Approaches for generating climate change scenarios for use in drought projections – a review

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Enquiries should be addressed to:

D. Kirono
CSIRO Marine and Atmospheric Research
Private Bag No 1, Aspendale, Victoria, Australia, 3195
Dewi.Kirono@csiro.au

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1   INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC 2007) reported a substantial body of research which supports a picture of a warming world with significant changes in regional climate systems. For instance, an increase in the area of the globe affected by drought under enhanced greenhouse gas conditions is likely, despite much variation between regions and across climate change scenarios (e.g. Sheffield and Wood 2008). Drought projections for Australia are generally based on global climate model (GCM) simulations since, in the absence of regional climate modelling studies, GCMs represent the most credible tools for estimating the future response of regional climates to anthropogenic radiative forcings. A set of 23 GCMs from research groups around the world is available from the Coupled Model Intercomparison Project 3 (CMIP3) database (http://www-pcmdi.llnl.gov). There are climate simulations of the 20th century driven by observed natural and anthropogenic factors, and simulations of the 21st century driven by three (B1, A1B and A2) greenhouse gas and aerosol emissions scenarios reported in the *Special Report on Emissions Scenarios* (SRES) (IPCC, 2000). Climate variables that are available in the database include air temperature, rainfall, specific humidity and solar radiation. Drought information is not available in the database, hence it has to be developed based on some of the available climate variables.

There are two main steps in estimating climate change impacts on future drought: (1) constructing climate change scenarios under enhanced greenhouse conditions; then (2) incorporating this information into drought index(es)/model(s) to provide estimations of what the future droughts may look like. As will be discussed further in section 2.2 there are many drought indices available for quantifying drought. However, regardless of the drought index being used, the required climate inputs remain relatively constant. As is the case for any modelling exercise, there are uncertainties in climate change for any given region in a given year in the future. These include uncertainties in (1) how much global warming will occur at any point in the future, (2) how the climate of a region will respond to that increase, and (3) how the regional climate change may affect regional droughts. In a risk assessment perspective, a regional drought projection has to therefore be constructed by considering all these sources of uncertainty.

This report describes approaches used for constructing climate projections from a set of climate model simulations for use in drought projections, particularly in Australia. The description includes the pros and cons of each approach with respect to the calculation process, data that are produced, and discussion of the main sources of uncertainty. Although the main focus is on research and approaches that are applied in Australia, the report also briefly discusses approaches applied elsewhere in the world.

Section 2 of the report reviews existing studies, particularly the various drought indices for estimating the impact of climate change on droughts in Australia. In section 3, some common techniques for constructing climate change information required by these drought indices are described, while typical approaches in managing uncertainties are discussed in section 4. Section 5 then provides some concluding remarks.

2 BACKGROUND

2.1 Climate change impacts on droughts in Australia

Despite the devastating socioeconomic and environmental impacts brought about by droughts (e.g. BoM 2004; Suppiah 2008), and the likelihood that human-induced global warming will increase the frequency of droughts in some parts of the world (IPCC 2007), there are relatively few studies examining potential impacts of climate change and drought occurrence in Australia (see Table 1 and Table 2). The first studies were undertaken in the 1990s, after which there has been little activity on this topic until some recent studies in the late 2000s.

These studies focussed on different regions, used a variety of drought indices (discussed in section 2.2), and applied climate change scenarios that were developed in different ways (discussed in section 3). Overall, the previous studies suggested that, under enhanced greenhouse conditions, more droughts would be likely over larger areas for some regions, while other regions would experience little detectable change.

Table 1 Summary of previous studies on estimating climate change impacts on droughts in Australia

Study	Focus	Location	Drought index	Climate change scenarios	Main results
Whetton et al. (1993)	Potential impacts of climate change on heavy rainfall and flooding, and drought occurrence	Nine sites in Australia	Soil water deficit (SWD)	A soil water balance driven by observed daily time series of rainfall and potential evaporation is adjusted for a doubled CO_2 climate futures as suggested by 5 GCMs	Significant drying may be limited to southern Australia. However, the direction of change in terms of the soil regime is uncertain at all sites and for all seasons, thus there is no basis for statements about how drought potential may change.
Kothvala (1999)	The duration and severity of drought for present-day moisture conditions, with a transient increase in CO_2	Eastern Australia	Palmer Drought Severity Index (PDSI)	Raw monthly mean temperature and monthly rainfall from NCAR CCM0 GCM to derive PDSI for the last three decades of the control and transient CO_2 simulations	More prolonged and more intense periods of drought under enhanced greenhouse conditions when compared to a similar time span of the present-day simulations.
CSIRO and BoM (2007)	Projections for future droughts	Australia	Soil moisture deficit index	Climate projections based on CCCma1 and CSIRO-Mk2, for the B1 and A1FI emissions scenarios, were applied to observed daily data from 1974-2003	Up to 20 per cent more drought-months over most of Australia by 2030, and 40 per cent by 2070 in eastern Australia and 80 per cent or more in south-western Australia.

Study	Focus	Location	Drought index	Climate change scenarios	Main results
Mpelasoka et al. (2007)	Spatial and temporal characteristics of drought duration, frequency and severity	Australia	PDSI	Raw monthly climate data (temperature, rainfall, specific humidity and incoming radiation) from CSIRO-Mk3.5 GCM to derive simulated PDSI for the 20th century and the 21st century (2051-2100). The 21st century run is forced with the SRES-A2 scenario.	Increase in frequency, intensity and duration of droughts, especially droughts defined by PDSI<-1 (moderate to severe droughts).
Mpelasoka et al. (2008)	Comparative study of a meteorological drought index and a soil-moisture-based drought index for estimating future drought characteristics	Australia	Rainfall deciles drought index (RDDI) and Soil moisture decile drought index (SMDDI)	Climate change scenarios were constructed by scaling the observed daily time series (1970-2004) with projected changes in monthly means for 2030 and 2070 informed by CCCMA1 and CSIRO-Mk2 GCMs, for B1 and A1Fi emissions scenarios.	Increases in drought frequency of soil-moisture-based droughts are greater than increases in meteorological drought frequency. By 2030, soil-moisture-based drought frequency increases 20-40 per cent over most of Australia with respect to 1975-2004 and up to 80 per cent over the Indian Ocean and southeast coast catchments by 2070.
Hennessy et al. (2008)	Assess how climate change may affect the concept of a one in 20-25 year exceptional circumstance event into the future for Australia	Seven regions over Australia	Used the critical threshold of the 5th percentile for exceptionally low rainfall and soil moisture, and the 95th percentile for exceptionally high temperature	Raw data from 13 GCMs, simulated using the A1B and A2 emissions scenarios, were used for exceptionally low rainfall and high temperature regimes. The critical thresholds are defined for the 20th-century simulation from each GCM, then future projections (up to ~2030) are constructed relative to this threshold. For exceptionally low soil moisture, daily climate change scenarios were constructed by perturbing the observation with scaling factors for ~2030 climate simulated by 13 GCMs.	The mean areas experiencing exceptionally hot years are likely to increase to 60-80 per cent. The mean areas experiencing exceptionally dry years are likely to occur more often and over larger areas in the south-west (i.e. south-west of Western Australia and Victoria and Tasmania regions) with little detectable change in other regions for 2010-2040. Exceptionally low soil moisture years are likely to occur more often, particularly in the south-west (i.e. south west of Western Australia and Victoria and Tasmania regions).

Study	Focus	Location	Drought index	Climate change scenarios	Main results
Johnson and Sharma (2009)	Compare future drought projections based on climate change scenarios constructed with different methods	Australia	Used the observed 5th percentile Standardised Precipitation Index (SPI) value to define a severe drought	Raw daily data from CSIRO-Mk3.5 GCM, for A2 emission scenario, monthly bias correction and nested bias correction GCM data. The GCM daily sequences are modified by using observed monthly and annual time series.	Drought frequencies are overestimated when using the raw GCM rainfall outputs.
Kirono et al. (2011)	Estimate drought characteristics in an enhanced greenhouse gas condition	Australia (Twelve regions)	Reconnaissance Drought Index (RDI).	Raw monthly data (rainfall, temperature, relative humidity, incoming radiation) from 14 GCMs for 1900-2100, for A1B and A2 emissions scenarios. The drought critical thresholds are defined for the 20th-century simulation from each GCM, then future projections are constructed relative to those thresholds.	A general increase in the spatial extent of drought and increases in frequency for some regions. Increases are not statistically significant over the north-west, north Queensland, Queensland east coast and central Queensland.
Mpelasoka et al. (2009)	Examine the dynamics of droughts	Australia (Twelve regions)	Modelled soil moisture drought index (SMDI)	GCM monthly rainfall and areal evaporation (derived from GCM solar radiation, air temperature and humidity fluxes) for 1901-2100, for A1B and A2 emissions scenarios, were translated to a 25km grid over Australia on the basis of quantile-quantile bias-correction relationships between the observed and simulated series for climate data (1951-2006).	For most regions, the change beyond 2030 is larger than that prior to 2030, but the uncertainty in projections also increases with time. Marked increases in the duration of drought events, attributed to the persistence of negative soil moisture anomalies, resulting from the decrease in mean rainfall projected by the majority of GCMs for most of Australia.

Table 2 Examples of global studies that have relevance to Australia

Study	Focus	Location	Drought index	Climate change scenarios	Main results
Wang (2005)	Examine the impact of greenhouse warming on soil moisture based drought indices.	Global	Soil moisture	Raw output from 15 GCMs simulated using the A1B emissions scenarios	Drier soil in the future, compared to that in the pre-industrial control run, over some regions, including Australia.
Burke and Brown (2008)	Explore uncertainty in the projections of future drought occurrence for four different drought indices	Global	SPI, precipitation and potential evaporation anomaly (PPEA), PDSI, Soil Moisture Anomaly	1x CO_2 versus 2x CO_2 Multiparameter ensemble (128 versions) of HadCM3, and 11 GCMs	The change in drought is highly dependent on the index definition, with SPI showing the smallest changes and PPEA the largest. Change in SPI is generally well correlated with all other indices.
Hirabayashi et al. (2008)	Future projections of extremes (flood and drought) in river discharge under global warming	Global	Daily river discharge	Raw output from MIROC (1.1 degree)	The drought frequency was projected to increase globally, while regions such as northern high latitudes, eastern Australia, and eastern Eurasia showed a decrease or no significant changes. Increases in the number of drought days during the last 30 years of the 21st century are significant for some regions, including western Australia.
Sheffield and Wood (2008)	Changes in drought occurrence	Global	Soil moisture	The 20th-century simulations (1961-1990) from 8 GCMs were used to represent present day drought conditions under contemporary climate. The 21st-century simulations (SRES B1, A1B, A2) from 8 GCMs were used to represent future climate.	Decreases in soil moisture globally for all scenarios with a correspondence between the spatial extent of severe soil moisture deficits and frequency of short-term (4-6 months duration) droughts from the mid-20th century to the end of the 21st.

2.2 Drought definitions and characteristics

Drought is a period of abnormally dry weather sufficiently prolonged because of a lack of rainfall (precipitation) that causes a serious hydrological imbalance and has connotations of a moisture deficiency with respect to water use requirements; therefore, it is regional specific and can be experienced differently for different sectors. Numerous indices have been proposed to quantify drought and these have tended to be categorised in the literature into four generic types of drought: meteorological, hydrological, agricultural, and socioeconomic (Wilhite and Glantz 1985). The first three physical drought types are associated with a deficiency in a characteristic hydrometeorological variable: (1) meteorological drought results from a shortage of precipitation, which often is exacerbated by high temperature and/or high evaporation; (2) hydrological droughts are related more to the effects of periods of precipitation shortfall on surface or subsurface water supply including streamflow, reservoir storage, and/or groundwater heights; and (3) agricultural drought links various characteristics of meteorological and hydrological drought to agricultural effects through soil water deficits and plant growth. The socioeconomic drought can be considered as a consequence of the other drought types: unless societal demand consistently exceeds natural supply, a socioeconomic drought will not occur without one or more of the other droughts (Keyantash and Dracup 2002). Some examples of drought indices, particularly those applied in drought impact studies in Australia, are presented in Table 3, and for an extensive listing of available indices, the reader is referred to, for example, WMO (1975), Keyantash and Dracup (2002), and White and Walcot (2009).

The use of drought indices enables researchers to quantitatively compare the current drought risk with that in say the next 30 years. Most of the existing studies use the meteorological (e.g. Hennessy et al. 2008) and agricultural drought indices (e.g. Mpelasoka 2007). Hydrological (Hirabayashi et al. 2008) and socioeconomic (Adamson et al. 2009) drought projections are relatively limited, which is probably related to the fact that analyses of these two indices require data that are less readily available.

Drought characteristics can include (a) drought intensity (the magnitude of the deficit below a threshold level); (b) drought duration (the time during which a variable is consistently below a threshold level); (c) areal coverage; and (d) drought frequency (which may refer to a number of events for a given region) (Dracup et al. 1980).

Table 3 Examples of drought indices applied for drought projections in Australia

Index	Formula/Definition	Original purpose	Data requirements
Annual rainfall (Hennessy et al. 2008)	Rainfall below the 5th percentile is defined as exceptionally low rainfall year	Identify exceptionally dry year for Exceptional Circumstance (EC) assistance	Annual rainfall
Annual mean temperature (Hennessy et al. 2008)	Temperature above the 95th percentile is defined as exceptionally hot year	Identify exceptionally hot year for EC assistance	Annual temperature
Standardized Precipitation Index (SPI) (McKee et al. 1993)	Drought magnitude: $$-\left(\sum_{i=1}^{n} SPI_i\right)$$ where SPI represents the z-score after a long-term P record is fitted to a gamma distribution of rainfall and normalised (White and Walcot 2009)	Emphasis on recovery from accumulated rainfall deficit (White and Walcott, 2009)	Monthly rainfall
Rainfall deciles (RDDI) (Gibbs and Maher 1967)	Lowest 10 per cent 'roughly' coincides spatially with area in drought (White and Walcot 2009)	Identify meteorological drought. Used by the Australian Bureau of Meteorology.	Monthly rainfall
Palmer Drought Severity Index (PDSI) (Palmer 1965)	Σ(water balance anomalies); moving mean (White and Walcot 2009)	Water balance for droughts	Monthly and/or daily rainfall and estimates of potential evapotranspiration (which require temperature, humidity, incoming solar radiation, etc.)
Soil Moisture Decile Index	Similar to RDDI but based on soil moisture time series instead of rainfall	Used operationally in the monitoring and assessment of conditions of the extensive Australian grazing lands	Daily rainfall and estimates of potential evapotranspiration (which requires temperature, humidity, incoming radiation, etc.) to estimate soil moisture through the use of a soil water balance and/or rainfall-runoff model
Reconnaissance Drought Index (Tsakiris et al. 2007)	Based on the ratio between rainfall and potential evapotranspiration	Identify meteorological drought	Monthly rainfall and estimates of potential evapotranspiration

3   APPROACHES FOR GENERATING CLIMATE CHANGE SCENARIOS FOR USE IN FUTURE DROUGHT SIMULATIONS

Regardless of the drought index being used, the data requirements are more or less the same for most drought indices. They include climate variables such as rainfall, temperature and/or potential evapotranspiration. The latter variable, in particular, is often estimated using off line models based on other climate variables including temperature, atmospheric humidity, incoming solar radiation, and wind speed. In this section, we describe common approaches for constructing climate change scenarios that can be used for future drought risk assessment.

The CMIP3 database, mentioned in section 1, archives monthly temperature and precipitation data for all 23 GCMs. However, for other climate variables, monthly data are available for less than 23 GCMs (see CSIRO and BoM 2007 for further details).

3.1   Use of raw GCM data

This approach directly uses raw GCM time series. In this case, the impact of climate change on drought is estimated by comparing the modelled future drought condition relative to the modelled historical drought condition. It assumes that the model is capable of reproducing the present climate in addition to modelling how the regional climate will evolve in response to changes in greenhouse gases and aerosols.

Examples of previous studies that applied this particular approach include those conducted by Wang (2005), which used soil moisture output from 15 GCMs; Hennessy et al. (2007), which considered annual temperature and annual rainfall data from 13 GCMs; Hirabayashi (2008), which applied daily discharge simulated by the MIROC (1.1. degree) GCM; and Kirono et al. (2011), which used annual rainfall and other monthly climate variables for estimating potential evapotranspiration from 14 GCMs.

As an illustration, the step-by-step procedure applied in Hennessy et al. (2008) is described as follows:

1   Define the baseline or present period (e.g. 1900-2007).

2   For each grid cell of the GCM, take the time series of the climate variables (e.g. annual rainfall and/or temperature) into consideration.

3   Use the time series to calculate the critical thresholds for each of the grid cells for the baseline period as defined in step 1. The threshold can be something like the 5th percentile for exceptionally low annual rainfall or the 95th percentile for exceptionally high annual temperature. This is done by sorting the time series from low to high values so that the 5th or 95th percentile can be defined (see Fig. 1).

4   Assign each year within the time series as either a drought or non-drought year event according to the threshold as defined in step 3 (Fig. 2).

5   After time series for each grid cell are prepared, the projections of quantities such as the areal extent and frequency of droughts over each region can be constructed. The areal extent is calculated each year as the percentage area of a region affected by a drought event while the frequency is the regional-average number of drought years (Jan-Dec) within a given period (e.g. 30 years) (e.g. Hennessy et al. 2008).

One of the advantages of this approach is its simplicity: climate change is estimated from model simulations by comparing the simulated future climate with the simulated present-day climate. The use of raw GCM data also helps to eliminate another component of uncertainty that comes from the subsequent use of impact modelling. Additionally, this technique is beneficial for drought assessment that requires continuous data. However, it should be noted that continuous simulated *daily* climate data from GCMs are often unavailable, and in those circumstances this approach will only be of use for drought indices/models that require monthly/annual climate variables. Another caveat of this method is that it assumes the GCMs are reliable in modelling the present and future climate systems. In this regard, although the technique does not require observational data per se, the availability of observed data will be essential for model validation purposes. One way to overcome this weakness is to normalise the GCM data using percentiles (Hennessy et al. 2008). Another way is to perturb the observed data using a factor informed by the GCM and/or to conduct bias correction to GCMs data as will be discussed in the following sub-sections.
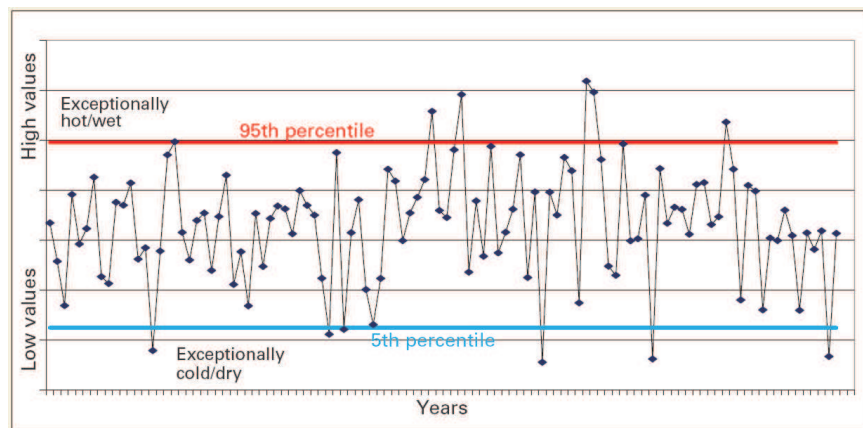
Fig. 1.   A schematic illustration of how a threshold of drought is defined (Source: Hennessy et al. 2008).
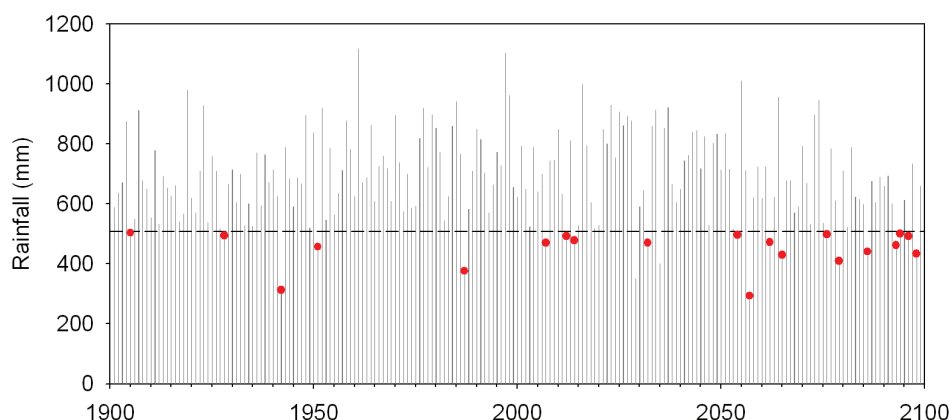
Fig. 2.   A schematic illustration of a drought/non-drought year event in the future relative to the 5th percentile threshold for 1900-2007 for a given location/grid-cell. In this particular example, the drought events (indicated by red circles) in the future are more frequent than those in the historical period.

3.2   Delta change (perturbation) approach

The 'delta-change' approach (Fowler et al. 2007), also called the 'perturbation' method (Prudhomme et al. 2002), constructs future climate time series by perturbing the historical observed climate time series by change factors based on GCM future and GCM historical climate simulations. There are two methods: (i) the constant scaling method and (ii) the quantile-quantile scaling method (also called the daily scaling method). They are simple and offer a practical solution in the construction of future climate scenarios.

3.2.1   Constant scaling method

In constant scaling, the entire observed historical time series for a given variable is perturbed by a constant factor determined from the mean changes simulated by a GCM. The change factors are available as a change per degree global warming (Whetton et al. 2005; CSIRO and BoM 2007). For rainfall it is presented as percentage (relative to 1975-2004) change per degree global warming, while for temperature it is presented as an absolute change per degree global warming (see Fig. 3). CSIRO and BoM (2007) constructed projections for annual and seasonal temperature, rainfall, relative humidity, solar radiation, wind speed, and potential evapotranspiration from most of the 23 GCMs available in the CMIP3 database (monthly projections for most of climate variables are available from www.csiro.au/ozclim). The seasonal and monthly projections, in particular, are useful for taking into account different changes in each of the seasons and/or months.
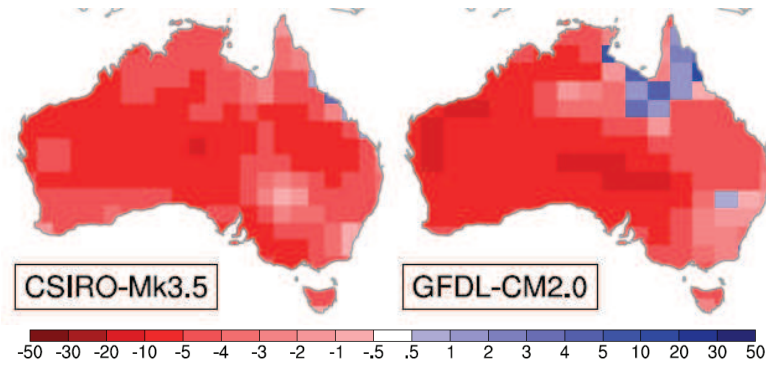
Fig. 3.   Percentage changes in annual rainfall per degree global warming as simulated by two GCMs.

Upon obtaining these projections, one needs to rescale these data with a range of global warming values representing different future times and/or different emissions scenarios (see section 4 for further discussion on uncertainty). IPCC (2007) provides estimates of global warming for the year 2100 for six emissions scenarios (B1, A1T, A1B, A2 and A1FI) (Fig. 4). Equivalent global warming values required for some transient analyses (e.g. 2030, 2050 and 2070) are not provided by the IPCC (2007). CSIRO and BoM (2007) therefore derived the global warming for selected years and emissions scenarios based on the IPCC's (2007) figure and Meehl et al. (2007) (Table 4). For example, the best estimates (multi-model median) of global warming for 2090-2099 relative to 1980-1999 are 1.8°C and 2.8°C for the B1 and A1B scenarios, respectively (IPCC, 2007). Multiplying the projected change (per degree global warming) for a given climate variable with a given global warming scenario yields a 'scaling factor' that can be used to perturb the observed historical climate time series for constructing future climate scenarios (e.g. ~2030-A1B scenario).

This approach considers the relative mean changes in seasonal or monthly climate variables which are fairly readily available. Therefore, this method is particularly useful in the construction of scenarios for different ensemble runs and different emissions scenarios to take into account the large uncertainty associated with global warming scenarios and the GCM simulations of local climatic conditions.

If monthly factors are unavailable, one can perturb the observations using the seasonal factors for constructing monthly future climate scenarios. For example, the scaling factor for summer (DJF) can be applied to the months of December, January and February while the scaling factor for winter (JJA) can be applied to the months of June, July, and August, etc.

Fig. 4.   Global average temperature (relative to 1980-1999) for Scenarios A2, A1B and B1 (shadings denote plus/minus one standard deviation range). The grey bars (right) indicate the multi-model mean warming (solid line within each bar) and the likely range of warming by the year 2100 for the six SRES marker scenarios. (Source: IPCC 2007 Figure SPM-5).

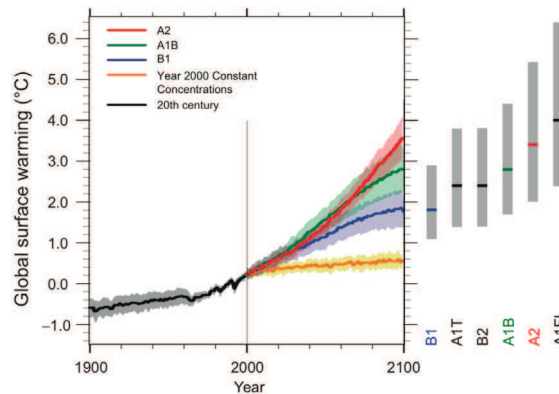Table 4   Global warming estimates [and representative ranges] relative to 1990 for selected years and emissions scenarios. (Based on IPCC, 2007a, Figure SPM-3 and Meehl et al. 2007). (Source: CSIRO and BoM 2007).

	2030	2050	2070
B1	0.75 [0.45-1.2]	1.1 [0.66-1.76]	1.5 [0.9-2.4]
B2	0.9 [0.54-1.44]	1.29 [0.77-2.06]	1.8 [1.08-2.88]
A2	0.8 [0.48-1.28]	1.4 [0.84-2.24]	2.25 [1.35-3.6]
A1B	0.9 [0.54-1.44]	1.53 [0.92-2.45]	2.13 [1.28-3.41]
A1T	1.0 [0.6-1.6]	1.7 [1.0-2.72]	2.2 [1.32-3.52]
A1F1	0.87 [0.52-1.39]	1.8 [1.08-2.88]	2.9 [1.74-4.64]

For example, Hennessy et al. (2008) and Mpelasoka and Chiew (2009) used the constant scaling method to construct future daily time series from observed daily rainfall time series using seasonal constant scaling factors. The method takes into account the projected changes in mean seasonal climate variables and assumes that the shape of the daily rainfall distribution stays the same in the future. However, such an assumption may not always be true because there is an indication for some regions that under enhanced greenhouse conditions, extreme rainfall is likely to be more intense even where a decrease in mean seasonal or annual rainfall is projected (CSIRO and BoM 2007). The following approach serves as an alternative in the face of this problem.

3.2.2   Quantile-quantile/daily scaling method

In this method, simulated changes in the daily frequency distribution of a given variable are applied to observed data (Chiew et al. 2008; Mpelasoka and Chiew 2009; Lucas et al. 2007). This is done for each month or season in two steps. First, the simulated changes are calculated for each quantile (e.g. deciles), then applied to the corresponding daily observed quantiles. For example, decile five changes in daily temperature are added to decile five observed daily temperatures. This may lead to an inconsistency between the mean change in the simulation and the mean change in the modified observed data. Therefore, a second step is needed to adjust all

modified observed data by the difference in the means (the scaling factor described in section 3.2.1).

This method requires simulated daily data from the GCMs. However, unlike monthly data, daily data in the CMIP3 database are only available for some time slices (e.g. 1981 to 2000, 2046 to 2065, and 2081 to 2100). Thus, unlike the scaling factors for the means, the scaling factors for each of the different rainfall quantiles are determined by comparing daily rainfall simulations from the GCMs for two 20-year time slices, 2046-2065 and 1981-2000 (e.g. Chiew et al. 2008). Figure 5 illustrates this method for a given GCM grid cell of a given season in the Murray Darling Basin (MDB) area.

The advantage of the quantile-quantile/daily scaling approach is that it provides data that resemble observations, i.e. the data look realistic. The disadvantages include the fact that sometimes the required observation data are not always available, and this approach only allows construction of transient climate change scenarios hence cannot be applied for drought studies requiring continuous data. In addition, results can be sensitive to the chosen baseline period.

North MDB (28.9°S, 148.1°E)
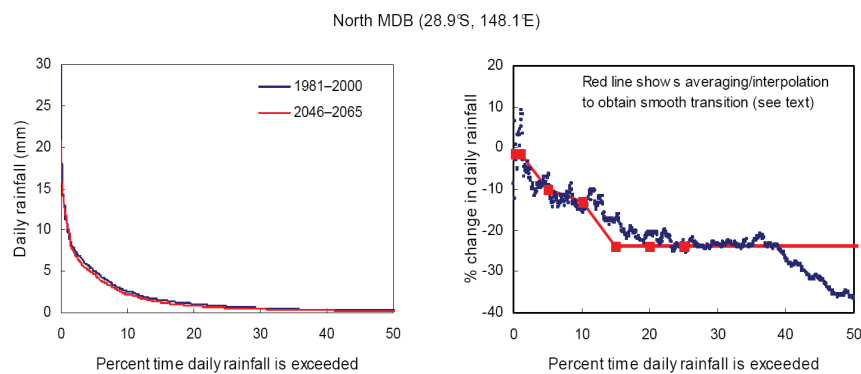
Fig. 5.   Examples showing the daily scaling method used to estimate changes in the different rainfall amounts. The left hand side plot compares distributions of daily rainfall between 2046-2065 and 1981-2000, while the right hand side plot shows the percent changes in different rainfall percentiles for 2046-2065 relative to 1981-2000. (Source: Chiew et al. 2008).

3.3   Use of GCM bias correction climate change projections

The bias correction approaches allow the use of GCM simulated time series while acknowledging the bias in the GCMs' outputs against the real world. Such an approach also serves as a technique to statistically downscale the coarser GCM grid size to a finer grid size which is often required in impact studies (hydrological processes, for example, occur on a much finer resolution than simulated within GCMs). The idea of bias correction is to adjust GCM output so that it statistically 'matches' the observations during a common historical overlap period (Fig. 6). In doing so, this method employs three datasets: (1) observed historical climatic time series (i.e. over the 20th century); (2) GCM-simulated historical time series; and (3) GCM-simulated future climatic time series (e.g. over the 21st century). The bias correction basis is developed by linking datasets (1) and (2) and bias correction is then applied to dataset (3).

There are a number of approaches to develop the basis for bias correction and these are discussed below.

3.3.1 Simple method

This technique corrects the GCM based on two statistical measures: mean and standard deviation. Imagine we have an observed time series of monthly rainfall and/or temperature for the period of 1900-2000 and a modelled time series from a given GCM for the period of 1900-2100. The future corrected GCM time series (i.e. 2001 to 2100) can then be constructed as follows (Smith, *pers. comm.* 2009):

for temperature

$$T_{corrected} = \overline{T_{obs}} + (T_{\mathrm{mod}} - \overline{T_{\mathrm{mod}}}) \frac{\sigma T_{obs}}{\sigma T_{\mathrm{mod}}}$$

while for rainfall

$$P_{corrected} = P_{\mathrm{mod}} \times \frac{\overline{P_{obs}}}{\overline{P_{\mathrm{mod}}}}$$

in which the bar and sigma indicate the average and standard deviation, respectively (for the 1900-2000 period).

This simple technique is most useful for a study requiring monthly data. In this case, the correction is conducted for each of the months and each of the locations in consideration.
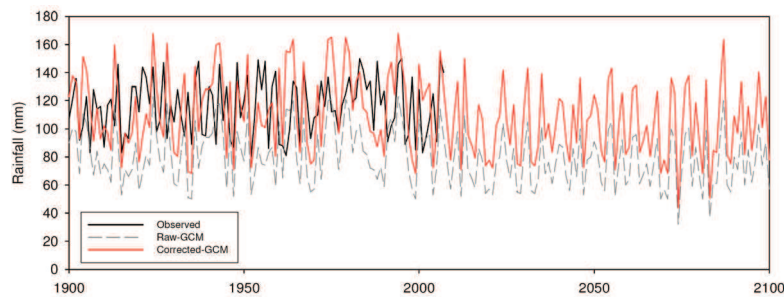
Fig. 6.   Illustration for a simple bias correction technique for GCM rainfall.

3.3.2 Distribution Mapping Bias correction

Wood et al. (2004) applied a quantile mapping (the empirical transformation of Panofsky and Brier 1968) to correct the monthly NCAR-DOE Parallel Climate Model climatology to the observed climatology of the Columbia River Basin (CRB) in the USA. A similar technique, called the daily translation method, has also been applied to daily rainfalls instead of monthly totals by Ines and Hansen (2006) for a crop simulation study in Kenya and by Mpelasoka and Chiew (2009) for a runoff projections study in Australia. Details of this technique are as follows (Wood et al. 2004; Lopez et al. 2009):

- For the historical overlap period (in which observations are available, e.g. 1970-1999) a distribution (e.g. gamma distribution) is fitted to the observed monthly rainfall and to the corresponding monthly rainfall from each GCM run.

- To correct for GCM bias in the period of observations, the quantile for any GCM monthly value is determined, after which that GCM monthly value is replaced with the amount corresponding to the closest quantile in the observed distribution.

- The corresponding daily data for that particular month in the observations used produces a daily series that is both bias corrected and has a realistic day-to-day structure.

- For the other period (e.g. 2000-2030), the model historical (1970-1999) distribution is used to compute the quantiles associated with each monthly value from the model in that period (2000-2030), and each model value is then replaced with the observation value closest to the mapped quantile, including the corresponding daily structure.

It must be noted that the method can also be applied to each of the four commonly defined seasons (summer, autumn, winter and spring) instead of to each of the months. A study by Mpelasoka and Chiew (2009) is an example of applying the seasonal approach.

After the bias correction is performed, the long-term mean monthly/seasonal climate variables of each GCM is similar to the observed mean, and represents a reasonable bias corrected estimate of precipitation over the catchment (Lopez et al. 2009). As such, results from the daily translation method also need to be rescaled such that the changes for the mean future rainfalls in the months/four seasons relative to the baseline (historical) GCM rainfalls are the same as the relative changes from the raw GCM data over a grid cell (Mpelasoka and Chiew 2009).

Since the Gamma transformation method is based on mapping observed and simulated quantiles of their corresponding Gamma distributions, this approach allows the mean and variability of a GCM to evolve in accordance with the GCM simulation, while matching all statistical moments between the GCM and observations for the base periods (Maurer and Hidalgo 2008). In other words, the technique preserves the model intraannual variability in the sense that the sequence of wet and dry months in the raw model data is replicated in the bias corrected data by sampling the corresponding wettest or driest quantiles in the observed distribution (Maurer et al. 2007).

3.3.3   Nested bias correction

The bias correction technique described above focused on monthly or daily statistics of rainfall. However, longer term variations in rainfall also need to be well modelled to enable accurate estimates of drought and the availability of water resources. Johnson and Sharma (2009) proposed a method called a nesting bias correction (NBC) technique; this technique involves nesting the GCM simulations into monthly and annual time series of observed data, such that monthly and annual means, variances and lag correlations are appropriately simulated. The two last measures are important for studies relating to drought projections, because if the models cannot reproduce the interannual variability they will presumably not be able to simulate the droughts correctly. For details of the technique, the reader is referred to Johnson and Sharma (2009). Their study demonstrates that, compared to a simple monthly bias correction (MBC),

NBC provides better performance in terms of prediction error at annual and interannual time scales. However, the MBC gives slightly better predictions.

Variability of Australian rainfall, hence droughts, has been linked to several regional and global climate teleconnections including the El Niño Southern Oscillation (ENSO), the Interdecadal Pacific Oscillation (IPO), the Southern Annular Mode (SAM), and the Indian Ocean Dipole (IOD) (e.g. McBride and Nicholls 1983; Power et al. 1999; Saji and Yamagata 2003; Hendon et al. 2007). Due to some limitations, it remains challenging to adequately simulate ENSO, for example, in the current GCMs (Collins et al. 2010). For this reason, the advantage of the bias-correction approach is that it addresses known GCM biases, which could be related to their weakness in reproducing regional and global climate drivers. This approach considers the observed historical climate data to correct the GCM modelled data for both the historical and future periods. In this case, it assumes that the biases in the model for the observed period remain the same in the future.

4   REPRESENTATION OF UNCERTAINTY

Section 3 provided information about the pros and cons of different approaches to construct climate change scenarios that can be used for drought assessment. This section describes the advantages and disadvantages of each of these approaches from the drought risk assessment perspective, i.e. whether the approach is advantageous/disadvantageous in terms of managing the ranges of uncertainty in climate change (section 4.1).

4.1   Uncertainty in regional climate change

The uncertainty surrounding regional climate change for a given future period can be attributed to at least two sources:

1 how much the global average surface temperature will increase by the period under consideration. This is a combination of uncertainties in the future evolution of greenhouse gas concentrations in the atmosphere and the 'climate sensitivity' (i.e. the sensitivity of area-weighted global average surface temperature to the increase in atmospheric greenhouse gas concentrations; and

2 how the regional climate will respond to an increase in global average surface temperature.

The first uncertainty can be sampled by considering a range of emissions scenarios such as those prepared by the IPCC 2000 (e.g. SRES-A1B, A2, A1FI, etc.) and the global warming in multiple climate models (see Fig.4 and Table 4 for global warming values relating to different emissions scenarios). The second uncertainty can be sampled considering the response of the regional climate to global warming in multiple climate models along with the global warming scenarios to generate a set of scenarios of regional climate change.

As an illustration, Hennessy et al.'s (2008) study considered 13 GCM simulations forced by the SRES-A1B and -A2 scenarios (Fig. 7). Unlike the projections in exceptionally hot years (where

all GCMs suggest potential increases in affected areas), those in exceptionally low rainfall years show a range of uncertainty (whereby some GCMs suggest a slight increase while others indicate a slight decrease). This is consistent with the fact that in Australia the range of projected changes in rainfall, allowing for GCM to GCM differences, is relatively large. This leads to the GCM selection problem issue being addressed by a number of studies with different views and approaches.

Whetton (2009) categorises these views into two broad conceptual testing methods: (1) applicability testing which tests whether the model provides suitably realistic data for the application in mind, and (2) reliability testing which tests the reliability of the enhanced greenhouse changes simulated by the model. The former includes questions such as does the model have the variables required by the study, does the model realistically simulate the current climate for the variables, seasons and locations that the study requires, etc. The latter, on the other hand, includes questions such as how well does the model simulate processes that drive its enhanced greenhouse response, and are the simulated trends in line with the observations, and so on. In Hennessy et al.'s study (2008), the 13 GCMs considered were selected on the basis that they are reasonably reliable in reproducing the observed mean climatology, and that they have climate data required for this particular study (i.e. annual temperature, annual rainfall, daily rainfall, daily potential evapotranspiration). In other words, they satisfy both the reliability and the applicability tests. Kirono and Kent (2009, 2010) demonstrate that the reliability of GCMs in reproducing the observed mean rainfall climatology, interannual variation and long-term trends does not necessarily correlate with the direction/magnitude of projected changes in drought affected areas for most regions in Australia. This implies that reducing the GCMs' sample by selecting only the better GCMs in a given analysis does not always mean a reduction in uncertainty. Thus, drought projections are probably best determined using climate scenarios from most of the available GCM simulations.
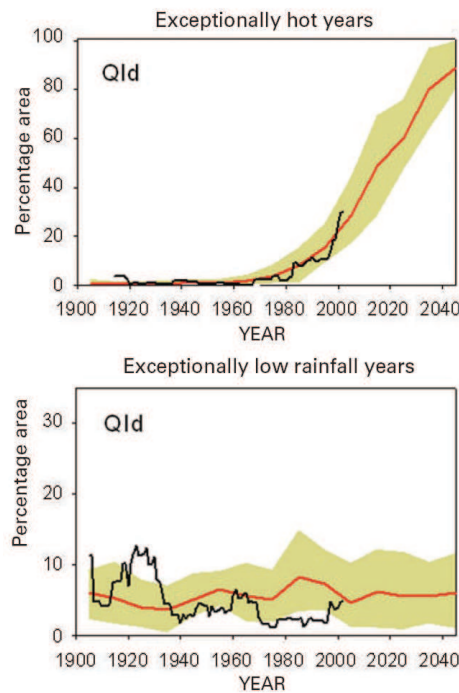
Fig. 7.   Observed and simulated percentage area with exceptionally hot years (upper) and exceptionally low rainfall years (lower) in Queensland for 1900-2040 based on 13 GCMs. The red lines are the multi-model means while the shading shows the range between the lowest and highest 10 per cent of model results, all smoothed by decadal averages. Observed data are smoothed by a 10-year moving average (black). (Source: Hennessy et al. 2008).

4.2   Uncertainty in climate change scenario construction for drought projections

As described in the preceding section, there are a number of techniques that can be used for constructing climate change scenarios for assessment of risks associated with droughts. The use of different approaches may introduce another uncertainty component in the overall drought projections and risk assessment studies. For example, Mpelasoka and Chiew (2009) compared the influence of scenario construction methods for rainfall on runoff projections. They found that the daily scaling and daily translation methods generally project higher extreme and annual future runoff than the constant scaling method. This is because daily scaling and daily translation methods take into account the increase in extreme daily rainfall simulated by the majority of the GCMs. The research of Johnson and Sharma (2009) indicated that, based on the CSIRO-Mk3.5 GCM data, drought frequency projections using the SRES-A2 scenario for 2080 are overestimated when using the raw GCM rainfall output in comparison to the scenarios constructed by simple bias correction and nested bias correction (Fig.8).

With regard to the need for considering the range of uncertainty in how the regional climate will respond to an increase in global average surface temperature (i.e. by considering as many GCMs as possible), the use of GCM raw data has an advantage. This is because most of the GCMs available in the CMIP3 dataset archive the monthly time series datasets over long periods (e.g. from ~1870 to 2100). However, the use of the raw data limits the consideration of

range of uncertainty due to different emissions scenarios. This is due to the fact that only selected emissions scenarios (e.g. the mid-range emissions scenarios called A1B and A2) were realised for most GCM simulations. Observations since 1990 show that we are tracking the highest IPCC emission scenario, called A1FI (Raupach et al. 2007) and global climate simulations have not been performed using that scenario.
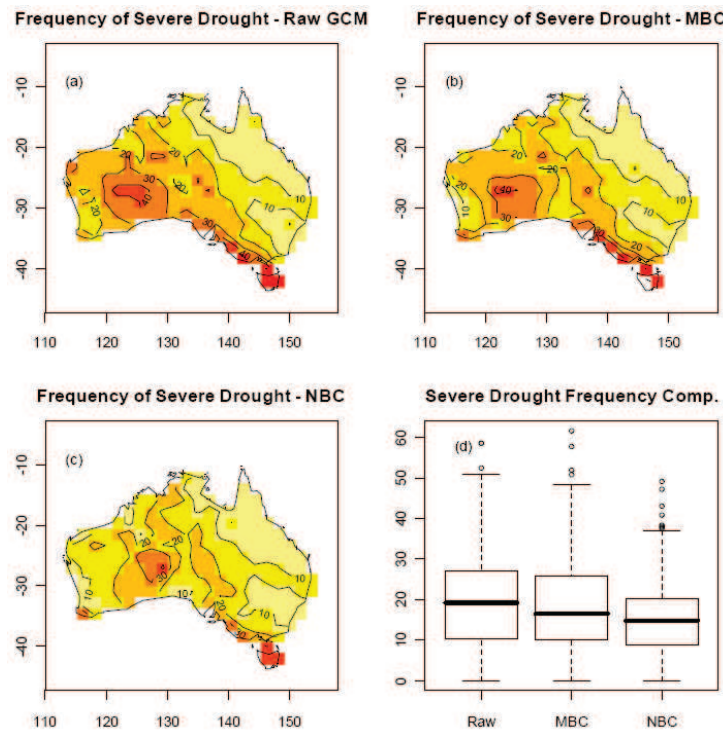

Fig. 8.   Maps and distribution values of severe drought frequency in 2080 for a) raw CSIRO-Mk3.5 GCM, b) monthly and c) nested bias correction (Source: Johnson and Sharma 2009).

In this regard, the use of a scaling approach for generating climate change scenarios is advantageous since it allows researchers to consider both uncertainties relating to the global warming for different emissions scenarios and the regional climate response as indicated by a variety of GCMs. However, the scaling approach assumes that the future climate distribution stays the same. This introduces an additional uncertainty because it is not clear whether the future climate distribution will be the same as that of the present or not.

Similar to the scaling approach, the use of the bias correction approach is advantageous since it allows the consideration of both uncertainties relating to the global warming response for different emissions scenarios and the regional climate response to global warming as indicated by a range of GCMs. However, this approach assumes that the biases in the model for the observed period remain the same in the future.

4.3   Uncertainty in drought indices

As described in Section 2.2., there are many available drought indices hence future projections of drought characteristics may depend on a specific definition of drought used. Burke and Brown (2007) conducted a study to examine the sensitivity of global projections of future drought to index definitions using four different drought indices (SPI, Precipitation Potential Evaporation Anomaly or PPEA, PDSI, and Soil Moisture Anomaly). They found that the change in percentage of the land surface experiencing drought is highly dependent on the index definition, with increases in SPI-based drought showing the smallest and increases in PPEA-based drought the largest (Fig. 9). Another study by Mpelasoka et al. (2008) using simulations from CCCma1 and CSIRO-Mk2 GCMs suggested that increases in the frequency of soil-moisture-based droughts are greater than increases in meteorological drought frequency. By 2030, soil-moisture-based drought frequency increases by 20-40 per cent over most of Australia with respect to 1975-2004 and up to 80 per cent over the Indian Ocean and southeast coast catchment by 2070. The authors recommended that the soil-moisture-based index (SMDDI) has to be more relevant to resource management than the meteorological drought index (RDDI) in that it accounts for the 'memory' of water states. In particular, consideration of soil-moisture delays and prolongs droughts, relative to meteorological droughts and tends to indicate a realistic severity and persistence for drought events.
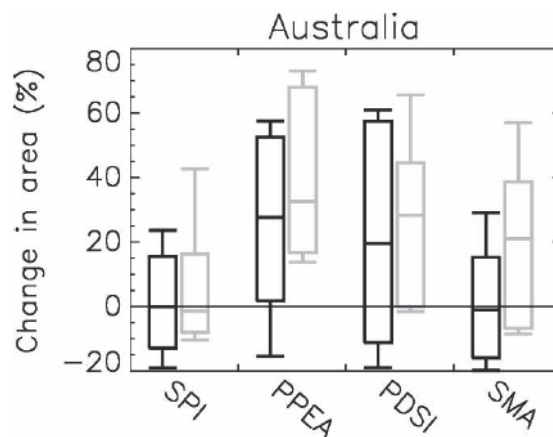

Fig. 9.   The uncertainty in the change in the percentage of the land surface in drought. The box shows the 25th to 75th uncertainty range and the whisker shows the 5th to 95th uncertainty range. The black boxes are results from a multiparameter ensemble (128 versions) of HadAM3 GCM while grey boxes are results from a multimodel (11) ensemble. (Source: Burke and Brown 2007).

5   CONCLUDING REMARKS

In this report we have discussed existing research for drought projections in Australia (and elsewhere in the world). In particular, the report has focused on describing the approach used for constructing climate variables scenarios from a set of climate model simulations for use in future drought risk assessments. This includes a discussion of the advantages and disadvantages of each technique with respect to a number of issues such as the assumptions applied, availability of necessary data, and the ability to sample the uncertainty.

The socio-economical and environmental consequences of drought in Australia can be devastating, hence drought risk assessments in response to future human-induced global warming are highly important. However, existing studies are relatively limited (Table 1). Each of these studies has a different focus in terms of the regions/locations, the drought indices and drought thresholds, the number of GCMs and/or emissions scenarios, and the way climate change scenarios were constructed.

The use of different drought indices for different research is inevitable since drought is a complex and multi-faceted phenomenon. As drought is a function of a mismatch between low water availability and the demand of human activities, it is regionally specific and can be experienced differently for different sectors. It is therefore likely that no single index could be effective for widespread, general usage in monitoring Australian climate variability (White and Walcott 2009) and its future projection.

Each of the drought indices has a unique potential for quantitatively comparing the current drought risk with that in, for instance, the next 30 years. Among the drought projections reviewed here, many of them consider the meteorological (e.g. Hennessy et al. 2008) and agricultural drought indices (e.g. Mpelasoka 2007). Hydrological (Hirabayashi et al. 2008) and socioeconomic (Adamson et al. 2009) drought projections are relatively limited since analyses of these two indices require data that are less readily available. Overall, the studies suggest that, under enhanced greenhouse conditions, some regions are likely to experience an increase while others show little detectable change and/or slight reduction in drought affected areas and/or drought frequency. It is also apparent that for more prolonged and more intense periods of drought (Kothvala 1999; Mpelasoka et al. 2009).

Similar to drought indices, it is also likely that no single approach can be considered as superior to any other approach in relation to developing climate change scenarios. Each technique has its own advantages and disadvantages: some are practical for constructing monthly climate scenarios while others are useful for daily data; some allow researchers to include all the sources of uncertainties relevant to climate change scenarios (e.g. emissions scenarios, and response from the regional climate to global warming as represented by a variety of GCMs), while others provide limited options to include all the possible uncertainties (Table 5). The most appropriate approach to adopt, therefore, will be dictated by the purpose and context of the particular study undertaken.

Table 5   Advantages and disadvantages of different approaches to construct climate change scenarios for drought risk assessments

Approach		Advantages	Disadvantages
Raw GCM Data		• Requires simple calculations. • Produces continuous data. • Eliminates uncertainty introduced by different approaches for constructing climate change scenarios and/or impact models.	• Applicable only to SRES-A1B and A2 emissions scenarios. • Observed soil moisture data for validating modelled soil moisture data are not always available. • Daily data availability is relatively limited.
Delta change (perturbation)	Constant scaling	• Requires simple calculations. • Can be used for daily data. • Can include all GCMs and all emissions scenarios.	• Produces transient scenarios. • Assumes that daily rainfall distribution in the future will stay the same as it is in the historical period. • Results can be sensitive to the chosen baseline period.
	Daily scaling	• Requires relatively simple calculations. • Can be used for daily data. • Can include all GCMs and all emissions scenarios. • Considers changes in future daily rainfall distribution.	• Requires relatively more complex calculations. • Produces transient scenarios. • Results can be sensitive to the chosen baseline period. • Archives for daily data are only available for a limited number of GCMs and are not available continuously.
Bias correction	Simple method	• Requires simple calculations. • Produces continuous data.	• Can be used for monthly or annual data. • Limited to SRES-A1B and A2 emissions scenarios. • Only considers the mean and standard deviation. • Assumes that the relationship between current observation and GCM data stay the same in the future.
	Distribution mapping	• Can be used for monthly or daily data. • Preserves the model interannual variability.	• Requires relatively more complex calculations. • Produces transient scenarios. • Assumes that the relationship between current observation and GCM data stay the same in the future.
	Nested	• Can be used for monthly or annual data. • Means, variances and lag correlations are appropriately preserved.	• Requires relatively more complex calculations. • Not applicable for daily data. • Assumes that the relationship between current observation and GCM data stay the same in the future.

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