Scoping study for the delivery of future runoff projections for Victoria

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Proposal summary

This scoping study outlines a proposal for the delivery of runoff projections for Victoria by December 2015. Briefly, we propose downscaling CMIP5 models using empirical scaling, comparison with analogue downscaled rainfall, and hydrological modelling using SIMHYD. The main differences between earlier projections by SEACI are the updated CMIP5 model dataset, new RCP scenarios, and the ready availability of analogue downscaling data. Anticipated work load is 0.5 FTE, and includes 0.15 FTE for modelling support (GCM/hydrological modelling).

1. Introduction

The Victorian Climate Initiative (VicCI) is a three-year regional climate initiative launched in May 2013 by the Victorian Department of Environment and Primary Industries (DEPI) – now the Victorian Department of Environment, Land, Water & Planning (DELWP) – the Bureau of Meteorology and CSIRO. As specified in the agreed Science Plan (see Appendix, section 0), Project 7 ('Identification and application of improved methodologies for water availability projections') was tasked with the design and, if time and resources permitting, delivery of future runoff projections for Victoria. This scoping study provides a review of methods used to construct runoff projections and outlines what combination of methods can currently be applied to meet a delivery of runoff projections to DELWP by December 2015. This study considers research conducted within VicCI, but also learnings from previous projection work in Australia, such as within the South-Eastern Australian Climate Initiative (SEACI) and elsewhere.

1.1. Previous runoff projections for Victoria

Over the past decade, three sets of runoff projections have been developed for the State of Victoria. These are: CSIRO/DSE projections in 2005 (Jones and Durack, 2005); projections due to SEACI in 2012 – described by Post and Moran (2011; 2013) and Moran and Sharples (2011); and the projections for Australia's NRM regions covering Victoria (CSIRO and Bureau of Meteorology, 2015). The CSIRO/DSE projections were estimated using a sensitivity-based model. The SEACI projections were based on empirically downscaled CMIP3 models forcing a hydrological model. The NRM projections were based on CMIP5 model outputs directly forcing an annual Budyko-curve model (Zhang et al., 2004; Teng et al., 2012c), and with associated mean soil-moisture change estimates from a monthly supply-and-demand model (Zhang et al., 2008).

1.2. Modelling procedure for runoff projections

Plausible impacts on the surface environment due to a warming atmosphere are typically assessed using a top-down modelling approach (Giorgi, 2008), and involves the following steps (Figure 1):

1. The selection of emissions pathway(s) and their simulated global climate response (by global climate models, GCMs)
2. Extraction of regional information from GCMs
3. Downscaling future climate information (as simulated by GCMs) to catchment scale
4. Hydrological modelling using downscaled climate input

Once projections of future runoff time series are obtained, different metrics can be produced that inform potential impacts to regional runoff characteristics. Examples of such metrics are: projected change in annual/seasonal runoff, changes in high flows, low-flow spells, drought durations, etc. Further, runoff projections can potentially be used as input to water supply system to provide estimates on system performance under climate change.

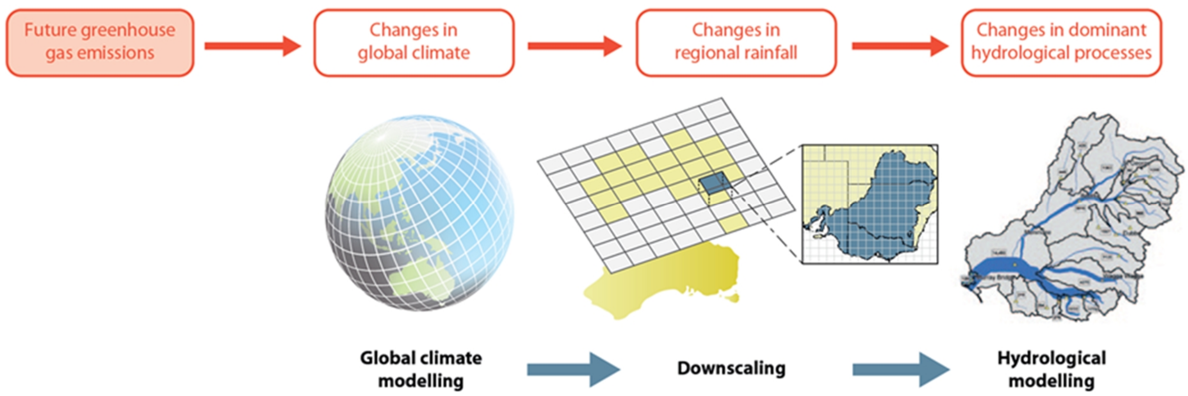

Figure 1: Top-down modelling for runoff projections (adapted from CSIRO, 2012, Figure 11).

1.3. Acknowledging and estimating uncertainty

Each step of the top-down approach illustrated in Figure 1 carries a degree of uncertainty (Giorgi, 2008). Estimating the associated uncertainty of runoff projections, and communicating it in such a way that it can be acknowledged in decision making processes, is one of the biggest challenges in modelling future hydro-climate projections. Ekström et al. (2015) separate sources of uncertainty in future climate projections into three types: (i) uncertainty in future influences on the climate, including greenhouse gas emissions; (ii) uncertainty in the climate system's response; and (iii) uncertainty due to natural variability.

The first source of uncertainty (future influences) is dominated by uncertainty in greenhouse gas emissions into the future. In the IPCC's fifth assessment report (AR5), representative concentration pathway scenarios (RCPs) define possible future emissions and atmospheric pollution levels (van Vuuren et al., 2011; IPCC, 2013). The choice and range of RCPs determines this first type of uncertainty. We discuss emissions scenarios in section 2.1.

The second source of uncertainty (climate response) comes from the large number of climate models, downscaling methods and hydrological models in use. Combinations of these not only provide different runoff projections, but can also provide a range of results, which can be interpreted as uncertainty in future projections due to our imperfect knowledge of the climate system. In most cases this uncertainty is very high (Giorgi, 2008). In general, uncertainty from the range of GCMs is larger than uncertainty from the choice of downscaling method, which in turn is larger than uncertainty from choice of hydrological model (Kay et al., 2009; Chen et al., 2011; Teng et al., 2012b; Westra et al., 2014b). There are numerous research activities both globally and in the context of south-eastern Australia that can be used provide contextual information about the likely range of uncertainty in future projections on a regional scale. While a range of downscaling methods exist for Australia (see e.g. Frost et al., 2011), estimating uncertainty due to downscaling in Australia is still a challenge due to the limited availability of downscaled data sets from different models (dynamical and statistical) in this region relative to the US and Europe (Kjellström and Giorgi, 2010, and articles therein; Mearns et al., 2013).

The third source of uncertainty (due to natural variability) is typically estimated by considering ensembles of modelling runs of GCMs where each run is initialised with slightly different, though plausible initial conditions (see particularly Peel et al., 2015). The model spread then represents variability due to internal climate variability rather than a response to a particular external forcing.

The relative importance of these three types of uncertainty are not constant in time but vary depending on the time horizon in question. Typically, uncertainty due to natural variability decreases over time, as the climate change signal becomes larger with respect to natural variability. Model (response) uncertainty more or less stays constant, with scenario uncertainty increasing as the time horizon increases (CSIRO and Bureau of Meteorology, 2014; Hawkins and Sutton, 2009).

1.4. Specification of deliverables

1.4.1. Format of runoff projections and associated deliverables

The target dates for runoff projections are guided by the planning requirements of end users of the runoff projections. Typically planning decisions are based on 5–10, and 50 years out from the present. Future climate and runoff below 10 years is dominated by high frequency variability in the climate system, and the occurrences of El Niño events, etc. Projections based on climate modelling is more suited for longer lead times, such as 25, 50+ years into the future. As such, 2040 and 2065 are suggested as target dates for future projections, but this needs to be guided by stakeholder requirements.

The precise format of rainfall and runoff projections is to be decided after consultation with stakeholders, but as a discussion point, the following is suggested by December 2015:

- Expected changes in annual and seasonal rainfall, temperature, runoff and PET for Victorian river basins (e.g. from Moran and Sharples' (2011) technical guidelines, and possibly divided into upper and lower reaches) derived from gridded projections across Victoria for 2040 and 2065 centred time-slices
- Ranges of variability of changes due to sources of uncertainty
- Qualitative assessment of sources of uncertainty not explicitly considered in the modelling process, such as from hydrological non-stationarity
- Reviewed official report describing methods and results

1.4.2. Projected rainfall and runoff characteristics

As part of the delivery of runoff projections, the VicCI Science Plan specified the identification of rainfall and runoff characteristics relevant to performance of water supply systems. At present, these have been identified in the VicCI Science Plan (see Appendix, section 0) as:

- Length of runs of dry years/below average cool season rainfall/runoff
- the extent to which projected drying in cool seasons is likely to be offset by increased rainfall/runoff in the warmer seasons
- Changes in the magnitude and frequency of daily/multi-day extremes and associated return periods

Techniques previously used to generate runoff projections in Australia do not allow for an adequate analysis of the above, due primarily to the rainfall-sequencing problem inherent in empirical downscaling (see section 2.4.1). The current approach outlined in this scoping study is thus unable to adequately model the above characteristics and so it is recommended that approaches to estimate these be developed as research products in the future.

2. Methods and uncertainty associated with the top-down modelling framework

A large body of research exists on GCM selection, downscaling methods, and rainfall-runoff modelling for future runoff projections in Australia. This research has considered both the relative performance of different methods available for the region, as well as the degree of uncertainty at each step of the top down approach. This section outlines the key elements of uncertainty in runoff projections and offers recommendations in relation to the delivery of runoff projections by December 2015.

2.1. Emissions scenarios and the presentation of model outcomes

The IPCC AR5 has four emissions pathway scenarios: RCP2.6; RCP4.5; RCP6.0 and RCP8.5, which are discussed at length in the IPCC (2013) AR5 report, as well as by van Vuuren (2011). The RCPs are named after their respective radiative forcing by 2100 relative to pre-industrial levels, and are roughly 2.6 Wm^{-2} (RCP2.6, strong mitigation, and decline of radiative forcing past 2100), 4.5 Wm^{-2} (RCP 4.5, medium-low, stabilisation at 2100), 6.0 Wm^{-2} (RCP6 medium-high, stabilisation at 2100), and 8.5 Wm^{-2} (RCP8.5, high, radiative forcing reaches 8.5 Wm^{-2} by 2100, and continues increasing afterwards). Although the IPCC does not assign probabilities to any RCP, RCP4.5 and RCP8.5 are often chosen to represent mid- and high level emission scenarios for climate mitigation and adaptation studies.

Earlier research noted by Moran and Sharples (2011) suggested that at that time, observed global greenhouse gas emissions were tracking either the IPCC AR4 A1FI or A1B scenarios. In terms of global temperature increase by the end of the 21st century, A1FI corresponds roughly to RCP8.5, and A1B corresponds roughly to RCP6 (Rogelj et al., 2012). In turn, the expected median global temperature increase by 2100 relative to 1988–1999 is around 4.4°C for RCP8.5, 2.5°C for RCP6.0 and 1.9°C for RCP4.5 (Rogelj et al., 2012, Table 2). More recent data (Peters et al., 2013; Friedlingstein et al., 2014) also have current and near-future GDP-growth-based projections (2010–2019) tracking at the higher end of the IPCC emissions scenarios.

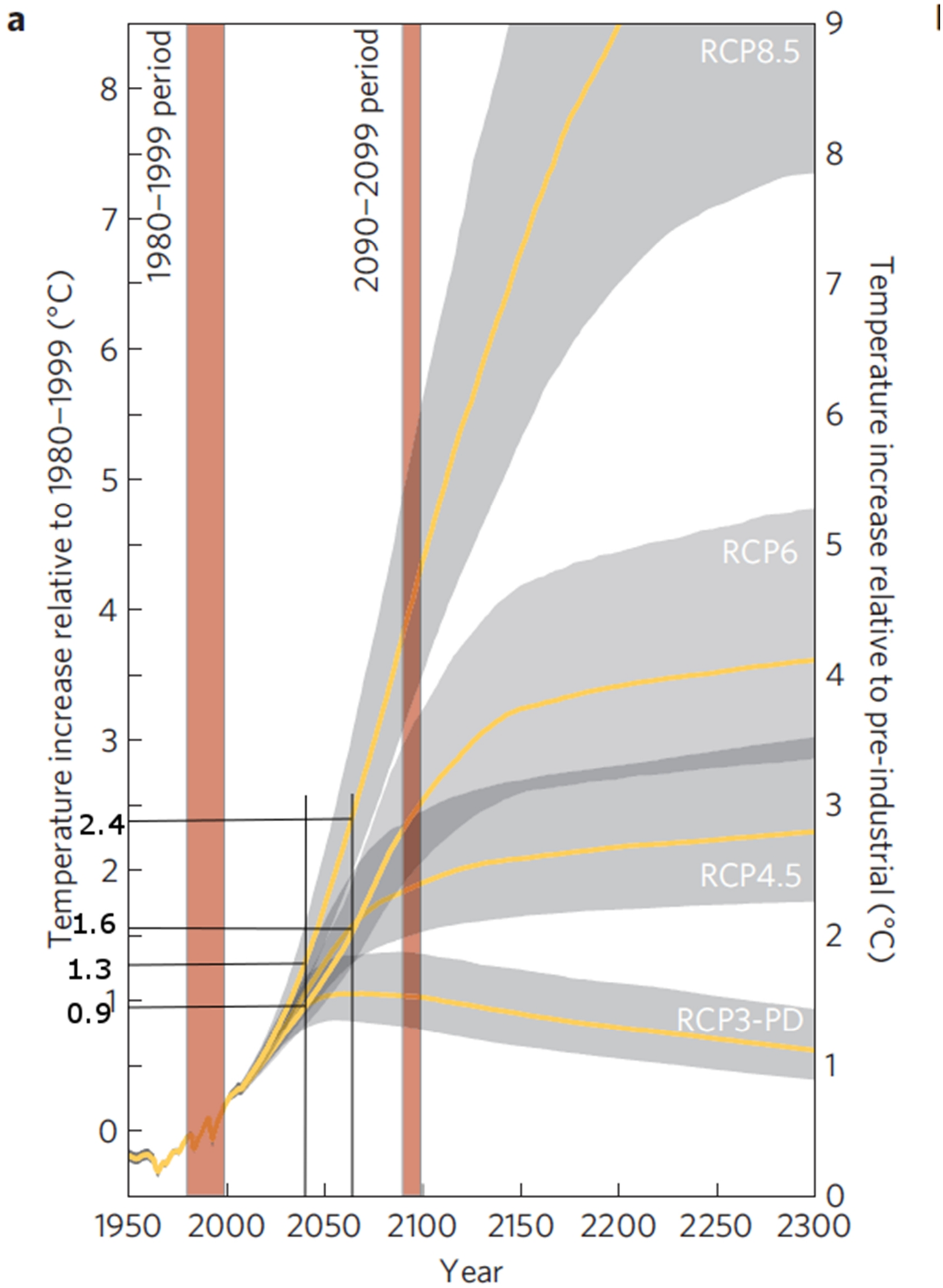

Figure 2: Warming by 2040 and 2065. Adapted from Rogelj et al. (2011, Figure 3).

Figure 2 shows that by 2040, there is little difference between the three lowest emissions scenarios, with warming around 0.9–1.0°C above 1980–1999, whereas RCP8.5 has an expected temperature increase of 1.3°C. By 2065, there is a large difference between scenarios, and this is consistent with the increasing uncertainty due to emissions as time progresses. However, both RCP4.5 and RCP6 converge around this time with an expected increase of 1.6°C above 1980–1999. RCP8.5 at 2065 has an expected increase of 2.4°C.

The choice of emissions scenario is related to the presentation of the range of model outcomes. Moran and Sharples (2011) note that there are two ways of defining the range of model outcomes, namely the ‘warming-weighted’ and the ‘impact-weighted’ approaches. The warming-weighted approach selects the lowest impact, typically as the 10th percentile (i.e. wet response), model outcome from the scenario with the least warming, and the highest impact as the 90th percentile (i.e. dry response) model outcome from the scenario with the most warming. In contrast, the impact-weighted approach chooses the wettest and driest impacts from amongst all different scenario/model combinations.

Previous experience suggests that under the impact-weighted method, the largest (i.e. driest) and smallest (i.e. wettest) impacts both occur from the emissions scenario with the greatest amount of warming (i.e. RCP8.5). More warming typically results in an intensification of the hydrological cycle, and experience in preparing previous projections (Post and Moran, 2011; 2012) has shown that the models that project an increase in rainfall in the future tend to project a larger increase in rainfall under scenarios with the greatest amount of warming.

In order to achieve consistency in the use of rainfall and potential evaporation data to calculate runoff, the 10th, 50th and 90th percentile modelled climate data for each grid cell are chosen in terms of mean annual runoff. That is, the GCM response for each grid cell is worked through to the runoff response before selection of the low/medium/high response. In the presentation of other variables (i.e. temperature, PET and seasonal rainfall) these ranges are calculated independently, but with a clear explanation (as per Moran and Sharples, 2011) that these cannot be combined meaningfully. As noted by Moran and Sharples (2011), the selected GCMs may differ between 2040 and 2065, and for consistency in this case, the GCM selected for 2065 will be used at 2040 as well.

2.1.1. Recommendation

In light of the fact that the extreme (i.e. 10th and 90th percentile) impacts are likely to occur under the RCP8.5 scenario, and also since current emissions are currently tracking very close to RCP8.5, this scenario will be used for future projections at the target dates (see section 2.4.6 for details on the downscaling method proposed). In a similar way to Moran and Sharples (2011), alternative scenarios (e.g. RCP4.5 and RCP6) can be considered using the impact weighted approach under RCP8.5 by recasting the impact at a later date. As an example, for future emissions following RCP6, the projected impact at 2040 under RCP8.5 is simply delayed by 10–15 years, and this information can inform the timing of adaptation responses.

2.2.Baseline climate period

The baseline climate period is chosen to be representative of current climate conditions. There are two distinct modelling requirements for the baseline climate, and these are: (i) a reference period for the development of change factors or bias corrections for future climate projections; and (ii) a reference period to which future projections can be compared (Chiew et al., 2009a). Owing to the often large biases in rainfall arising from GCMs (see section 2.3), and the fact that historical GCM runs don't match historical variability (e.g. the timing of drought years), GCM climate data cannot be used directly to force hydrological models, rather GCM data is used to inform climate downscaling methods (see section 2.4).

Especially for drier catchments, the uncertainty arising from different definitions of the climate baseline can be of a similar order of magnitude to the uncertainty arising from GCM selection (Post and Moran, 2013; Moran and Sharples, 2011). The IPCC TAR stated that the climate baseline 'should be representative of the present-day or recent average climate in the study region and of a sufficient duration to encompass a range of climatic variations, including several significant weather anomalies (e.g., severe droughts or cool seasons).' The high degree of hydroclimatic variability in south-eastern Australia, and particularly since average rainfall during the Millennium Drought was among the driest multi-year average in the historical record, makes choice of climate baseline for Victoria problematic.

Three main issues are associated with the choice of baseline climate: (1) having the climate baseline representative of the current climate, as informed by historical data and our understanding of the impact on rainfall from climate change; (2) having a sufficiently long baseline period to average out interannual variability due to, for example, El Niño events; and (3) having a sufficiently long baseline period to provide future time series for applications (e.g. recurrence intervals of extreme events for infrastructure planning decisions).

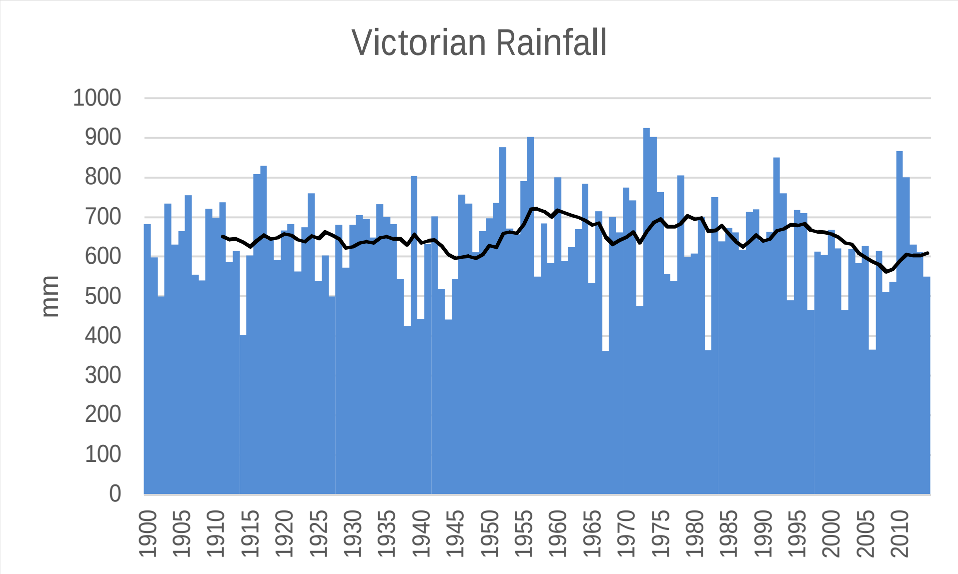

Figure 3: Historical rainfall for Victoria (taken from Bureau of Meteorology climate data). The 12-year moving average is shown as a black line.

Figure 3 shows mean annual rainfall in Victoria, based on data from the Bureau of Meteorology (2015). Two main decadal features are evident: the relatively wetter period after the 1950s, which corresponds broadly to the commencement of a negative phase of the Inter-decadal Pacific Oscillation (IPO), a low-frequency mode of variability of Pacific Ocean sea surface temperatures that moderates the effect of El Niño events (Power et al., 1999), and the severe reduction in rainfall corresponding to the Millennium Drought (1997–2009). Annual rainfall averaged over selected time periods of interest is shown in Table 1.

Table 1: Mean annual rainfall for Victoria for different time periods (taken from Bureau of Meteorology climate data)

Description	Time period	Mean annual rainfall (mm)	Relative difference from long-term mean annual rainfall (%)
Millennium drought	1997-2009	561.3	-13%
MDBSY calibration period	1975-2006	630.4	-3%
IPCC AR5 climate baseline extended	1986-2014	630.9	-3%
MDBSY extended	1975-2014	632.3	-2%
Proposed change-factor baseline	1976-2005	634.7	-2%
IPCC AR5 climate baseline	1986-2005	640.4	-1%
IPCC AR4 climate baseline extended	1961-2014	643.5	-1%
Entire BoM record	1900-2014	647.9	0%
Post-1950s	1950-2014	656.9	1%
IPCC AR4 climate baseline	1961-1990	660.2	2%
Negative IPO phase	1950-1985	677.9	5%
Post-Millennium drought	2010-2014	691.7	7%

From Table 1, we see that 1950–1985 (which roughly corresponds with a distinct negative IPO phase) is among the wettest periods, with 5% more mean annual rainfall than the long-term average; this period also corresponds to the period of the most growth of major water storages in the MDB (CSIRO, 2008). The Millennium drought is the driest period of those considered, with a 13% reduction in mean annual rainfall, which was accompanied by large reductions in runoff occurring in the southern MDB (Potter et al., 2010).

The IPCC climate baseline during the fourth assessment report (AR4) was 1961–1990, which corresponds to a relatively wet period in Victoria (Table 1; Chiew et al., 2009a). This climate baseline has subsequently been updated for the fifth assessment report (AR5) to 1986–2005 (IPCC, 2013, p. 1034). This corresponds with the start of the IPCC representative concentration pathway (RCP) scenarios of 2006, and was also used by CSIRO and Bureau of Meteorology (2015). The AR5 climate baseline is slightly drier than the long-term average, with 3% less mean annual rainfall (Table 1). The time period 1975–2006 was used as a hydrological model calibration period for the Murray-Darling Basin Sustainable Yields project (Chiew et al., 2008; 2009c), mainly as it was considered a long enough time period for hydrological model calibration, but short enough to have a relatively small land-use and infrastructure change component.

There is a strong argument for choosing a baseline climate period of at least 30 years, rather than the 20 year periods chosen by the IPCC, due to the higher interannual variability of rainfall and runoff in Australia (e.g. Peel et al., 2004). The IPCC's AR5 states that it is 'likely' that anthropogenic influences have altered the global hydrologic cycle (IPCC, 2014). Research in SEACI and VicCI have confirmed the role of climate change on rainfall patterns for Australia, particularly the 'expansion of the tropics' (e.g. CSIRO, 2012). This suggests that a recent baseline is more appropriate than a longer baseline covering the first half of the 20th century. Since there is little difference between recent ~30 year sequences (Table 1), the baseline of 1976-2005 is suggested for use in deriving downscaled climate data. This baseline time period is similar to the baseline from most other relevant studies, and is compatible with the RCP scenarios, which commence at 2006.

For characterising recent climate, however, a baseline period including more recent data is advisable. The 1975–2014 baseline period is similar in terms of mean annual rainfall (Table 1) and captures a greater amount of recent variability including the full extent of the Millennium Drought, ongoing cool-season rainfall declines, as well as the 2010 heavy rainfall events. However, the use of a methodology that derives future projections by applying changes to the 40-year baseline period 1975–2014 (e.g. empirical scaling, see section 2.4.1 does not allow for future runoff time-series of more than 40 years to be produced. This may be important, e.g. for long-term dam resilience studies. In this case, stochastic data generation may be appropriate, however this would not be possible by December 2015.

2.2.1. Recommendation

A climate baseline of at least 30 years baseline is desirable in order to accommodate the full range of hydroclimatic variability in rainfall and runoff in Victoria, as well as from the point of view of hydrological modelling. For deriving the downscaled climate data (i.e. comparing historical GCM to future GCM data), the 1976–2005 period provides a sufficiently long period of time, is reasonably consistent with older studies (e.g. Chiew et al., 2008; 2009c), and is close to a 10-year extension of the IPCC AR5 climate baseline. For the scaling of observed historical data, the period 1975–2014 provides a fuller characterisation of recent climate events, and this baseline will be scaled to provide future rainfall events (see section 2.4.6 for details on the recommended downscaling method).

If longer projected runoff time series (e.g. 100+ years) are required for system planning purposes, it is suggested that the baseline be extended to cover the 20th century (e.g. the entire SILO/AWAP record). Alternatively, a stochastic data generation approach may be used to generate longer time series, but this would be a research product to be developed after December 2015.

2.3.GCM representation of the regional climate

GCM model results from the Coupled Model Intercomparison Projects (CMIP3 and CMIP5) are the data basis for future climate projections. For most variables, there is broad similarity between CMIP3 and CMIP5 globally (IPCC, 2013), and in Australia (Murphy et al., 2014; Westra et al., 2014b), with the largest effect being slight decreases in humidity and solar radiation in southern Australia (CSIRO and Bureau of Meteorology, 2015, Appendix A).

2.3.1. GCM skill in representing observed hydro-climate variability

Smith and Chandler (2009) analysed the ability of CMIP3 models to model both rainfall over the Murray-Darling Basin, as well as ENSO. They recommended the use of five GCMs: ECHAM5, GFDL2.0, GFDL2.1, MIROC3.2 (hires) and UKMO_HADCM3. These five models all show a reduction in spring and winter rainfall, the seasons in which the majority of runoff is produced in SEA, and the range of uncertainty is reduced. This is essentially due to similar model structures amongst the five selected models (Smith and Chandler, 2009).

Other research in SEACI (Kirono and Kent, 2011; CSIRO, 2012) examined the ability of 23 CMIP3 models to reproduce historical climate variability in south-eastern Australia (SEA). This is important as rainfall in SEA is intimately linked to climate-ocean indices such as the El-Niño Southern Oscillation (ENSO), the Indian Ocean Dipole, the Southern Annular Mode and the Sub-Tropical Ridge (STR) (CSIRO, 2012). The models were found broadly to capture the mean annual climatology of these climate indices, but not the inter-annual variability. No model was found to be consistently better at modelling relevant climate variability in SEA. Although the projected decline in rainfall using the better models was lower for SEA, the range of uncertainty was not reduced (CSIRO, 2012). Kirono and Kent (2011) calculated skill scores for GCMs based on their ability to reproduce mean, variability and trends in rainfall and PET. Their top-five models for Victoria were MIROC-M, GISS-E-R, CSIRO-Mk3.0, IAP, and MIROC-H.

McMahon et al. (2015a) assessed CMIP3 models not for skill in representing regional climate processes, but rather with a focus on hydrological applications. They assessed the GCMs' ability to model annual and monthly rainfall and temperature and climate type globally. The five models recommended were HadCM3, MIROCm, MIUB, MPI and MRI. Exclusion of the other models reduced somewhat the range of future rainfall estimates (i.e. the GCMs projecting large global increases in rainfall were not judged as adequate models), and this is qualitatively similar to the results of Smith and Chandler (2009), albeit for different study areas.

CSIRO and Bureau of Meteorology (2015) outline a comprehensive assessment of CMIP5 models' ability to simulate temperature, precipitation and climate features (e.g. ENSO, IOD). CMIP5 models generally underpredict winter rainfall in Southern Australia, although it is noted that this effect is mostly confined to Tasmania. The report outlines a number of deficiencies in certain models (Table 5.6.1). Yet for future projections, no model is excluded or weighted due to 'possible detrimental effects' (CSIRO and Bureau of Meteorology, 2015, p. 83). Work in Project 5 of VicCI has recently focused on tailoring the CSIRO and Bureau of Meteorology (2015) GCM selection work specifically to Victoria.

To this end, Grose et al. (2015, accepted), and related work in Project 5 of VicCI, examined CMIP5 climate models performance from the perspective of modelling the subtropical ridge (STR). Generally, CMIP5 models project an increase and shift in the STR, which would tend to decrease cool-season rainfall, although the observed relationships between the STR and Victorian rainfall are not modelled well by the CMIP5 GCMs (Grose et al., 2015). However, eliminating the six poorest models in terms of STR does not appreciably change rainfall projections (Grose et al., 2015, Figure 9). The ability of CMIP5 models to simulate prolonged long-term droughts (as characterised by the length of runs of no wet months) comparable to the Millennium Drought was also examined by Project 5. While projected long-term droughts are present in the 21st century model runs, the duration of these droughts are all shorter than the Millennium Drought. Further, there was no significant difference between the modelled length of dry periods in the 20th and 21st centuries. These findings suggest that CMIP5 modelling runs may underestimate cool season rainfall reductions and prolonged drought occurrences (VicCI, 2015, draft). Progress by VicCI on assessing CMIP5 models is promising, but explicit guidance is required from project 5 to eliminate or otherwise select GCMs for runoff projections.

Knutti et al. (2010b) suggest that eliminating models in this way can be beneficial for regional assessments, however they note that there are 'no simple rules or criteria to define this'. Generally, GCM performance changes depending on the selection criteria and study region. Other studies (e.g. Chiew et al., 2009b; Teng et al., 2012b; Westra et al., 2014b; 2014c) have also found that using better performing GCMs does not actually reduce the range of results, particularly when the climate projections are subsequently downscaled. This is perhaps due to the fact that a GCM skilful in reproducing historical climate does not necessarily result in more skilful simulations of future climates (Knutti et al., 2010a).

2.3.2. Recommendation

Although numerous studies find no appreciable reduction in uncertainty using selected GCMs when combined with downscaling, there is no particular reason why poorly performing GCM models should be included. The difficulty in GCM selection, however, is determining the criteria for exclusion or inclusion in a defensible and coherent manner. For the purposes of empirical scaling (see below), scaling factors can be calculated for all available data as easily as any particular subset of models. As such, empirical scaling is initially proposed for all available CMIP5 models with suitable data. As noted above, Project 5 has studied GCM performance in simulating recent climate variability, and guidance from Project 5 will be sought for the purposes of GCM selection.

2.4. Downscaling methods

Downscaling refers to the process of disaggregating climate data from GCMs (with spatial resolution in the order of 100km×100km) to a finer spatial resolution in order to provide regionalised climate information (Ekström et al., 2015). Due to their finer resolution, downscaled projections are considered more usable for hydrological models that simulate processes on much finer scales than GCMs. Downscaling involves many fundamentally different approaches to achieve a finer resolved climate projection (e.g. Fowler et al., 2007; Chen et al., 2011; Ekström et al., 2015). Briefly, downscaling methods can be categorised as: (1) 'empirical' downscaling or 'change-factor methods', which relate changes in the distribution of historical GCM rainfall to future GCM rainfall, and then apply these changes to observed rainfall; (2) statistical downscaling methods, which develop a statistical relationship between GCM atmospheric variables and observed rainfall and then apply that relationship to derive future rainfall from future GCM variables; and (3) dynamical downscaling methods, where regional climate models (RCMs) are used, which model the physical climatic processes at smaller spatial scale informed by a larger scale GCM. Sometimes empirical scaling methods are classified as statistical downscaling approaches, but it is useful to separate these methods as they are really based on different conceptual approaches. Empirical scaling methods vary in the nature of the change factors used (i.e. from a simple linear factor to probability distribution transformations). This section describes and evaluates the benefits and limitations of different downscaling methods. The focus is primarily on downscaling rainfall, as its effect on runoff is relatively larger compared to the effect of changes to potential evapotranspiration on runoff (Chiew, 2006; Potter and Chiew, 2011; Chiew et al., 2014). However, we review potential evapotranspiration downscaling in section 2.4.5.

A fundamental assumption for all statistical downscaling methods is that any derived relationships remain constant into the future. Of course, without, or even with the benefit of, additional knowledge (such as may be derived from physically based climate models), this assumption is difficult to verify (Giorgi, 2008). Dynamical downscaling provides localised climate information using a physically based method. However, bias can be high using these methods (e.g. Wilby et al., 2000; Piani et al., 2010; Teng et al., 2015) owing to model assumptions and the fact that such methods are not explicitly calibrated to station data. However, dynamical downscaling methods may be better suited to explore the effect of changes in hydroclimatic processes than scaling or statistical methods. It is recognised that success in downscaling is dependent on the skill of GCMs in reproducing relevant climate characteristics (Ekström et al, 2015).

The feasible choices for downscaling GCM rainfall data for delivery by December 2015 are essentially those investigated by Frost et al. (2011), and include (a detailed assessment of each method is given in sections that follow):

- Empirical scaling methods, which relate changes in the distribution of historical GCM rainfall to future GCM rainfall, and then apply these changes to observed rainfall (e.g. Prudhomme et al., 2002, Chiew et al., 2009c, and related studies)
- Direct bias correction of GCM output, sometimes called daily translation method (i.e. the development of a transfer function between historical GCM output and historical observations, and applying this to future GCM output) (e.g. Mpelasoka and Chiew, 2009)
- Statistical downscaling methods, namely:
    - Analogue method, sometimes called SDM (Timbal et al., 2006, Teng et al., 2012a)
    - Non-homogeneous Hidden Markov Model (NHMM) downscaling (Hughes et al., 1999; Charles et al., 1999; Fu et al., 2013)
- Dynamical downscaling methods, namely:
    - Weather Research and Forecasting (WRF) model (Evans and McCabe, 2010)
    - Conformal-Cubic Atmospheric Model (CCAM) (McGregor, 2005; McGregor et al., 2008)

Many downscaling comparisons have been conducted (see, e.g. Fowler et al., 2007; Chen et al., 2011). Frost et al. (2011) provide a comprehensive comparison of the performance of different downscaling methods in Australian. Generally, winter rainfall is more successfully downscaled than summer rainfall (Fowler et al., 2007; Haylock et al. 2006), and rainfall in wetter climates is more easily downscaled than in drier climates. Although there is a range of results, most studies generally conclude that no single downscaling method is better, and this is largely because, like with GCMs, different downscaling methods are tailored for different applications. The choice of downscaling method needs to be principally determined by the end use of the climate information, and uncertainty resulting from this choice needs to be communicated (Fowler et al., 2007; Chen et al., 2011). In the Australian context, Frost et al. (2011) recommends using empirical scaling methods for regional water resource planning applications, due principally to the method's robustness. Chiew et al. (2010) found that results from daily scaling typically lie within the range of other regionally available downscaling methods.

2.4.1. Empirical scaling methods

A range of scaling methods exists for downscaling, ranging in complexity from one-parameter to distribution-based approaches. Typically, each season's data is scaled separately to account for climatic differences between seasons. These scaling methods include:

- One-parameter scaling. This method simply scales each day's rainfall equally (e.g. Maraun et al., 2010; Teng et al., 2012a), and is typically used to ensure seasonal and annual averages are equal.
- Differential scaling of percentiles (e.g. Chiew et al., 2008; 2009c). This method seeks to preserve information about future changes in the distribution of daily rainfall. GCM output suggests that the relative changes in high rainfall events and low rainfall events may be different in the future. This is often combined with one-parameter scaling.
- Quantile mapping using specified distributions. Here, specific distributions are fitted to the data, and quantiles of daily rainfall are mapped from one distribution to the other. Teng et al. (2015) provide examples of this method, albeit for bias correction rather than downscaling. This method has the advantage of providing an easy way to extrapolate outside of the historical record, although the distribution used needs to be correctly specified and assessed.
- Quantile mapping using empirical distributions. This method is similar to the previous method, but no assumptions are required. Westra et al. (2014b) use this approach for downscaling climate data in South Australia. However, it is not clear how to extrapolate large rainfall events using this method, and there is a potential issue with increased variance of estimates due to single outlying rainfall events.

Empirical scaling is generally robust (Frost et al., 2011) and results typically lie within the envelope of other downscaling methods (Chiew et al., 2010). The main issue with empirical scaling is, however, that future rainfall is always retains the historical sequence of rainfall events. Empirical scaling thus cannot capture future changes to rainfall sequencing (e.g. an increasing length of day-to-day dry spells).

2.4.2. Bias correction of GCM output

The main problem with empirical downscaling is the fact that, whatever the scaling method chosen, future rainfall is always a scaled version of historical rainfall. This may tend to underestimate variability, and cannot alter the observed rainfall sequence so that wet and dry spells essentially remain constant (Frost et al., 2011). One way around this is to bias correct GCM projections of rainfall directly. Essentially the same scaling methods outlined above are used, except the scaling parameters are calculated by deriving relationships between historical GCM data compared to historical observations rather than future GCM data compared to historical GCM data. This allows more flexibility in modelling changes to rainfall amounts and occurrences (Mpelasoka and Chiew, 2011). Arguably however, the ability of GCMs to predict detailed, second-order characteristics of rainfall is limited (Ines and Hansen, 2006; Hagemann et al., 2011). As such, the applicability of direct bias correction of GCM output is questionable in the current context.

2.4.3. Statistical downscaling

Statistical downscaling involves relating large-scale atmospheric variables (often MSLP, wind, temperature, humidity, etc.) to observed local-scale rainfall with a view to use those relationships to generate future downscaled rainfall amounts and occurrences from future GCM atmospheric variables. There are a variety of both parametric and non-parametric ways of doing this (see Fowler et al., 2007; Chen et al., 2011; Frost et al., 2011). Statistical downscaling methods are generally time and computationally intensive activities, although relatively much less computationally expensive than dynamical downscaling methods (Ekström et al., 2015). These methods generally require modellers well versed in the methods to properly calibrate the relationships and apply the methods (Chiew et al., 2010; Ekström et al., 2015).

The analogue or SDM method (Timbal et al., 2006, Teng et al., 2012a; CSIRO and Bureau of Meteorology, 2015) downscales GCM rainfall by resampling from the historical record. Briefly, the method searches for days in the historical record with climate features similar to GCM output for a given day (i.e. searches for a climate analogue) and uses the historical rainfall amounts on that day. Being essentially a non-parametric approach, the analogue method has the conceptual advantage of not assuming any fixed relationship between atmospheric variables and rainfall. Although this method results in reduced range of uncertainty for future projections (Teng et al., 2012a), this essentially is due to the same relationship between atmospheric variables and rainfall being used. As such, this may underestimate the true uncertainty from downscaling. Teng et al. (2012a) also note that bias correction is needed if we are to use the analogue method as input to hydrological models as high rainfall events in particular are underestimated (see also Frost et al., 2011). Analogue (SDM) downscaling projections for Victoria have been developed as part of the 'projections for Australia's NRM regions' (CSIRO and Bureau of Meteorology, 2015), and the product already developed could potentially be used at least for comparative purposes. CSIRO and Bureau of Meteorology (2015) report that analogue downscaling results project greater autumn rainfall declines in south-east Australia compared to GCMs, and this may be more physically realistic given the lack of ability of GCMs to adequately represent changes to the STR as identified by Grose et al. (2015) – see section 0.

The Non-homogeneous Hidden Markov Model, or NHMM method (Hughes et al., 1999; Charles et al., 1999; Fu et al., 2013) defines distinct 'hidden' weather states according to atmospheric variables, which determine rainfall occurrences. Weather states change according to a first-order Markov process. NHMM was recently used to downscale climate change information for the Onkaparinga Catchment in South Australia (Charles and Fu, 2015). Frost et al. (2011) found NHMM produced a wide range of historical statistics adequately. In a comparison of the ability of different downscaling methods to reproduce rainfall and runoff, Chiew et al. (2010) showed NHMM was consistently the best method (out of analogue, GLIMCLIM, NHMM and CCAM). However, spatial correlation of rainfall and hence runoff is largely not captured by NHMM (Chiew et al., 2010; Frost et al., 2011). Westra et al. (2014b) assessed NHMM for hydrological applications in South Australia and found many rainfall characteristics were not well captured by NHMM. Given the time frame and resources available, it is considered not possible to properly develop NHMM downscaling for runoff projections by December 2015.

2.4.4. Dynamical downscaling

The physically based nature of dynamical downscaling methods suggests that dynamical downscaling is most appropriate for exploring the effects of changing hydroclimatic processes on runoff, or 'physical plausibility of change' (Ekström et al., 2015). It is also suggested that dynamical downscaling can provide additional benefit over regions with large climatic and/or topographic heterogeneity (Ekström et al., 2015; CSIRO and Bureau of Meteorology, 2015), where empirical or statistical methods may be unable to model the finer scale processes. The other downscaling methods outlined above largely assume stationary (i.e. non-changing) hydroclimatic relationships, and this may lead future projections not including any changes in these relationships. Bias correction is typically needed for dynamical downscaling, and dynamical downscaling typically has very long model run times limiting its usefulness for regional water assessments. Available data sets for the region at present are based on output from the CCAM (McGregor, 2005; McGregor et al., 2008) and WRF (Evans and McCabe, 2010). Teng et al. (2015) bias corrected WRF output for Victoria and found that non-stationary bias (i.e. bias between WRF and observed rainfall differing across different time periods) made bias correction problematic. However, Chen et al. (2011) are more optimistic, finding in their study that RCM biases can effectively be cancelled out through calibration of hydrological model. However, research in VicCI has not yet delivered a convincing case for using dynamic downscaling for regional runoff projections.

2.4.5. Downscaling of potential evapotranspiration (PET)

A range of different potential evapotranspiration formulations are available, ranging from simple temperature-based approaches to physically based formulas such as Penman-Monteith. In general, rainfall-runoff models have been found to be largely insensitive to the choice of PET formulation, provided the formulation is used consistently (Oudin et al., 2005a; 2005b). However, the use of simpler PET formulations for future projections is problematic (McMahon et al., 2015a; 2015b), largely due to the pan evaporation paradox (e.g. Roderick et al., 2009a; 2009b; Donohue et al., 2010), in which pan (i.e. point potential) evaporation has recently been observed to decrease concurrently with increases in maximum temperature. This paradox has largely been resolved with the recognition that changes in secondary atmospheric variables (particularly wind speed) have offset the effect of rising temperatures on PET. However, this suggests that these secondary variables must be considered for future projections of PET.

McMahon et al. (2015b) note that GCMs model wind speeds, humidity, and net incoming radiation relatively poorer than temperature. As such, while the Penman-Monteith method is preferred from a conceptual viewpoint, modelling historical PET based on a simple model of just the ratio of temperature to radiation provided better estimates. They conclude that, given the current large uncertainties in projections of secondary atmospheric variables from GCMs, a relatively simple method for modelling PET is preferred.

Two approaches to downscaling potential evapotranspiration appear in the literature. These two approaches are: stochastic, or 'weather generator', methods (Wilks and Wilby, 1999); and scaling approaches, similar to empirical scaling of rainfall.

In an application of the stochastic framework, Charles and Fu (2015) calculated downscaled potential evapotranspiration based on Morton's areal potential evapotranspiration. Here, temperatures, solar radiation and vapour pressure deficit are extracted from SILO data. These are normalised, Box-Cox transformed, and then correlations between variables are calculated. Once these variables are sufficiently whitened, synthetic time series of residuals are calculated, which are then converted back into synthetic atmospheric variables, which then have monthly trends calculated from GCM data added back in.

Chiew et al. (2009c) apply a scaling factor approach to atmospheric variables used to calculate Morton's PET. These downscaled variables are then used to scale historical (SILO) atmospheric variables, which produce a future PET time series. Finally, the future PET time series is compared to historical PET time series so that single scaling factors for each season are calculated. Westra et al. (2014b) apply empirical quantile mapping to downscale PET. Such scaling approaches are consistent with the empirical scaling approach for rainfall.

2.4.6. Recommendation

Empirical (seasonal) scaling is recommended for downscaling GCM outputs for the current round of future projections based on the following observations:

- Projected runoff from daily scaling methods typically lies within the envelope of results from different downscaling methods (Chiew et al., 2010)
- A comprehensive downscaling comparison for Australia conditions recommended empirical scaling for water resource availability and planning studies (Frost et al., 2011).
- The implementation of empirical scaling does not require specific additional personnel.
- There are some remaining uncertainties around other methods (such as underestimation of wet days using analogue downscaling; underestimation of spatial correlation using NHMM; bias correction issues with dynamical downscaling).

The empirical scaling parameters will be estimated using the seasonal scaling method. For a given GCM and scenario output, the average simulated seasonal rainfall (or other climate variables required to calculate PET, e.g. maximum temperature, relative humidity and incoming radiation) is calculated around the target date (2040 or 2065). The GCM historical average of the variable being considered is then used to estimate the scaling parameters. Using this method, internal variability in GCM response at a given date (for example a given GCM projection may have an overall declining trend in rainfall, but a relatively wet period around 2040) is averaged out using the range of GCMs being considered.

Given that analogue downscaling results are available for a subset (around 20) of CMIP5 GCMs, but only for a limited selection of unimpaired catchments of Victoria (27 in total), it is proposed to ensure that these catchments are included and results are generated to facilitate a comparison of the two. These can be used to examine differences in runoff projections for the context of downscaling uncertainty.

2.5. Hydrological modelling

2.5.1. Choice of rainfall-runoff model

There are several lumped conceptual hydrological models available for modelling runoff for Victoria (e.g. Vaze et al., 2011). These include SIMHYD, AWBM, Sacramento, GR4J, SMARG, and IHACRES, each varying in conceptual design. The number of parameters to calibrate also varies, ranging from four for GR4J through to 14 for Sacramento. Testing these models across south-eastern Australia found GR4J and Sacramento performed best, although there is little difference in performance among the rainfall-runoff models studied (Vaze et al., 2011).

The change in future runoff is influenced by the change in climate inputs and the change in the climate-runoff relationship (i.e. hydroclimate or hydrologic non-stationarity). In modelling runoff change resulting from change in climate inputs, the largest uncertainty comes from the uncertainty in future rainfall projections. Westra et al. (2014c), Teng et al. (2012b) and others show that the uncertainty in modelled future runoff resulting from the uncertainty in GCM rainfall projection is four to five times larger than the uncertainty from rainfall-runoff model selection and hydrological non-stationarity.

2.5.2. Hydrological non-stationarity

The term ‘hydrological non-stationarity’ (e.g. Milly et al., 2008; Chiew et al., 2013) refers here to hydrological models not adequately capturing changes in hydrological processes, which thus results in runoff bias. Climatically different periods can see the emergence of different hydrological processes dominating runoff production and streamflow. The Millennium Drought in south-eastern Australia saw large reductions in the rainfall-runoff ratio (Potter et al., 2011; 2013; Saft et al., 2015). Declining groundwater levels in south-west Western Australia has seen a consequent reduction in runoff ratios (Petrone et al., 2010; Hughes et al., 2012) and to a lesser extent in south-eastern Australia (Petheram et al., 2011;

CSIRO, 2012). The groundwater component of many rainfall-runoff models is insufficiently complex to model changes in surface-groundwater connection. This can be seen as an example of hydrological non-stationarity, and results in biases in modelled runoff when transferring parameter sets to climatically different validation periods (Vaze et al., 2010; Coron et al., 2012), as well as optimal parameters changing during different time periods (Potter et al., 2013). Recently, some success has been achieved in modifying the GR4J model to better account for hydrological non-stationarity, such as incorporating time-varying parameters (Westra et al., 2014a), catchment water stores able to accumulate deficits, and explicit modelling of land use (Hughes et al., in review), as well as different objective functions (Vaze et al., 2012; Hughes et al., in prep.). However, evaluating the success of efforts to counter hydrological non-stationarity for future runoff projections is hindered by the confounding effects of uncertainty in the number of, and changes to, farm dams, as well as possible changes in vegetation types and water use efficiency as a consequence of increased CO_2 in the future. The uncertainty associated with hydroclimate and hydrologic non-stationarity, and the approaches used by hydrological models to account for this, could be as large as the uncertainty in the future climate projections discussed earlier, particularly for projections into the more distant future (Chiew et al., 2014).

2.5.3. Recommendation

The modelling of future runoff resulting from change in future climate is influenced mainly by the future climate projections. The uncertainty from choice of hydrological model is relatively small compared to the uncertainty in the future rainfall projections from GCMs. For this reason, a simple hydrological modelling approach should be sufficient. If projections are required mainly at selected catchments/basins, it is best to use one of the more commonly-used models (such as SIMHYD) calibrated against observed streamflow in these catchments. Where catchments are ungauged, parameter values from the closest gauged catchments can be used to model runoff in the ungauged catchment.

3. Timeframe and resources

3.1.Tasks required for delivery

Table 2: proposed tasks for recommended method

	TASKS	SPECIFICATION OF TASKS	ADDITIONAL CONSIDERATIONS	TIME
		Summary of minimum work leading to output/deliverable	**Additional considerations, and potential additional work providing more information**	
		[Project schedule for contract]		
1	Catchments and streamflow data	Collate catchments and streamflow dataset, curate and prepare data. Data already available. Discuss with DELWP.	Discuss/finalise with DELWP on precise reporting regions (e.g. upper and lower catchments?).	1 week
2	Climate data	Calculate SILO/AWAP data for catchments: for rainfall use area-weighted grid cell sum, for PET use Morton's areal potential evaporation		2 weeks
3	Hydrological model calibration	Use SILO/AWAP gridded climate data inputs. Calibrate SIMHYD against available (i.e. 1976-2013) streamflow data to optimise NSE-bias objective function.	Depending on streamflow data availability, length of data, consistency across catchments, may use a longer period and/or include more recent data.	2 weeks
4	Historical runoff simulation	Simulate daily runoff using above optimised parameters, at 0.05° grid across Victoria for period of SILO/AWAP data (1895-now). For ungauged catchments/grid, use optimised parameter values from closest calibrated gauged catchment.		1 week
5	Evaluate rainfall-runoff model simulations	Interpret quality of modelling results		2 weeks
6	Calculate catchment	Post processing of archived CMIP5 GCM outputs and estimation of change in future rainfall and PET relative to historical	With appropriate personnel this task can hopefully be carried out in parallel with tasks 2-5	2 weeks

	averaged GCM outputs			
7	GCM selection	Obtain guidance from Project 5 on GCM selection	Liaise with Project 5, and write report section on justifying decisions	2 weeks
8	Empirical scaling factors from GCMs	Calculate empirical scaling factors (for the four seasons and annual) for all available CMIP5 GCMs for RCP8.5, for future versus current/historical - GCM simulations for 2026-2055 (representing '2040') relative to 1976-2005 (representing 'current') and GCM simulations for 2051-2080 (representing '2065') relative to 1976-2005.	Discuss/finalise with DELWP on 'future' projections required and adjust periods accordingly. May also compare NRM SDM simulations. Scaling factors for alternative scenarios (e.g. RCP4.5) can aditionally be modelled for comparison, but the low/medium/high range of results will be based on changes derived from RCP8.5 at the target dates as specified in the scoping study.	2 weeks, +1-2 weeks for SDM downscaling comparison
9	Future runoff simulation	Simulate future runoff using above scaling factors to scale historical daily runoff sequence. Simulation will be carried out for 40 years (1975-2014). Output is 40-year runoff simulations for current conditions (1975-2014), 40-year future around '2040' and 40-year future around '2065', informed by each of the selected GCMs for RCP8.5.	Alternatively, depending on need (e.g. longer sequences for planning purposes), 100+ year sequences may be produced by scaling longer climate baseline periods (see considerations on climate baseline selection in section 2.2 of the scoping study.	2 weeks
10	Change in future runoff	Estimate change in future runoff by comparing future runoff simulation versus current runoff simulation. Outputs include percentage change in runoff (seasonal, annual), rainfall and PET for GCMs.		1 week
11	Presentation and database on results	For 0.05^{o} grids across Victoria, and for the DELWP catchments/basins, data on percentage change in all the above and range of results (10th percentile, median, 90th percentile).	May also explore (things to consider) - consistent with NRM projections, all 42 GCMs versus removing a couple, SDM). All available outputs can be presented, but discuss with DELWP on actual series (or empirical scaling factors) for strategy development (median and range for RCP8.5 for future modelling for '2040' relative to current and '2065' relative to current).	4 weeks

12	Report	Report writing and proofing	According to the recommendations in this report, quantified uncertainty will be the range of results from different GCMs, can also provide qualitative/contextual information on other sources of uncertainty (e.g. from choice of scenarios/downscaling methods) as estimated in the above tasks.	4 weeks

3.2. Currently available data and requirements

Gridded data-drill SILO climate data (Jeffrey et al., 2001) is available for Victoria with a current and up-to-date license. The climate data currently exists from 1 January, 1889 to 28 February 2013. Alternatively, AWAP data is also available (although some extra processing will be required to put this into a usable format). If this processing is not too onerous, it is proposed to use AWAP data.

The CMIP5 database is provided by the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and is mirrored in Australia on the NCI facility. This data is free to use for research purposes. The database consists of 65 GCMs from 31 institutes and each has 'decadal' (or time-slice) simulations and 'long-term' simulations.

WRF model runs for Victoria are available via the NSW/ACT Regional Climate Modelling (NARCliM) project and have already been processed and analysed in previous research for project 7 (Teng et al., 2015). Downscaled analogue (SDM) climate data is available through the NRM project for around 20 GCMs.

Catchment boundaries are generally available, and it is anticipated that no further processing is required, provided that standard catchments/regions are used for the projections.

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Appendix: Extract from VicCI Science Plan, 2013

Project 7. Identification and application of improved methodologies for water availability projections

The aim of this project is to provide information about model behaviour and methodological choices that can improve the reliability and usefulness of runoff projections for mid- to long-term future time horizons (2040 and 2065), which are needed for the next round of Water-Supply Demand Strategies (WSDS) in 2016.

The 2012 projections of streamflow for Victoria utilised information derived from the SEACI2 runoff projections, including estimates for a low, medium, and high climate change scenario as well as a 'return to dry' conditions scenario. These projections were informed by climates simulated by the third Coupled Model Intercomparison Project (CMIP3), which underpinned the climate projections presented in the Intergovernmental Panel of Climate Change (IPCC) fourth assessment report (AR4).

Future flow scenarios for the next WSDS will be based primarily on information from climates simulated in CMIP5 used for informing the IPCC's fifth assessment report (AR5), due to be finalised in 2014. In comparison to CMIP3, CMIP5 comprise a larger data set, with many models operating at higher resolution and with more complex physics (Meehl and Bony, 2011). Further, the updated scenarios will draw on information on model evaluation, ensemble creation and downscaling outputs generated in other international and national research initiatives, These initiatives include:

- Downscaling outputs accessible via the World Climate Research Programme (WCRP) strategic framework: CORDEX: A CoOrdinated Regional climate Downscaling Experiment the CORDEX (Giorgi et al., 2009)
- Model evaluation insights and other methodological learnings from the ongoing CSIRO lead Climate Change Projection framework, providing regional climate projections for the Natural Resources Management clusters – a project funded by the Commonwealth Government's Department of Climate Change and Energy Efficiency (DCCEE).
- Dynamical downscaling outputs (10km) from the NSW government funded NSW/ACT regional Climate Modelling (NARCliM) project (publically available from mid-2014).
- Learnings from relevant ongoing ARC research grants concerning hydroclimate non-stationarity and uncertainties associated with GCM runs, e.g. University of Melbourne ARC Linkage Project LP 100100756, "Narrowing the scatter and assessing the uncertainty of climate change projections of Australian river flows".

Work conducted in Project 7 will be integrated with outcomes from Project 5, which will provide guidance on CMIP5 model characteristics in terms of skill in representing regionally important rainfall drivers.

Project 7 will focus on the following research questions:

a. Can statistical downscaling tools provide useful insight into the origin of the range of projections from CMIP5 models and associated uncertainties?
b. What CMIP5 models show best skill in reproducing rainfall characteristics that define regional flow characteristics, with regard to the spatial and temporal behaviour of runoff in space and time across different meteorological seasons and time frames?
c. How are outputs from different CMIP5 models and subsequent downscaling methods most appropriately merged into projections of future streamflow?

d. What existing bias-correct methods are best suited to adjust distributional characteristics of climate model data to observed data(a process necessary in order to use model output directly in hydrological models that are conditioned on relationships based on observed data)? Whilst a wide range of methods have been proposed, such as monthly scaling of the mean (Fowler and Kilsby, 2007), delta change method (Hay et al., 2000), power law correction (Leander and Buishand, 2007, Leander et al., 2008), quantile mapping (Bennett et al., 2012) and nested methodologies to capture persistence at different time-scales (Johnson and Sharma, 2011, 2012), there are concerns that the method can interfere with the interpretation of the climate change signal by altering the spatiotemporal field of consistency, and modify relationships amongst variables by violating conservation principles (Ehret et al., 2012). The choice of approach is non-trivial, where a poor choice can significantly impact the range of the projected changes.
e. What are the best methods for generating updated runoff projections for ~2040 and 2065?

A first order draft of the proposed work to be undertaken for Project 7 is outlined below. This outlines the general direction of the research although details will be refined in developing the Annual Work Plans for the Project.

- Evaluate seasonal rainfall trends and relevant predictors used to statistically downscale rainfall (e.g., MSLP, atmospheric flow and humidity) in CMIP5 models: e.g. use the statistical downscaling tools to provide insight into the rainfall projections and the origin of the range of projections from CMIP5 models. A particular focus will be to quantify the role of coarse model resolution on the severity and the uncertainty of the rainfall projections for Victoria.

  [Note: While downscaled climate change projections will be generated with the Bureau of Meteorology's analogue-based statistical downscaling technique as part of National NRM Climate Futures program, specifically for this VicCI Program, the analogue downscaling tool will be further used to better understand the rainfall projections from the CMIP5 GCMs and shed further light on the uncertainties of these projections.]

- Undertake an evaluation of methodologies for bias correction of existing dynamically downscaled data, such as outputs from CSIRO's Conformal Cubic Atmospheric Model (CCAM) (McGregor and Dix, 2008), and available integrations of the Weather Research and Forecasting (WRF) model (Skamarock and Klemp, 2008). Suitable methods will be identified following a literature survey.

- Using reanalysis data as input to downscaling methods, assess output from dynamical downscaling (with identified bias-correction methods) and other downscaling methodologies, such as analogue scaling (Frost et al., 2011, Timbal and McAvaney, 2001), against observed gridded rainfall data (such as AWAP). The comparison of methodologies provides important insights into the strengths and weaknesses of different methods in terms of capturing processes occurring on spatial scales smaller than the grid resolution of the host GCM. Further, the downscaled rainfall from various methods will be used to estimate runoff, which will be assessed against observed stream flow.

- In the context of the GCM evaluation undertaken in Projects 1-6, provide an assessment of which CMIP3/CMIP5 models are most suited to provide the climate change signal for the updated runoff projections for Victoria. Of key importance here is the ability of downscaled data (using GCM baseline climate) to robustly and realistically capture rainfall and runoff characteristics that are important for water supply planning purposes and flood risk evaluation in Victoria. The identification of such characteristics will be based on stakeholder knowledge of how climate can influence the performance of water supply systems (see examples below), and refined in a small workshop with contributions from CSIRO and Victorian water managers. Characteristics that are likely to be important include representation of:
  - length of runs of below average rainfall/runoff years and years of below average cool season rainfall/runoff;
  - relative contribution and seasonality of different rainfall processes (e.g. warm vs. cool season rainfall)
  - magnitude and frequency of daily/multi-day extreme rainfalls, and return periods for different daily/multi-day rainfall amounts and related consequences for flood risks.

  [Note: The types of metrics outlined above will be calculated for baseline climates of GCMs identified as reliably simulating regionally important rainfall drivers in Project 5. The GCM-downscaled metrics will subsequently be validated against observed data sets of rainfall and runoff.]

- Considering available downscaled data sets and user needs, provide an evaluation of the utility of the downscaled projections in the light of the assumptions and uncertainties involved, and identify the most appropriate format, scale and projection method for delivering the 2045 and 2065 runoff projections for Victoria – time permitting and depending on data availability, these projections will be delivered within the timeframe of VicCI together with at least qualitative information on model/method uncertainty.

  [Note: The temporal and spatial scales and format for delivery of these projections will be determined when developing the relevant Annual Work Plan, but is likely to involve characterisation of expected changes in annual and seasonal runoff at the level of upper/lower AWRC river basins for a range of plausible future climates].

- In addition to runoff projections, design and, if time and data permitting, deliver projections of key runoff characteristics, such as those identified in point c.

- Potentially, via a case study, assess the relative importance of climate risks to the performance of water supply systems in comparison to other inputs that are set/managed by water corporations, such as the adopted system reliability or other performance criteria, the setting of restriction rule curves, target filling curves, other operational rules and procedures and the level of demand.

Time period (mths from commencmt)	2013 1-6 months	2013-2015 7-30 months	2015-2016 31-36 months
CSIRO	Initiate review of bias correction methods. Identify most appropriate bias correction technique for available dynamical downscaled rainfall products. Conduct workshop with Victorian water cooperation and CSIRO to identify important rainfall/runoff characteristics for water supply planning.	In collaboration with researchers in Project 5. Assess model skill in terms of capturing rainfall characteristics that are relevant to shaping regional flow regimes. Evaluate performance of bias-corrected downscaled rainfall available beside the BoM-analogue approach to simulate observed streamflow and compare them against the analogue based approach	Identify appropriate projection method from a scientific robustness and ease of implementation perspective. Develop (and potentially implement) recommended methodology for generating updated runoff projections for 2040 and 2065. Derive information on changes in key runoff characteristics from the data sets used for the updated projections.
BoM		Conduct necessary analogue scaling for VicCI given outcomes in P.5 Evaluate seasonal rainfall trends and relevant predictors used to statistically downscale rainfall Evaluate analogue downscaled rainfall characteristics (at spatial resolution of downscaled data set) which are important for hydrologic processes, water	Collaborative work on including analogue output data in user orientated projection outputs, e.g. information on model uncertainty in deriving key rainfall/runoff characteristics.

		resources planning and flood risk evaluation. Jointly developed optimum bias correction methods for the analogue downscaled rainfall.	

Expected outcomes of the project are a recommended methodology for delivering updated runoff projections, and time and resources permitting, the actual delivery of these updated projections across the State for 2040 and 2065, and an assessment of the relative importance of climate risks to the performance of water supply systems.

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