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Climate risk assessments in New South Wales using publicly available stochastic climate data

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Abstract: Successful management of river systems requires an accurate quantification of climate risk (e.g., potential drought severity). Traditionally, such risk has been quantified using instrumental measurements of rainfall/streamflow (which are ~ 100-120 years long). However, hydroclimatic processes are inherently random and vary at multidecadal timescales, meaning instrumental timeseries may not properly characterise climate risk. Stochastic models – which are statistical models used to generate synthetic hydroclimatic timeseries that account for randomness and climate variability – can be used to better characterise climate risk. As such, using stochastic model outputs as rainfall-runoff/river systems model inputs can improve our understanding on river system vulnerabilities and lead to better management decisions.

Considering the usefulness of stochastic models, in this study we demonstrate how stochastic climate data can be used in conjunction with river systems models to characterise climate risk in a water management context. The stochastic data, which has undergone a rigorous Quality Assurance process, has been produced by the NSW Government and is publicly available via the SEED portal (https://datasets.seed.nsw.gov.au/dataset/water-modelling-stochastic-climate-data/). We present outputs from river system models for different Northern Rivers valleys in NSW (Border Rivers, Gwydir, Namoi, and Macquarie). More specifically, we analyse stochastic 12, 18, and 24-month inflows for a major reservoir in each valley. Stochastic inflows were then compared with the 12, 18, and 24-month minimum inflow derived from a river system simulation using instrumental data inputs. This statistic is of interest because, for these time windows, the observed minimum inflow is used to inform stakeholder water allocations.

We found that (a) minimum storage inflows derived stochastic data are lower than those derived from instrumental data; and (b) consecutive periods where stochastic inflows are lower than the corresponding instrumental-derived minimum are possible. Considering the importance of the minimum inflow statistic to operational water management, overestimating minimum storage inflows – potentially over multiple consecutive allocation periods – can lead to sub-optimal management outcomes. Given the limitations of using only instrumental measurements to characterize climate risk, the availability of state-wide stochastic climate data in NSW provides opportunities to re-evaluate existing water management plans/policies. The method presented in this study – which demonstrates how stochastic climate data can be used in climate risk assessments – is general and can be applied to other river systems and management-relevant statistics. As such, we encourage other NSW water managers to use this study, and the available stochastic climate data, as a guide when performing future climate risk assessments.

Keywords: *Climate risk, water management, stochastic climate*

1. INTRODUCTION

Successful management of river systems requires a sustainable distribution of water resources to various stakeholders (e.g., town water supplies, irrigators, industry, and the environment). This can involve a variety of management strategies. Such strategies include, but are not limited to, storing water for future use via dams and allocating water resources to stakeholders assuming conservative future storage inflows (i.e., that future inflows are equal to the lowest historic inflow).

Underpinning these water management strategies is an understanding of climate variability and risk (e.g., the potential severity of a two-year drought). Typically, this risk is quantified using instrumental measurements of rainfall (which are available, at most, from ~1890s onwards) and streamflow, which are often much shorter. However, hydroclimatic processes are inherently random and vary at multidecadal timescales (Kiem, Franks and Kuczera, 2003; Koutsoyiannis, 2010). This means that the instrumental record contains 4-5 cycles of multidecadal climate variability (Vance et al., 2015) – is this enough to properly characterize historic climate risk and, by extension, ensure sustainable river system management? In this study, we use a new, publicly available climate dataset that accounts for the inherent randomness of hydroclimatic processes to re-examine water management relevant climate statistics and risk. The dataset, available for climate stations across New South Wales, was created using stochastic models calibrated to various sources of historic climate information.

Stochastic models are statistical models used to generate synthetic climate timeseries with similar statistics to the instrumental records, but with a different sequencing of wet/dry years (Srikanthan and McMahon, 2001, 2005). When generating synthetic timeseries, these models are parameterized such that important statistic features of climate timeseries (such as mean, variance, and Lag-1 autocorrelation) are preserved. However, each timestep is partly comprised of a randomly generated number (Matalas, 1967). By introducing randomness, different – but plausible – sequences of wet/dry years are generated. This provides a more robust characterization of baseline climate risk. Because stochastic data can better quantify climate risk, metropolitan water authorities have used stochastic climate data (e.g., rainfall, potential evapotranspiration) as a hydrological/water system model input when performing climate risk assessments and evaluating water system performance (Berghout and Lockart, 2022; Lockart and Berghout, 2022).

Stochastic models have been widely used by urban water managers to better characterize climate risk. However, producing reasonable, coherent stochastic data for hundreds of climate stations across several climate zones – something required for large, interconnected river systems – remains a challenging task (Renard et al., 2022). This is because the stochastic climate timeseries must (a) produce reasonable statistics at daily, monthly, annual, and multi-annual timescales (Tsoukalas, Makropoulos and Koutsoyiannis, 2018); (b) preserve spatial correlations between climate stations (Frost et al., 2007); and, crucially, (c) produce realistic flow outputs when used as a hydrological model input (Nguyen, Bennett and Leonard, 2022). Furthermore, demonstrating that these key features are replicated requires a rigorous model calibration/validation Quality Assurance (QA) process (Bennett et al., 2018).

In response to these limitations, there have been recent developments in stochastic modelling techniques that preserve sub-annual statistics/spatial correlations across thousands of sites (Bennett et al., 2018) and produce more robust characterizations of annual/multi-annual variability (Henley et al., 2011). These developments allow spatially and temporally consistent stochastic data to be generated for many climate stations across a large domain.

In accordance with these developments, the NSW Department of Planning and Environment (DPE) has recently developed a state-wide stochastic climate dataset to inform longer-term water management plans for different water management zones. This data, which is publicly available via the SEED portal (https://datasets.seed.nsw.gov.au/dataset/water-modelling-stochastic-climate-data/), comprises 10,000-year daily timeseries for ~2000 rainfall/evapotranspiration stations. The dataset has undergone extensive QA and has been deemed suitable for long-term water security assessments (NSW Government, 2023).

The development and QA of a publicly available, state-wide stochastic dataset allows existing water management decisions/assumptions to be revisited. In this study, we demonstrate how stochastic data can be used in conjunction with rainfall-runoff and river systems models to assess climate risk in a water management context. The case study is focused on minimum storage inflows in regulated NSW river systems, an important statistic that influences stakeholder water allocations in various water sharing plans (WSPs).

Minimum inflow statistics are important because, when determining stakeholder water allocations, an assessment of current dam storage and future inflows (assumed to be the historic minimum inflow) is performed to estimate the future available resource. From this future available resource, operational losses (e.g., losses due to storage/river evaporation) and carry-over water entitlements are subtracted. The remaining future resource is used to allocate water to different stakeholders (e.g., town water supply, irrigators). By using stochastic data as an input into a regulated river system model, it's possible to evaluate the fidelity of minimum inflow statistics derived from instrumental data. To do so for different regulated systems in NSW, in this study we explore:

- Whether stochastic inflows are lower than the instrumental-derived minimum inflows. Overestimation of minimum inflow statistics can lead to sub-optimal management outcomes in regulated systems; for instance, reduced environmental flows and overestimated stakeholder allocations.
- Whether stochastic inflows are lower than the instrumental-derived minimum inflows over consecutive allocation periods. Overestimation across consecutive allocation periods can limit system recovery and further stress the river system.

2. DATA AND METHODS

A key purpose of this study is to demonstrate how publicly available stochastic climate data – produced by DPE and available online – can be used in conjunction with hydrological/river systems models to better estimate management-relevant flow statistics. To do so, we examined storage inflows in the NSW Northern Rivers regulated systems, which comprises the Border Rivers; Namoi; Gwydir; and Macquarie water management zones managed by the DPE (Figure 1). A single storage from each zone was selected (Table 1).

Key inflow statistics used when managing these systems are the lowest 12/18/24-month inflow derived from the historic record. These time periods are used by DPE in different regulated systems to estimate future available resources (a key calculation when allocating water to stakeholders). Therefore, we performed a theoretical climate risk assessment comparing instrumental derived minimum inflows with stochastic minimum inflows.

This case study, and stochastic climate risk assessments in general, require:

1. Identification of management-relevant climate risk statistics (e.g., 12/18/24-month minimum inflows).
2. Identification of relevant climate stations and flow gauges.
3. Calibration of rainfall-runoff and river systems models using observed climate/flow data.
   (a) DPE uses Sacramento and Source for these respective modelling tasks (Dutta et al., 2013). These models are calibrated using SILO patched point climate data (Jeffrey et al., 2001).
4. Calibration/generation of stochastic climate data for the identified stations.
5. Generation of instrumental and stochastic flow data using the calibrated rainfall-runoff models.
6. Use stochastic/instrumental-derived flow data as an input into a calibrated river system model.
   (a) River system model outputs can then be used to calculate/analyse target statistic (i.e., minimum storage inflows).
   (b) Model outputs from DPE's RWS were used for this analysis (NSW Government, 2022). These models simulate the existing river system and management rules using stochastic climate inputs.
7. Comparison of stochastic river system model outputs with corresponding instrumental 'base case' model outputs. The instrumental 'base case' model simulates the existing river system and management rules using instrumental inputs.

Step 7 typically involves the derivation of the stochastic sampling distribution for each statistic. The stochastic data is then assigned into non-overlapping 'replicates' of equal length to the corresponding instrumental period (e.g., ~130-years). The statistic for each replicate is then calculated. The subsequent sampling distribution provides an estimate of statistical uncertainty. It can be used to validate stochastic outputs by demonstrating that the instrumental-derived statistic is captured by the stochastic sampling distribution.

Depending on the specific kind of climate risk assessment/statistics being calculated, subsequent steps may vary. Such steps can include, but are not limited to, calculating the frequency/magnitude that some management relevant threshold is exceeded (Hashimoto, Stedinger and Loucks, 1982). For this case study, we (a) calculated the frequency that the stochastic 12-month minimum inflows were lower than instrumental-derived minimum storage inflows; and (b) assessed if these periods extended over consecutive periods. To reflect that, for regulated systems, water allocations based on the minimum inflow statistic can be made multiple times per-year, this assessment was performed for consecutive, non-overlapping six-month periods.

Note that, for both case studies, the stochastic data is being compared to the corresponding statistic from the instrumental 'base case' model simulation (not the observed flows). We did this to ensure that using stochastic inputs in a calibrated river system model did not introduce new inflow biases (e.g., due to some missed feature in the stochastic climate model – Nguyen, Bennett and Leonard, 2022). This also ensured that any potential stochastic inflow biases were not confounded by biases in the calibrated river system model. Future assessments using observed data is left for future work.

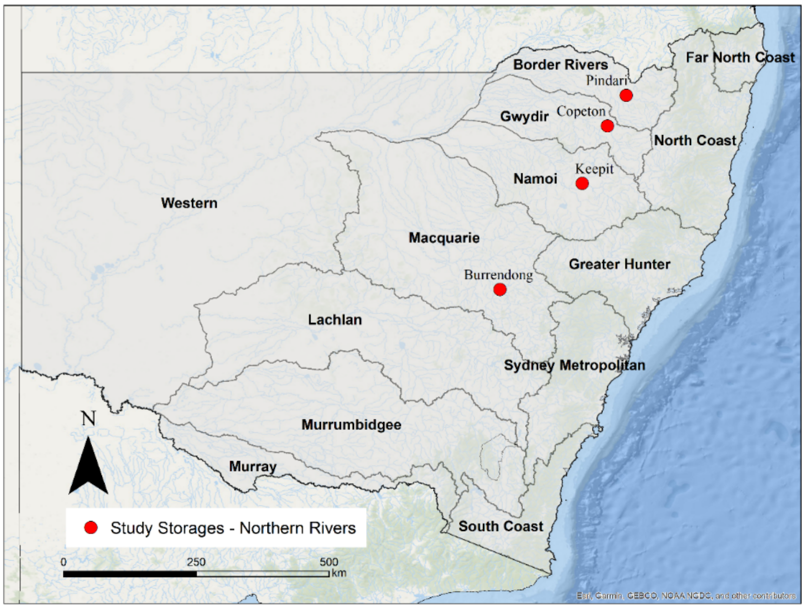

Figure 1. Location of Northern Rivers storages used in this study

Table 1. Northern Rivers storages used in this study. Minimum inflow statistics are derived from the instrumental-data river system model run.

Storage name	Valley	12-month minimum (ml)	18-month minimum (ml)	24-month minimum (ml)
Pindari	Border Rivers	9,673	19,472	43,415
Copeton	Gwydir	8,650	25,785	54,940
Keepit	Namoi	8,526	34,272	66,003
Burrendong	Macquarie	22,094	69,643	85,060

3. RESULTS

For each storage, sampling distributions for 12, 18, and 24-month minimum inflows are shown in Figure 2. From Figure 2, we can see that:

- The sampling distributions consistently captures the corresponding instrumental-derived statistics. This means that the stochastic climate data produces reasonable outputs when used as a rainfall-runoff and river system model input (this is not always the case – Nguyen, Bennett and Leonard, 2022).
- For all storages/statistics, there are instances where the minimum stochastic statistic is lower than the corresponding instrumental-derived statistic.

Figure 3 demonstrates the number of consecutive six-month stochastic periods where inflow is less than the corresponding instrumental-derived minimum. This reflects how water allocations – which require an estimate of future inflow – are updated sub-annually. We can see that:

- For some storages/statistics, the stochastic inflow was less than the instrumental-derived minimum for up to four consecutive six-month periods.
- For a 10,000-year stochastic model run (comprised of 20,000 six-month periods), stochastic inflows were, at most, less than the instrumental-derived minimum for ~170 six-month periods.

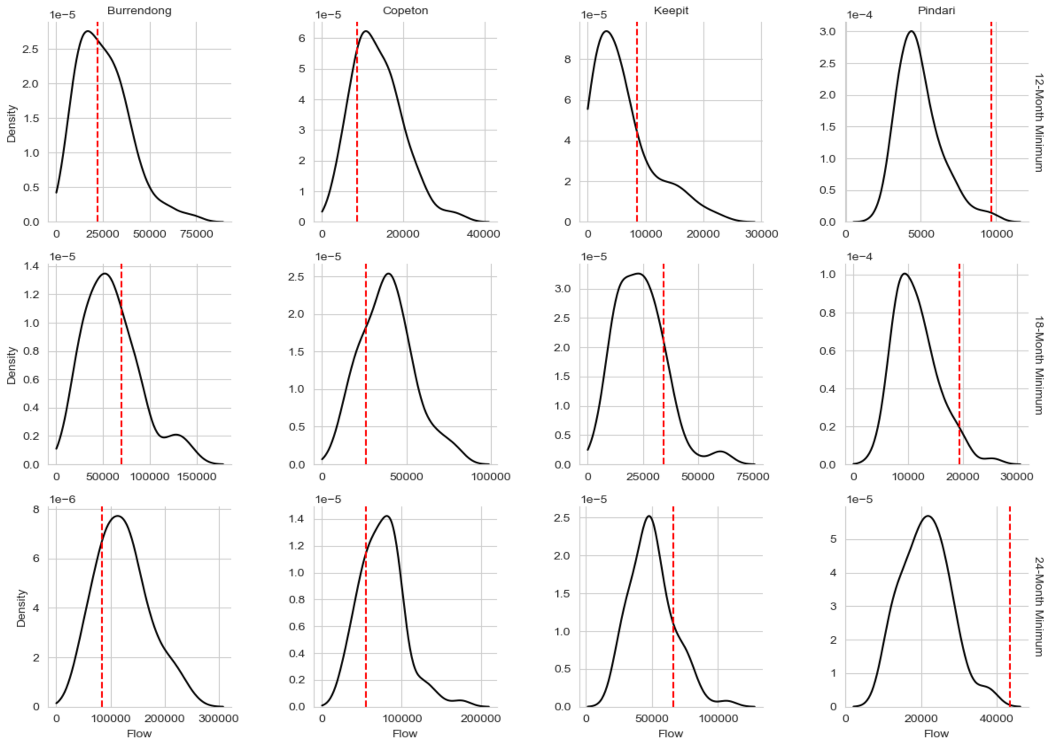

Figure 2. Stochastic minimum storage inflow distribution and corresponding statistic from instrumental model run (red dashed line)

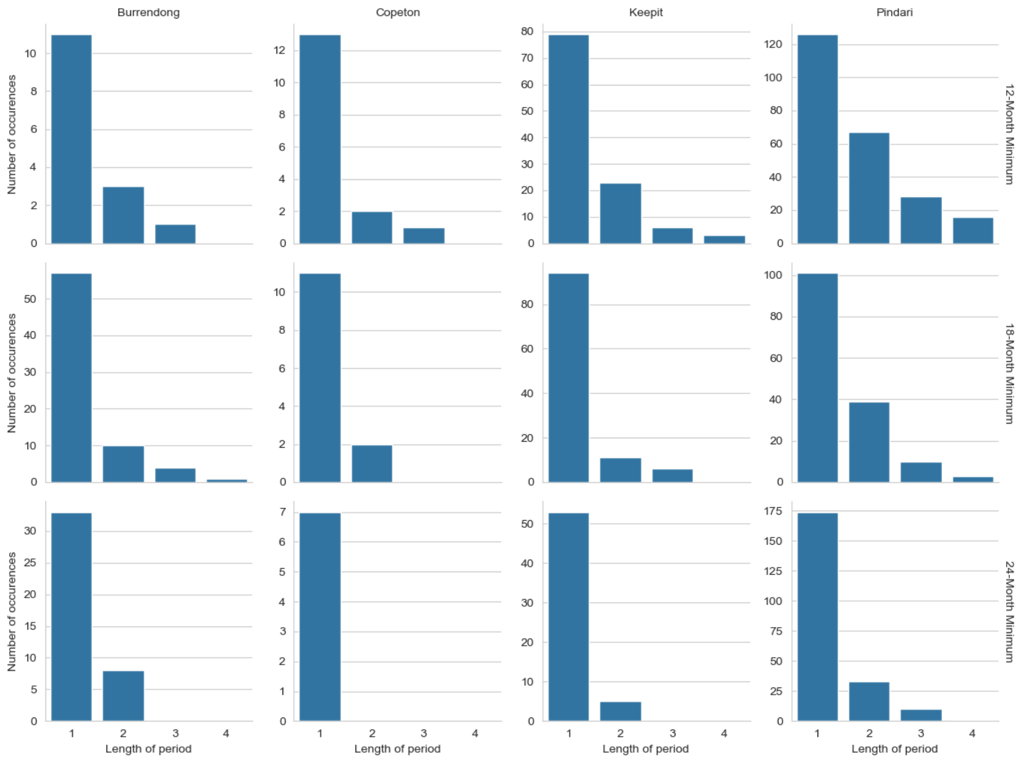

Figure 3. Consecutive 6-month periods where the stochastic minimum inflow is less than the instrumental-derived minimum inflow

5. DISCUSSION AND CONCLUSION

In this study, we presented a case study that quantified water-management relevant climate statistics (i.e., minimum inflows to storages) using publicly available stochastic data. These stochastic statistics were compared against corresponding instrumental-derived statistics. These instrumental-derived statistics are currently used when determining water allocations in NSW.

This case study highlights potential limitations with using only instrumental climate data to characterize climate risk, demonstrating that (a) minimum storage inflows derived from instrumental data are higher than those derived from stochastic data; and (b) consecutive periods where stochastic inflows are lower than the corresponding instrumental-derived minimum are possible. These results reflect the stochastic data replicating two key feature of the climate system; long-term climate variability and randomness. Long-term climate variability means that ~100-130 years of instrumental data does not fully represent long-term climate risk. Randomness means that instrumental climate measurements represent just one plausible realization of climate variability – more severe sequences are plausible.

Considering the importance of the minimum inflow statistic to operational water management, overestimating minimum storage inflows can lead to sub-optimal management outcomes. Furthermore, the potential for minimum inflows to be overestimated over consecutive six-month periods can prevent system recovery and exacerbate the associated effects of reduced environmental water and overestimated stakeholder allocations.

Considering the potential limitations of using only instrumental measurements to quantify risk, the availability of state-wide stochastic climate data in NSW provides opportunities to re-evaluate existing water management plans/policies. The method presented in this study – which demonstrates how stochastic climate data can be used in climate risk assessments – is general and can be applied to other river systems and management-relevant statistics. As such, we encourage other NSW water managers to use this study, and the available stochastic climate data, as a guide when performing future climate risk assessments.

Although this study highlights limitations with using only instrumental measurements to characterize climate risk, we emphasize the rarity of the instrumental-derived minimum in the 10,000-year stochastic model runs. In most cases, the instrumental minimum inflow may be a sufficient heuristic for a conservative estimate of future inflow. However, given that (a) the instrumental record contains limited cycles of multi-decadal climate variability; and (b) anthropogenic climate change may impact regional streamflow, future climate risk assessments may have to be conducted using additional sources of climate information. Such sources include, but are not limited to, stochastic climate data and climate model projections.

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