Revision Note 1

This report addresses the comments from the reviewer 1 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 old manuscript (lines 14-16 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 km^2 or 1 gauge/212 km^2. 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 in the ANUSPLIN program 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 lines 28-33 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 x 4 km) 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 lines 101-102 as: “The elevation ranges between 0 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 around 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 2.3 Quality control for the hourly rainfall data** in the revised manuscript lines 174-188 as:

> Close inspection of initial analyses of the hourly rainfall data indicated that there were significant numbers of false zeroes in the data leading to underestimation of rainfall during periods of high rainfall. This is a common problem with rainfall data, particularly when they are recorded automatically. These values are hard to detect by applying simple thresholds. As noted by Hutchinson et al. (2009), rainfall occurrence is more spatially coherent than rainfall amounts. An initial trivariate spline analysis of the hourly occurrence data was therefore conducted to detect and automatically remove false zeroes.
>
> Positive rainfalls were set to an occurrence value of 1 and zero rainfalls were set to an occurrence value of 0. The spline analysis used the same underpinning DEM resolution and elevation scaling as optimised for the rainfall amount analysis. Zero hourly rainfall values were deemed to be false, and removed from the data set, when the interpolated occurrence value exceeded 0.5. The limited spatial coverage of the data set led to instabilities when the data values were almost all positive or almost all zero. This was overcome by setting a constant error standard deviation of 0.25, consistent with the automatically derived error standard deviations when there were significant numbers of zeroes and ones. This ensured that sufficient smoothing was applied to the data to interpolate spatially stable occurrence patterns with a robust dependence on the data values. A total of 42,193 false zeroes were removed from a total number of 15,737,817 data values, amounting to 0.26% of the data. Close inspection of the analyses indicated that the false zero detections were reliable. The results for the occurrence analysis for a high rainfall day are described in Appendix B.

We added **Sub-section 2.5** in the revised manuscript lines 205-225 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 using ArcGIS program. 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). This corresponds to a 100-fold exaggeration of the impact of elevation on precipitation patterns compared to the impact of horizontal position. In this study for hourly splines, a was calibrated in the range from 1000 to 10,000, corresponding to vertical exaggerations ranging from 100-fold to 10-fold. 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 **Section 3 Results** in the revised manuscript lines 294-310 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, as derived in the initial analyses with no removal of false zeroes. 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 an optimum DEM focal distance of around 5 km and an optimum elevation scaling of around 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}. These tables were recalculated after false zeroes were removed by the spline occurrence analysis described above, with DEM focal distance set to 5 km and elevation scaling set to 4000. The resulting patterns were similar to those shown in Table 3 and Table 4, with an optimum

DEM focal distance of around 5 km and a slightly larger elevation scaling of around 5000. There was little difference between the performance with these two elevation scales. All the remaining analyses were completed on the data with false zeroes removed, using the initially determined 5 km DEM focal distance and elevation scaling of 4000.

The impact of including the DEM as an independent variable was further quantified in Table 5. It shows that, compared to the bivariate analysis, the optimal trivariate analysis reduced the MAPE by about 4% for light rainfall days and by about 2% for medium to heavy rainfall days. The trivariate analysis reduced the MAR by about 16% across all days.

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

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}	0.0884	0.0505	0.0851	0.0420
> 1 mmh^{-1}	0.9007	0.4378	0.8816	0.3681

We also added in lines 413-434 in the **Discussion** in the revised manuscript as:

> Compared to daily or monthly data, the hourly data contains significantly more zeros, 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 zeros from the data. False zeros 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 transformation parameter *a* and the DEM focal distance are around 4000 to 5000 and 5 km, respectively. The optimal DEM focal distance of 5 km 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. On the other hand, the optimal elevation scaling of around 4000 to 5000 corresponds to a vertical exaggeration of around 20. This is somewhat less than the vertical exaggeration of around 100 found with spatial analyses of rainfall at broader time scales by Hutchinson (1995) and Johnson et al. (2016). This suggests that hourly rainfall, though significantly influenced by elevation, has a less consistent dependence on elevation than rainfall values recorded at broader time scales.
>
> The initial hourly rainfall occurrence analysis appears to have been effective in detecting and removing the many false zeroes that can arise with automatically recorded hourly rainfall data. This was aided by the limited spatial extent of this rainfall analysis. The detections would likely to be less reliable when applied to sites with no relatively near neighbours.

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.

Revision Note 2

This report addresses the comments from the reviewer 2 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 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.

We edited **Sub-section 2.3 Quality control for the hourly rainfall data** in the revised manuscript lines 174-188 as:

Close inspection of initial analyses of the hourly rainfall data indicated that there were significant numbers of false zeroes in the data leading to underestimation of rainfall during periods of high rainfall. This is a common problem with rainfall data, particularly when they are recorded automatically. These values are hard to detect by applying simple thresholds. As noted by Hutchinson et al. (2009), rainfall occurrence is more spatially coherent than rainfall amounts. An initial trivariate spline analysis of the hourly occurrence data was therefore conducted to detect and automatically remove false zeroes.

Positive rainfalls were set to an occurrence value of 1 and zero rainfalls were set to an occurrence value of 0. The spline analysis used the same underpinning DEM resolution and elevation scaling as optimised for the rainfall amount analysis. Zero hourly rainfall values were deemed to be false, and removed from the data set, when the interpolated occurrence value exceeded 0.5. The limited spatial coverage of the data set led to instabilities when the data values were almost all positive or almost all zero. This was overcome by setting a constant error standard deviation of 0.25, consistent with the automatically derived error standard deviations when there were significant numbers of zeroes and ones. This ensured that sufficient smoothing was applied to the data to interpolate spatially stable occurrence patterns with a robust dependence on the data values. A total of 42,193 false zeroes were removed from a total number of 15,737,817 data values, amounting to 0.26% of the data. Close inspection of the analyses indicated that the false zero detections were reliable. The results for the occurrence analysis for a high rainfall day are described in Appendix B.

We added **Sub-section 2.5** in the revised manuscript lines 205-225 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 using ArcGIS program. 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). This corresponds to a 100-fold exaggeration of the impact of elevation on precipitation patterns compared to the impact of horizontal position. In this study for hourly splines, a was calibrated in the range from 1000 to 10,000, corresponding to vertical exaggerations ranging from 100-fold to 10-fold. 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 **Section 3 Results** in the revised manuscript lines 294-310 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, as derived in the initial analyses with no removal of false zeroes. 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 an optimum DEM focal distance of around 5 km and an optimum elevation scaling of around 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}. These tables were recalculated after false zeroes were removed by the spline occurrence analysis described above, with DEM focal distance set to 5 km and elevation scaling set to 4000. The resulting patterns were similar to those shown in Table 3 and Table 4, with an optimum DEM focal distance of around 5 km and a slightly larger elevation scaling of around 5000. There was little difference between the performance with these two elevation scales. All the remaining analyses were completed on the data with false zeroes removed, using the initially determined 5 km DEM focal distance and elevation scaling of 4000.

The impact of including the DEM as an independent variable was further quantified in Table 5. It shows that, compared to the bivariate analysis, the optimal trivariate analysis reduced the MAPE by about 4% for light rainfall days and by about 2% for medium to heavy rainfall days. The trivariate analysis reduced the MAR by about 16% across all days.

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

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}	0.0884	0.0505	0.0851	0.0420
> 1 mmh^{-1}	0.9007	0.4378	0.8816	0.3681

We also added in lines 413-434 in the **Discussion** in the revised manuscript as:

> Compared to daily or monthly data, the hourly data contains significantly more zeros, 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 zeros from the data. False zeros 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 transformation parameter *a* and the DEM focal distance are around 4000 to 5000 and 5 km, respectively. The optimal DEM focal distance of 5 km 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. On the other hand, the optimal elevation scaling of around 4000 to 5000 corresponds to a vertical exaggeration of around 20. This is somewhat less than the vertical exaggeration of around 100 found with spatial analyses of rainfall at broader time scales by Hutchinson (1995) and Johnson et al. (2016). This suggests that hourly rainfall, though significantly influenced by elevation, has a less consistent dependence on elevation than rainfall values recorded at broader time scales.

The initial hourly rainfall occurrence analysis appears to have been effective in detecting and removing the many false zeroes that can arise with automatically recorded hourly rainfall data. This was aided by the limited spatial extent of this rainfall analysis. The detections would likely to be less reliable when applied to sites with no relatively near neighbours.

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.

Reference

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