Hourly rainfall from daily records – a method of fragments now and into the future

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ABSTRACT

Continuous simulation run-off models are widely used to simulate and predict the future behaviour of operational mine site water management systems, final void lakes and landform evolution.

Most models are constrained to operate on a daily timestep by the limited availability of suitably representative long-term short-duration rainfall data sets. However, some hydrological and geomorphic processes are governed by long-term sub-daily rainfall variability.

Our paper presents an approach to generate hourly data sets from long daily records, based on sub-daily rainfall patterns extracted from surrounding 'donor' rain gauges to enhance the rainfall record and overcome data limitations using the regionalised method of fragments (Westra *et al,* 2012).

The approach uses 'IFD conditioning' to ensure consistency with the expected intensity-frequency-duration (IFD) characteristics for the site and incorporates the latest guidance from Australian Rainfall and Runoff (ARR) v4.2 and downscaled Coupled Model Intercomparison Project Phase 6 (CMIP6) climate model predictions to account for the expected impact of climate change on rainfall intensity and seasonality.

The paper provides an example of processing a daily rainfall data set and combining it with sub-daily records from surrounding areas to generate 136 years of hourly rainfall data that matches the Bureau of Meteorology IFD curves. The example includes adjustment to align with current and future CMIP6 climate horizons.

The resultant data sets can be more confidently used to make reliable predictions about future water management and mine closure challenges, to inform decisions about water storage design, pump capacity, and flood mitigation measures even where site data is scarce.

INTRODUCTION

Overview

Daily timestep continuous simulation (CSM) numerical models (Boughton, 2003) are widely used to simulate the behaviour of water management systems and landforms through the mine life cycle (Temme, *et al*, 2011; Hancock *et al,* 2017).

However, some applications require sub-daily inputs to appropriately represent physical processes. For example, releases or overflows from water storage systems may be too short-lived to be adequately represented by daily run-off models. Similarly, Landform Evolution Models (LEMs) are increasingly used to assess the stability and evolution of landscapes over geological timescales (Hancock, *et al* 2025). Some models – such as CAESAR-Lisflood – can use sub-daily rainfalls to better represent the intensity and frequency of events, which are the key determinants of gully erosion extent, sediment transport and final landform. Studies by Hancock, Verdon-Kidd and Lowry (2017), Coulthard and Skinner (2016), and Skinner *et al* (2020) have demonstrated that, when using historical and stochastically generated rainfall sequences, sub-daily rainfall variability greatly affects landscape evolution.

While representative historical daily climate records of over 100 years duration can be drawn throughout Australia from nearby weather stations or gridded products (the Australian Bureau of Meteorology (BoM) or Queensland Government (SILO, Jeffrey *et al,* 2001) service), sub-daily rainfall records are rarely of sufficient quality or duration to capture the full climate variability, particularly in Northern Australia (McQuade, Arthur and Butterworth, 1996; Coulthard and Skinner, 2016).

The paper's objective is to present a methodology for deriving hourly rainfall data corresponding to daily rainfall data sets that are aligned with the expected Intensity Frequency Duration (IFD) characteristics of local rainfalls and can be adapted to incorporate projected rainfall changes under future climate scenarios.

DEFINING THE PROBLEM

Importance of representative rainfall data

Various studies have established that sub-daily rainfall data can lead to significantly different predictions in sediment yields and erosion patterns compared to daily, lumped, or time-averaged data.

Hancock, Verdon-Kidd and Lowry (2017) tested the sensitivity of modelled erosion rates to small changes in rainfall input at a study site located in the Northern Territory (NT) of Australia, At that site, only three complete (>85 per cent) long-term records of daily data were available from nearby recording stations, and only two sub-daily records were available within the entire NT with 40 years of 6 min pluviograph. In the absence of long-term data sets, A novel approach of employing stochastically generated daily rainfall data (derived using the DRIP model based on Darwin Airport records) was used to provides inputs to the CAESAR-Lisflood LEM to simulate 100 years of landform evolution on a proposed rehabilitated mine landform at Corridor Creek.

This research found that each stochastically generated rainfall scenario produced a unique pattern of erosion and sediment output, highlighting the sensitivity of landform evolution to small changes in rainfall sequences and the non-linear nature of these processes.

Limitations of available data sets

The method demonstrated its value as a risk-based approach, but underline the importance of using representative data sets reflecting local rainfall variability in predicting future sediment transport, erosion form and evolution.

This information is of particular importance for the design and testing of rehabilitated landscape systems such as post-mining landscapes.

Unfortunately, sufficiently well-conditioned rainfall pluviograph data sets are often either too short, not representative of the location, or are at a temporal resolution that is too coarse for use in these models.

Hancock, Verdon-Kidd and Lowry (2017) demonstrated that synthetic stochastic sub-daily rainfall can reproduce the very rare storm events that drive landform evolution and erosive processes. There is a need to ensure that data sets used in the modelling make the best use of the available information on rainfall, including capturing the IFD characteristics of the local area, both under current and future climate conditions, as discrepancies may have significant impacts on the modelled basin profile and shape from long-timescale simulations.

Impacts of climate change on rainfall

In March 2024, Engineers Australia (EA) in partnership with the Australian Government's Department of Climate Change, Energy, the Environment and Water (DCCEEW) released an update to the Australian Rainfall and Runoff (ARR) Guideline known as version 4.2 (Ball *et al,* 2019) which included a revision to the chapter relating to Considerations of Climate Change. The update focuses on the impact of climate change on design rainfalls of interest in flood modelling – and provides an approach to generating future rainfall IFDs based on projected global temperature increases. The update excludes guidance for incorporating climate change impacts into continuous simulation studies. The guidance recommends adjusting near-term rainfalls for temperature increases that have occurred in the period since the historical rainfall was collected.

In the method described in the present paper, the generated rainfall sequence can be conditioned to match a target's current or future climate IFD.

Further, the results of downscaled global climate modelling undertaken for the CMIP6, can be used to adjust the data set to be consistent with long-term seasonal rainfall projections for selected climate scenarios (Shared Socio-economic Pathways (SSPs) and time horizons).

METHODOLOGY

The following methodology outlines the authors' approach to generating hourly data sets from long daily records. The approach is based on sub-daily rainfall patterns extracted from surrounding 'donor' rain gauges to enhance the rainfall record and overcome data limitations. In this way, the authors' approach provides the necessary hydrologic input to enable the modelling of long-term processes that are governed by rainfall variability.

Conceptual overview

Figure 1 illustrates the methodology for generating climate-adjusted sub-daily rainfall data. This process is divided into two main steps:

1. *Disaggregation of daily rainfall totals using the regionalised method of fragments*: This step takes a daily rainfall record at the point of interest (POI) (as a long-term sub-daily record is often unavailable) along with sub-daily records at nearby gauges, and stochastically generates a sub-daily rainfall record matching the observed daily totals (Boughton, 1999; Westra *et al,* 2012; Dykman *et al*, 2024).
2. *Adjusting results to match predicted changes to seasonal rainfall totals and intensity in future climate scenarios:* In this step, the rainfall record is adjusted to match changes to seasonal totals predicted by downscaled global climate models and changes to intensity described in ARR 2019 (Ball *et al,* 2019) for a given climate scenario.

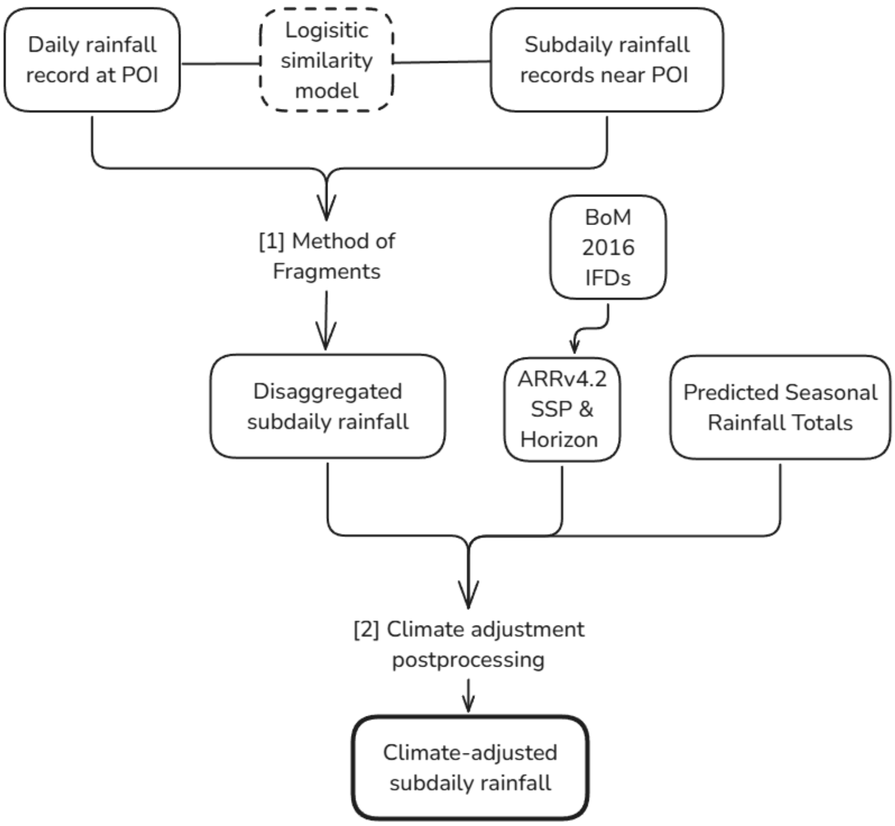

FIG 1 – Process to generate climate-adjusted, disaggregated sub-daily data from a daily rainfall record.

It is worth noting that the climate-adjusting techniques in step 2 are applicable to any sub-daily rainfall record – they do not necessarily require data produced by the method of fragments. The regionalised method of fragments was chosen because it does not require a long-term sub-daily rainfall record at the POI, but another method may be substituted. These steps and their respective inputs and outputs are discussed in further details.

Example application – generating future climate (2090) rainfall at Millmerran, Qld

This section provides a more detailed explanation of the proposed method by applying it to a real-world example: generating a climate-adjusted sub-daily rainfall series for the year 2090 (SSP3) at a point of interest in Millmerran, Queensland.

Step 1 – Disaggregating the daily rainfall record using the method of fragments

As is often the case, Millmerran does not have a long-term sub-daily rainfall record to work with directly. Therefore, the authors employed the regionalised method of fragments) to generate a sub-daily record matching known daily rainfall totals, using data from nearby sub-daily gauges. This process is often referred to as disaggregation.

Inputs

As input for this step, the authors used:

- 116 years of patched point daily rainfall totals (1889–2025) for the Millmerran Post Office BoM rainfall station (station number 41069) from the SILO rainfall database. The Millmerran Post Office station (27.874S, 151.271E) commenced operation in January 1900 and provides a 98 per cent complete daily record for 114 years. This station will be referred to as the 'Target' station. Where observed data is missing, it is infilled with data interpolated from surrounding daily data sets.
- Hourly rainfall records gathered from 101 stations throughout southern Qld. This data was obtained from the BoM and the Department of Regional Development, Manufacturing and Water (RDMW). These will be referred to as the 'donor' stations. Records ranged from 2 to 71 years in length, with a mean length of 28 years. Approximately 45 per cent of the data in these records was missing. These locations are shown in Figure 2.
- A latitude, longitude, elevation and distance to the nearest coast for all stations.

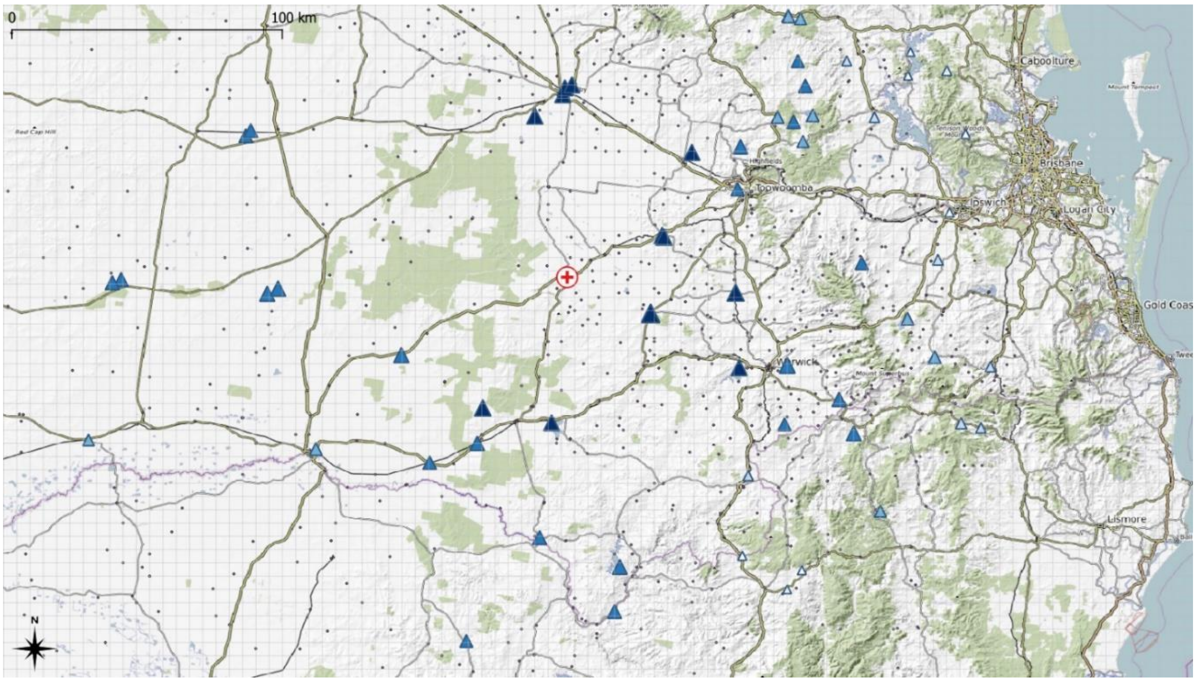

FIG 2 – Target and donor stations. NB: Target daily station at Millmerran PO is shown in red. Donor pluviographic stations shown as triangles. The similarity to target is shown by size and colour of donor triangle. Larger and darker triangles were calculated to be similar to target station. Other BoM daily stations are shown as points and BoM IFD grid is overlain for scale.

Process

Disaggregated data was obtained from the above inputs using a Python implementation of the Regionalised Method of Fragments (Westra *et al,* 2012). Below is a high-level overview of this process:

- Donor stations were ranked by their 'similarity' to the target station, based on a multivariate logistic regression model. The regression model considered latitude, longitude, the product of latitude and longitude, elevation and distance to the nearest coast. Book 2 ARR 2019 provides the logistic regression coefficient values in Table 2.7.7 (Ball *et al,* 2019).
- Data from donor stations was pooled to create a 50-year sampling data set of rainfall 'fragments' – hourly rainfall extracts from the donor station data, each 24 hrs in length. Fragments were preferentially drawn from donor stations by order of their similarity ranking, and fragments with any missing data were discarded. The sampling of fragments continues searching until sufficient donor locations are assembled to define the pool of fragments available in the database.
- For each daily total at the target station, a group of candidate fragments would be found that had a similar daily total, fell in the same part of the year and had similar rainfall levels on immediately preceding and succeeding days.
- These candidate fragments were sampled based on a harmonic distribution determined by the inverse of their similarity ranking. The sampled fragment is then scaled to match the daily total observed at the target station and becomes the sub-daily disaggregation for that day.

More details of this process are described in Westra *et al* (2012) or Book 2 of ARR 2019 (Ball *et al,* 2019).

Output

The method of fragments produced a 116-year simulated hourly rainfall record matching the daily totals at the Millmerran PO target station. The output is shown in Figure 3, zooming in on a randomly selected day in that series.

Because the sampling process introduces an element of randomness, the method is stochastic and can be used to generate any number of unique disaggregated records.

FIG 3 – Hourly rainfall data set disaggregated from daily rainfall data set using Method of Fragments showing progressive magnification of the series.

Step 2 – Adjusting rainfalls to match future climate predictions

This step adjusts rainfall based on predictions of how rainfall patterns will change in future climate scenarios (Visser *et al*, 2023).

Discrete events of each duration were recursively identified within the continuous series. Starting with short-duration events, each event was adjusted to meet the ARR 2019 uplift target for that duration. As longer-duration events encapsulate shorter-duration events, they require conditioning to ensure that the applied adjustment has not compounded overall and not exceeded the desired uplift in the IFD.

While global climate models predict increases in extreme rainfall intensity over Australia, seasonal totals may increase or decrease depending on location and time horizon. Rainfall events which were not identified for uplift were factored to match seasonal rainfall change predictions from downscaled CMIP6 climate modelling.

Two key sources were used to inform this adjustment:

1. ARR 2019 v4.2 Climate change factors are calculated using temperature increases from the IPCC AR6 Report (Ball *et al,* 2019; Wasko, 2024; IPCC, 2023, Stocker *et al* 2013). These factors are used to scale Intensity-Frequency-Duration (IFD) characteristics based on predicted temperature change. In general, these factors predict that yearly rainfall maxima will increase exponentially with temperature according to Equation 1. This equation is applied to each interval/AEP to calculate future IFDs.
2. Seasonal precipitation predictions from the Queensland Future Climate Dashboard (Trancoso *et al,* 2024). These are gridded predictions derived from downscaled CMIP6 climate model results (Chapman, *et al* 2024) about how seasonal rainfall totals will change for a given time frame, climate scenario and location. In general, these predict that seasonal rainfall totals will remain the same or decrease in 2090 for SSP3 pathway across most of Queensland.

$$I_p = I \times \left(1 + \frac{\alpha}{100}\right)^{\Delta T} \tag{1}$$

where:

I	historical rainfall depth (taken from Australian Bureau of Meteorology (BoM, 2016) IFDs)
I_p	projected rainfall depth for the climate scenario
α	rate of change parameter (from tables provided by the ARR)
ΔT	change in global temperature projection for the design period (SSP3@2090)

Combined, these two sources tell us that (in general):

- Intense rainfall events (the yearly maxima represented by IFD statistics) will increase in severity as mean global surface temperatures increase in future climate scenarios.
- Total rainfall volumes in Queensland will mostly remain the same or decrease in future climate scenarios.

The method for adjusting sub-daily rainfalls presented here attempts to align with both predictions. At a high level, it scales intense events up to match predicted IFDs, while scaling overall rainfall volumes down to match predicted seasonal totals. The IFD statistics are calculated for the generated hourly record and compared with the BoM IFD statistics. An iterative post-processing step then conditions the synthetic hourly record to ensure that the frequency of different durations of storm intensity is accurately represented.

Inputs

The inputs for the authors' climate-adjusting method were as follows:

- The BoM (2016) IFD curve for the target location (with and without adjustment as per ARR 2019 V4.2 recommendations below).
- Climate change IFD uplift factors as per the ARR 2019 V4.2 (Ball *et al,* 2019) as shown in Book 2 Figure 2.7.13.

- Five simulated sub-daily records at Millmerran PO were obtained as outputs from Step 1 above. Only one daily record is necessary to perform this step, additional simulations were used to assess consistency in the results.
- Predicted percentage changes in seasonal rainfall totals for SSP3 in the year 2090, as per the Queensland future climate dashboard (Trancoso *et al,* 2024).

Process

Future climate adjustment was performed in two steps. First yearly maximum rainfalls were scaled to match the uplifted IFDs predicted by ARR V4.2. This will be referred to as the 'IFD constraining stage'. Non-maximal rainfalls (rain not part of a yearly maxima for any duration) were then scaled to align with predicted seasonal rainfall totals. This will be referred to as the 'seasonality adjustment stage'.

The IFD constraining stage used a modified version of the algorithm described by Woldemeskel *et al* (2016). The process at a high level is as follows:

- IFDs (rainfall depths for a set of durations and AEPs) are calculated for the generated sub-daily rainfall.
- These IFDs are compared with a set of target IFDs. In this case, these were SSP3 2090 statistics uplifted from the BoM (2016) using the ARR V4.2 factors. The metric used to compare two IFDs was the absolute relative percent difference (ARPD), described by Equation 2. See Table 1 for an example of this comparison.

  The duration with the highest average ARPD is selected as the 'priority duration'. This is the duration which least closely matches the target IFD statistics. In Table 1, two hrs is the priority duration with an average ARPD of 49 per cent.
- All rainfall that is part of a yearly maximum for the priority duration is rescaled to match the target IFDs for that duration. This rescaling is conducted according to the equation provided by Woldemeskel *et al* (2016).
- Steps 1–4 are repeated until the IFD statistics for the generated rainfall are acceptable, similar to the target IFDs. Figure 4 shows the convergence of the raw generated sub-daily data to the uplifted SSP3 2090 statistics over 15 iterations.

$$\text{ARPD}(a,b) = \frac{|a-b|}{\frac{a+b}{2}} \tag{2}$$

TABLE 1

Example comparison between IFD statistics using ARPD.

	AEP (%)						
Duration	**63%**	**50%**	**20%**	**10%**	**5%**	**2%**	**1%**
2 hrs	44%	49%	56%	56%	53%	46%	39%
6 hrs	37%	39%	42%	41%	40%	38%	35%
12 hrs	34%	34%	33%	33%	32%	33%	32%
1 day	29%	30%	29%	26%	23%	20%	17%
2 days	27%	28%	29%	29%	27%	26%	25%
4 days	27%	27%	27%	28%	29%	32%	34%
7 days	23%	23%	22%	21%	21%	20%	20%

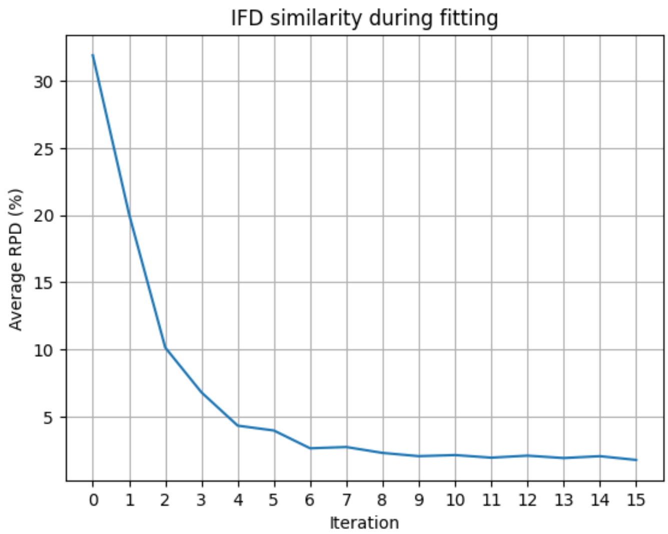

FIG 4 – ARPD convergence between generated and uplifted IFDs over 15 iterations.

The seasonality adjustment stage is simpler. Now that the yearly maxima rainfalls have been rescaled (usually increased), the seasonality adjustment stage rescales the non-maximal rainfall to match the predicted changes in seasonal totals – maximal rainfalls cannot be scaled at this stage as IFDs would be affected. This is achieved as follows:

- 'Expected' seasonal totals T_E are calculated by summing rainfall for each season (DJF, MAM, JJA, SON) across the original daily rainfall record and multiplying by seasonal adjustment factors.
- Maximal seasonal totals T_M are calculated by summing rainfall for each season across all rainfall that is part of a yearly maximum for some duration.
- Non-maximal seasonal totals T_{NM} are calculated by summing rainfall for each season across all rainfall that is not part of a yearly maximum.
- These totals are used to calculate a seasonal scaling factor S for each season, according to Equation 3. This factor represents the required scaling of non-maximal rainfalls to match predicted changes in seasonal totals.
- Non-maximal rainfalls are then scaled according to the rescaling factor for their season.

$$\mathrm{S} = \frac{T_E - T_M}{T_{NM}} \tag{3}$$

Output

The output of this future climate adjustment is sub-daily rainfall that matches both the ARR V4.2 uplifted IFDs as well as the Queensland Future Climate Dashboard CMIP6 future climate seasonal rainfall changes. An example is shown in Figure 5 for a single duration. Table 2 presents the IFD results from the uplifted BoM IFD using ARRV4.2 compared to the value achieved within the continuous sequence. For ease of comparison, Table 3 provides the percentage discrepancy across the IFD.

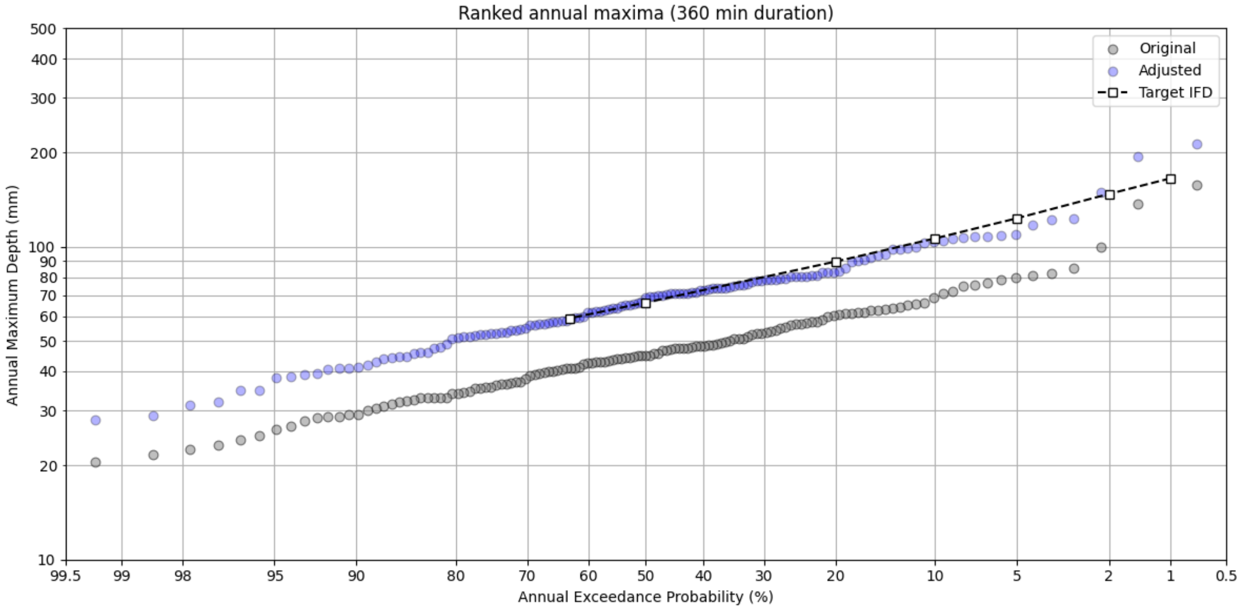

FIG 5 – Adjusted IFD (single duration) showing adjustment to future climate IFD.

TABLE 2

Results of IFD conditioning MoF to ARR v4.2 SSP3 2090.

Duration (min)	AEP 63.2%	50%	20%	10%	5%	2%	1%
120	34.6 / 32.5	37.2 / 36.8	47.4 / 50.9	56.4 / 61.0	67.2 / 71.2	85.2 / 85.4	102.5 / 96.7
360	43.7 / 42.8	47.8 / 48.1	62.5 / 65.1	73.9 / 77.2	86.5 / 89.5	105.5 / 107.0	122.0 / 120.0
720	51.1 / 51.5	56.8 / 57.5	75.7 / 77.1	89.3 / 90.8	103.3 / 104.0	123.0 / 124.0	138.8 / 139.0
1440	61.6 / 62.1	68.4 / 69.6	92.2 / 93.1	110.6 / 109.0	130.5 / 125.0	160.1 / 148.0	185.5 / 166.0
2880	73.7 / 74.2	82.5 / 83.6	111.8 / 113.0	133.2 / 134.0	155.5 / 154.0	187.0 / 183.0	212.7 / 206.0
5760	84.1 / 85.5	96.4 / 96.9	134.5 / 134.0	159.8 / 159.0	184.0 / 185.0	215.4 / 222.0	238.9 / 251.0
10080	92.6 / 91.8	105.9 / 104.0	148.6 / 143.0	178.4 / 171.0	208.1 / 200.0	248.3 / 238.0	279.7 / 268.0

Note: MoF value/Future Climate Target value.

TABLE 3

Results of IFD conditioning MoF raw to BoM (BoM, 2016).

Duration	AEP						
	63.2%	50%	20%	10%	5%	2%	1%
3 hrs	6.30%	1.10%	-7.10%	-7.80%	-5.80%	-0.20%	5.80%
6 hrs	2.10%	-0.60%	-4.10%	-4.40%	-3.40%	-1.40%	1.70%
12 hrs	-0.80%	-1.20%	-1.80%	-1.70%	-0.70%	-0.80%	-0.10%
24 hrs	-0.80%	-1.70%	-1.00%	1.50%	4.30%	7.90%	11.10%
2 days	-0.70%	-1.30%	-1.10%	-0.60%	1.00%	2.20%	3.20%
4 days	-1.70%	-0.50%	0.40%	0.50%	-0.50%	-3.00%	-4.90%
7 days	0.90%	1.80%	3.80%	4.20%	4.00%	4.20%	4.30%

Discussion and application

Our approach describes how an hourly rainfall data set can be generated from surrounding sub-daily data sets, which is consistent with the IFD and a daily record for a point of interest.

Where a target site extends over a wide geographical area, the process can be repeated by adjusting the inputs to represent the daily rainfall and IFD based on gridded data or additional daily rainfall data.

The process can be repeated at a location to generate long IFD-conditioned millennial length rainfall sequences, or to generate any number of data sets at the same location to develop a risk-based understanding of the variance in model outcomes.

The MoF-generated rainfall approach addresses limitations identified in earlier studies on landform evolution modelling:

- Temporal Variability: The MoF-generated rainfall methods can assimilate nearby rainfall observations while anchoring the rainfall statistics to replicate the occurrence of short-duration, high-intensity events that drive nonlinear erosion responses, which daily rainfall would miss.
- Spatial Heterogeneity: MoF approaches may better capture the spatial rainfall variability that influences long-term channel network evolution by simulating convective rainfall cells and orographic effects.
- Avoiding the need to utilise LEM parameter calibration to 'correct' sediment yields from smoothed rainfall inputs.
- Preserving the geomorphic signature of rainfall variability, particularly for climate change projections where storm intensity/frequency may shift.
- Enabling more accurate simulation of sediment 'pulses' and their cascading impacts on valley floor deposition.

This highlights the potential for MoF rainfall generation to bridge the gap between LEMs' process representation and the spatiotemporal complexity of real precipitation patterns.

ACKNOWLEDGEMENTS

Code and data availability. The code described in this study was Python 3.11 and was adapted from the method described in Dykman *et al* (2024). The data presented in this paper can be made available on request from the corresponding author. The CAESAR-Lisflood model used is freely available under a GNU licence.

The data set of the Australian rainfalls can be obtained from the Australian Bureau of Meteorology. Daily and sub-daily rainfalls are available at <http://www.bom.gov.au/climate/data/>

Intensity Frequency Duration (IFD) design rainfalls were obtained from the Australian Bureau of Meteorology at <http://www.bom.gov.au/water/designRainfalls/revised-ifd/>

Projections of changes to mean annual rainfall from <https://www.climatechangeinaustralia.gov.au/en/projections-tools/climate-futures-tool/detailed-projections/>

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