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Scaling of historical sub-daily rainfall datasets to represent future climate conditions

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ABSTRACT

The impact of climate change on the spatial and temporal distribution of future rainfall is complex. The consensus predictions from general circulation models (GCMs) indicate long-term reductions in average annual rainfall over much of Australia, while various lines of evidence suggest increases in the intensity of heavy rainfall.

With the release of version 4.2, Australian Rainfall and Runoff (ARR v4.2) provides clear guidance for scaling design rainfall intensities by projected global temperature increases. However, this event-based approach is not directly applicable to the continuous simulation modelling (CSM) of floods. CSM relies on the representation of smaller rainfalls in the days, or even months prior to a flood to accurately represent antecedent catchment moisture and runoff response.

This paper outlines an approach to developing future climate rainfall at an hourly timestep for CSM. Historical hourly rainfall sequences were used as a basis to preserve spatial distribution throughout study catchments. The historical datasets were scaled to reflect the predicted annual and seasonal changes from climate models while also reproducing the scaled intensity-frequency-duration (IFD) characteristics of the original data.

While design rainfall events can be readily adjusted using design uplift factors determined using the ARR v4.2 guidance, applying the same scaling to a long-duration continuous record for CSM is less straightforward. This is mainly due to the problem of nested maxima: annual maxima for shorter durations are often part of maxima for longer durations, meaning that scaling one duration could inadvertently affect others. As ARR v4.2 scaling factors increase for shorter durations, nested maxima must be scaled by conflicting factors. The methodology herein presents a novel approach to addressing this problem by first constraining heavy rainfall to the uplifted IFD characteristics before scaling the sub-maximal observations to reproduce annual and seasonal GCM projections.

Application of the adjusted rainfall records to CSMs revealed a varying and non-linear relationship between flood peaks and the scaled future rainfall, which appears to be explained by the depletion of soil moisture stores by additional rainfall prior to the runoff-producing rain.

INTRODUCTION

Overview

The Darling Downs is traversed by critical sections of the National Land Transport Network and seven state highways, making up a total network spanning over 1,307 km and including 1,549 highway culverts and 57 highway bridges.

In 2024, the Queensland Department of Transport and Main Roads (TMR) undertook the Darling Downs Flood Study (DDFS) to help prioritise infrastructure upgrades across this network.

The study focussed on whole-of-link closure characteristics by developing continuous historical water level sequences at each major bridge and culvert crossing, which reflect the actual historical interdependence and relative timing of floods in adjacent catchments.

Hourly streamflow datasets were generated by long-term continuous simulation modelling (CSM) (1889 to 2024) using URBS (documented in Cullen et al, 2025) and gridded hourly rainfall and evapotranspiration datasets created specifically for the project's 116,410 km^2 catchment area (Millard et al, 2025). This approach implicitly accounted for the complex interactions between antecedent conditions and the temporal and spatial variation of rainfall.

A key objective of the study was to assess the potential impact of future climate change on network closure times. For the DDFS, TMR adopted the average of rainfall and evaporation projections for Shared Socioeconomic Pathways (SSPs) SSP2 and SSP3 at the 2090 climate horizon.

The URBS CSMs were used to generate alternative streamflow datasets representing future climate conditions based on existing hourly climate datasets, meeting the following criteria:

- preserve the inter-catchment dependence of rainfalls represented in the base case climate datasets;
- achieve consistency with version 4.2 of Australian Rainfall and Runoff (ARR v4.2); and
- reflect the long-term changes to annual and seasonal rainfall projected by general circulation models (GCMs) for the selected SSPs and climate horizon.

This paper outlines the approach to developing hourly timestep future climate rainfall time series for use in the CSMs and briefly describes the impact on peak discharges derived from the CSM.

Defining the Problem

While ARR v4.2 (Ball et al., 2019) provides clear guidance on scaling design rainfalls to account for climate change, there is no clear consensus on how CSM rainfalls should be adjusted.

Changes in long-duration seasonal rainfall and evaporation are likely key drivers of changes in catchment moisture prior to the arrival of flood-inducing rainfall events. Long-term climate datasets for CSM models must accurately reflect predicted changes in antecedent conditions in the days or even months preceding a flood to predict the impact on runoff.

The impact of climate change on the spatial and temporal distribution of future rainfall is complex and multifaceted. The consensus predictions from GCMs indicate long-term reductions in average annual rainfall over much of Australia. Conversely, various lines of evidence suggest increased evaporation and a significant increase in the intensity of heavy rainfall (Wasko, et al, 2024). Taken together, these projections

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indicate an increase in rainfall variability, characterised by more intense rainfall events alongside longer spells of low or negligible rainfall.

Federal and state government authorities provide climate change datasets suitable for use in hydrological modelling. Daily rainfall and evaporation datasets such as those available from the Climate Change in Australia (CCiA) website (https://www.climatechangeinaustralia.gov.au/en/obtain-data/application-ready-data/) and the Queensland Future Climate Dashboard website (https://www.longpaddock.qld.gov.au/qld-future-climate/dashboard-cmip6/) are derived from dynamically downscaled GCM results prepared for the Coupled Model Intercomparison Project Phase 6 (CMIP6). To remove the effect of systemic bias and more accurately reflect local conditions, observational data is usually scaled by average (annual, seasonal or monthly) factors derived from the downscaled results for the SSP and climate horizon of interest.

While this approach produces future-climate datasets consistent with historical variability, it is simplistic and overlooks changes in variability induced by climate change. More sophisticated scaling techniques, such as quantile-quantile scaling, can help better match the variability of the GCM results. However, for the DDFS project, it was crucial that climate change rainfalls were also consistent with the change in design rainfalls derived in accordance with the climate change recommendations of ARR v4.2.

While design rainfall events can be readily adjusted using uplifted IFDs using the guidance of ARR v4.2, applying the same scaling to a long-duration continuous record for CSM is less straightforward. This is mainly due to the problem of *nested maxima*: annual maxima for shorter durations are often part of maxima for longer durations, meaning that scaling one duration could inadvertently affect others. ARR v4.2 scaling factors increase for shorter durations, which presents a problem, as nested maxima must be scaled by conflicting factors. The methodology herein presents a novel approach to addressing this problem while maintaining consistency with the GCM projections.

METHODOLOGY

The approach outlined below was developed to transform historical rainfall records into future climate rainfall sequences for CSM, incorporating both projected changes to rainfall depths from GCMs and intensity increases as per ARR v4.2. This was achieved through a two-phase process:

1. IFD Constraining: Annual rainfall maxima were adjusted to match scaled IFD curves in accordance with the ARR 2019 guidelines (Ball et al., 2019). This led to an increase in total rainfall depth.
2. Total depth scaling: The remaining (sub-maximal) rainfall values were proportionally scaled to ensure that total rainfall depths aligned with CMIP6 projections. This typically required a reduction in sub-maximal rainfall to maintain consistency with projected totals.

Input

Inputs for the adjustment approach were as follows:

- An hourly rainfall record at the point of interest (POI);
- IFD curves derived from the hourly rainfall record at the POI;
- IFD curves derived from the hourly rainfall record at the POI uplifted as per ARRv4.2 for the desired SSP and time horizon; and,
- Rainfall depth scaling factors derived at the POI from downscaled CMIP6 GCM results for the desired SSP and time horizon.

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IFD Constraining

In the first phase of the adjustment process, values from the rainfall record that were part of an annual maximum for any duration were adjusted to better match the ARRv4.2 uplifted IFDs.

The nested maxima problem, described above, was overcome using a modified implementation of the iterative IFD constraining algorithm proposed by Woldemeskel et al. (2016). The modified algorithm is described below.

1. IFD relationships (rainfall depths for a set of durations and Annual Exceedance Probabilities (AEPs)) are calculated for the historical rainfall record by fitting the Generalised Extreme Value distribution to the annual maxima using LH moments (Wang, 1997). A longer record improves the reliability of these estimates, particularly for more extreme AEPs.
2. Calculated IFDs are evaluated against the uplifted target IFDs. This is achieved by comparing IFD values for each AEP/duration using the symmetric relative difference (SRD). In Equation 1 below a represents the target IFD value and b the corresponding calculated IFD value.

$$\mathrm{SRD}(a,b) = \frac{2|a-b|}{a+b}$$

Equation 1: Symmetric Relative Difference (SRD)

3. The duration with the highest average SRD is selected as the 'priority' duration, i.e. the duration that least closely matches the target IFD.
4. An *annual maximum rainfall rescaling factor* F is calculated for the priority duration (see Section 2.1 of Woldemeskel et al., 2016). This factor is then damped with a user-defined parameter $0 < d \leq 1$ to find a *damped scaling factor* R that moves from 1 to F as d increases. This is done to encourage convergence, as simply scaling by F on each iteration often leads to over-correction and instability. All rainfall values that are part of a yearly maxima for the priority duration are then scaled by R.

$$R = 1 - ((1-F) \cdot d)$$

Equation 2: Calculating the damped adjustment ratio

5. Steps 1-4 are repeated until the IFDs for the adjusted rainfalls are acceptably similar to the target IFDs, or until a maximum number of iterations is reached.

Convergence of the adjusted record IFDs to the target IFDs typically occurs within 15 iterations of the constraining algorithm, as measured by averaging the SRD across all durations and AEPs. Figure 1 compares the resultant annual maxima series (AMS) to the AMS of the original rainfall dataset and the target climate change IFD curve for three durations of interest.

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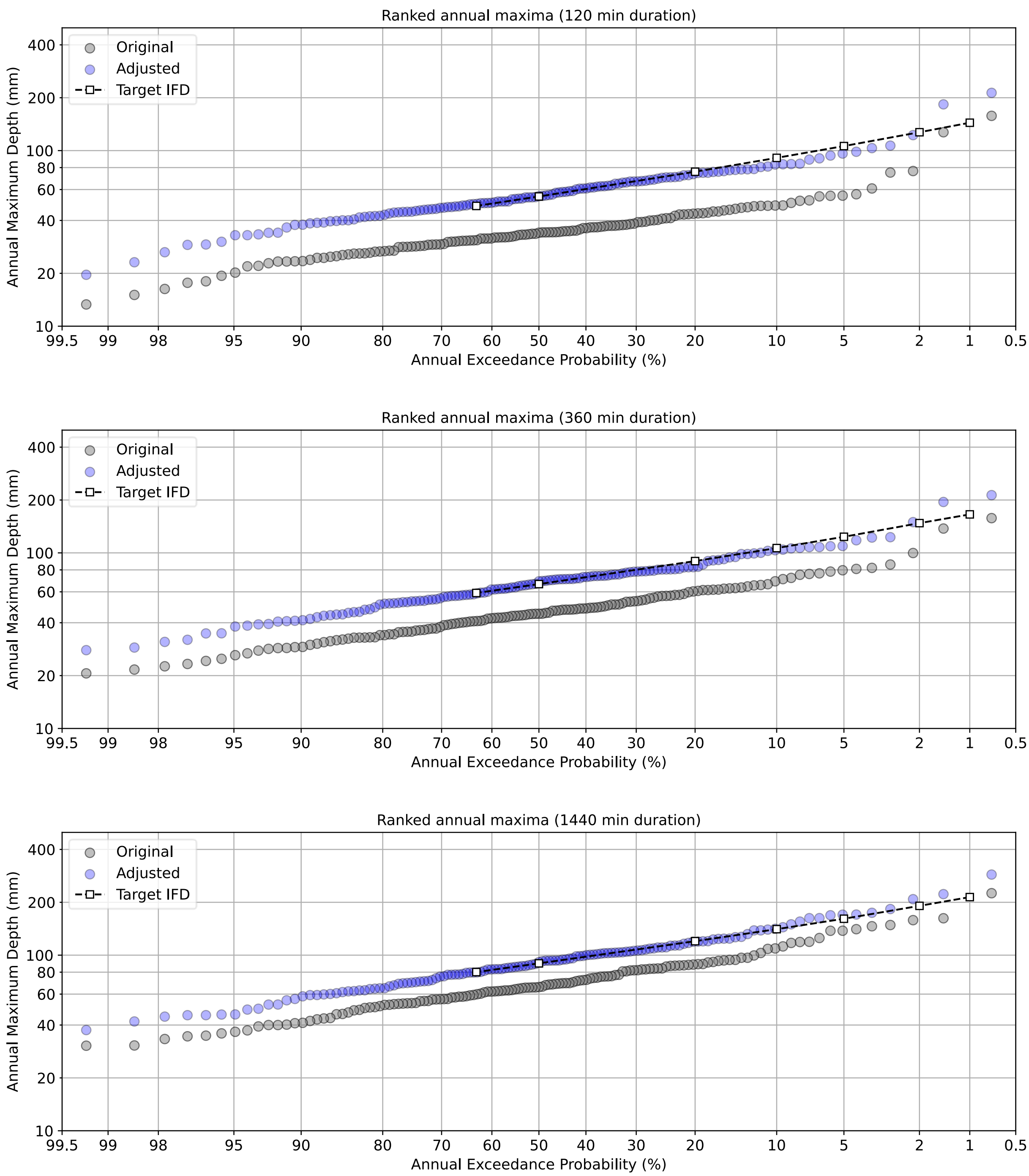

Figure 1: Comparison of target IFD with annual rainfall maxima before and after IFD constraining

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Total Depth Scaling to CMIP6 GCM Projections

Rainfall and evaporation projections based on GCMs prepared for CMIP6 are available from the Queensland Future Climate Dashboard (QldFCP-2). The QldFCP-2 website provides scaling factors from an ensemble of 15 regional climate models carefully selected to meet the requirements of the region. The projections were dynamically downscaled using the Conformal Cubic Atmospheric Model (CCAM) to generate high resolution (10 km) grids. The models were used to simulate:

- the 1850-2014 period with observed greenhouse gas concentrations and other forcings.
- trajectories of future global emissions of greenhouse gases for the Shared Socioeconomic Pathways (SSPs).

From these projections, annual and seasonal evaporation and rainfall adjustment factors can be derived at any location for a 20-year period of interest (centred on 2030, 2050, 2070 or 2090 compared to the baseline).

Table 1 below shows the projected percentage change in average annual rainfall and evaporation compared to the base case climate scenario at several key locations throughout the study area for the Study SSP and 2090 climate horizon. Average annual rainfalls across the study area are predicted to reduce by between 4% and 10% by 2090. Average annual evaporation across the study area is predicted to increase by between 20% and 25% in 2090 compared to the 1986 to 2025 base case climate scenario.

Table 1 Projected future increase in annual climate averages (2090)

Locations	Rainfall (%)	Evaporation (%)
Toowoomba	-7.5	20.7
Dalby	-9.3	22.9
Warwick	-6.9	20.8
Miles	-8.0	24.1
Roma	-4.5	24.8
Goondiwindi	-5.3	23.9

Evaporation scaling factors based on seasonal percentages were directly applied to the historical evapotranspiration record for use in the CSM. However, rainfall values that were part of an annual maximum for any duration could be changed at this stage, as IFDs would be affected. Therefore, the objective in this step was to adjust total rainfall depth by scaling the remaining (sub-maximal) rainfalls only. This can be expressed as:

$$\alpha V_O = V_M + \beta V_{NM}$$

where:

- V_O is the total depth of rainfall in the *original* record
- V_M is the total depth of rainfall in the *adjusted* record that is part of an annual maximum for some duration
- V_{NM} is the total depth of remaining (sub-maximal) rainfall in the *adjusted* record
- α is the CMIP6 rainfall scaling factor for the climate scenario of interest
- β is a scaling factor for the sub-maximal rainfall

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Rearranging for β:

$$\beta = \frac{\alpha V_O - V_M}{V_{NM}}$$

Equation 3: Finding the sub-maximal depth scaling factor

Since all variables other than β are known, equation 3 was used to determine the appropriate scaling factor. After IFD constraining, this factor was then used to scale all sub-maximal rainfall values in the record, achieving the desired total depth change while preserving uplifted IFDs. This process can be applied annually or independently by month or season, as desired.

Extreme cases where $V_M > \alpha V_O$ are theoretically possible. This can occur when the predicted IFD uplift and total depth reductions are irreconcilable. In such cases β would become negative and this approach would no longer be applicable. However, this situation has not been encountered in applications of the method so far.

Output

This approach produced a continuous adjusted hourly rainfall record with three useful characteristics:

1. Adherence to predicted increases in the intensity of extreme rainfall events predicted by IFD uplift, as per ARR V4.2.
2. Adherence to projected changes in total rainfall depths, as per CMIP6.
3. Improved preservation of realistic temporal and spatial rainfall patterns compared to synthetic rainfall generation approaches.

RESULTS

The scaled rainfall and evapotranspiration time series were imported into the CSM models to test the effect of climate change on the flow time series. Figure 2 shows an example of the effects of climate change scaling on the rainfall timeseries and continuous simulation model results.

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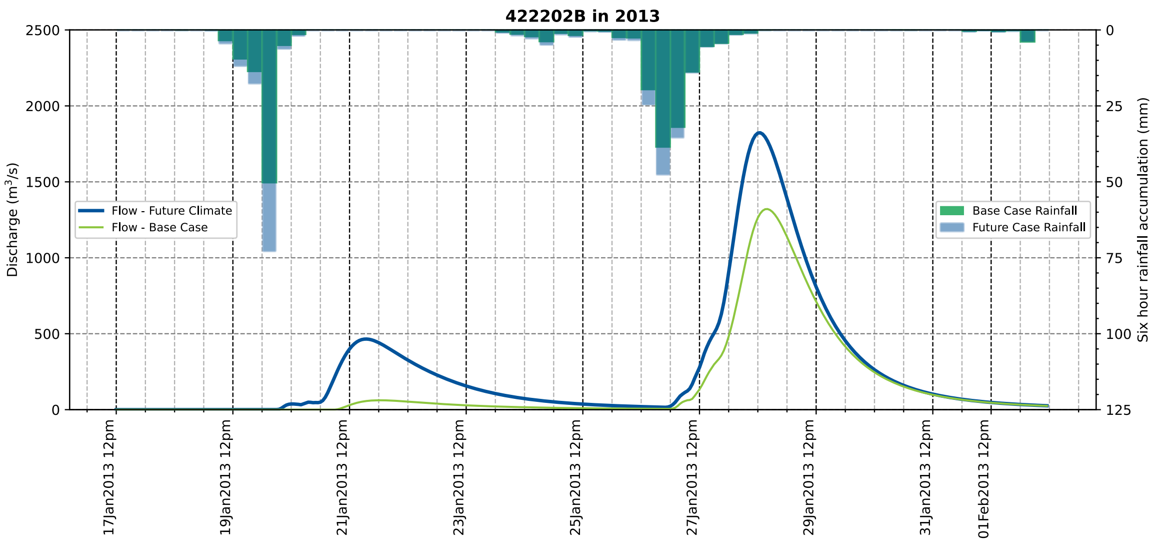

Figure 2: Comparison of base case and future climate CSM hyetographs and hydrographs

Annual maxima discharge time series were extracted from the CSM model results, and design discharges were derived using flood frequency analysis (Cullen et al, 2025). The resultant design discharges obtained at several locations are compared in Table 2, which shows that frequent AEP flood events will increase in magnitude most significantly, with rare flood events experiencing a lesser increase in flood magnitude. In summary:

- 50% AEP discharges are predicted to increase by factors of between 1.6 and 2.3 (average 1.9);
- 10% AEP discharges are predicted to increase by factors between 1.6 and 1.9 (average 1.7); and
- 1% AEP discharges are predicted to increase by factors of between 1.2 and 2.0 (average 1.5).

Table 2: Effect of climate change on CSM-derived design discharges for the project SSP at 2090

Location		50% AEP			10% AEP			1% AEP		
	Area (km^2)	Base Case (m^3/s)	Future Case (m^3/s)	Factor	Base Case (m^3/s)	Future Case (m^3/s)	Factor	Base Case (m^3/s)	Future Case (m^3/s)	Factor
417205A Moonie Rv at Flinton	5,378	128	273	2.13	722	1,241	1.72	1,487	2,170	1.46
416415A Macintyre Brook at Booba Sands	4,092	111	235	2.12	831	1,595	1.92	3,741	5,127	1.37
422332 Gowrie Ck at Oakey	142	66.1	91.8	1.39	230	376	1.63	550	816	1.48
422343A Charleys Ck at Chinchilla	3,461	55.8	130	2.33	419	651	1.55	1,902	2,327	1.22
422310C Condamine Rv at Warwick	1,360	90.3	190	2.10	707	1,150	1.63	1,697	2,542	1.50
422319B Dalrymple Ck at Allora	246	55.4	89.7	1.62	239	395	1.65	513	743	1.45
422202B Dogwood Ck at Gilweir	3,010	188	333	1.77	934	1,526	1.63	2,678	3,597	1.34
422333A Condamine Rv at Loudons Bridge	12,380	236	387	1.64	1,113	1,939	1.74	3,298	6,458	1.96

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DISCUSSION

The ratio of the future climate peak discharges to the base case discharges is significantly higher than the ARRv4.2 scaling factors applied to the rainfall intensities. This is somewhat surprising, as the effect of the long-term decrease in rainfall and increase in evapotranspiration might be expected to decrease antecedent catchment moisture conditions and hence increase catchment losses.

The variation flood magnitude is non-linear with AEP – with the increase in peak flow greatest for more frequent AEPs. This possibly indicates that the expected decrease in antecedent moisture is offset by increases in rainfalls immediately prior to the flood-producing rainfall (which may be factored up due to being part of a longer-duration large rainfall event in the AMS). It is unclear whether this is an artefact of the adopted methodology or a likely outcome of the impacts of climate change.

CONCLUSION

This paper demonstrates a methodology for scaling baseline timeseries to generate rainfall and evapotranspiration datasets suitable for use in CSM, which:

- are consistent with version 4.2 of Australian Rainfall and Runoff (ARR v4.2); and,
- reflect the long-term changes to annual and seasonal rainfall projected by general circulation models for the selected SSPs and climate horizon.

The ratio of the resultant climate change peak discharges is significantly higher than the ARRv4.2 scaling factors applied to the rainfall intensities, with the increase in peak flow greatest for more frequent AEPs. The reasons for this non-linear behaviour warrant further investigation – as there are significant consequences for the performance of hydraulic structures under a future climate.

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BIOGRAPHY

First Author is Michael Batchelor. With thirty years' experience, Michael has contributed to the planning, design and delivery of major infrastructure projects across Australia. He has undertaken numerous flood studies, design assessments and water resource yield studies for major road, mining and water resource projects. Michael has also authored the water resources chapters of a number of environmental impact statements. He has designed water supply dams, water distribution systems, stream diversion works, sedimentation dams and associated drainage systems for diverse locations, especially across northern Australia.

Second Author is Lindsay Millard. Working with a strong focus on hydrologic analysis. His expertise extends to flood and water resource modelling for natural resource management projects, the transport and mining sectors, and flood risk assessments for local Councils. He has led hydrologic and hydraulic modelling on multiple design flood studies and has extensive experience using industry software. Lindsay has played a pivotal role in flood studies and floodplain management plans, overseeing their delivery and ensuring their technical quality. His projects have involved the calibration of historic events, assessment of mitigation options, flood damage assessments, consequence and cost-benefit analysis. https://au.linkedin.com/in/lindsaymillard

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