailed quality control of the data" should be "After cleaning, disaggregating, and completing a detailed quality control of the data" I think...

Figure 7) The first and last row could be removed without loss of clarity...

We adapted all the minor comments in the revised manuscript.