Dear Editor,

We appreciate the effort of Sivarajah Mylevaganam to read and review our submission HESS-2024-228, “Very high spatial and temporal resolution rainfall data for accurate flood inundation modelling”.

However, while some comments from Sivarajah Mylevaganam are helpful, others are out of the scope of our study or show a lack of knowledge in the field. For example, improving the resolution of Landsat images is not related to generating higher-resolution rainfall surfaces.

We decided to provide brief explanations for these comments to avoid confusion for SM and other future readers.

Regarding comments 1, 2, and 3 on the academic writing and presentation style:

We are research scientists from the Commonwealth Scientific and Industrial Research Organisation (Australia’s national science agency) and The Australian National University with solid knowledge of hydrology. We have published many journal papers in Q1 journals, so we are confident in our academic writing style to provide a clear and good-quality manuscript without flaws. All the maps, figures, and tables in the manuscript are created by the authors. We confirmed that Figure 1 was created using ArcMap, with the shapefile showing locations of hourly and daily gauge stations and the catchment domain, and the base map showing the topography of the study area.

Regarding comments 5 and 6 on the quality of the hourly and daily datasets:

The hourly and daily rainfall datasets were provided by the Bureau of Meteorology. Because of the artifact of measuring devices, the data can contain unreasonably high or low (including negative) values. Therefore, quality control was applied to the datasets before using them in the interpolation model. The hourly and daily thresholds of rainfall values were set after considering the weather conditions of the catchment, observing plots of hourly time series, and comparing data from hourly gauges with other nearby gauges. These thresholds can vary for different areas and different catchments so they should not be referred anywhere else. Moreover, the revised version of 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.

Regarding comments 9 and 10 on the scope of the study:

The scope of our study is not to focus on disaggregating the daily grid (e.g., ANUClimate) to an hourly grid nor applying AI/ML to improve the interpolation of gridded rainfall surfaces. To clarify this further, we cited other work on the disaggregation of gridded datasets in the introduction of the manuscript:

> *Acharya, S. C., Nathan, R., Wang, Q. J., and Su, C.-H.: Temporal disaggregation of daily rainfall measurements using regional reanalysis for hydrological applications, Journal of Hydrology, 610, 127 867, https://doi.org/https://doi.org/10.1016/j.jhydrol.2022.127867, 2022.*

Westra, S., Mehrotra, R., Sharma, A., and Srikanthan, R.: Continuous rainfall simulation: 1. A regionalized subdaily disaggregation approach, Water Resources Research, 48, https://doi.org/https://doi.org/10.1029/2011WR010489, 2012.

Breinl, K. and Di Baldassarre, G.: Space-time disaggregation of precipitation and temperature across different climates and spatial scales, Journal of Hydrology: Regional Studies, 21, 126–146, https://doi.org/https://doi.org/10.1016/j.ejrh.2018.12.002, 2019.

Moreover, the radar data in the study area have some artifacts as shown in the comparison with other gridded datasets, it is not feasible to develop an AI/ML algorithm to relate the radar data and the existing hourly and daily gauged data to predict the correct values of hourly radar values.

Regarding other comments including comment 12:

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.

Accordingly, we have revised the title in the revised manuscript to: "**Elevation dependent spatial interpolation of hourly rainfall for accurate flood inundation modelling**".

This reflects the enhanced focus on the detailed analysis of topographic dependence conducted by the revised paper. We have also included a detailed analysis of the impacts of elevation transformation on the performance of the interpolation model in the revised manuscript, including calibration of the supporting DEM resolution and calibration of the elevation transformation parameter *a*.

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).

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.”