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Comparing instrumental, palaeoclimate, and projected rainfall data: Implications for water resources management and hydrological modelling

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ABSTRACT

Study Region: The Lockyer Catchment, Queensland, Australia.
Study Focus: Future rainfall projections are usually presented as a percentage change from current climate, where current climate is defined using relatively short instrumental records. However, palaeoclimate reconstructions demonstrate that instrumental data does not capture the full range of climate variability that has occurred. Understanding natural climate variability, and how it compares to climate model projections for the future, requires the use of (a) instrumental and palaeoclimate data to quantify the range of historical variability and (b) climate model data to quantify if/how things could change in the future. Considering this, we compare instrumental, palaeoclimate, and projected rainfall statistics for the Lockyer Catchment.
New hydrologic insights for the region: We found that, in the Lockyer Catchment, instrumental data insufficiently captures past variability and plausible projections of rainfall decreases in the future. We also found that at mid-21st and late 21st century time periods decreases in annual average rainfall, rainfall variability, and ninetieth percentile rainfall outside the confines of instrumental and palaeoclimate variability are plausible. Also, when considering variability in the palaeoclimate record compounded with projected rainfall trends, much larger decreases in rainfall are plausible than when only considering instrumental and projected rainfall. The implications of these results are discussed in terms of (a) calculating the sustainable yield of water supply catchments and (b) estimating catchment runoff using hydrological models.

1. Introduction

In Australia, current water management plans and associated infrastructure have been developed using statistics derived from a relatively short ~100-year instrumental record (Franks, 2002; Verdon-Kidd and Kiem, 2010). However, interannual to multidecadal fluctuations in various oceanatmospheric processes (e.g. El Niño/Southern Oscillation (ENSO), Interdecadal Pacific Oscillation (IPO)), the complex interactions between such processes, and the various spatial and temporal rainfall responses to such interactions highlight the need for more extensive data describing the climate system than that available in the instrumental record (Verdon-Kidd and Kiem, 2009; Johnson et al., 2016; Kiem et al., 2016; Gergis and Henley, 2017).

Palaeoclimate reconstructions based on proxy data offer a potential solution to this issue, contextualising instrumental climate

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and providing more robust baseline statistics that describe the climate system (Griffin and Anchukaitis, 2014; Ho et al., 2015; Vance et al., 2015). These reconstructions can be inferred using local proxy data (i.e. tree rings (Allen et al., 2019), coral luminescence (Lough, 2011)), remote proxy data (i.e. ice core snow accumulation (van Ommen and Morgan, 2010v; Vance et al., 2013; Tozer et al., 2016)), or a combination of both (Palmer et al., 2015; Freund et al., 2017). These independently sourced palaeoclimate reconstructions can provide multiple lines of evidence regarding the nature of past climate variability (Kiem et al., 2016).

Australian reconstructions extending beyond the last 500 years show that the wet and dry epochs observed in the instrumental record are not unprecedented (in terms of duration, severity, and intensity) and are within the confines of natural variability (Verdon-Kidd et al., 2017; Palmer et al., 2015; Vance et al., 2015; Tozer et al., 2016). For example, Vance et al., 2015 identified the occurrence of eight 'megadroughts' (> 5 years) in southeastern Australia over the last millennium (the longest being 39 years). Given droughts of this severity have not occurred in the instrumental period, this highlights limitations with using instrumental data to calculate hydroclimatic risk when developing water management plans and infrastructure (Tozer et al., 2018).

Considering this recent research, the translation of palaeoclimate information into a useful format for water managers has been identified as a key future research area in Australian flood and drought adaptation (Johnson et al., 2016; Kiem et al., 2016). However, incorporating palaeoclimate data into the development and testing of water management plans comes with unique challenges. Issues such as the unavailability of palaeoclimate records that are statistically related to climate in a specific catchment, palaeoclimate records of insufficient length to record the full extent of natural variability, and palaeoclimate records of unsuitable format for inclusion in hydrological models are barriers to the application of palaeoclimate data in water management (Tingstad et al., 2014). Such issues need to be directly accounted for if water management strategies are to be robust under natural climate variability into the future.

Although palaeoclimate reconstructions provide helpful insights regarding the extent of natural climate variability, consideration of past climate alone does not necessarily equate to a secure water source in the future. How anthropogenic climate change will influence future rainfall in relation to variability in the instrumental and palaeoclimate reconstructions must also be considered (Kiem and Verdon-Kidd, 2011). Such information is obtained from Global Climate Models (GCMs), the main tools for projecting future climate.

The various GCM rainfall projections for Australia differ in sign and magnitude and, at regional scales, are biased. For example, annual rainfall in southeast Queensland is projected to change -4.8 ± 22.1 % by 2090 under a high emissions future (Irving et al., 2012) (further examples of Australian rainfall projection uncertainty can be found in Grose et al., 2015 and Dowdy et al., 2015). GCMs also simulate climate at a relatively coarse horizontal resolution (~200 km x 200 km), so cannot properly account for sub-grid scale processes (such as topographical heterogeneities and convective cloud processes) that influence regional rainfall (Rummukainen, 2010). Hence, rainfall processes are parameterised, which can cause uncertainty between models and bias with respect to observations.

GCM rainfall projections are also typically presented as a percent change with respect to a subset of rainfall in the instrumental record. For example, the latest Intergovernmental Panel on Climate Change (IPCC) report examined projected rainfall changes with respect to a 1986–2005 baseline (Collins et al., 2013). Projections are rarely analyzed with respect to natural variability evident in the palaeoclimate record (or even the full range of variability evident in the instrumental record). Given that palaeoclimate reconstructions typically reveal past natural climate variability not captured in the instrumental record, analysing projected climate change within a palaeoclimate context provides greater insights as to how climate may change in future with respect to the past.

Ault et al. (2014) provides an example of how palaeoclimate, projected, and instrumental data can be better used to characterise drought risk. When all available hydroclimatic data (i.e. instrumental, palaeoclimate, and projected) was considered, they calculated an 80 % chance of multi-decadal drought occurring in the southwest United States over the next century (which was previously thought to be 50 % when only instrumental and projected rainfall were considered). In an Australian based study, Cook et al. (2016) examined the future trajectory of east Australian hydroclimatic extremes within the context of the Australia and New Zealand Summer Drought Atlas (ANZDA) of Palmer et al. (2015), a palaeoclimate reconstruction of the Palmer Drought Severity Index (PDSI). In late-21st century projections for coastal Queensland, the probability of a PDSI value equal to or drier than the lowest value in the ANZDA (which had an instrumental period probability of < 1 %) was found to be 5 %.

These studies highlight the utility of analysing projected climate change within a context of natural variability in the palaeoclimate record, and suggest limitations with approaches that analyse GCM projections with respect to an instrumental record subset. If the instrumental record does not capture the full extent of past hydroclimatic variability, how can anthropogenic influences on hydroclimate be understood if comparing projections to instrumental record subsets? Limited research has been conducted analysing GCM projections within context of the longer-term past, particularly at the catchment scale that water management decisions are made.

Examining how rainfall has changed prior to the instrumental period and how it might change in the future under global warming also has significant implications for our understanding of the rainfall-runoff relationship (and therefore catchment yields). Traditional water management approaches have considered this relationship stationary, meaning that for a particular catchment the proportion of unit runoff change per unit rainfall change is constant. However, for some catchments, the strength of the rainfall-runoff relationship will vary (i.e. is non-stationary) (Saft et al., 2015). As these non-stationarities have been identified during the instrumental period, if pre-instrumental variability and GCM projection uncertainty are outside the confines of instrumental variability limitations with treating the rainfall-runoff relationship as stationary will be amplified.

Understanding the physical processes driving non-stationary rainfall-runoff relationships is an ongoing area of research. Although climate variability plays an important role, the internal catchment responses to climate variability (which will vary between catchments) have a greater influence on rainfall-runoff non-stationarity (Saft et al., 2016; Deb et al., 2019b). For example, variations

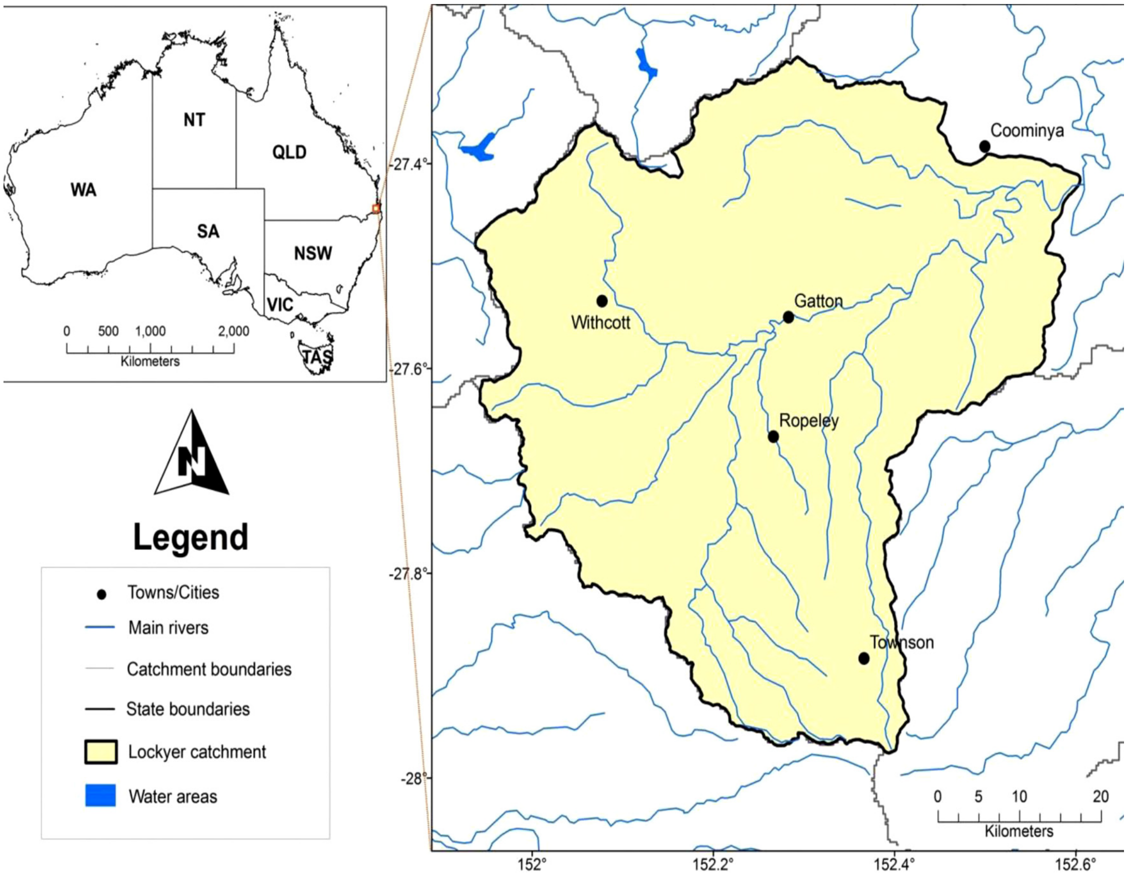

Fig. 1. The Lockyer Catchment (study site).

in the interactions between surface water (SW) and groundwater (GW), whereby fluctuations in the groundwater table can change the sign of the groundwater contributions to the surface water (i.e. change from a "loosing stream" to a "gaining stream") can drive variations in the rainfall-runoff relationship (Deb et al., 2019a, 2019b). Changes in vegetation cover and behaviour under climate variability (Ajami et al., 2017) or enhanced atmospheric $C0_2$ (Chiew et al., 2014) may also contribute to observed rainfall-runoff non-stationarity.

The dynamic response of internal catchment processes to climate variability, which drive non-stationary rainfall-runoff relationships, can explain the difficulties in extrapolating observed catchment behaviour to different climate conditions (a significant problem in assessing future water system performance). Therefore, in order to better understand the roles that these processes may have in estimating future runoff, quantifying the range of possible catchment climates (both past and future) is crucial. As such, the aim of this study is to compare past (instrumental and palaeoclimate) rainfall variability and future rainfall projections in the Lockyer Catchment, Queensland, Australia (Fig. 1). This catchment was selected because:

- Catchment rainfall varies at interannual and multidecadal time scales (Power et al., 1999).
- The rainfall-runoff relationship in the catchment in non-stationary (Cui et al., 2018).
- Instrumental, palaeoclimate, and projected rainfall data are available for the catchment (Vance et al., 2013; Kiem et al., 2020).

The comparison of instrumental, palaeoclimate, and projected rainfall data is the first step in assessing the strength of current water management strategies and informing the development of robust adaptation strategies that ensure water security under climate variability and change. In this study, we will examine if the instrumental record in the Lockyer Catchment captures natural variability in the palaeoclimate record and if projected changes in future rainfall are within or outside the confines of instrumental/palaeoclimate variability. The implications of this analysis for water management strategies developed using instrumental data and for current hydrological modelling practices are then discussed. Although our analysis is focused on Lockyer Catchment rainfall, the results and implications of this study can be generalised to other catchments with a) climate influenced by sources of interannual to multidecadal variability (e.g. ENSO, IPO) and b) non-stationary rainfall-runoff relationships.

2. Data

2.1. Instrumental period rainfall

An indication of rainfall experienced during the instrumental period was derived from the Australian Water Availability Project (AWAP) dataset, which provides gridded rainfall data across Australia at a 5 km spatial resolution (Raupach et al., 2009). The average of the AWAP rainfall grids lying within the Lockyer Catchment boundary was calculated from 1900 to 2015 and used for further analysis. This time series/period is hereafter referred to as “instrumental rainfall” and the “instrumental period” respectively throughout this paper.

2.2. Palaeoclimate rainfall reconstruction

The palaeoclimate rainfall reconstruction of Vance et al., 2015 was used for this study, providing area-averaged Lockyer Catchment annual rainfall from 1000 to 2012. Area-averaged rainfall was calculated by first reconstructing the individual AWAP grids lying within the catchment boundary (using a linear regression reconstruction model), then averaging the reconstructed grid values for each year.

The reconstruction is based upon a statistically significant correlation between east Australian rainfall and summer sea salt accumulation at the Law Dome ice core in East Antarctica, which are both influenced by atmospheric circulation patterns driven by ENSO/IPO variability (Vance et al., 2013, 2015). The correlation between the Law Dome proxy and Lockyer Catchment rainfall varies between IPO phases, with a statistically significant correlation during IPO positive (Pearson correlation of ∼0.41) and no significant correlation during IPO negative (Kiem et al., 2020). As such, this reconstruction can be used to analyse pre-instrumental rainfall during IPO positive phases which, in the Lockyer Catchment (and, in general, eastern Australia), are associated with dry conditions (Power et al., 1999). For a more detailed analysis/explanation of the reconstruction used in this study, including a comparison of drought risk quantified using the instrumental rainfall record versus the ∼1000-year rainfall reconstruction, refer to Kiem et al., 2020.

Although there are other proxies/reconstructions that could have been used for this study, this reconstruction was selected as it a) captures a prolonged period of decreased rainfall occurring from ∼1000 to 1150 CE and b) is annually resolved. Annually resolved reconstructions derived from biological proxies (i.e. tree ring width, coral luminescence) were not considered as they were of insufficient length to capture this dry period and other east Australian reconstructions that did capture this dry period (i.e. Barr et al., 2019) were not annually resolved.

Statistics derived from the driest 116-year period (coinciding with the length of the AWAP time series) in the 1013 year reconstruction (1146–1261 CE, hereafter referred to as ‘Palaeo-Dry’) were used for further analysis.

2.3. Climate model rainfall projections

GCM simulations of rainfall were taken from the Coupled Model Intercomparison Project Phase 5 (CMIP5). CMIP5 provides a coordinated experimental framework under which GCMs are run (details available in Taylor et al., 2012). GCM simulations using Representative Concentration Pathways (RCPs) 2.6, 4.5 and 8.5 were examined in this study. Historical simulations of rainfall were taken from 1900 to 2005 (the time period with rainfall data overlapping instrumental rainfall). GCM future projections were separated into different time periods, 2041 – 2060 (mid-21st century climate) and 2081 – 2100 (late 21st century climate).

3. Methods

3.1. Climate model selection

Climate models were selected for this study using the Climate Change in Australia Climate Futures Detailed Projections Tool (available at https://www.climatechangeinaustralia.gov.au/en/climateprojections/climate-futures-tool/detailed-projections/). The Climate Futures Detailed Projections Tool provides the projected percent change in average annual rainfall for various RCP/time period (with respect to a 1986–2005 baseline) seen in CMIP5 GCMs over a region of interest (Clarke et al., 2011; Whetton et al., 2012). For each RCP/time period outlined in Section 3.3, we selected the CMIP5 model showing the greatest decrease in average

Table 1
Climate models selected for the study.

Scenario	Driest Model
RCP2.6 Mid Century (2041 – 2060)	GFDL-ESM2M
RCP2.6 Late Century (2081 – 2100)	MPI-ESM-MR
RCP4.5 Mid Century (2041 – 2060)	MPI-ESM-MR
RCP4.5 Late Century (2081 – 2100)	GFDL-CM3
RCP8.5 Mid Century (2041 – 2060)	MPI-ESM-MR
RCP8.5 Late Century (2081 – 2100)	GFDL-ESM2M

annual rainfall for the region covering the Lockyer Catchment (Table 1). GCMs explicitly advised against use as a representative model for the region on the CCIA website (https://www.climatechangeinaustralia.gov.au/en/, recommendations on this website are based on the comprehensive model evaluation study of Moise et al., 2015), were not considered.

This approach captured the lowest plausible bound on GCM uncertainty for each scenario/time period. Note that, for some GCMs, the same CMIP5 experiments (i.e. RCP8.5, historical) have been simulated with different initial states, start-up methods, and physics scheme parameterisations. For this analysis, the choice of ensemble member had little influence on the resultant projection statistics (see Table S1 in the Supplementary Material). As such, if a GCM had multiple ensemble members for either the historical or future simulations, the first ensemble member (denoted as r1i1p1 using the 'rip' nomenclature associated with each GCM simulation) was selected for further analysis. For each time period, we also analysed projected data for the next driest model (see Table S3 and Table S4 in the Supplementary Material) – these projections were similar to those from the models shown in Table 1.

Given the relatively small size of the study catchment (relative to the coarse horizontal resolution of GCM grids), downscaled projections could better capture spatial changes in rainfall. However, considering that the application of different statistical or dynamical downscaling methods does not provide a consistent projection signal different from the CMIP5 ensemble in eastern Australia (Grose et al., 2015), and that downscaling adds little value to coarser resolution gridded data for the study area (Di Virgilio et al., 2020), downscaled climate model projections were not considered. Although we did not use downscaled projections, it should be noted that specific downscaling methods may introduce greater rainfall projection uncertainty in eastern Australia than that evident in the CMIP5 GCM ensemble (Grose et al., 2015). For an in-depth look at climate model projections for the study area, we refer the reader to Grose et al. (2015) and Grose et al. (2020).

Please note that in subsequent post-processing, stochastic modelling, and analysis of the projected data we are treating transient time slices (i.e. a small section of a trending time series) as a stable climate (i.e. has reached an equilibrium with no forced trend). This comes with limitations, as for a given RCP scenario the use of transient versus longer term projections (which have reached a quasi-equilibrium, for example the extended RCP experiments that continue out to 2300) can result in different estimates of regional climate variability (King et al., 2020). However, not all of the selected models have extended simulations that allow analysis of stable projected climates and we considered sampling the lower bound of GCM uncertainty to be more important for our study.

3.2. Post-processing of climate model rainfall data

Given the tendency for GCM simulations of instrumental period climate to have systematic biases in relation to observed climate values (i.e. instrumental measurements), and the assumption that this bias will hold for future projections, climate projections are typically post-processed to remove this bias (Johnson and Sharma, 2011; Teutschbein and Seibert, 2012; Nguyen et al., 2017). This study used a distribution-based Change Factor (CF) approach, at a quartile resolution, as a post-processing method (Chiew et al., 2003). This approach calculates the relative change in average rainfall (the CF) at quartile 'n' seen in the modelled future climate ($\mu_{MF)}$ with respect to that in the modelled historical (i.e. instrumental period) climate (μ_{MC}) (Eq. 1). The CF is then applied to the observed (AWAP) annual rainfall total 'P' in year 'x' within corresponding quartile 'n' to obtain a scaled rainfall time series (Eq. 2)

$$CF_{\mathrm{n}} = \mu_{MF,}\mathrm{F}_{\mathrm{n}}/\mu_{MC,\mathrm{n}} \tag{1}$$

$$P_{Scaled\mathrm{x,n}} = P_{observed\mathrm{x,n}} * CF_{\mathrm{n}} \tag{2}$$

The application of a CF was used in this study as a means of conserving the relative rainfall trends seen in the model projections while removing bias in the raw GCM outputs. Although the CF approach is not an explicit bias correction method, by applying the projected changes seen in GCM simulations to the instrumental period we remove the need to use raw GCM outputs and the biases that are associated with them. A distribution-based approach was implemented as it can better preserve any changes in variability present in model simulations (compared to mean-based approaches) (Yang et al., 2010; Anandhi et al., 2011). The CF approach is also one of the recommended methods for the creation of application-ready climate change data for use in detailed climate impact statements in Australia (CSIRO and Bureau of Meteorology, 2015), and has been used in numerous climate change impact studies (Kiem et al., 2008; Kirby et al., 2014; Mortazavi-Naeini et al., 2015).

CFs derived from all GCM scenarios presented in Table 1 were applied to the instrumental (instrumental period catchment average from 1900 to 2015) and 'Palaeo-Dry' (reconstructed catchment average from 1146 to 1261 CE) rainfall time series. This accounts for the natural variability in the instrumental/palaeoclimate records compounded with the largest plausible rainfall trend seen in GCM projections and allowed a comparison of plausible 'worst case' scenarios (i.e. the difference in the most extreme climate change projections applied to the instrumental record compared to climate change projections applied to the combined instrumental and palaeoclimate record). The underlying assumption is that climate variability seen in the instrumental/palaeoclimate records can occur in the future, and that it is reasonable to superimpose climate model trends on this climate variability. More specifically, we are assuming that the regional rainfall response to increased atmospheric $C0_2$ would have been the same for the instrumental and 'Palaeo-Dry' time periods.

3.3. Comparing instrumental, Palaeoclimate, and projected rainfall statistics

10,000 stochastic replicates 116-years in length were generated for historical (instrumental, 'Palaeo', 'Palaeo-Dry') and post-processed rainfall time series using the freely available eWater Stochastic Climate Library (SCL, https://toolkit.ewater.org.au/Tools/Default.aspx). The SCL uses an annual, first order autoregressive model that has been tested for use in Australian climate (Srikanthan et al., 2002). Model parameter uncertainty is explicitly accounted for when generating replicates with the SCL (using the method of Thyer et al., 2002), which allowed the characterisation/comparison of the uncertainty in different rainfall statistics.

Sampling distributions of mean, standard deviation, 10th percentile annual rainfall total, and 90th percentile annual rainfall total were calculated from stochastic replicates of each data set. All sampling distributions reproduced the corresponding statistic from the respective modelled time series. 95 % confidence intervals of each sampling distribution were calculated by identifying respective 2.5 and 97.5 percentile values. Palaeoclimate and projected sampling distributions with confidence bounds outside those calculated from the corresponding instrumental distribution were noted. It is important to note that the focus here is on annual statistics (because SCL uses only lag-1 autocorrelation) and further research is required to ensure that interannual to multidecadal persistence of dry events is realistically captured in the stochastic replicates.

A Perkins Skill Score (PSS) (Perkins et al., 2007) was also used to compare the sampling distributions of both palaeoclimate and projected data with the corresponding instrumental distribution. The PSS measures the proportion with which two distributions overlap. A score of zero means there is no overlap between distributions and a score of one means that the two distributions overlap perfectly. In order to calculate the PSS, instrumental and “Palaeo-Dry”/projected sampling distributions were binned in increments of ten, the proportion of samples (out of a total of 10,000) contained in each respective bin was calculated, and the minimum proportion found for each overlapping bin was then summed. Eq. 3 displays the PSS formula used in this study:

$$\Sigma_1^n \text{minimum}(\text{Proportion}_{\text{instrumnetal}}, \text{Proportion}_{\text{Palaeo-Dry/Projected}}) \tag{3}$$

Where n is the number of bins.

4. Results

The sampling distributions and 95 % confidence intervals for mean, standard deviation, 10th percentile annual rainfall, and 90th percentile rainfall for different scenarios in the Lockyer Catchment are shown in Fig. 2 and Table 2 respectively. When examining these results, the following observations can be made:

- Decreases in mean and ninetieth percentile total outside the confines of instrumental and palaeoclimate variability are plausible for each RCP/time period analysed, regardless of the historical data set (i.e. instrumental or Palaeo-Dry) to which the CF was applied. Applying a CF to the driest 116-year period in the palaeoclimate record resulted in much larger decreases in mean and

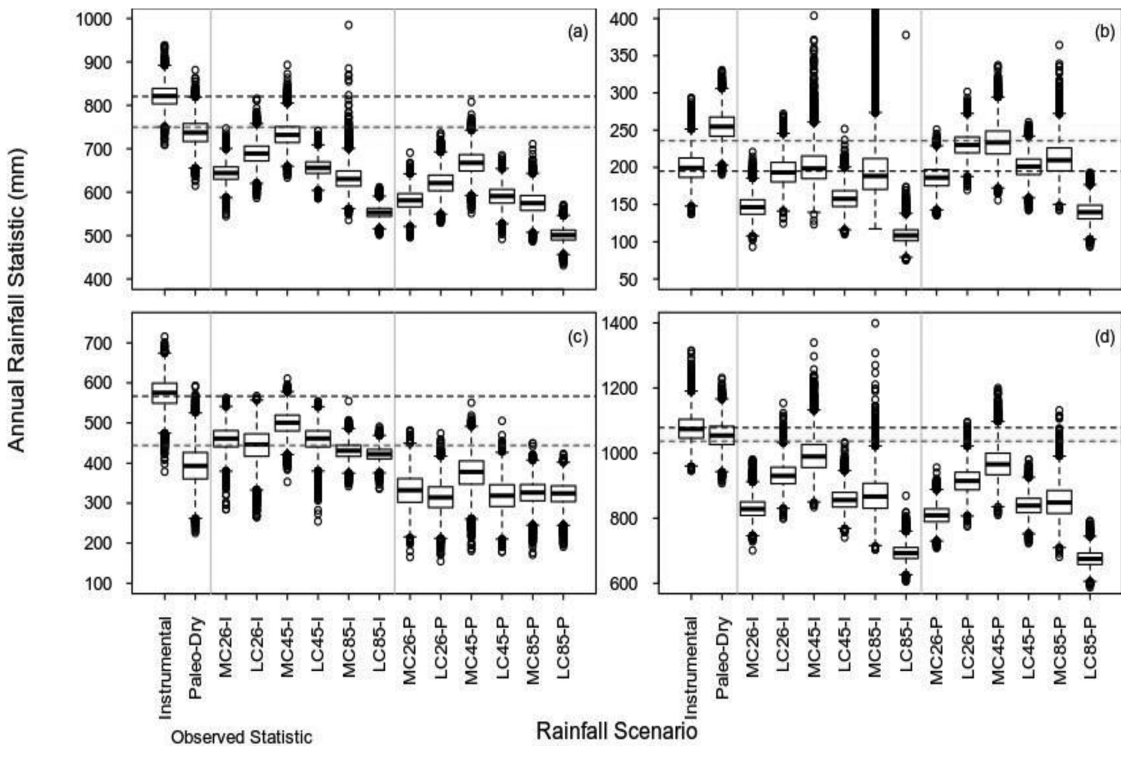

Fig. 2. Sampling distributions for annual (a) mean; (b) standard deviation; (c) tenth percentile total and; (d) ninetieth percentile total rainfall for different rainfall scenarios in the Lockyer Catchment. MC and LC denote mid-21st century and late-21st century time periods; 26, 45, and 85 denote respective RCP scenarios; and I and P denote the historical data set (instrumental or Palaeo-Dry) to which the driest plausible model trends were applied using a change factor.

Table 2
95 % confidence intervals of sampling distributions for different annual rainfall scenario statistics in the Lockyer Catchment. Also shown are the Perkins Skill Scores obtained when comparing respective sampling distributions with the corresponding instrumental sampling distribution. Confidence intervals lower than the 2.5 percentile value in the corresponding instrumental (palaeo-dry) sampling distribution percentile are shown in bold (italicised). Semi-colons separate confidence intervals/skill scores for instrumental/Palaeo-Dry rainfall scenarios compounded with projected rainfall trends.

Statistic	Scenario	95 % Confidence Interval	PSS
Mean	Instrumental	[770, 873]	1
	Palaeo-Dry	[**677**, 799]	0.139
	RCP2.6 Mid Century$_{(I;P)}$	[***602***, ***688***] ; [***537***, ***625***]	0.009 ; 0
	RCP2.6 Late Century$_{(I;P)}$	[***637***, **742**] ; [***568***, **678**]	0.0149 ; 0.006
	RCP4.5 Mid Century$_{(I;P)}$	[**681**, 790] ; [***612***, **723**]	0.1075 ; 0.0069
	RCP4.5 Late Century$_{(I;P)}$	[***618***, **696**] ; [***544***, ***639***]	0.0011 ; 0
	RCP8.5 Mid Century$_{(I;P)}$	[***585***, 694] ; [***526***, ***628***]	0.0049 ; 0.001
	RCP8.5 Late Century$_{(I;P)}$	[***527*** ; ***583***] ; [***468***, ***535***]	0 ; 0
Standard Deviation	Instrumental	[163, 243]	1
	Palaeo-Dry	[218, 294]	0.1687
	RCP2.6 Mid Century$_{(I;P)}$	[***120***, *179*] ; [***156***, 218]	0.1233 ; 0.7110
	RCP2.6 Late Century$_{(I;P)}$	[***158***, 235] ; [*200*, 263]	0.8785 ; 0.9302
	RCP4.5 Mid Century$_{(I;P)}$	[***161***, 261] ; [*193*, 282]	0.9302 ; 0.4249
	RCP4.5 Late Century$_{(I;P)}$	[***130***, *192*] ; [*170*, 232]	0.2505 ; 0.8875
	RCP8.5 Mid Century$_{(I;P)}$	[***145***, 317] ; [*171.2*, 265]	0.6969 ; 0.7979
	RCP8.5 Late Century$_{(I;P)}$	[***89***, ***134***] ; [***115***, 163]	0.0057 ; 0.0767
Tenth Percentile Total	Instrumental	[493, 643]	1
	Palaeo-Dry	[**300**, 493]	0.0516
	RCP2.6 Mid Century$_{(I;P)}$	[**394**, 517] ; [***251***, **414**]	0.0954 ; 0.0041
	RCP2.6 Late Century$_{(I;P)}$	[**343**, 520] ; [***241***, **390**]	0.0989 ; 0.0024
	RCP4.5 Mid Century$_{(I;P)}$	[**439**, 556] ; [***281***, **455**]	0.2630 ; 0.0180
	RCP4.5 Late Century$_{(I;P)}$	[**392**, 513] ; [***244***, **401**]	0.0850 ; 0.0033
	RCP8.5 Mid Century$_{(I;P)}$	[**388**, **471**] ; [***263***, **384**]	0.0234 ; 0.0009
	RCP8.5 Late Century$_{(I;P)}$	[**385**, **455**] ; [***256***,**377**]	0.0112 ; 0.005
90th Percentile Total	Instrumental	[997, 1171]	1
	Palaeo-Dry	[**974**, 1142]	0.813
	RCP2.6 Mid Century$_{(I;P)}$	[***772***, ***901***] ; [***752***, ***870***]	0.0019 ; 0.001
	RCP2.6 Late Century$_{(I;P)}$	[***860***, 1018] ; [***854***, 999]	0.0829 ; 0.0516
	RCP4.5 Mid Century$_{(I;P)}$	[***899***, 1113] ; [***879***, 1074]	0.3714 ; 0.2396
	RCP4.5 Late Century$_{(I;P)}$	[***797***, ***930***] ; [***777***, ***908***]	0.0057 ; 0.0017
	RCP8.5 Mid Century$_{(I;P)}$	[***771***, 1008] ; [***757***, ***966***]	0.0526 ; 0.0227
	RCP8.5 Late Century$_{(I;P)}$	[***647***, ***751***] ; [***627***, ***732***]	0 ; 0

tenth percentile rainfall than applying a CF to the instrumental record.

- Decreases in mean and ninetieth percentile total rainfall outside the confines of instrumental variability were observed in the palaeoclimate record outside the confines
- A lower standard deviation was observed in the instrumental record than in the driest 116-year period in the palaeoclimate record

Also shown in Table 2 are the PSSs obtained when comparing sampling distributions for palaeoclimate/projected rainfall scenarios with the corresponding instrumental period sampling distribution. Note that the PSS calculates the proportion of overlap between sampling distributions, with a score of 1 meaning total overlap, and a score of 0 meaning no overlap.

When comparing Palaeo-Dry and instrumental sampling distributions, mean, standard deviation and tenth percentile rainfall distributions shared 13.9 %, 16.9 % and 5.1 % overlap respectively, whereas ninetieth percentile rainfall distributions shared 81.3 % overlap. When comparing future scenarios with the instrumental record, both late-21st century RCP8.5 mean rainfall sampling distributions had no overlap with the instrumental mean rainfall sampling distribution (i.e. a PSS of 0). Out of all future scenarios, the mean sampling distribution for mid-21st century RCP4.5 (with the CF applied to the instrumental record) had the highest proportion of overlap with the corresponding instrumental distribution with ~11 %. For each statistic analysed, all late-21st century RCP8.5 sampling distributions had less than 10 % overlap with the corresponding instrumental sampling distribution. Such small percentages of overlap highlight the limitations of assuming instrumental period climate is representative of future climate.

An example of the divergent sampling distributions possible over the same catchment is shown in Fig. 3. Displaying the mean sampling distributions for instrumental, Palaeo-Dry, and the trends seen in the driest late-21st century RCP8.5 simulation superimposed on instrumental/Palaeo-Dry time series', it is shown that even considering parametric uncertainty in the instrumental record may not capture any of the plausible mean climate states that could arise if rainfall were to follow the trends in the driest CMIP5 model. It also shows that even driest ~100 year period in the palaeoclimate record may not capture the lower bound of GCM projection uncertainty. Like Figs. 2, 3 also demonstrates larger projection uncertainty if applying climate model trends to palaeoclimate data, instead of only applying to instrumental data as per common practice.

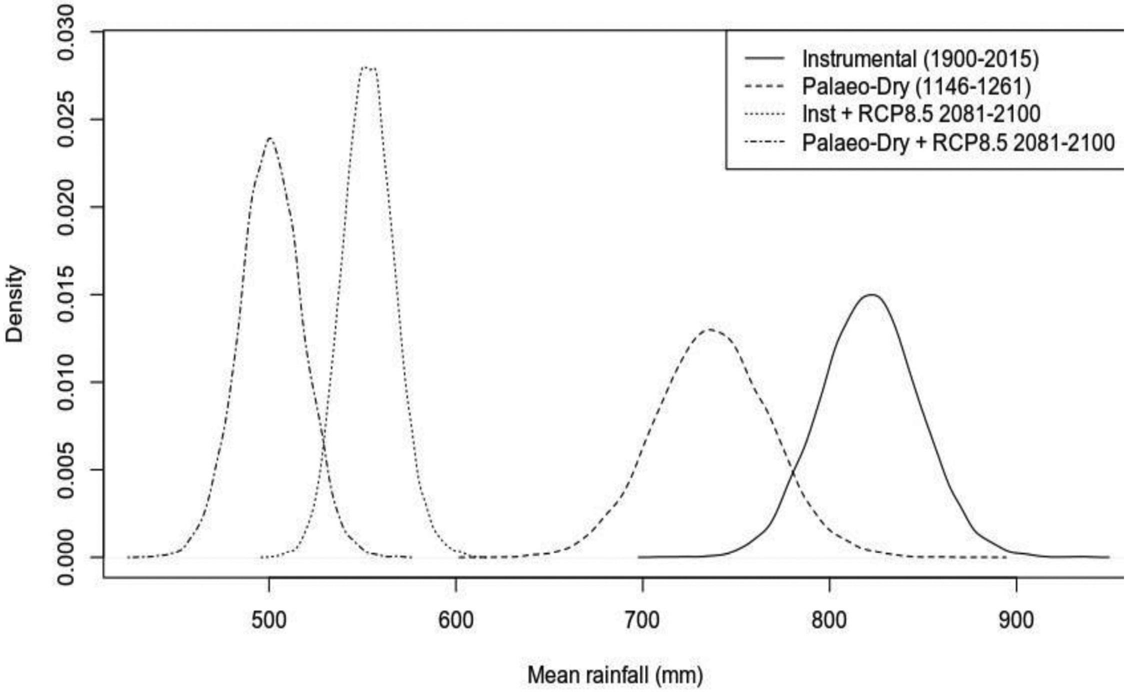

Fig. 3. Sampling distributions of mean annual rainfall for different rainfall scenarios in the Lockyer Catchment. Sampling distributions for future scenarios were obtained by applying the largest plausible decreasing trend in the CMIP5 ensemble for the study region to the instrumental and palaeoclimate data sets.

5. Discussion

The results show that changes in climate state outside that experienced in the instrumental record are plausible now and into the future. Given that such large changes are evident in both the palaeoclimate record and in climate model projections, water management strategies developed using only instrumental data will underestimate current/future hydroclimatic risk. This has implications for current and future performance of water management systems and the estimates of sustainable yield underpinning water supply system operations. As demonstrated by the PSSs in Table 2 and the mean sampling distributions in Fig. 3, even considering parameter uncertainty in the instrumental record when estimating sustainable yield (i.e. Berghout et al., 2017) may not expose the water system model to mean climates that are plausible now (i.e. the “Palaeo-Dry”) and in future (i.e. the driest GCM from the Late 21st Century RCP8.5 projection scenario). However, as water supply systems have inherent redundancy to handle extreme events not experienced in the instrumental period, evaluating the performance of existing water supply systems using a combination of instrumental, palaeoclimate, and projected model data is a key recommendation of this study.

Although we have demonstrated that the instrumental record is not representative of past/future climate, some questions naturally arise from our analysis: Are these dry palaeoclimate/projected scenarios likely to occur in the future? And should our water supply systems be updated now to handle such extreme scenarios, or should updates be made as such scenarios occur? In reality, prescribing accurate probabilities of these dry epochs occurring in the near future is difficult (Lempert et al., 2003). Given this difficulty, the most appropriate way a water supply system/management plan could be updated in future remains an ongoing area of research (Hall et al., 2012; Borgomeo et al., 2018). Regardless of how water supply systems are updated in future, the triggers for when and ways how these systems could be updated are strongly influenced by what kinds of climates are considered plausible in the future (i.e. Culley et al., 2016; Borgomeo et al., 2016). An important contribution of this study is the demonstration of how limits on plausible future rainfall change can be identified.

The application of a CF to a dry epoch in the palaeoclimate record was also presented as a simple way of illustrating variability seen in palaeoclimate records compounded with climate model projection trends. This highlights a significant limitation with comparing projected trends with respect to an instrumental period subset (i.e. IPCC’s 1986–2005 baseline, WMO’s 1960–1990 baseline) when estimating the potential impacts of climate change. By failing to consider the full range of natural climate variability, these approaches will underestimate the full range of climate conditions that are plausible and give an unrealistic assessment of future hydroclimatic risk.

Although combining palaeoclimate and GCM data can better estimate the full range of projection uncertainty, this application comes with inherent limitations. First, as this is a statistical method, no physical mechanism is proposed that could drive such large decreases in rainfall. In future, further CMIP5 model evaluation studies (extending the work of Moise et al., 2015) or updated climate model structures/simulations (i.e. outputs from CMIP6, Eyring et al., 2016) may find the changes identified in this study as implausible. However, water managers must make decisions based on the best information currently available and it may not be feasible to wait for new model evaluations/simulations. Second, by applying the same CFs to different historical periods, we are assuming that climate sensitivity (i.e. how a model projects rainfall to change given a specific increase in atmospheric $C0_2$) is independent of the climate state to which climate forcings are applied. This assumption is probably flawed – the same climate forcings applied to different baseline climates can result in different projected trends (Deser et al., 2020). Although this is a limitation of the method, given the limited understanding as to how rainfall could change given different climate baselines, we proposed the heuristic application of the same CF to different historical periods. Third, as the Law Dome ice core record is a remote proxy it is unable to capture local synoptic events that influence catchment rainfall (Tozer et al., 2016). As such, the skill of the palaeoclimate reconstruction is constrained and the stochastic modelling of the palaeoclimate time series may inadvertently capture high frequency variability not related to catchment processes. Fourth, although the application of a distribution-based CF used in this study preserved the projected changes evident at different rainfall quartiles, this scaling method can distort non-targeted rainfall variables/relationships (i.e. the serial dependence of the time series or the value of the 99th percentile rainfall total). The inverse peturbation method of Guo et al. (2018), which identifies stochastic model parameters that preserves these variables/relationships while reproducing the coincident change in statistics of interest (i.e. rainfall mean and standard deviation), offers a potential avenue for generating physically consistent stochastic traces for use in evaluating the performance of water supply systems (and climate impact assessments in general).

A bottom-up approach can be used to evaluate the performance of water supply systems under the palaeoclimate/projected scenarios generated in this study (Prudhomme et al., 2010; Brown et al., 2012). This approach involves assessing the performance of a water supply system under hypothetical climates (such as those produced in this study), thereby identifying scenarios where the water supply system does not meet operational requirements (Herman et al., 2016). The inclusion of climate model projections in these bottom-up assessments generally involves the peturbation of an instrumental subset based on the magnitude of change seen in future projections (i.e. Turner et al., 2014; Mortazavi-Naeini et al., 2015). However, as demonstrated in Figs. 2 and 3, this method may not capture the most extreme, plausible "worst-case" rainfall scenario. An important contribution of this study is the demonstration of a method that derives a plausible "worst-case" scenario (i.e. the driest ~100 year period in the last ~1000 years compounded with the largest, plausible decrease in rainfall under global warming) not currently captured when only considering instrumental and projected rainfall data. This "worse-case" scenario can then be used to inform stochastic weather generation within a bottom-up assessment framework.

Even though these bottom-up approaches can be used to evaluate water management strategies under climate variability/change, the extreme climate variability that a single catchment can experience may amplify existing limitations of the conceptual rainfall-runoff models used in water management (and therefore underpinning these bottom-up evaluations). For instance, as hydrological models assume the rainfall-runoff relationship is stationary, the model parameters identified during calibration are considered robust under climate variability. However, under multi-year drought conditions, for some catchments this assumption of stationarity is inadequate (Saft et al., 2015). Non-stationary rainfall-runoff relationships, driven by changing surface water-ground water interactions (Deb et al., 2019b), dynamic vegetation cover/behavioural responses to climate variability (Ajami et al., 2017) and vegetation responses to increased atmospheric CO_2 (Chiew et al., 2014), must be accounted for in order to accurately estimate stream flow when evaluating the performance of a water management plan under palaeoclimate variability and climate change.

There are numerous calibration/operational strategies that could improve the performance of conceptual rainfall-runoff models when simulating runoff under the climate scenarios identified in this study. For example, models calibrated to a dry (non-dry) period can perform well under a similarly dry (non-dry) future period (Li et al., 2012). There may also be an optimal parameter set that performs satisfactorily across many different climate states (Fowler et al., 2016). Time varying parameterisations, whereby model parameters change based on the current catchment/climate state, is another approach that could improve the accuracy of hydrological model runoff simulations climate variability/change (Westra et al., 2014; Pathiraja et al., 2016).

The selection/application of robust (i.e. able to accurately simulate runoff) model parameters is important when estimating future runoff but, given the significant climate variability/change found plausible in this study, it may not overcome the structural limitations of many conceptual rainfall-runoff models used in water management (Pathiraja et al., 2018; Stephens et al., 2019). These models have no explicit representation of the physical processes driving non-stationary rainfall-runoff relationships (e.g. surface water-ground water interactions), which can bias runoff estimates (Deb et al., 2019a). As such, seemingly robust estimations of future runoff (i.e. consistent estimates between different conceptual rainfall-runoff models calibrated to similar climate conditions) may also be similarly biased (Guo et al., 2018b). As our results show that catchment climates can plausibly change to states with no instrumental-period analogue (under both preinstrumental and projected climate scenarios) and recent research has demonstrated the limited ability of conceptual rainfall-runoff models to accurately simulate runoff under climate conditions not experienced during the calibration period (Deb and Kiem, 2020; Stephens et al., 2020), current hydrological model structures seem poorly suited to estimate future runoff. Clearly, the further study of the physical processes driving rainfall-runoff non-stationarity under climate variability/change, and the incorporation of such processes into hydrological models, is an important area of further research (Blöschl et al., 2019) with implications for the current/future performance of existing water supply systems.

6. Conclusions

In conclusion, this study explored the differences in instrumental, palaeoclimate, and projected rainfall statistics over the Lockyer Catchment, which is a catchment with a climate influenced by interannual to multidecadal variability (e.g. ENSO, IPO). The key findings of this study are:

- Water management strategies developed using only instrumental data underestimate, or at least misrepresent, current/future hydroclimatic risk.
- Considering projected changes in hydroclimate with respect to only instrumental data results in underestimation of future hydroclimatic uncertainty.
- For each RCP/time period analysed, decreases in mean rainfall outside the confines of instrumental and palaeoclimate variability are plausible.
- Compounding the most extreme palaeoclimate epoch with the largest GCM trend is presented as a way of generating a plausible "worst-case" scenario for use in bottom-up assessment frameworks.

Given that current water management plans were developed using instrumental data, and that the hydrological models underpinning these plans were calibrated to the instrumental record, our results have implications for the development of future water management plans. In particular, the evident mischaracterisation of current and future hydroclimate/hydroclimatic risk by the instrumental record has consequences for:

- The accuracy of sustainable yield estimates derived from instrumental-period climate conditions.
- The ability of conceptual rainfall-runoff models to accurately simulate runoff under climate conditions for which there are no instrumental-period analogue.

Although we have discussed the implications of this research from a water management/hydrological modelling perspective, the issues highlighted in this study are applicable to natural resources management/environmental modelling in general.

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CRediT authorship contribution statement

Matthew S. Armstrong: Conceptualization, Resources, Writing - review & editing. **Anthony S. Kiem:** Conceptualization, Resources, Writing - review & editing. **Tessa R. Vance:** Conceptualization, Resources, Writing - review & editing.

Declaration of Competing Interest

The authors have no competing interests to declare

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ejrh.2020.100728.

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