Revision Note 1

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”

The manuscript presents an hourly rainfall product at 1 km resolution, derived by disaggregating daily station data (where needed) to an hourly scale and interpolating using a thin-spline method. The authors compare their dataset to existing rainfall products and demonstrate improvements. The manuscript is generally well-written and structured. However, I find the novelty of the study lacking. The thin-plate spline method has been previously used for spatial interpolation of climatic variables (by Hutchinson, one of the authors), and the authors do not propose any methodological advancements (unless I overlooked them) from what has been published in the past. Similarly, the disaggregation approach appears overly simplistic compared to more sophisticated state-of-the-art methods. Given the limited methodological innovation, I question the suitability of this paper for HESS. A more appropriate venue might be a journal focusing on dataset development.

Thank you for your evaluation.

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 5 km 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 in the old and revised manuscript.

We addressed the comments from the reviewer in detail below.

1. **I suggest revising the title. A 1 km resolution is not necessarily "very high," and the precipitation dataset (why focus only on rainfall?) has applications beyond flood inundation modeling.**

We changed the title of the paper to: “Elevation dependent spatial interpolation of hourly rainfall for accurate flood inundation modelling”, reflecting the enhanced focus on the detailed analysis of the topographic dependence.

2. **Lines 9-10: The CHRain dataset is compared to other gridded datasets available in Australia, but does it outperform them? This should be clarified.**

We edited lines 9-10 in the revised manuscript as: “The spatial and temporal analyses indicate that the CHRain dataset outperforms other gridded datasets currently available in Australia in representing the sub-grid distribution as well as the daily and hourly variation of rainfall across the study area”

3. **Line 10: A correlation of 0.948 is quite high, but was it calculated using all the data involved in interpolation and merging? A "leave-one-out" validation approach would provide a more reliable assessment.**

In our study area, the hourly data gauges are sparse, so we have to disaggregate some daily data into hourly. The average rain gauge density in the catchment is 143 gauges/30,389 km2 or 1 gauge/212 km2. Therefore, we want to use all the available hourly data to improve the coverage of the rainfall splines. Instead, we evaluated the sum of 24-hour rainfall with daily measurements at 169 gauges that were not used in the interpolation. The revised paper now reports “leave-one-out” validation statistics to supplement these comparisons.

4. **Line 20: The same citation is used for two different statements on lines 19 and 20. Please verify.**

We removed the citation in line 20 in the revised manuscript.

5. **Lines 21-23: This section discusses temporal variability, but what about spatial variability? Given its impact on flood modeling, I recommend considering the following references: https://doi.org/10.5194/hess-17-2195-2013 and https://doi.org/10.5194/hess-21-1559-2017**

There were not many studies that investigated the impacts of the spatial resolution of rainfall data on hydrological applications, more specifically on the performance of hydrodynamic models. Thank you for your reference suggestion. We added these in the revised manuscript in line 27 as:

“Peleg et al. (2013) analysed the subpixel rain distribution by comparing the data from radar with point measurements at high density gauges. The results shows that a density of 3 rain gauges per radar pixel (4 km^2) will allow an adequate presentation of radar rainfall.”

“Peleg et al (2017) indicated a valuable contribution of spatial distribution of rainfall (26% contribution) on the total variability of modelled urban drainage network.”

6. **Lines 26-27: This sentence seems disconnected from the surrounding discussion.**

We removed lines 26-27 in the revised manuscript.

7. **Lines 29-30: The phrase "1 km to 12 km" is unclear. Since stations provide point-scale data and radar typically operates at 1 km resolution (but may not cover all of Australia), this should be clarified.**

Details of the gridded datasets available in Australia and used in the analysis were mentioned in Table 1 in the old and revised manuscripts. To avoid confusion, we removed the text “1 km to 12 km” in the Introduction of the revised manuscript.

8. **Lines 72-75: GCMs are not designed to simulate observed rainfall. The current wording is misleading, and I suggest removing references to GCMs in this context.**

We removed line 72-75 in the revised manuscript.

9. **Line 99: "Changes significantly" should be quantified. What is the elevation difference?**

We added the text in the revised manuscript: "The elevation ranges between -6.065 m and 934.6 m across the catchment."

10. **Sections 2.1 and 2.5. Do you simply apply the thin-plate spline as suggested by Hutchinson? If so, what is the novelty of your approach?**

As described above, the revised version of the paper has incorporated two key methodological advancements. It now describes the joint optimisation of the supporting DEM resolution and elevation scaling, now assessed to be 5 km and 4,000 respectively. It has also implemented a new robust process to automatically detect false zero data values by analysing the hourly occurrence data.

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:
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> 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

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).
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> 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."

11. **Section 2.4: If the closest station is 10 km away (just giving an example), the correlation may be too low for reliable disaggregation... A sensitivity analysis using stations at varying distances could provide insights into the method's limitations.**

We agree that the density of hourly gauges is coarse in some areas in our catchment. We have no better option than to use the rainfall pattern from the nearest hourly station to a daily station to disaggregate the daily data at that station. To reduce the uncertainty of choosing the disaggregation, we also used the observed movement of rainfall from the radar data to select suitable nearby hourly gauges to disaggregate data from daily to hourly (mentioned in Section 2.4 in the old and revised manuscripts). Since we don't have many stations to choose from in the areas and the 2nd nearest hourly station can be much further away from the nearest one, it will not be beneficial to do a sensitivity analysis using stations at varying distances to improve the disaggregated data.

12. **Line 203: Why is alpha not treated as a calibration parameter?**

The revised paper now optimises the alpha parameter, as well as the elevation scaling. This is described in point 10.

13. **Lines 231-232: The manuscript reports too many goodness-of-fit measures. Why include both NSE and KGE, for instance? I suggest focusing on two distinct indices that provide complementary information.**

The NSE metric is popularly used in other studies to compare modelled and observed rainfall data (i.e., Hatono et al., 2022). We removed the KGE metric in the revised manuscript to reduce the complication.

Reference

Hatono, M., Kiguchi, M., Yoshimura, K., Kanae, S., Kuraji, K., and Oki, T.: A 0.01-degree gridded precipitation dataset for Japan, 1926-2020, Scientific Data, 9, https://doi.org/10.1038/s41597-022-01548-3, 2022.

Lewis, E., Quinn, N., Blenkinsop, S., Fowler, H. J., Freer, J., Tanguy, M., Hitt, O., Coxon, G., Bates, P., and Woods, R.: A rule based quality control method for hourly rainfall data and a 1 km resolution gridded hourly rainfall dataset for Great Britain: CEH-GEAR1hr, Journal of Hydrology, 564, 930–943, https://doi.org/https://doi.org/10.1016/j.jhydrol.2018.07.034, 2018.

Sharples, J. J., Hutchinson, M. F., and Jellett, D. R.: On the Horizontal Scale of Elevation Dependence of Australian Monthly Precipitation, Journal of Applied Meteorology, 44, 1850 – 1865, https://doi.org/10.1175/JAM2289.1, 2005.