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Use of climatic partitions for stochastic rainfall modelling

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Abstract: Climate variability is a significant and well-known contributor to variations in streamflow, particularly at inter-annual and inter-decadal scales. This poses a significant challenge for estimation methods that rely on historical data up-to and at the annual timescale, but that do not account for inter-annual variability. One such method is to use stochastic modelling to simulate a range of climatic conditions, thus it is important to ensure that these models incorporate climatic variability to provide a more comprehensive analysis.

Numerous studies have investigated inter-annual climatic variability using Australian hydrologic records and demonstrated the role of multi-annual to multi-decadal climate cycles, as informed by indices such as the Interdecadal Pacific Oscillation (IPO). This paper analyses variation in the strength of climatic influence on different catchments in Australia. The main objective is to demonstrate the method of incorporating climatic influences on stochastic modelling over a large region. To account for different degrees of climatic influence across catchments, a stochastic model is calibrated depending on the state of the IPO index. Specifically, the climate record is partitioned into years that are in an IPO positive state and other years in the IPO negative state. The persistence in each state means that there is an increased likelihood of dry or wet multi-year sequences compared to what would happen from randomly sampling from a single homogeneous climate state.

The study region is taken from the Murray Darling Basin, covering eight catchment groupings with a total of 949 precipitation sites and 796 evaporation sites, including the (i) Border catchment, (ii) Gwydir catchment, (iii) Lachlan catchment, (iv) Macquarie catchment, (v) Namoi catchment, (vi) Queensland catchments, (vii) Southern catchments (mostly Victoria), and (viii) Western catchments (NSW). Across this domain, annual rainfall totals can range from less than 200 mm to more than 1800 mm. There is a clear variation in the strength of individual gauges and catchments to the IPO signal. Catchments with a stronger signal include the Western, Macquarie and Namoi catchments, in which the highest percent differences in annual rainfall totals between the IPO +ve and IPO –ve stages are respectively: 13.6%, 11.9%, and 10.7%. In contrast, the Southern and Border catchments have a weaker signal with respective differences of 3.3% and 6.9%.

To implement these observations within a stochastic model, a separate rainfall model is fitted to each IPO partition along with a method to indicate the dwell time in each state. The calibration to each state is performed independently. Unsurprisingly, the partition into two states impacts the parameter values of the chosen model so that the model in the IPO –ve state has parameters that result in wetter conditions than the parameters identified from the IPO +ve state. Here the latent variable model (Bennett et al., 2018) was used for the stochastic rainfall model. Two model parameters the mean μ and standard deviation σ of the latent variable rainfall are analysed to show the shift in values between states. A simulation was conducted to demonstrate that the stochastic data is able to replicate the same shift between the climate states as the observed data, whereby each site has a different signal strength.

Although there are inherent uncertainties associated with estimating IPO phases, this method is able to represent multi-annual persistence in the climate, which is an important outcome for assessing risks associated with water resource management and planning.

Keywords: *Stochastic rainfall model, IPO, climate partitions*

1. INTRODUCTION

Climate variability is a significant and well-known contributor to variations in streamflow. Climatic variation in hydrologic variables has been demonstrated at inter-annual and inter-decadal scales (Nalley et al. 2016). The persistence of climatic states poses a significant challenge for methods seeking to estimate risks associated with the abundance and flux of water in the landscape. Stochastic models are an important tool for assessing hydroclimatic risks by generating a range of synthetic climatic conditions that are equally likely to occur as those observed in the past (Moraga et al. 2022). Stochastic modelling approach can incorporate climatic partitions to account for the persistence of the climate at inter-annual and inter-decadal timescales.

In Australia, there is significant variation in the strength of the climatic influence for different catchments. Extensive records of sea-surface temperatures, pressure differences and other oceanic variables have been used to explore these underlying relationships across the catchments, including the use of indices such as the Southern Oscillation Index (SOI) in the Pacific Ocean, the Dipole Mode Index (DMI) of the Indian Ocean and the Interdecadal Pacific Oscillation (IPO) (Leonard 2010). Numerous studies have investigated the role of inter-annual climatic variability in Australian hydrologic records (Chiew et al. 1998; Simmonds and Hope 1997; Verdon and Franks 2005). With respect to extreme values, Franks and Kuczera (2002) found that the distribution of extreme values differed significantly due to a shift in the IPO in 1945 across 41 streamflow records in New South Wales. Kiem et al. (2003) studied ENSO using a regional flood index based on 40 streamflow sites across for New South Wales and found that flood-risk levels are strongly linked to both ENSO and IPO. The links between ENSO and IPO were emphasised using reconstructed paleo-climate records over a 400 year period (Verdon and Franks 2006). The role of IPO was identified in modulating eastern Australian droughts (Palmer et al. 2015). These studies demonstrate that the IPO (which is based upon multidecadal variations in sea surface temperatures in the Pacific Ocean) is associated with multi-decadal climate cycles in Australian rainfall and streamflow that influence flood and drought risk.

The objective of this paper is to demonstrate a method for accommodating climatic influences within a stochastic model over a large region. The discussion will explore implications of climatic variability while considering the climate partitions based on the IPO index.

2. METHOD

Climate data for the input of stochastic modelling were integrated from observed historical data (since the 1980s) and paleoclimate data (obtained from sources such as tree rings, ice cores, cave deposits, and coral growth) (Figure 1). This was followed by the climate partition process based on the IPO index. In other words, the IPO driver is employed to induce multi-annual and decadal memory via an alternating sequence of either the IPO positive or negative phase, each having varying lengths. Next, the partitioned climate data were applied to generate 10,000-year time series of stochastic rainfall data for a large number of sites. The study used the stochastic rainfall model of Bennett et al. (2018), which utilises the latent-variable approach to simulate rainfall occurrences and amounts. A comparison between the IPO +ve and IPO –ve states was conducted to demonstrate the importance of climatic influences on stochastic modelling.

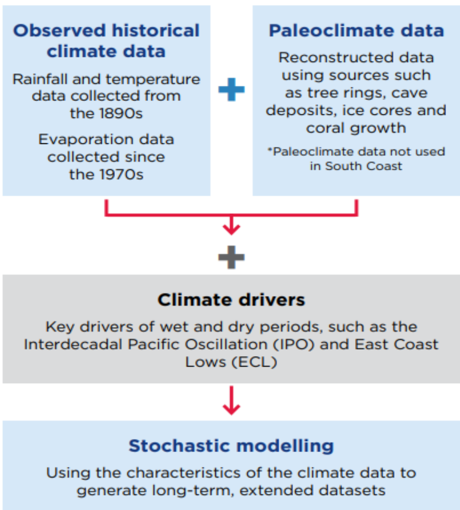

Figure 1. Use of IPO for stochastic models

2.1. Climate partition based on the IPO index

The IPO data in this study was obtained for the period 1854-2018 using the IPO index from Henley et al. (2015). The Hadley SST version of the IPO was used, which displays positive and negative states of the IPO in different periods (Figure 2). As estimates are not available in the first/last 5 years of the record because the IPO is designed as a low-pass filter, the state of the IPO in 2012 was assumed for the period out to 2018 rather than excluding this period from the calibration. The IPO was used to partition data and calibrate the model separately for each partition. The partition years for the positive phase are 1877-1888, 1896-1907, 1912-1942, 1978-1997, while the negative phase includes 1889-1895, 1908-1911, 1943-1977, 1998-2012 (+ 2013-2018 assumed).

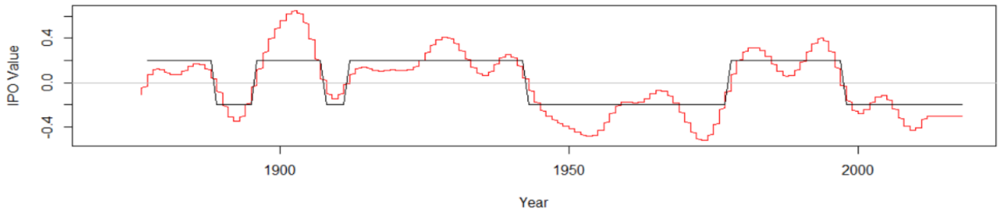

Figure 2. Timeseries of the IPO (red) showing positive and negative states (black)

Henley et al. (2011) developed a weighted average of seven paleoclimatic timeseries, including tree rings and coral from about the Pacific Ocean, to produce a combined paleo IPO signal (referred to as the CPIPO index). A comparison between the instrumental IPO timeseries and the CPIPO timeseries shows a favourable comparison (Nash Sutcliffe efficiency, 0.75, and comparable distributions of run-lengths) (Henley et al., 2011). The distribution of run lengths was analysed to identify the gamma distribution as the most appropriate model to represent the dwell time in each IPO phase. It can be seen from Figure 3, the dwell-times distribution of CPIPO exhibits a lower mean but higher variance than that of the instrumental IPO.

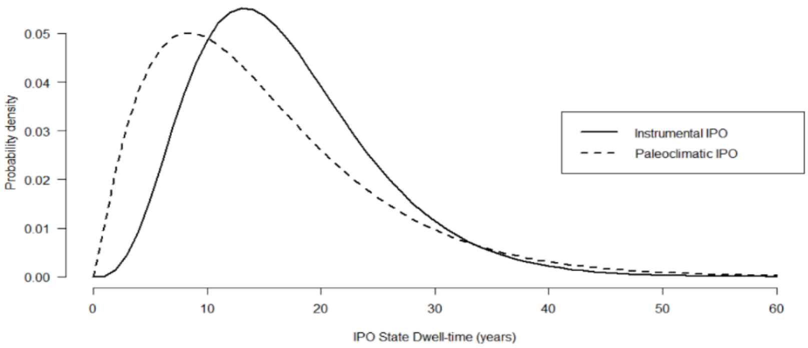

Figure 3. Distribution of dwell-times for the IPO phases (from Henley et al. 2011)

The Henley et al. (2011) model is at the annual timescale and is used to generate long timeseries of alternating IPO states. The Bennet et al. (2018) model simulates at the daily timescale, but is calibrated to separate IPO phases so that relevant parameters are simulated depending upon the state. The modelling approach assumes that the IPO timeseries is stationary, dwelling an equal amount of time in each state. It is worth noting that recent results by Vance et al. (2022) suggest that this assumption may be limited, but further work is required to confirm that result with additional records.

2.2. Application

The impacts of IPO partitions are considered for the Murray Darling Basin in New South Wales and Queensland. There are 8 catchments in total in this region, including Border, Gwydir, Lachlan, Macquarie, Namoi, Queensland, Southern, and Western. This studied area has 949 precipitation sites and 796 evaporation sites, distributed throughout the region, with a denser distribution in the east and south (Figure 4). While the Bennet et al. (2018) model incorporates correlation across all basins, the reporting in this paper focuses on the marginal differences between states rather than the spatial correlation.

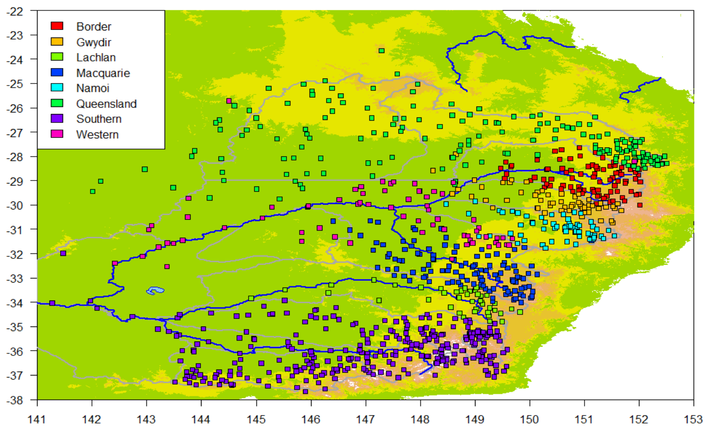

Figure 4. Location of rainfall sites by catchments in New South Wales

2.3. Analysis of IPO partitioned rainfall

Partitioning the rainfall timeseries by the IPO demonstrates a systematic shift in amounts between the two climate states through the region. The average difference by catchments in annual rainfall between the IPO states is summarized in Table 1. The highest percent difference between the IPO and non-IPO models occurred in the Western region (13.6%), then the Macquarie (11.9%) and Namoi (10.7%). The Southern region has the lowest percent difference at 3.3%.

Table 1. Summary of average difference by catchments in annual rainfall between the IPO states and corresponding percentage difference relative to the mean annual rainfall

Catchment	Annual rainfall difference (mm)	Difference (%)
Border	47.0	6.9
Gwydir	64.3	9.1
Lachlan	63.0	9.2
Macquarie	75.0	11.9
Namoi	74.1	10.7
Queensland	48.4	8.3
Southern	25.4	3.3
Western	58.9	13.6

The spatial distribution of the influence of the IPO is shown in Figure 5. The color of each point represents the difference between the annual total rainfall within the IPO+ and IPO– states relative to the overall annual rainfall total from the entire period, i.e. a relative difference. There is a clear spatial pattern, with catchments along the NSW coastline and in the southern region showing little difference while sites in the interior region across NSW show a strong difference.

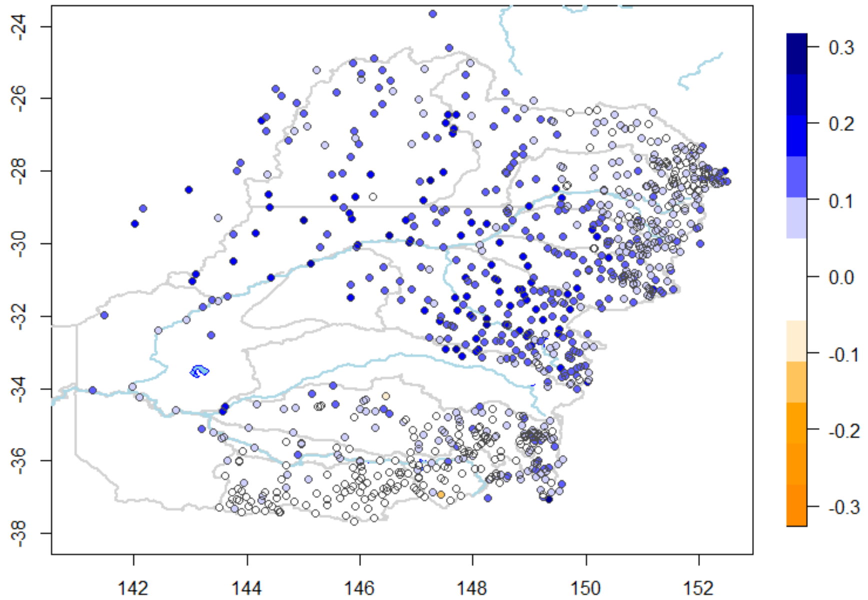

Figure 5. Spatial distribution of IPO rainfall data across the region. Blue points represent the positive impacts of IPO, while the negative impacts of IPO are orange

3. RESULTS

3.1. Impacts of the IPO on calibration of stochastic rainfall models

The rainfall data corresponding to respective positive and negative IPO states are used to calibrate a stochastic rainfall model for each state. Figure 6 shows a comparison of differences in parameter values between the states for two parameters of the latent variable model, the mean μ and standard deviation of a normal distribution. Note that the latent variable model truncates simulated values below zero to represent dry days and because most locations typically have more than 50% dry days the parameter for the mean μ is negative (so that the area of the distribution below 0 mm exceeds 0.5). Comparing the 1:1 line and the regression line, the IPO– state results in parameters with a higher mean but a lower standard deviation. However, there is considerable scatter between the parameters for each site and there is parameter correlation between the mean and standard deviation parameter, such that it is not obvious that the parameters from the IPO– state result in wetter simulations. For this reason, the only way to evaluate the impact of the calibration is via an integrated method, i.e. by simulation of the identified parameters for each state and comparison to expected properties.

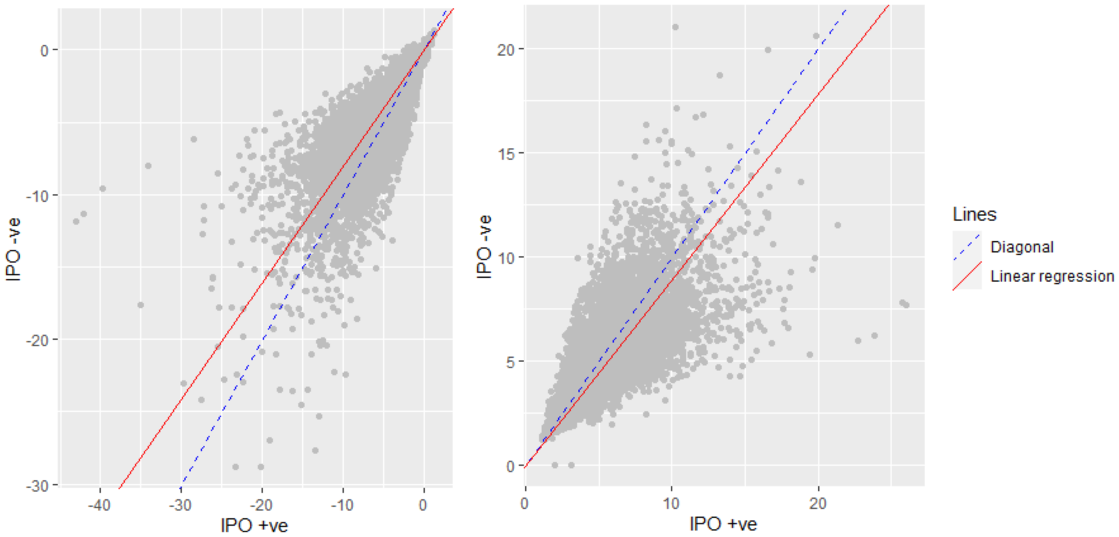

Figure 6. Change in the model parameters, mean μ (left) and standard deviation σ (right), due to a change in the IPO negative and positive phases

3.2. Stochastic simulation

The models for each state were simulated for 100 replicates. Figure 7 shows the annual rainfall totals in the IPO positive and negative states for both observed and simulated data, and that the model simulations are consistent across all the sites within each catchment. Specifically, Figure 7 shows the 95% confidence interval of mean values (referring to narrower blue and red shaded regions) and the 95% confidence of all annual totals (referring to wider light blue and light red shaded regions) for two IPO negative and positive states respectively. In general, there is a strong rainfall gradient and significant variation from year to year. Within a single year, annual rainfall totals can range from less than 200 mm to more than 1800 mm. Note that the last two subfigures show a larger range due to higher rainfall in those regions.

From Figure 7, it is clear there is a difference in the simulated mean for each state that matches the observations, but also that there is considerable overlap in magnitude between the states, emphasizing that the difference is mostly observed *on average*. The main feature of the stochastic simulation (not shown in Figure 7) is that the climatic states persist so that the respectively wetter and drier conditions (on average) occur over multiple years in a row.

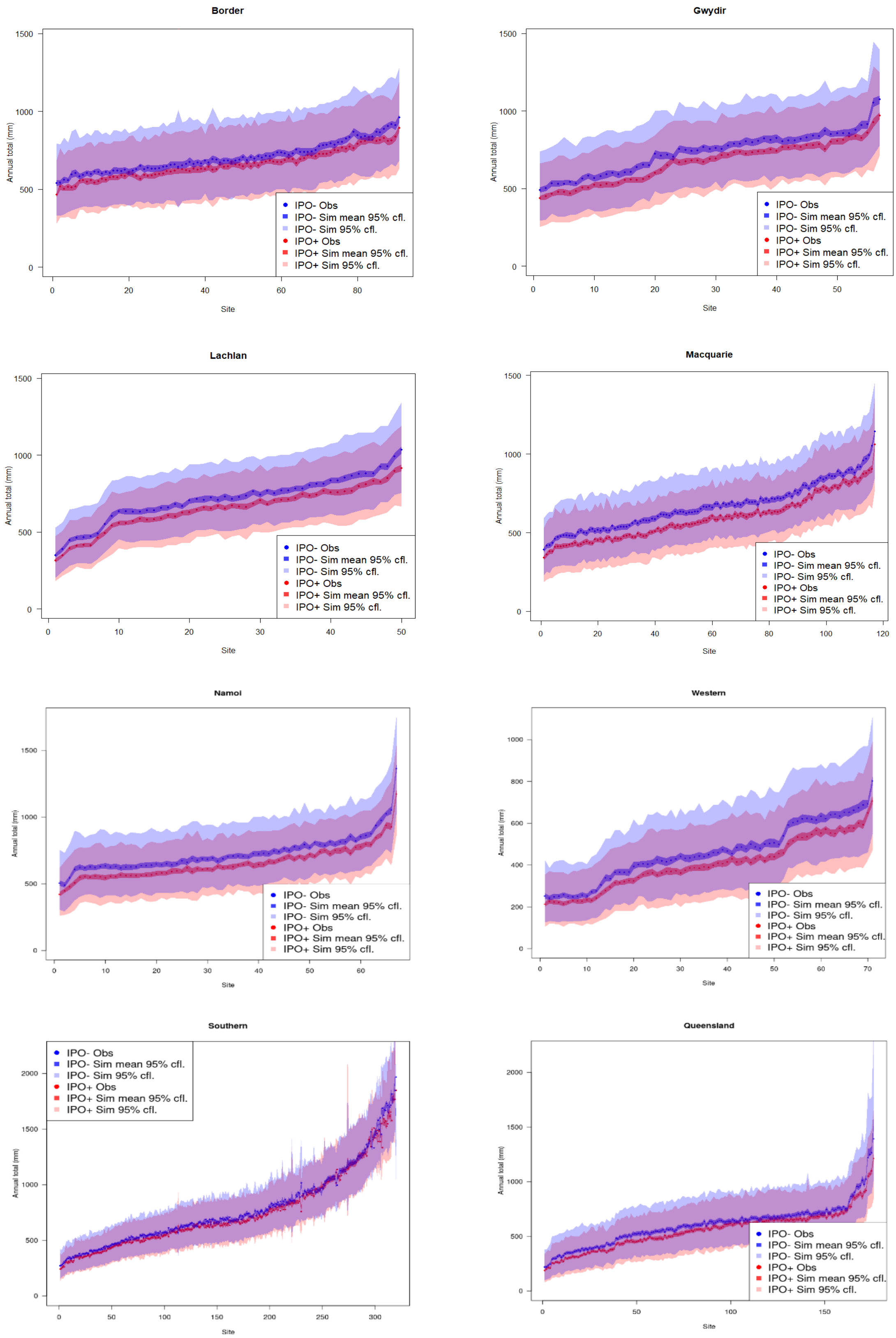

Figure 7. Annual rainfall totals at the sites of each catchment sorted in ascending order. Each vertical bar represents 1 site

4. DISCUSSION AND CONCLUSION

A stochastic rainfall model was calibrated using observed data from each of two IPO states, corresponding to respectively wetter and drier conditions. Combined with a model that can stochastically simulate the dwell time in each state, this provides a structure that increases the likelihood of dry or wet multi-year sequences compared to what would happen from randomly selecting monthly data from the historical record alone. The ability for climatic states to persist represents a valuable outcome from a stochastic model, since numerous hydrological risks are strongly linked to the influence of climate variability and persistence (such as the impact of drought on a reservoir).

The impact of using climatic partitions in a stochastic model is directly proportional to the influence of an index on observed timeseries. For locations where there is little difference between climate states, the models within each state become increasingly similar, leading to negligible impact from their use. Where there are multiple climate drivers, there needs to be further consideration of the benefits of partitioning data according to more states, since there is an increase in the number of parameters and the amount of data per partition to be able to identify those parameters. In other words, model selection and the relevance of identified climate states is an important element of the design of any stochastic model.

ACKNOWLEDGEMENTS

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