Environmental Modelling & Software 96 (2017) 68–82

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

# Evaluating four downscaling methods for assessment of climate change impact on ecological indicators

Jun Wang [a, *], Rory Nathan [a], Avril Horne [a], Murray C. Peel [a], Yongping Wei [a, b], John Langford [a]

[a] Department of Infrastructure Engineering, The University of Melbourne, Australia
[b] School of Geography, Planning and Environmental Management, The University of Queensland, Brisbane, Australia

ARTICLE INFO

*Article history:*
Received 11 October 2016
Received in revised form
27 April 2017
Accepted 15 June 2017
Available online 6 July 2017

*Keywords:*
Climate change
Downscaling
Environmental flows
Time-averaged metrics
Sequence-dependent metrics

ABSTRACT

Assessments of climate change impacts on freshwater ecosystems are generally based on global climate models (GCMs) and ecologically relevant "time-averaged" hydrological indicators derived from long-term records. Although uncertainties from GCMs have been recognized, the influence of downscaling methods remains unclear. This paper evaluates the influence of applying different downscaling methods of increasing complexity (annual scaling, monthly scaling, quantile scaling, and weather generator method) on the assessment of ecological outcomes. In addition to time-averaged indicators, "sequence-dependent" metrics which involve ecological dynamics by considering the impacts of flow sequencing are also adopted. In a case study in Australia, the condition of river red gum forest was assessed. Results show that the choice of downscaling methods can be of similar importance as that of GCMs in ecological impact studies. Where sequence-dependent metrics are adopted, more sophisticated downscaling techniques should be used to better represent changes in the frequency and sequence of flow events.


## 1. Introduction

Water resources around the globe are becoming increasingly stressed as human demand for water increases (Vörösmarty et al., 2010). There is now significant evidence that climate change, exhibited through altered precipitation patterns and temperature, will alter the global hydrological cycle and local catchment hydrology to exacerbate these stresses (Arthington et al., 2006; Poff and Zimmerman, 2010; Poff et al., 2015). At the same time, there is growing awareness and understanding of the implications of hydrological alterations for freshwater ecosystem health (Dudgeon et al., 2006; Poff et al., 2010, 1997). It is important therefore to understand the implications of a changing climate for not only human water uses, but also for the instream environment those uses depend on (Döll and Zhang, 2010; Poff et al., 2015). However, when assessing the impact of climate change, it is important to consider the method used to represent those changes in the context of the objectives of most interest.

There is an extensive literature examining the impacts of climate change on water resources, however few focused specifically on ecological outcomes. A large number of these studies have focused purely on instream hydrology and long term average flow conditions (e.g. Beyene et al., 2010; Chiew et al., 2009; Lauri et al., 2012). Studies focused primarily on water availability have tended to adopt simple ecologically relevant hydrological indicators to infer ecological outcomes (e.g. CSIRO, 2008). Where studies have included environmental outcomes, the most common approach has been to assess the ecologically relevant hydrological indicators at the seasonal and annual scale (Döll and Zhang, 2010; Laizé et al., 2014; Piniewski et al., 2014). Only a handful of studies have adopted more complex approaches. For example, in addition to hydraulic indicators of direct relevance to habitat (e.g. water depth), Htun et al. (2016) and Walsh and Kilsby (2007) used a habitat-suitability based approach, and Battin et al. (2007) used a population model, where responses of fish or waterbirds were investigated. As our understanding of environmental flow requirements improves, it has been gradually acknowledged that it is difficult to characterize the dynamics of ecological response using simple hydrological flow indicators as they do not capture the complexity of the interactions involved. It thus may be necessary to adopt assessment methods based on process-oriented descriptions of

* Corresponding author. Department of Infrastructure Engineering, The University of Melbourne, Parkville, Victoria, 3010, Australia.
*E-mail address:* thujunw@gmail.com (J. Wang).

http://dx.doi.org/10.1016/j.envsoft.2017.06.016
1364-8152/

ecological dynamics particularly at inter-annual scale, for example, the state and transition succession theory (Zweig and Kitchens, 2009), for long-lived species (Anderson et al., 2006; Hickey et al., 2015).

There has been significant scientific research aimed at representing climate change derived at the global or regional scale in a way that is relevant to the assessment of water resources at the local scale. Global climate models (GCMs) are the primary tool for understanding and projecting changes in the global climate and their outputs have been widely used in impact studies (Maraun et al., 2010). Despite their physical basis and the ability to represent historical climate, GCMs have two key limitations. Firstly, there are substantial uncertainties between GCMs and within a GCM (Peel et al., 2015); the former largely reflects the epistemic uncertainties related to model structure and parameterization, and the latter to aleatory uncertainties associated with the random nature of natural processes and the initial state and forcing variables (Beven, 2015; Ekström et al., 2015). These uncertainties can result in large differences between simulations, and are usually addressed by analyzing simulations from multiple GCMs or different ensemble members (e.g. Chiew et al., 2009; Lauri et al., 2012; Thompson et al., 2014). Secondly, GCM outputs are of too coarse a scale to be directly used in catchment-scale impact studies (e.g. see Fowler et al., 2007). Numerous downscaling techniques have been developed to derive local climate change information from large scale GCMs outputs (Maraun et al., 2010). The two primary categories of downscaling techniques are (1) dynamic downscaling, which obtains regional information by nesting a high-resolution regional climate model within a GCM, and (2) statistical downscaling, which relates large scale climate variables to local scale climate variables (Trzaska and Schnarr, 2014). Although dynamic downscaling is more conceptually appealing, it has not been popular in impact studies due to the computational cost and limitations of regional climate models (Fowler et al., 2007). In contrast, statistical downscaling has been more widely applied (Trzaska and Schnarr, 2014). Under the broad category of statistical downscaling, there are a number of methods from the simplest constant scaling method to more sophisticated regression models and weather generator methods.

Different downscaling techniques yield differences in local climate change characterizations, and these differences affect the evaluation of changes to the hydrological regime (Chen et al., 2011a; Hay et al., 2000; Mpelasoka and Chiew, 2009). Even though GCMs generally represent the largest source of uncertainty in climate change impact assessments (Kay et al., 2009; Minville et al., 2008), the influence of downscaling methods, depending on the hydrological indicators assessed, could be of a similar magnitude to that of GCMs (Chen et al., 2013, 2011b; Prudhomme and Davies, 2009; Teutschbein et al., 2011). The need to consider both GCMs and downscaling techniques on issues related to catchment hydrology has been well recognized. However, in ecological impact studies, although the uncertainty from GCMs has been considered, the influence of downscaling methods has not previously been assessed. Existing literature has tended to adopt multiple GCMs to assess the impact on instream environment derived from hydrological alterations whilst adopting only a single downscaling method (Battin et al., 2007; Döll and Zhang, 2010; Piniewski et al., 2014; Thompson et al., 2014). The majority of these studies have adopted simple statistical downscaling approaches, such as the monthly-scale constant scaling method (Döll and Zhang, 2010; Htun et al., 2016; Piniewski et al., 2014; Walsh and Kilsby, 2007).

This paper examines the implication of using different downscaling methods for the assessment of freshwater ecosystem conditions. The choice of a downscaling method – as with the choice of a GCM – introduces uncertainty into the assessment of climate change impacts. This uncertainty reflects both the differences in the ability of each method/model to adequately represent climate change (i.e. epistemic uncertainty) and the *natural variability* (i.e. aleatory uncertainty) of the system being analyzed (Beven, 2015). The latter is of particular importance to the assessment of ecological impacts as different environments or river typologies have evolved to cope with different levels of natural variability, known as the ecosystem resilience (Poff and Matthews, 2013). Climate change impacts both the frequency and variability of flow conditions, and thus methods which consider this explicitly may be expected to provide a more realistic assessment of the impacts. This paper considers three deterministic downscaling methods (constant scaling applied on the annual scale and the monthly scale, and the quantile scaling method) and a stochastic downscaling method (based on the use of a weather generator), the latter of which is able to consider the natural variability in climate sequences. We consider the type of hydrological indicators that are typically used to assess ecological impacts, and include more sophisticated metrics that consider ecological dynamics, which is important when considering the influence of natural variability (Section 2). A brief introduction to the four downscaling methods are provided in Section 3. The Ovens River, Australia, is used as a case study to explore the influence of applying different downscaling methods on ecological outcomes (Section 4). Results are presented in Section 5, and the importance of the selection of a downscaling method on the assessment of ecological impacts is discussed in Section 6.

## 2. Assessment of hydrological alterations affecting ecological outcomes

The natural flow paradigm is a central element of many environmental flow assessment methodologies (Acreman et al., 2014). The natural flow paradigm suggests that the entire flow regime is critical to the integrity of river ecosystems, and this can be represented through key flow components described by their magnitude, frequency, duration, timing and rate of change (Poff et al., 1997). Modifications of the components will have cascading effects on an ecosystem's ecological integrity. Although it is still unclear how the modifications transfer quantitatively to ecological responses, it has been demonstrated that the risks to ecosystem health increase with the degree of hydrological alterations (Döll and Zhang, 2010; Poff and Zimmerman, 2010). The natural flow regime thus provides the baseline for quantifying flow alterations to assess the impact of human activities and climate change on instream environment (Poff et al., 1997; Poff and Zimmerman, 2010).

There are a large variety of hydrological indicators that have been developed to characterize flow regimes and to quantify hydrological alterations (Olden and Poff, 2003). Broadly, studies have attempted to select a range of hydrological indicators that are representative of the ecologically relevant flow regime (e.g. the Indicators of Hydrological Alteration; Richter et al., 1996). Flow alterations are calculated by comparing the hydrological indicators of changed flow series to a reference flow series, which is usually representative of "undisturbed" conditions. Hydrological indicators remain the most commonly used metrics for assessing the ecological impacts at a catchment scale. In this paper, they are referred to as "time-averaged" metrics, as they are based on statistical analysis of long-term records and do not explicitly consider the sequencing of flow conditions.

River ecosystems are shaped by a combination of the flow regime and internal feedbacks that are heavily dependent on the sequencing of particular flow events (Anderson et al., 2006). This has recently led to a series of more complicated indices, which

include the process-oriented descriptions of ecological dynamics. Ecosystem succession has multiple trajectories and endpoints and is dominated by climatic (and hence hydrologic) variability. Non-spatial conceptual frameworks representing the succession patterns have been developed for assessing the conditions of instream population and communities in a changing environment. Hydrological indicators alone (e.g. Overton et al., 2014) or in combination with other climatic and hydraulic factors (e.g. Zweig and Kitchens, 2009) have been used as the forcing functions for state transitions. Such indices considering state transitions require examination of the sequences of flow events and cannot be represented by linear mathematical models. In this paper, such indices are referred to as "sequence-dependent" metrics.

## 3. Downscaling methods

To translate large spatial scale climate simulations to local scale climate projections, we adopt four statistical downscaling methods, namely (i) constant scaling applied on the annual scale (annual scaling), (ii) constant scaling applied on the monthly scale (monthly scaling), (iii) quantile scaling applied separately for each of the twelve months, and (iv) a weather generator method applied separately for each of the twelve months. A brief introduction to the four methods is provided below, with more details provided in Appendix A.

Constant scaling methods (also referred to as change factor method, delta change method, or perturbation method) assume that the relative changes between the future and historical climates are reasonably projected by GCMs even if the GCMs are biased (Fowler et al., 2007; Johnson and Sharma, 2011). Future precipitation series are constructed through multiplying the historical records by the ratio between the GCM simulations of future period and reference period (Hay et al., 2000). It is termed constant scaling since changes in different percentiles of precipitation magnitudes are assumed equal. However, the change factors can be calculated and applied on different time scales, e.g. the annual scale and the monthly scale. In contrast, quantile scaling applies different factors for different precipitation percentiles, usually on the daily scale. Scaling approaches are simple and able to consider multiple GCMs (Johnson and Sharma, 2011). For this reason, they are very commonly adopted in water resources impact studies (Anandhi et al., 2011). But they are unable to consider changes in the number of rain days or the sequencing of wet and dry conditions (Diaz-Nieto and Wilby, 2005). This is a potential limitation as projections by GCMs suggest that future climate will also see changes in the frequency of rain days and dry spells (Polade et al., 2014).

Weather generators are stochastic models for generating daily climate series at a given location. The statistical properties of simulations are controlled by the weather generator's parameters which can be viewed as a statistical encapsulation of the observed climate (Wilks, 2010). Future climate series can be generated by adjusting the parameters of the weather generator according to the projections by GCMs. Parameter perturbation is based on either changes in monthly statistics (e.g. Zhang, 2013) or daily variations in atmospheric circulation (e.g. Kilsby et al., 2007). Wilks (2010) provided a review of the two types of weather generator downscaling methods and concluded that they both perform well in a wide range of application studies so that it is difficult or impossible to tell which one is better. In this study, the weather generator's parameters, including the probability of precipitation occurrence and the parameters of precipitation distribution function, are perturbed using the monthly-adjustment procedure, allowing changes in both the precipitation magnitudes and the sequences of wet and dry days.

Although other complicated statistical downscaling and dynamic downscaling methods have the potential to provide more realistic projections (Fowler et al., 2007; Johnson and Sharma, 2011), the above four methods have been selected for several reasons. Firstly, they have been widely used in impact studies due to their ease of application and their ability to consider a wide range of GCMs. Second, by manipulating historical records or generating synthetic series of required lengths, they can provide long time series, which are required for ecological condition assessments. This may be particularly important if the historical record contains periods of extended droughts, as such events are generally not well represented by GCMs (van Oldenborgh et al., 2005; Xie et al., 2014). In contrast, the length of time series downscaled by regression models or dynamic downscaling methods is limited by the length of available GCM simulations. Third, complicated statistical downscaling and dynamic downscaling methods need to be first validated over the reference period which is a laborious process (Ekström, 2016; Wood et al., 2004), and it is unclear whether the ability of a GCM to reproduce historical conditions translates into realistic future projections (Johnson and Sharma, 2011).

The four methods adopted present increasing levels of complexity in representing changes in climate (specifically precipitation in this study). The three scaling methods merely change the magnitude of precipitation and the sequencing remains identical to that contained in historical records: the annual scaling method involves adjustment by a single factor, while monthly scaling uses a separate factor for each month; quantile scaling involves the use of a factor that varies with the magnitude of precipitation. The weather generator method considers changes in both the precipitation amounts and the sequences of wet and dry days, which thus reflects the natural variability in the streamflow regime.

## 4. Application

The Ovens River catchment, Victoria, Australia, is used to examine the influence of applying different downscaling techniques on the assessment of climate change impacts on ecological conditions. The case study focuses on the river red gum forest in the lower Ovens floodplain. We apply the four downscaling methods presented in Section 3 and assess the ecological implications using both time-averaged and sequence-dependent metrics (Section 2).

### 4.1. Study area

The Ovens River catchment is located in the south-eastern Murray-Darling Basin (MDB) of Australia, covering an area of 7813 km$^2$ (Fig. 1). The Ovens River joins the Murray River downstream of Peechelba. Spatial and temporal variability of precipitation is large, but winter is typically the wettest season (CSIRO, 2008).

The catchment retains many of its natural characteristics, with significant native vegetation and limited water use and on-stream storage (CSIRO, 2008). While the lower catchment has been cleared for grazing, cropping and pine plantations, over half of the catchment is covered with native vegetation. There are two main on-stream storages whose capacities are only 5% and 7% of their annual inflows respectively. Water use in this catchment is capped, allowing 58 GL/year of interception (farm dams and forestry plantations) and 25 GL/year for watercourse diversions (Murray–Darling Basin Authority, 2010). The average annual streamflow at the gauge of Peechelba (reference number 403241) is estimated as 1775 GL (CSIRO, 2008).

A number of key environmental assets have been identified in this catchment (Murray–Darling Basin Authority, 2010), providing important habitats for many species. Substantial changes in climate

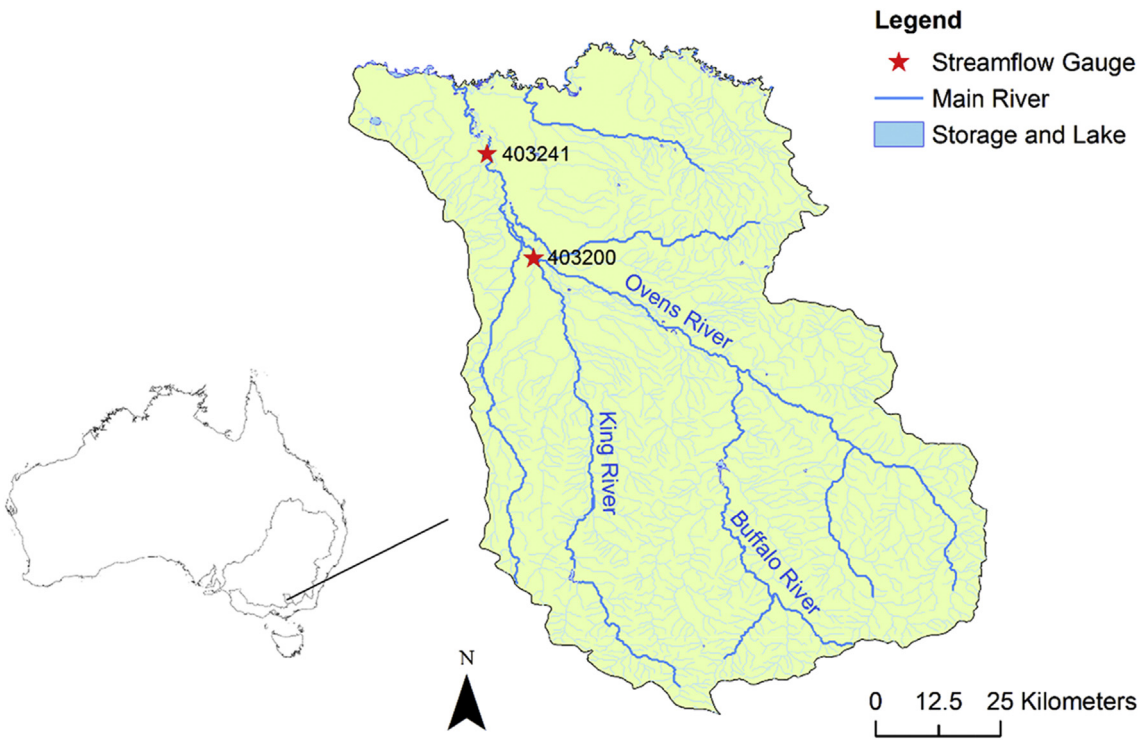


**Fig. 1.** Map of the Ovens catchment.

are likely to occur (CSIRO and Bureau of Meteorology, 2015), but previous impact studies have mainly focused on water availability, using simple hydrological indicators to provide implications for ecological outcomes (e.g. CSIRO, 2008). As one of the last largely unregulated rivers in the MDB, the Ovens River maintains a near natural flow regime under the current conditions (Davies et al., 2012). Evaluation of hydrological alterations induced by climate change affecting freshwater ecosystems in this catchment could therefore provide valuable reference for other catchments in the MDB.

### 4.2. Ecological indicators for river red gum forests

The downstream reach of the Ovens River includes areas of nationally significant wetlands (Environment Australia, 2001) where river red gum forest is the dominant vegetation. In practice, it is necessary to consider a number of flow indicators to fully understand the environmental water requirements of a particular vegetation community (Murray–Darling Basin Authority, 2010). However, since the aim of this paper is to evaluate the implications of different downscaling methods rather than to undertake a condition assessment of the river red gum forest, it is considered sufficient to illustrate the sensitivity to different downscaling methods using a single representative flow indicator relevant to such assessments.

For a river red gum forest to maintain a healthy condition, it is necessary that it be flooded for a specified minimum period (preferably in winter and spring) every one to three years (Roberts and Marston, 2011). The magnitude of the flow required to achieve overbank flooding obviously varies with location, and for the river red gum forest located at the downstream end of this catchment, the identified "site-specific flow indicator" (SFI) is 10,000 ML/day for a total duration of 14 days with a minimum consecutive period of 7 days between June and May for 35.4% of years. The annual sequences of SFI being achieved or not achieved are the basis for both time-averaged metrics and sequence-dependent metrics.

The river red gum forest can tolerate flow conditions that result in more infrequent inundations, but under such conditions the forest's health is likely to deteriorate (Roberts and Marston, 2011). The forest's condition at any point in time is dependent on the initial condition and the sequence of inundations over the period of interest: the healthier the forest at the beginning, the greater its tolerance to successive dry periods. Conversely, the poorer the forest's condition at the beginning, the lower its tolerance to missing out on subsequent inundations. This dynamic dependence on initial state and flood sequences may be represented by the conceptual framework developed by Overton et al. (2014), as shown in Fig. 2. This framework shows how the river red gum forest can transition between different condition states, including both the degradation and recovery pathways defined on the basis of

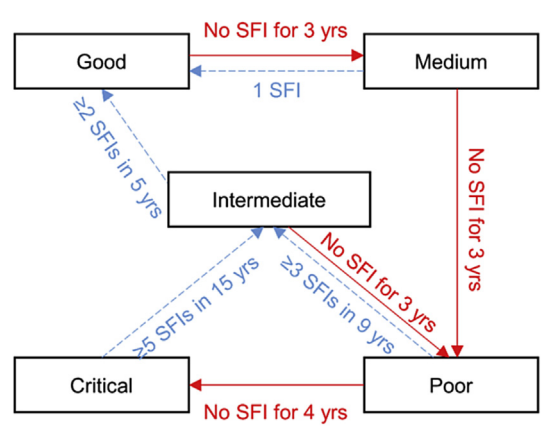


**Fig. 2.** Conditions and transition (stress (solid lines) and recovery (dashed lines)) pathways of river red gum forest (adapted from Overton et al., 2014), where SFI is a "site-specific flow indicator" of ecological relevance.

inundation occurrences. For example, if not inundated for three consecutive years, a forest in good condition would deteriorate to medium condition, while restoration from medium to good condition requires one successful inundation.

The actual health condition of the river red gum forest is represented by these sequence-dependent metrics, i.e. the condition of the forest at any point in time is dependent on previous annual sequences of successful and unsuccessful inundations, which are in turn affected by precipitation patterns. This dependence cannot be characterized by time-averaged metrics, e.g. the frequency of inundations and the intervals between them, which calculate the statistics of particular flow components over a period without considering the influence of sequencing.

### 4.3. Methods and data

The case study aims to explore the impact of different downscaling techniques on the assessment of river red gum forest condition, using both time-averaged and sequence-dependent metrics. This is done for selected climate scenarios, including a baseline scenario and a set of future scenarios. The constructed climate series are input to a rainfall-runoff model, from which resulting streamflow series are used to derive the various flow indicators.

The period of 1951–2015 is used to provide a baseline for evaluating the impact of climate change on the forest condition. This period has been selected for several reasons, namely: (1) it represents a period that is sufficiently long for the forest to transition between a range of condition states as outlined in Fig. 2, (2) it covers several periods of extended dry conditions, and (3) it represents the period over which concurrent records of temperature, rainfall, and streamflow observations are available. Historical daily precipitation data are obtained from the Australian Water Availability Project dataset (AWAP; Jones et al., 2009) at a spatial resolution of $0.05^\circ \times 0.05^\circ$ across the continent. Historical daily areal potential evapotranspiration (APET) for the same grids are calculated from relevant climate variables using Morton's wet environmental areal evapotranspiration algorithms (Morton, 1983).

Future climate is estimated by comparing projections of a future period (2040–2059) under the Representative Concentration Pathways 4.5 emission scenario and a reference period (1986–2005). The adopted reference period, 1986–2005, is consistent with the work by CSIRO Bureau of Meteorology (2015), and is also suggested by IPCC (2013). Climate series representative of future climate are then developed for a period of equivalent length to the baseline (1951–2015). For precipitation, simulations on a daily time step from 13 selected GCMs are available from the Coupled Model Intercomparison Project Phase 5 (CMIP5) multi-model ensemble. Details of the 13 GCMs are provided in Appendix B. Future daily precipitation are derived using the four downscaling methods, i.e. annual scaling, monthly scaling, quantile scaling and weather generator method. For areal potential evapotranspiration (APET), monthly changes at the original GCM spatial resolution are obtained from the Climate Change in Australia website (CSIRO and Bureau of Meteorology), which enable the application of the annual scaling and monthly scaling approaches for generating APET time series for selected climate scenarios. In water limited environments, estimates of actual evapotranspiration in rainfall-runoff models are limited by soil-moisture rather than atmospheric demand, thus daily fluctuations in APET have little influence on daily hydrological modelling compared with precipitation (Boughton and Chiew, 2007; Oudin et al., 2005), and it is considered sufficient to represent changes in APET by simple monthly scaling.

A lumped conceptual daily rainfall-runoff model, SIMHYD (Chiew et al., 2002), is used to simulate daily flow series for the selected climate scenarios. SIMHYD was calibrated against the flow records at the Wangaratta station (gauge number 403200), with adjustments to account for the impacts of water diversion and impoundment. These adjustments, estimated using a well-developed and calibrated river system model (SKM, 2013), were generally restricted to the lowest 15% of flows, which are well below the flow thresholds relevant to the inundation of the forest.

There is often a statistical bias, particularly at low values, in precipitation series generated using weather generator models (e.g. Wilks, 1999). The adopted procedure for deriving bias-corrected streamflows representative of current and future climates using the stochastic weather generation are shown in Fig. 3. First, parameters of the weather generator representing *current climate* are determined using historical precipitation records; 50 replicates of precipitation series are stochastically generated and are input to the rainfall-runoff model to produce 50 replicates of streamflow series. A quantile-scaling algorithm is then adopted to bias correct the streamflow series. For future scenarios, the parameters of the weather generator are perturbed to be representative of *future climate* and stochastically generated 50 replicates of future precipitation series are used to derive 50 replicates of future streamflow series which are then bias corrected using the same quantile-scaling approach that was developed for the current climate conditions.

## 5. Results

The impacts of different downscaling techniques on daily precipitation distributions, and on the resulting hydrological and ecological indicators, are presented separately below.

### 5.1. Precipitation scenarios

All of the four downscaling methods suggest changes in mean annual precipitation ranging from about −11% to +8% based on selected GCMs. Consistent with previous literature, there is little difference in mean annual precipitation projection derived using

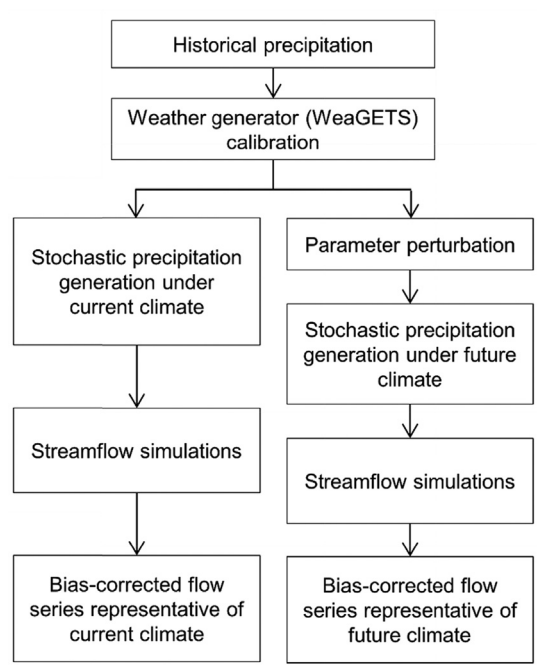


**Fig. 3.** Procedures for deriving streamflows using the stochastic weather generation.

different downscaling methods for a single GCM (e.g. Chen et al., 2013; Johnson and Sharma, 2011). However, differences are apparent when assessed on finer time scales, as discussed in detail below.

Comparing the results of using the annual scaling and monthly scaling methods, the former assumes constant changes in all months, while the latter allows for seasonal variation. With reference to one GCM as an example, the ACCESS1.0 with annual scaling predicts changes in mean monthly precipitation in all months to be −4.2%. In contrast, the use of the monthly scaling method suggests changes in mean monthly precipitation ranging from −27.3% in August to +78.7% in December. As can be seen by comparing Fig. 4a and b, the decrease in daily precipitation in August derived using monthly scaling method is more significant than that implied by the annual scaling method. Consideration of changes in seasonal variation is important when assessing ecological impacts since these variations will affect the wet and dry patterns of river flow within a year.

Compared with the monthly scaling method, application of the quantile scaling method yields differences in precipitation variability at the daily scale (Johnson and Sharma, 2011). Again using the ACCESS1.0 projections for August as an example, the quantile scaling method yields different changes in different precipitation percentiles (Fig. 4c). Typically, changes in 50$^{th}$ and 90$^{th}$ percentiles are −37.5% and −33.4% respectively, whereas identical percentage changes (−27.3%) are suggested for all percentiles by the monthly scaling method. Such differences in changes of different precipitation magnitudes will be amplified when used to derive streamflow.

The weather generator method allows for changes in the sequencing of wet and dry days as well as in the precipitation magnitudes on wet days. Analysis of historical records in this catchment shows that the unconditional probability of a wet day in a month is positively correlated with the monthly precipitation total, namely an increase in mean monthly precipitation total generally means an increase in the average number of wet days and vice versa. Changes regarding the number of wet days require adjustments to be made to the distribution of precipitation depths to preserve the statistics of monthly values. Continuing with the ACCESS1.0 projections for August as an example, the 50 replicates of daily precipitation derived using the weather generator are shown as a tight group of red lines in Fig. 4 (d); the average daily precipitation on wet days is reduced by 22.1% with the reduction in monthly total being 27.3%. It is worth noting that the group of grey lines in Fig. 4 (d) show the weather generator replicates representative of current climate; these replicates exhibit a small degree of bias, where the median of the replicates at the 50$^{th}$ percentile precipitation depth is 0.3 mm higher than the observed.

### 5.2. Hydrological impacts

The differences among precipitation scenarios are usually amplified when applied to a hydrological model (Seguí et al., 2010). A comparison of Figs. 4 and 5 demonstrates that changes in precipitation due to the application of different downscaling methods are disproportionally increased when translating into changes in streamflow. For example, while the change in 50$^{th}$ percentile precipitation projected using the annual scaling method is only −0.1 mm/day (−3.9%), the corresponding change in 50$^{th}$ percentile streamflow is $-0.07 \times 10^4$ ML/day (−14.5%). In comparison, the reduction in 50$^{th}$ percentile precipitation projected by monthly scaling is −0.7 mm/day (−25.5%), but the reduction in 50$^{th}$ percentile streamflow is $-1.68 \times 10^4$ ML/day (−33.3%). While the quantile scaling method suggests a much greater reduction in the

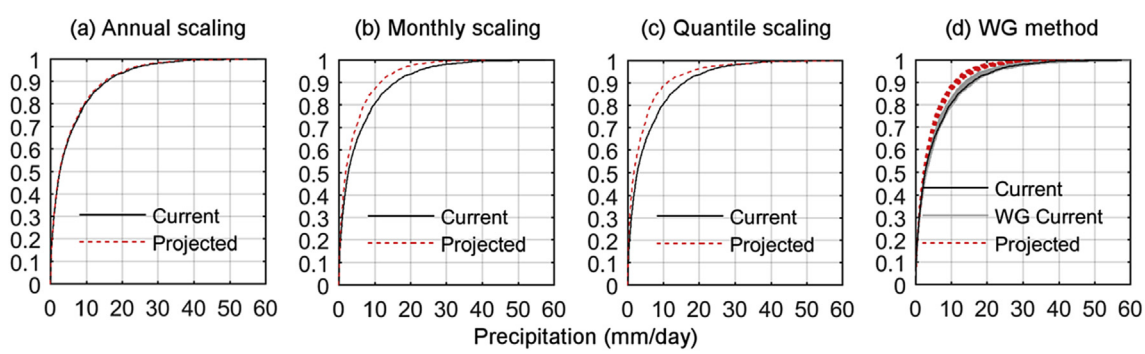


**Fig. 4.** Empirical cumulative distribution functions of daily precipitation in August projected by ACCESS1.0 using different downscaling methods.

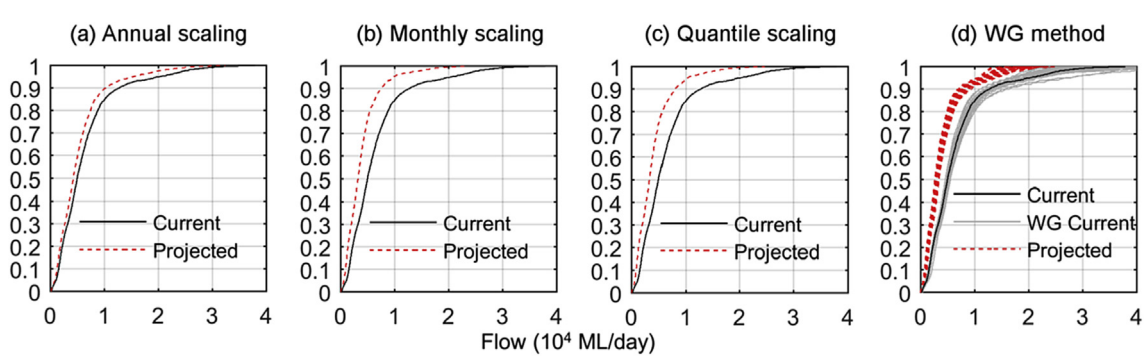


**Fig. 5.** Empirical cumulative distribution functions of daily flow in August projected using ACCESS1.0 outputs with different downscaling methods.

50th percentile precipitation compared to the monthly scaling method (see Section 5.1), the difference in the 50th percentile flow is rather less ($-1.68 \times 10^4$ ML/day ($-33.3\%$) by monthly scaling and $-1.76 \times 10^4$ ML/day ($-34.9\%$) by quantile scaling) due to the differential changes in other precipitation percentiles. The nature of these differences is consistent with observations made by Mpelasoka and Chiew (2009), who pointed out that the quantile scaling method yielded different changes in extreme and annual runoff due to its ability to take account of the distinctive changes in extreme daily rainfalls which generate significant runoff. Use of the weather generator has the additional benefit of being able to consider different temporal sequencing associated with natural variability in the occurrence of wet days. This provides a more realistic assessment of the impact of climate change on ecological indicators as a change in the number of wet days can have an appreciable impact on streamflows. Some indication of these differences is evident in the increased spread of the cumulative distributions of streamflows (Fig. 5d) compared to precipitations (Fig. 4d). The manner in which such changes may influence the assessment of ecological condition is discussed in the following section.

Fig. 6 illustrates the flow duration curves simulated with climate projections from the 13 selected GCMs downscaled by the four downscaling methods. Given our focus on high flows for ecologically beneficial floodplain inundation, only the top 10% of flows are presented. In general, selection of GCMs has a larger influence on estimating high flow exceedances than the choice of downscaling methods. However, the differences resulting from application of different downscaling techniques increase with flow magnitude. For example, as shown in Fig. 6, flows exceeded 10% of the time predicted with the annual scaling method range from $0.51 \times 10^4$ to $0.94 \times 10^4$ ML/day ($-34.2/+21.3\%$ compared with current), while those predicted by using the quantile scaling method range from $0.52 \times 10^4$ to $1.04 \times 10^4$ ML/day ($-33.0\%/+34.9\%$ compared with current). In contrast, higher flows exceeded 2% of the time range from $0.98 \times 10^4$ to $2.12 \times 10^4$ ML/day ($-42.1\%/+25.9\%$) when using the annual scaling method, but from $1.05 \times 10^4$ to $2.65 \times 10^4$ ML/day ($-37.6\%/+57.5\%$) when using the quantile scaling method. With 50 replicates generated for each of the thirteen GCMs, the weather generator method generally gives the largest range for each flow percentile.

### 5.3. Ecological impacts

Changes in time-averaged and sequence-dependent metrics indicating ecological outcomes are given below.

#### 5.3.1. Time-averaged metrics

Fig. 7 presents the percentage of years that the identified "site-specific flow indicator" (SFI), which is 10,000 ML/day for a total duration of 14 days with a minimum consecutive period of 7 days between June and May, is achieved over the modelling period from 1951 to 2015 under different climate scenarios. Under climate change, only one GCM (CanESM2) projects an increase in the frequency of SFI events regardless of which downscaling method is used (and this include all of the replicates provided by the weather generator method), while a decreased frequency is predicted by most other scenarios. In general, the range of impacts arising from the choice among the four downscaling methods on time-averaged metrics is less than that from the choice of GCMs, but the differences are still appreciable. For example, the difference across GCMs in the percentage of years that SFI is achieved when applying the annual scaling method varies from a minimum of 7.7% (for the HadGEM2-ES model) to a maximum of 43.1% (for the CanESM2

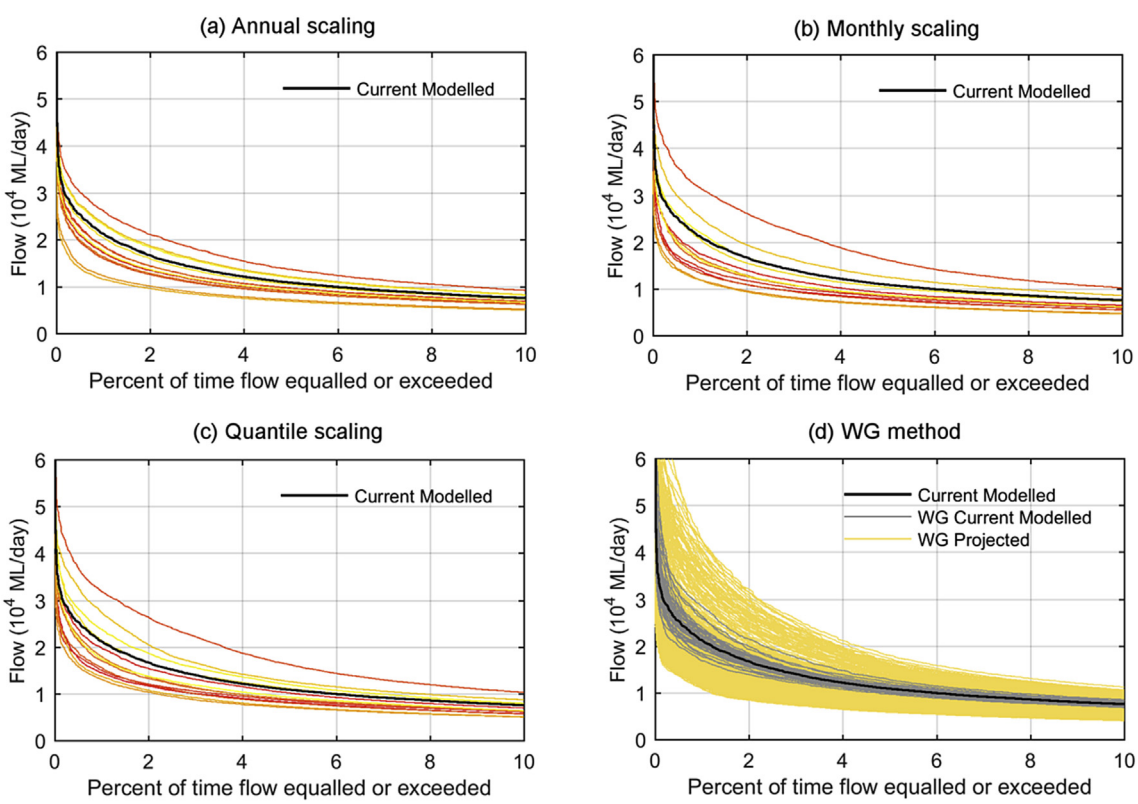


**Fig. 6.** Flow duration curves estimated using different GCM projections and downscaling methods. Thin lines represent results from different GCMs, where information on the GCMs are provided in Appendix B.

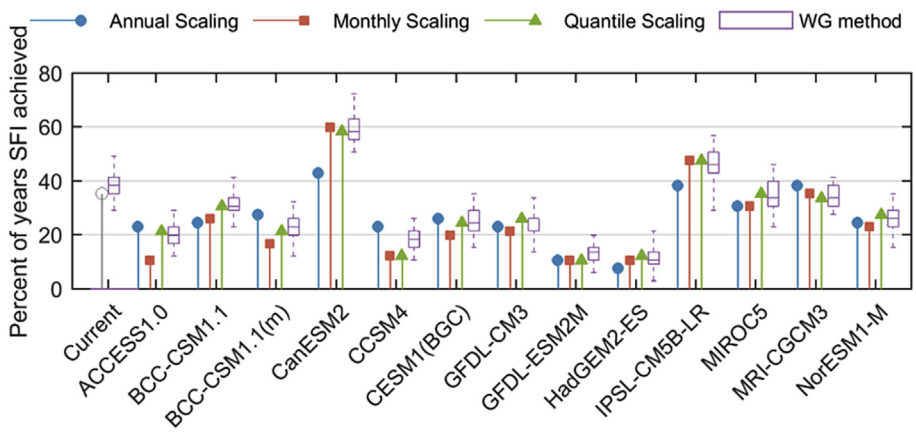


**Fig. 7.** Frequency of SFI events over the modelling period 1951–2015. Whisker boxes show from top to bottom the maximum, 75th percentile, 50th percentile, 25th percentile and minimum of the results of the 50 replicates obtained from the weather generator.

model), a range of 35.4%. By comparison, with the CanESM2 model, the choice of downscaling method indicates that the percentage of years that SFI is achieved varies from 43.1% using the annual scaling method to 60.0% using the monthly scaling method, with the 50 replicates from the weather generator method range from 40.0% to 66.2%. Typically, the choice of a GCM determines whether the frequency is higher or lower than that under the current scenario, while the choice of downscaling methods affects to what extent the condition is better or worse off. However, there is no clear consistency in the nature of the differences arising from the application of different downscaling methods, i.e. there is no rule which downscaling method provides the most conservative projections. Use of the weather generator does, however, make it clear that the impacts of climate change on the variability of flow conditions yield changes that *lie outside* the range expected under current climatic conditions, that is, the ecosystem will need to cope with changes in flow regime that lie outside the natural conditions to which it has adapted. This is evident from the fact that the distribution of outcomes associated with each individual GCM (purple box plots in Fig. 7) largely does not overlap the distribution of outcomes expected under current climate.

For ecosystems, the intervals between SFI events are as important as their occurrences, as the length of the interval determines the likely ecological condition of the asset prior to a watering event, and hence the benefits that can be derived from a given flow event (as shown in Fig. 2). The intervals projected by different GCMs and downscaling methods are shown in Fig. 8. There is larger variation in the length of intervals (Fig. 8) than was seen when looking at the frequency of SFI achievements (Fig. 7). The majority of the differences are due to the choice of a GCM, but in some cases, the choice of downscaling methods has a similar degree of influence. For example, the 50th percentile interval between SFI achievements obtained using the 13 GCMs downscaled with quantile scaling ranges from 1 to 7 years, while the results obtained using HadGEM2-ES downscaled with the four methods ranges from 4.5 to 11 years. Conversely, quite similar results are obtained using the four downscaling methods for IPSL-CM5B-LR. Again, there is no clear consistency in the nature of the differences arising from the applications of different downscaling methods, but as with the previous example, it is again seen that the weather generator results indicate changes to the flow regime that lie outside what may be expected under current climatic conditions.

To understand the overall impact on ecological outcomes it is necessary to consider both the frequency of occurrence (Fig. 7) and the distribution of intervals (Fig. 8). Generally, shorter intervals occur with higher frequency and indicate better conditions. But this is not always the case. One such example may be seen by comparing the quantile scaling and the weather generator methods to the BCC-CSM1.1 GCM. From Fig. 7 it is seen that the percentage of years that the SFI is achieved when using the quantile scaling

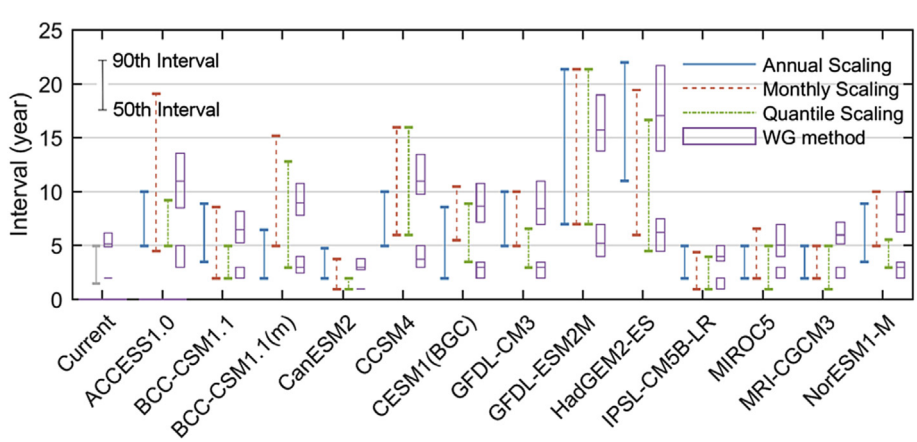


**Fig. 8.** Intervals between the years that the SFI is achieved. The boxes of the weather generator method show from top to bottom the 75th percentile, 50th percentile and 25th percentile of the 50 replicates for each of the 50th and 90th percentile intervals.

method is 30.8%, and the 25th – 75th percentile range of the 50 stochastic replicates covers a range from 29.2% to 33.8%. However Fig. 8 shows that the corresponding impacts on the intervals *between* SFI events are appreciably different, where the 90th percentile interval for the quantile scaling method is 5 years, and 25th – 75th range around the 90th percentile obtained from the 50 replicates is 5.3–8.2 years. These differences in the predicted frequencies and interval distributions are originally related to the alterations in the sequencing of years when the SFI is achieved or not, which is also reflected in the assessment of ecological conditions, as described in the following section.

### 5.3.2. Sequence-dependent metrics

By assuming that the river red gum forest is in "medium" condition at the start of the modelling period, the condition in each year is determined according to the transition pathways shown in Fig. 2. Across different GCMs, there are evident differences in the number of years in which the forest is assessed as being in "good" or "critical" condition. "Medium", "intermediate" and "poor" conditions are transitional states and variations in these assessments are relatively small (refer to Figure C1 in Appendix C). Fig. 9 shows the differences in the proportion of time in which the forest is assessed as being in "good" and "critical" conditions, as obtained from applying the four downscaling methods to each GCM. For the majority of the GCMs, the range of results across the annual scaling, monthly scaling and quantile scaling methods (the grey bars for different GCMs in Fig. 9a) based on the time in "good" condition is less than 20%. There are however three GCMs (BCC-CSM1.1, BCC-CSM1.1(m) and NorESM1-M) where the variation in results ranges around 40%. When the weather generator method is used, a wider range of results across the replicates can be seen, which reflects the impact of natural variability on the sequences under changed climatic conditions. For some GCMs (e.g. BCC-CSM1.1 and CanESM2), the 25th – 75th percentile box of the 50 replicates lies within the range of the three scaling methods. But there are also a number of GCMs (e.g. GFDL-CM3 and MRI-CGCM3) where the 25th – 75th percentile box and the range of the three scaling methods hardly overlap. The results based on the time in "critical" condition are not dissimilar, with a number of GCMs showing significant variation in results across the three scaling methods (e.g. BCC-CSM1.1(m), results vary between 12.3% and 66.2%). When using the weather generator method, wider ranges and various results can be seen, though – in contrast to the time-averaged metrics shown in Figs. 7 and 8 – it is seen that there is greater overlap in the range of outcomes between some GCMs and current conditions. While the variation in results across GCMs is evident, Fig. 9 (and Figure C1 in Appendix C) demonstrates that the variation due to the choice of downscaling methods is also substantial and of a similar magnitude to the variation due to the choice of GCMs.

To better understand what is driving these variations in the results across GCMs and downscaling methods, Fig. 10 provides an example of the timeline of condition states assessed under different climate scenarios based on both GCM and downscaling method selections. The star symbol marks the occurrence of an SFI event, noting that with the right timing, these can trigger transitions between different condition states (as illustrated in Fig. 2). Under the current scenario, the forest's condition varies between "good" and "medium" before the 2000s due to frequent achievements of the SFI, but then gradually deteriorates to "critical" during the 2000s. Under the future scenarios, it is seen that changes in the sequencing of SFI events leads to significant alterations in the condition timeline.

For a given GCM, the impact of downscaling techniques on the frequency and timing of SFI events – and hence on ecological outcomes – can be appreciable (Fig. 10). When the sequence of wet and dry years remains unchanged (as assumed by the annual scaling, monthly scaling and quantile scaling methods), the timing of SFI events missed or added can be of significant importance to ecological outcomes. Taking the results of ACCESS1.0 with annual scaling and quantile scaling as an example, although the sequences of SFI events are identical during the 1960s–1980s, a single SFI event missed in 1958 when using the quantile scaling method causes the forest's condition to deteriorate to "poor" and "critical" much earlier than when the annual scaling method is used. However, when the sequencing of wet and dry years are also allowed to vary (as considered by the weather generator method), there is greater variability in the ecological outcomes. For example, Fig. 10d shows the results for a weather generator replicate that has the same number of SFI events as obtained from the quantile scaling method (Fig. 10c), whereas the difference in timing suggests appreciably different ecological outcomes. In contrast, Fig. 10e shows a weather generator replicate with fewer SFI events but better ecological outcomes. It should be stated that results of the weather generator method shown in Fig. 10 merely highlight the impact of hydrological sequences on ecological outcomes; the value of considering multiple replicates is not in the analysis of any single

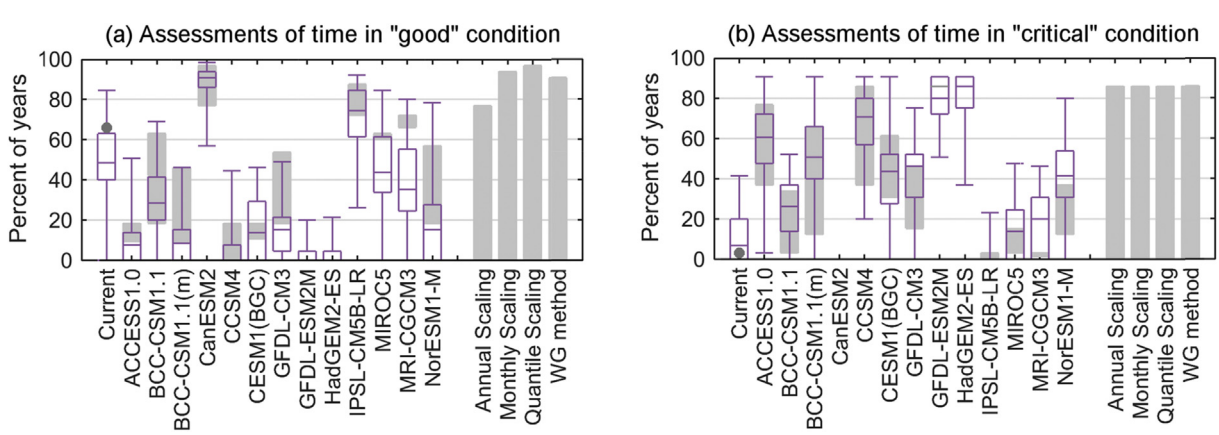


**Fig. 9.** Assessments of the proportion of time the forest is in "good" and "critical" condition. The grey bar for each GCM presents the range of results obtained from the annual scaling, monthly scaling and quantile scaling methods. Whisker boxes show from top to bottom the maximum, 75th percentile, 50th percentile, 25th percentile and minimum of the 50 replicates provided by the weather generator method. The range of results obtained by the four different downscaling methods for all GCMs are shown at the right hand side of each plot, where the weather generator method is represented by the median of the 50 replicates obtained for each GCM.

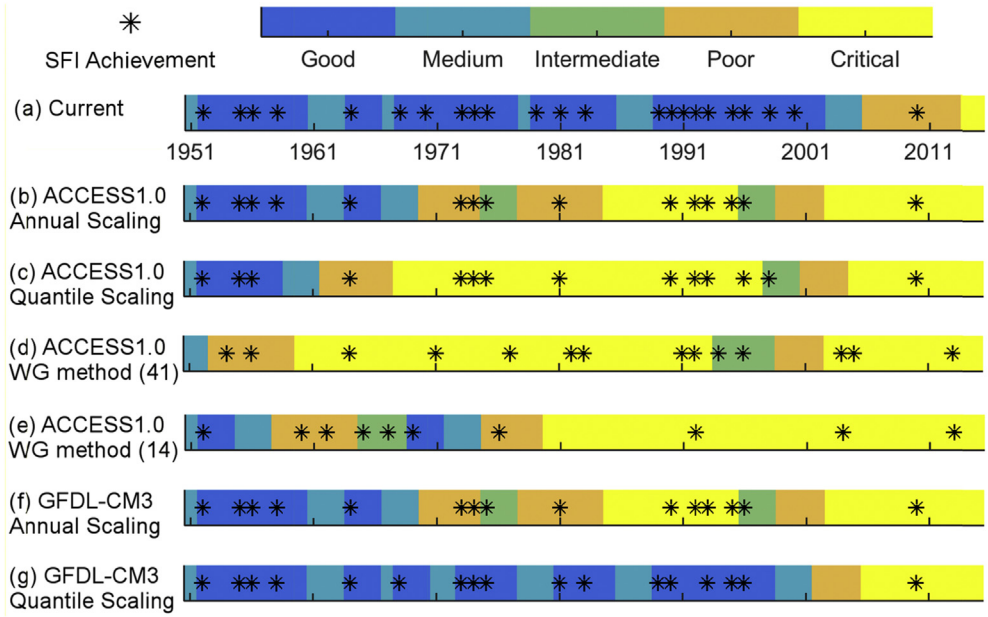


**Fig. 10.** Variation in condition states over the modelling period for selected GCMs and downscaling methods. The number in the bracket following "WG method" indicate the replicate member.

replicate, but rather in the analysis of the degree of change compared to the range of the outcomes under natural variability, as shown in Figs. 7–9.

While it is clear that the choice of GCMs has a marked influence on the assessment of the impact of climate change on ecological outcomes, Fig. 10 highlights the additional uncertainty introduced by the choice of downscaling method. For example, when the annual scaling method is used, assessments based on ACCESS1.0 and GFDL-CM3 are the same (Fig. 10b and f), which means the selection of ACCESS1.0 or GFDL-CM3 does not affect the assessment of ecological conditions; but when the quantile scaling is applied, the selection of ACCESS1.0 or GFDL-CM3 has substantial impacts on the sequencing of SFI events and hence the forest's conditions (Fig. 10c and g).

It is also evident from Fig. 10 how the adoption of sequence-dependent metrics yields different implications from the assessment of time-averaged metrics given in Section 5.3.1. Small differences in either the frequency or timing of SFI events can lead to appreciable differences in the assessment of ecological conditions. With reference to the results of ACCESS1.0 with annual scaling and quantile scaling methods, while the differences in the frequency of SFI events and interval statistics are small (Figs. 7 and 8), the differences in the assessment of condition states are substantial (Figure C1 and Fig. 10); that is, if the quantile scaling method is used instead of the annual scaling method, the period of being in "critical" condition is predicted to be twice as long.

## 6. Discussion and conclusions

This paper investigates the relative importance of downscaling methods in the assessment of instream ecological outcomes. Four statistical downscaling methods were applied to a real catchment to assess the impact of climate change induced hydrological alterations on river red gum forest's condition, based on both time-averaged and sequence-dependent ecological metrics.

The results from the case study show, consistent with previous publications (e.g. Chen et al., 2011b; Mpelasoka and Chiew, 2009), that there is little variation in the changes in mean annual precipitation derived using different downscaling methods. However, there are differences in the estimates of changes on daily, seasonal and inter-annual timescales from the application of different downscaling methods, and the differences are translated disproportionally into the variations in hydrological simulations. For extreme high flows, application of different downscaling methods could nearly double the range of the results across different GCMs. Comparing the influences of selecting different GCMs and adopting different downscaling methods on the assessment of ecological condition, it is found that the choice of GCM is the largest source of uncertainty in the results, but the choice of downscaling is also an appreciable source of uncertainty (refer to Section 5.3).

There is a significant body of literature discussing the appropriate indicators for hydrological impacts on instream environment (Anderson et al., 2006; Poff et al., 2010; Poff and Zimmerman, 2010). This study examined both time-averaged and sequence-dependent ecological metrics, i.e. those purely based on statistics of flow events over an extended period, and those which consider the impacts of the sequencing of flow events. Statistics of the annual achievements of a site-specific flow indicator (SFI) describing the flow magnitude, duration and timing of flooding required to maintain the river red gum forest in healthy condition is used as a set of time-averaged metrics. The results show that under climate change, the majority of GCMs predict a decrease in the frequency of SFI events, with only one out of thirteen GCMs indicating an increase in frequency. The choice of downscaling methods has a lesser, but still appreciable, influence on the results; however, there is no clear consistency in the nature of the differences arising from the choice of downscaling methods. Figs. 7 and 8 illustrate that the choice of downscaling method impacts on both the interval between SFI events and their frequency of occurrence, and hence this leads to differences in assessed ecological outcomes (Fig. 10).

Sequence-dependent metrics, based on conceptual models showing how the condition of an ecological endpoint changes

through time in response to a flow sequence, are designed to incorporate some of the complexity of ecosystems and the influence of the sequencing of flow events (Overton et al., 2014). The results for the Ovens catchment show that climate change will lead to a significant increase in the number of years that river red gum forest is in critical condition. When using sequence-dependent metrics, the choice of downscaling methods is shown to introduce a similar level of uncertainty as the choice of GCMs, though when time-averaged metrics are assessed, the choice of GCMs has a larger influence on the results. As discussed in Section 5.3.2, these more complex ecological metrics consider the frequency and timing of SFI achievements, so that small changes in the sequencing of these events can lead to appreciable changes in ecological conditions in the longer term.

There are a number of aspects that were not considered within this study. Firstly, among the various categories of downscaling methods, dynamic downscaling and other sophisticated statistical downscaling methods such as regression models were not evaluated. These methods have been widely used in hydrological studies but applications in other areas are relatively limited due to the high requirement of computation or data. Secondly, this study focused on the uncertainty from the choice of downscaling techniques and therefore, only one greenhouse gas emission scenario has been considered. GCM simulations are driven by emission scenarios, which also have been demonstrated to introduce uncertainty into impact assessments (e.g. Thompson et al., 2014). Thirdly, it is assumed that the hydrological model parameters calibrated to historical records are still valid under a changing climate, which may be inappropriate. In the future, more research is needed on evaluating different categories of downscaling methods in assessing ecological outcomes with adoption of appropriate hydrological models and ecological indicators. Finally, it was assumed that the defined SFI was accurate as determined through previous studies. There are uncertainties associated with the ecological relevance of low and high flow events and these have not been examined. In reality, these SFIs may not all act as thresholds, but rather, there may still be marginal benefit from providing flows slightly below the threshold (Horne et al., accepted).

This paper has shown the influence of downscaling methods when assessing instream ecological outcomes under climate change. Annual scaling and monthly scaling have been very popular in water resources impact studies due to their simplicity and speed of use. Where the ecological metrics selected are based on seasonal flow statistics and are independent of antecedent flow and ecological conditions, these approaches may still be suitable. But where daily scale information is important (e.g. where fluctuations in daily flow behavior influence ecological health and function), more complicated downscaling techniques such as the quantile scaling and the weather generator method should also be considered. The selection of downscaling methods becomes more important if the frequency of occurrence and intervals between events are included within the metrics. While the median result obtained by the weather generator method is directly comparable to the results obtained from the deterministic downscaling procedures, it has the added benefit of being able to capture the influence of changes to the flow regime that result from expected shifts in the seasonal frequency of rain days under a warmer climate, which can have important implications for environmental condition. That is, the method is able to provide insights about the extent to which conditions in a warmer world might lie outside the range of conditions that could be expected under the current climate. This is particularly the case for sequence-dependent metrics where the sequencing of flow events is essential. In these cases, scaling methods may underestimate the impact of climate change, as they are unable to consider changes in precipitation frequency or sequences of wet and dry days. This paper does not provide guidelines for choosing downscaling methods, but rather, it demonstrates the importance of selecting an appropriate downscaling method and considering the associated uncertainty when investigating the impact of climate change on water resources management concerning river health outcomes.

## Software and data availability

- WeaGETS is a Matlab-based stochastic weather generator. It is freely available online at http://www.mathworks.com/matlabcentral/fileexchange with due acknowledgement for academic research purposes only.
- SIMHYD is a daily conceptual rainfall-runoff model. It is freely available in the toolkit of Rainfall Runoff Library (http://toolkit.ewater.org.au/Tools/RRL).
- The Coupled Model Intercomparison Project (CMIP5) Model Output Archive is freely available with registration for non-commercial research and educational purposes (cmip-pcmdi.llnl.gov).
- The Australian Water Availability Project (AWAP) dataset has been developed by the AWAP Team, CSIRO Marine and Atmospheric Research. Data files are available to authorized users, given in ESRI binary raster format. Contacts: Mr. Peter Briggs, CSIRO Ocean Atmosphere Flagship. Email: peter.briggs@csiro.au.
- Gauged streamflow data were obtained from the Water Data Online portal hosted by the Australian Bureau of Meteorology (http://www.bom.gov.au/waterdata)

## Acknowledgements

This research was partially supported by Australian Research Council Linkage Project (LP130100174). Murray Peel and Yongping Wei are the recipients of an Australian Research Council Future Fellowship (respectively, FT120100130 & FT130100274). We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modelling groups (listed in Table B.1 of this paper) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. The authors are grateful for the thoughtful comments provided by two anonymous reviewers, which prompted significant improvements to the manuscript.

## Appendices

### A. Downscaling methods used in this study

#### A.1. Annual scaling

The annual scaling method involves multiplication of the daily values by a fixed factor, which is obtained by comparing the annual means of simulations for future period and reference period (Eq. (A.1)).

$$P^{fut}_{y,m,d} = \frac{\overline{aP^{\mathrm{GCM},fut}}}{\overline{aP^{\mathrm{GCM},his}}} P^{\mathrm{Obs},\ his}_{y,m,d} \tag{A.1}$$

where subscript *fut* represents future conditions, and *his* represents historical conditions; *y* stands for a specific year, *m* for month, and *d* for day; *aP* is for annual precipitation simulated by GCMs.

### A.2. Monthly scaling

Monthly scaling applies the constant factor on the monthly scale (Eq. (A.2)). Precipitation ratios are calculated for each month separately so that variations of changes in magnitude in different months can be incorporated, but the sequence of rain days and the changes in magnitude relative to the mean remain unchanged.

$$P^{fut}_{y,m,d} = \frac{\overline{mP^{\mathrm{GCM},\,fut}_m}}{\overline{mP^{\mathrm{GCM},\,his}_m}} P^{\mathrm{Obs},\,his}_{y,m,d} \tag{A.2}$$

Where $mP$ is the monthly precipitation simulated by GCMs, and other variables are as defined above.

### A.3. Quantile scaling

Quantile scaling, or daily scaling, adjusts daily observations with different factors dependent on precipitation magnitude (Eq. (A.3)). A single set of quantile-adjustment factors can be applied year-round, or else they can be applied on a seasonal or monthly basis. Generally, there are four steps. First, empirical cumulative distribution functions (ECDFs) for GCM simulations of the future and reference periods are estimated. Second, the ECDFs are divided into several bins (i.e. range of exceedance percentiles) and a change factor is calculated for each bin. Third, the ECDF for historical records is estimated and divided into the same set of percentile exceedance bins. Finally, the historical precipitation is multiplied by the change factor relevant to its given exceedance percentile. In this study, the ECDFs are divided into 100 bins of equally spaced exceedance percentiles and change factors are calculated for each month separately. With this approach, the precipitation magnitude of wet days is factored variably according to the magnitude and month of occurrence, but the sequence of rain days remains unchanged.

$$P^{fut,q}_{y,m,d} = \frac{dP^{\mathrm{GCM},\,fut,q}_m}{dP^{\mathrm{GCM},\,his,q}_m} P^{\mathrm{Obs},\,his,q}_{y,m,d} \tag{A.3}$$

where $dP$ is the daily precipitation for wet days simulated by GCMs and q is the exceedance percentile.

### A.4. Weather generator based method

The weather generator used is WeaGETS (Chen et al., 2012, 2010), which is a versatile stochastic daily weather generator. Other weather generators can also be used (e.g. Wang and Nathan, 2007), but this model was selected because the source code was easily accessible and configured in Matlab to suit the other modelling steps involved. The WeaGETS model as originally formatted was applied to climate variables aggregated over fortnightly periods. It provides three models for generating the occurrence of precipitation (first, second and third-order Markov chain models), four distributions to generate rainfall depths (one-parameter exponential distribution, two-parameter gamma distribution, three-parameter skewed normal Pearson III distribution, and three-parameter mixed exponential distribution) and two schemes (conditional or unconditional) to simulate maximum and minimum temperatures. It also provides an option to correct the variability of low-frequency events.

In this study only the function to generate precipitation series is used, and the model was adapted to vary model parameters by individual months (rather than fortnightly periods). When employed as a downscaling tool, the first order-Markov chain is usually more practical since it only has two parameters (Chen et al., 2012). In a first-order Markov chain, the probability of wet or dry depends on the status of the previous day. The dependence is characterized by two transition probabilities $p_{01}$ and $p_{11}$, which represent a wet day following a dry day, and a wet day following a wet day respectively. Precipitation magnitude is estimated using the two-parameter gamma distribution, whose probability density function is given in Eq. (A.4):

$$f(x) = \frac{(x/\beta)^{\alpha-1}\exp[-x/\beta]}{\beta\Gamma(\alpha)} \tag{A.4}$$

The four parameters $\{p_{01}, p_{11}, \alpha, \beta\}$ are fit to historical records for each of the twelve months separately. The parameters are then modified to reflect conditions relevant to the adopted climate scenario, as simulated by the GCM models. The key steps involved in perturbing the parameters are outlined below, and further details may be found in Wilks (1999) and Zhang (2013).

The two conditional probabilities $p_{01}$ and $p_{11}$, and the unconditional probability of precipitation occurrence $\pi$ have been found to provide good linear correlations with mean monthly precipitation (Zhang, 2013). Linear relationships for the three correlation parameters ($p_{01}$, $p_{11}$ and $\pi$) can be developed using historical records, and the two parameters with the highest explained variance are adjusted to represent future conditions using the fitted linear regression equations. The remaining correlation parameter is estimated by re-arranging Eq. (A.5) as required:

$$\pi = \frac{p_{01}}{1 + p_{01} - p_{11}} \tag{A.5}$$

The two parameters of the gamma distribution can be expressed in terms of the mean $\mu$ and variance $\sigma^2$ of non-zero daily precipitation amounts (Eq. (A.6) and Eq. (A.7)). Furthermore, $\mu$ and $\sigma^2$ can be estimated using the adjusted monthly mean, monthly variance, unconditional probability of daily precipitation occurrence, and lag-1 autocorrelation of daily precipitation, from Eq. (A.8) and Eq. (A.9):

$$\alpha = \frac{\mu^2}{\sigma^2} \tag{A.6}$$

$$\beta = \frac{\sigma^2}{\mu} \tag{A.7}$$

$$\mu = \frac{P_m}{N_m \pi} \tag{A.8}$$

$$\sigma^2 = \frac{\sigma_m^2}{N_m \pi} - \frac{(1-\pi)(1+r)}{1-r}\mu^2 \tag{A.9}$$

where $P_m$ is the adjusted mean monthly precipitation, $N_m$ is the number of days in the month, $\sigma_m^2$ is the simulated monthly variance. The lag-1 autocorrelation of daily precipitation $r$ can be estimated using Eq. (A.10).

$$r = p_{11} - p_{01} \tag{A.10}$$

The adjusted parameters are input to WeaGETS to generate an ensemble of realizations that are consistent with future climate.

## B. List of GCMs used in this study

**Table B.1**
GCMs projections used in this study.

| Model Name | Modelling Centre (or Group) | Resolution (°latitude × °longitude) | Ensemble used in this study |
|---|---|---|---|
| ACCESS1.0 | Commonwealth Scientific and Industrial Research Organization/Bureau of Meteorology, Australia | 1.25 × 1.875 | r1i1p1 |
| BCC-CSM1.1 | Beijing Climate Centre, China | 2.7906 × 2.8125 | r1i1p1 |
| BCC-CSM1.1(m) | Beijing Climate Centre, China | 1.1215 × 1.125 | r1i1p1 |
| CanESM2 | Canadian Centre for Climate Modelling and Analysis, Canada | 2.7906 × 2.8125 | r1i1p1 |
| CCSM4 | National Centre for Atmospheric Research, USA | 0.9424 × 1.25 | r1i1p1 |
| CESM1(BGC) | National Centre for Atmospheric Research, USA | 0.9424 × 1.25 | r1i1p1 |
| GFDL-CM3 | Geophysical Fluid Dynamics Laboratory, USA | 2 × 2.5 | r1i1p1 |
| GFDL-ESM2M | Geophysical Fluid Dynamics Laboratory, USA | 2.0225 × 2.5 | r1i1p1 |
| HadGEM2-ES | Met Office Hadley Centre, UK | 1.25 × 1.875 | r1i1p1 |
| IPSL-CM5B-LR | Institute Pierre Simon Laplace, France | 3.75 × 1.8947 | r1i1p1 |
| MIROC5 | Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan | 1.4008 × 1.4063 | r1i1p1 |
| MRI-CGCM3 | Meteorological Research Institute, Japan | 1.1215 × 1.125 | r1i1p1 |
| NorESM1-M | Bjerknes Centre for Climate Research, Norwegian Meteorological Institute, Norway | 1.8947 × 2.5 | r1i1p1 |

## C. Time in each condition state assessed by the three scaling methods

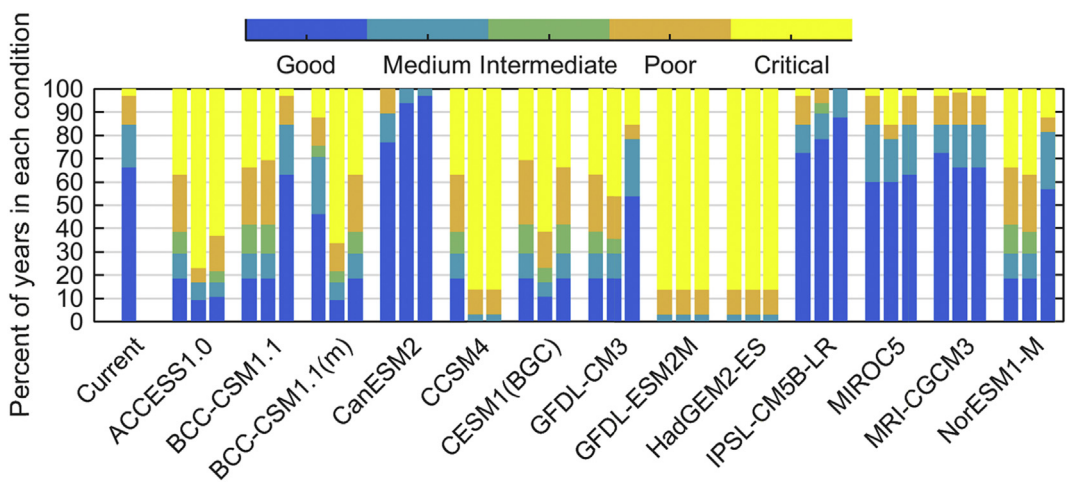


**Fig. C.1.** Percentage of years in each condition state. For each GCM group, from left to right: annual scaling, monthly scaling, and quantile scaling methods.

## References


Acreman, M., Arthington, A.H., Colloff, M.J., Couch, C., Crossman, N.D., Dyer, F., Overton, I., Pollino, C.A., Stewardson, M.J., Young, W., 2014. Environmental flows for natural, hybrid, and novel riverine ecosystems in a changing world. Front. Ecol. Environ. 12, 466–473. http://dx.doi.org/10.1890/130134.

Anandhi, A., Frei, A., Pierson, D.C., Schneiderman, E.M., Zion, M.S., Lounsbury, D., Matonse, A.H., 2011. Examination of change factor methodologies for climate change impact assessment. Water Resour. Res. 47, 1–10. http://dx.doi.org/10.1029/2010WR009104.

Anderson, K., Paul, A., McCauley, E., Jackson, L., Post, J., Nisbet, R., 2006. Instream flow needs in rivers and streams: the importance of understanding ecological dynamics. Front. Ecol. Environ. 4, 309–319.

Arthington, A.H., Bunn, S.E., Poff, N.L., Naiman, R.J., 2006. The challenge of providing environmental flow rules to sustain river ecosystems. Ecol. Appl. 16, 1311–1318.

Battin, J., Wiley, M.W., Ruckelshaus, M.H., Palmer, R.N., Korb, E., Bartz, K.K., Imaki, H., 2007. Projected impacts of climate change on salmon habitat restoration. Proc. Natl. Acad. Sci. U. S. A. 104, 6720–6725. http://dx.doi.org/10.1073/pnas.0701685104.

Beven, K., 2015. Facets of uncertainty: epistemic uncertainty, non-stationarity, likelihood, hypothesis testing, and communication. Hydrol. Sci. J. 6667 http://dx.doi.org/10.1080/02626667.2015.1031761, 150527103244004.

Beyene, T., Lettenmaier, D.P., Kabat, P., 2010. Hydrologic impacts of climate change on the Nile River Basin: implications of the 2007 IPCC scenarios. Clim. Change 100, 433–461. http://dx.doi.org/10.1007/s10584-009-9693-0.

Boughton, W., Chiew, F., 2007. Estimating runoff in ungauged catchments from rainfall, PET and the AWBM model. Environ. Model. Softw. 22, 476–487. http://dx.doi.org/10.1016/j.envsoft.2006.01.009.

Chen, J., Brissette, F.P., Chaumont, D., Braun, M., 2013. Performance and uncertainty evaluation of empirical downscaling methods in quantifying the climate change impacts on hydrology over two North American river basins. J. Hydrol. 479, 200–214. http://dx.doi.org/10.1016/j.jhydrol.2012.11.062.

Chen, J., Brissette, F.P., Leconte, R., 2010. A daily stochastic weather generator for preserving low-frequency of climate variability. J. Hydrol. 388, 480–490. http://dx.doi.org/10.1016/j.jhydrol.2010.05.032.

Chen, J., Brissette, F.P., Leconte, R., 2011a. Uncertainty of downscaling method in quantifying the impact of climate change on hydrology. J. Hydrol. 401, 190–202. http://dx.doi.org/10.1016/j.jhydrol.2011.02.020.

Chen, J., Brissette, F.P., Leconte, R., Caron, A., 2012. A versatile weather generator for daily precipitation and temperature. Trans. ASABE 55, 895–906. http://dx.doi.org/10.13031/trans.57.10685.

Chen, J., Brissette, F.P., Poulin, A., Leconte, R., 2011b. Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed. Water Resour. Res. 47, 1–16. http://dx.doi.org/10.1029/2011WR010602.

Chiew, F.H.S., Peel, M.C., Western, A.W., Singh, V.P., Frevert, D., 2002. Application and testing of the simple rainfall-runoff model SIMHYD. Math. models small watershed hydrology Appl. 335–367.

Chiew, F.H.S., Teng, J., Vaze, J., Post, D.A., Perraud, J.M., Kirono, D.G.C., Viney, N.R., 2009. Estimating climate change impact on runoff across southeast Australia: method, results, and implications of the modeling method. Water Resour. Res. 45, 1–17. http://dx.doi.org/10.1029/2008WR007338.

CSIRO, 2008. Water Availability in the Ovens. A Report to the Australian Government from the CSIRO Murray-Darling Basin Sustainable Yields Project. CSIRO, Australia, 100pp.

CSIRO and Bureau of Meteorology. Climate Change in Australia. http://www.climatechangeinaustralia.gov.au/(Accessed 26 march 2016).

CSIRO and Bureau of Meteorology, 2015. Climate Change in Australia Information for Australia's Natural Resource Management Regions: Technical Report. CSIRO and Bureau of Meteorology, Australia.

Davies, P.E., Stewardson, M.J., Hillman, T.J., Roberts, J.R., Thoms, M.C., 2012. Prepared by the Independent Sustainable Rivers Audit Group for the Murray– Darling Basin. Sustainable Rivers Audit 2: the Ecological Health of Rivers in the Murray-Darling Basin at the End of the Millennium Drought (2008-2010), vol. 3.

Diaz-Nieto, J., Wilby, R.L., 2005. A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the River Thames, United Kingdom. Clim. Change 69, 245–268. http://dx.doi.org/10.1007/s10584-005-1157-6.

Döll, P., Zhang, J., 2010. Impact of climate change on freshwater ecosystems: a global-scale analysis of ecologically relevant river flow alterations. Hydrol. Earth Syst. Sci. 14, 783–799. http://dx.doi.org/10.5194/hess-14-783-2010.

Dudgeon, D., Arthington, A.H., Gessner, M.O., Kawabata, Z.-I., Knowler, D.J., Lévêque, C., Naiman, R.J., Prieur-Richard, A.-H., Soto, D., Stiassny, M.L.J., Sullivan, C.A., 2006. Freshwater biodiversity: importance, threats, status and conservation challenges. Biol. Rev. Camb. Philos. Soc. 81, 163–182. http://dx.doi.org/10.1017/S1464793105006950.

Ekström, M., 2016. Metrics to identify meaningful downscaling skill in WRF simulations of intense rainfall events. Environ. Model. Softw. 79, 267–284. http://dx.doi.org/10.1016/j.envsoft.2016.01.012.

Ekström, M., Grose, M.R., Whetton, P.H., 2015. An appraisal of downscaling methods used in climate change research. Wiley Interdiscip. Rev. Clim. Chang. 6, 301–319. http://dx.doi.org/10.1002/wcc.339.

Environment Australia, 2001. A Directory of Important Wetlands in Australia, third ed. Environment Australia, Canberra.

Fowler, H.J., Blenkinsop, S., Tebaldi, C., 2007. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. Int. J. Climatol. 1578, 1547–1578. http://dx.doi.org/10.1002/joc.

Hay, L.E., Wilby, R.L., Leavesley, G.H., 2000. A comparison of delta change and downscaled GCM scenarios for three mountainous basins in the United States. J. Am. Water Resour. Assoc. 36, 387–397. http://dx.doi.org/10.1111/j.1752-1688.2000.tb04276.x.

Hickey, J.T., Huff, R., Dunn, C.N., 2015. Using habitat to quantify ecological effects of restoration and water management alternatives. Environ. Model. Softw. 70, 16–31. http://dx.doi.org/10.1016/j.envsoft.2015.03.012.

Horne, A.C., Szemis, J.M., Webb, J.A., Kaur, S., Stewardson, M.J., Bond, N., and Nathan, R. (accepted) Informing environmental water management decisions: using conditional probability networks to address the information needs of planning and implementation cycles. Environ. Manag. (accepted 1/4/2017).

Htun, H., Gray, S.A., Lepczyk, C.A., Titmus, A., Adams, K., 2016. Combining watershed models and knowledge-based models to predict local-scale impacts of climate change on endangered wildlife. Environ. Model. Softw. 84, 440–457. http://dx.doi.org/10.1016/j.envsoft.2016.07.009.

IPCC, 2013. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.

Johnson, F., Sharma, A., 2011. Accounting for interannual variability: a comparison of options for water resources climate change impact assessments. Water Resour. Res. 47 http://dx.doi.org/10.1029/2010WR009272.

Jones, D.A., Wang, W., Fawcett, R., 2009. High-quality spatial climate data-sets for Australia. Aust. Meteorol. Oceanogr. J. 58, 233–248.

Kay, A.L., Davies, H.N., Bell, V.A., Jones, R.G., 2009. Comparison of uncertainty sources for climate change impacts: flood frequency in England. Clim. Change 92, 41–63. http://dx.doi.org/10.1007/s10584-008-9471-4.

Kilsby, C.G., Jones, P.D., Burton, A., Ford, A.C., Fowler, H.J., Harpham, C., James, P., Smith, A., Wilby, R.L., 2007. A daily weather generator for use in climate change studies. Environ. Model. Softw. 22, 1705–1719. http://dx.doi.org/10.1016/j.envsoft.2007.02.005.

Laizé, C.L.R., Acreman, M.C., Schneider, C., Dunbar, M.J., Houghton-Carr, H., Florke, M., Hannah, D.M., 2014. Projected flow alteration and ecological risk for Pan-European rivers. River Res. Appl. 30, 299–314. http://dx.doi.org/10.1002/rra.

Lauri, H., De Moel, H., Ward, P.J., Räsänen, T.A., Keskinen, M., Kummu, M., 2012. Future changes in Mekong River hydrology: impact of climate change and reservoir operation on discharge. Hydrology Earth Syst. Sci. http://dx.doi.org/10.5194/hess-16-4603-2012.

Maraun, D., Wetterhall, F., Chandler, R.E., Kendon, E.J., Widmann, M., Brienen, S., Rust, H.W., Sauter, T., Themeßl, M., Venema, V.K.C., Chun, K.P., Goodess, C.M., Jones, R.G., Onof, C., Vrac, M., Thiele-Eich, I., 2010. Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user. Rev. Geophys. 48, 1–38. http://dx.doi.org/10.1029/2009RG000314.1.INTRODUCTION.

Minville, M., Brissette, F., Leconte, R., 2008. Uncertainty of the impact of climate change on the hydrology of a nordic watershed. J. Hydrol. 358, 70–83. http://dx.doi.org/10.1016/j.jhydrol.2008.05.033.

Morton, F.I., 1983. Operational estimates of areal evapotranspiration and their significance to the science and practice of hydrology. J. Hydrol. 66, 1–76. http://dx.doi.org/10.1016/0022-1694(83)90177-4.

Mpelasoka, F.S., Chiew, F.H.S., 2009. Influence of rainfall scenario construction methods on runoff projections. J. Hydrometeorol. 10, 1168–1183. http://dx.doi.org/10.1175/2009JHM1045.1.

Murray–Darling Basin Authority, 2010. Guide to the Proposed Basin Plan: Technical Background. Murray–Darling Basin Authority, Canberra.

Olden, J.D., Poff, N.L., 2003. Redundancy and the choice of hydrologic indices for characterizing streamflow regimes. River Res. Appl. 19, 101–121. http://dx.doi.org/10.1002/rra.700.

Oudin, L., Michel, C., Anctil, F., 2005. Which potential evapotranspiration input for a lumped rainfall-runoff model? Part 1-Can rainfall-runoff models effectively handle detailed potential evapotranspiration inputs? J. Hydrol. 303, 275–289. http://dx.doi.org/10.1016/j.jhydrol.2004.08.025.

Overton, I.C., Pollino, C.A., Roberts, J., Reid, J.R.W., Bond, N.R., McGinness, H.M., Gawne, B., Stratford, D.S., Merrin, L.E., Barma, D., Cuddy, S.M., 2014. Development of the Murray-Darling Basin Plan SDL Adjustment Ecological Elements Method. Report prepared by CSIRO for the Murray-Darling Basin Authority, Canberra.

Peel, M.C., Srikanthan, R., McMahon, T.A., Karoly, D.J., 2015. Approximating uncertainty of annual runoff and reservoir yield using stochastic replicates of global climate model data. Hydrol. Earth Syst. Sci. 19, 1615–1639. http://dx.doi.org/10.5194/hess-19-1615-2015.

Piniewski, M., Laizé, C.L.R., Acreman, M.C., Okruszko, T., Schneider, C., 2014. Effect of climate change on environmental flow indicators in the Narew Basin. Pol. J. Environ. Qual. 43, 155–167. http://dx.doi.org/10.2134/jeq2011.0386.

Poff, N.L., Allan, J.D., Bain, M.B., Karr, J.R., Prestegaard, K.L., Richter, B.D., Sparks, R.E., Stromberg, J.C., 1997. The Natural Flow Regime: a paradigm for river conservation and restoration N. Bioscience 47, 769–784. http://dx.doi.org/10.2307/1313099.

Poff, N.L., Brown, C.M., Grantham, T.E., Matthews, J.H., Palmer, M. a., Spence, C.M., Wilby, R.L., Haasnoot, M., Mendoza, G.F., Dominique, K.C., Baeza, A., 2015. Sustainable water management under future uncertainty with eco-engineering decision scaling. Nat. Clim. Chang. 1–23. http://dx.doi.org/10.1038/nclimate2765.

Poff, N.L., Matthews, J.H., 2013. Environmental flows in the Anthropocence: Past progress and future prospects. Curr. Opin. Environ. Sustain 5, 667–675. http://dx.doi.org/10.1016/j.cosust.2013.11.006.

Poff, N.L., Richter, B.D., Arthington, A.H., Bunn, S.E., Naiman, R.J., Kendy, E., Acreman, M., Apse, C., Bledsoe, B.P., Freeman, M.C., Henriksen, J., Jacobson, R.B., Kennen, J.G., Merritt, D.M., O'Keeffe, J.H., Olden, J.D., Rogers, K., Tharme, R.E., Warner, A., 2010. The ecological limits of hydrologic alteration (ELOHA): a new framework for developing regional environmental flow standards. Freshw. Biol. 55, 147–170. http://dx.doi.org/10.1111/j.1365-2427.2009.02204.x.

Poff, N.L., Zimmerman, J.K.H., 2010. Ecological responses to altered flow regimes: a literature review to inform the science and management of environmental flows. Freshw. Biol. 55, 194–205. http://dx.doi.org/10.1111/j.1365-2427.2009.02272.x.

Polade, S.D., Pierce, D.W., Cayan, D.R., Gershunov, A., Dettinger, M.D., 2014. The key role of dry days in changing regional climate and precipitation regimes. Sci. Rep. 4 http://dx.doi.org/10.1038/srep04364, 8pp.

Prudhomme, C., Davies, H., 2009. Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 2: future climate. Clim. Change 93, 197–222. http://dx.doi.org/10.1007/s10584-008-9461-6.

Richter, B.D., Baumgartner, J.V., Powell, J., Braun, D.P., 1996. A method for assessing hydrologic alteration within ecosystems. Conserv. Biol. 10, 1163–1174. http://dx.doi.org/10.2307/2387152.

Roberts, J., Marston, F., 2011. Water Regime for Wetland and Floodplain Plants. National Water Commission, Canberra.

Seguí, P.Q., Ribes, A., Martin, E., Habets, F., Boé, J., 2010. Comparison of three downscaling methods in simulating the impact of climate change on the hydrology of Mediterranean basins. J. Hydrology 383 (1), 111–124. http://dx.doi.org/10.1016/j.jhydrol.2009.09.050.

SKM, 2013. Ovens River REALM Model Input Data and Model Update. Final report prepared for the Department of Environment and Primary Industries and Goulburn-Murray Water. (Unpublished).

Teutschbein, C., Wetterhall, F., Seibert, J., 2011. Evaluation of different downscaling techniques for hydrological climate-change impact studies at the catchment scale. Clim. Dyn. 37, 2087–2105. http://dx.doi.org/10.1007/s00382-010-0979-8.

Thompson, J.R., Laizé, C.L.R., Green, A.J., Acreman, M.C., Kingston, D.G., 2014. Climate change uncertainty in environmental flows for the Mekong River. Hydrol. Sci. J.

1–20. http://dx.doi.org/10.1080/02626667.2013.842074.
Trzaska, S., Schnarr, E., 2014. A Review of Downscaling Methods for Climate Change Projections. United States Agency for International Development by Tetra Tech ARD, pp. 1–42.
van Oldenborgh, G.J., Philip, S.Y., Collins, M., 2005. El Niño in a changing climate: a multi-model study. Ocean. Sci. 1, 81–95. http://dx.doi.org/10.5194/os-1-81-2005.
Vörösmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S.E., Sullivan, C.A., Liermann, C.R., Davies, P.M., 2010. Global threats to human water security and river biodiversity. Nature 467, 555–561. http://dx.doi.org/10.1038/nature09549.
Walsh, C.L., Kilsby, C.G., 2007. Implications of climate change on flow regime affecting Atlantic salmon. Hydrol. Earth Syst. Sci. 11, 1127–1143. http://dx.doi.org/10.1080/09613210500491514.
Wang, Q.J., Nathan, R.J., 2007. A method for coupling daily and monthly time scales in stochastic generation of rainfall series. J. Hydrol. 346, 122–130. http://dx.doi.org/10.1016/j.jhydrol.2007.09.003.
Wilks, D.S., 2010. Use of stochastic weather generators for precipitation downscaling. Wiley Interdiscip. Rev. Clim. Chang. 1, 898–907. http://dx.doi.org/10.1002/wcc.85.
Wilks, D.S., 1999. Multisite downscaling of daily precipitation with a stochastic weather generator. Clim. Res. 11, 125–136. http://dx.doi.org/10.3354/cr011125.
Wood, A.W., Leung, L.R., Sridhar, V., Lettenmaier, D.P., 2004. Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Clim. Change 62, 189–216. http://dx.doi.org/10.1023/B:CLIM.0000013685.99609.9e.
Xie, S., Deser, C., Vecchi, G.A., Collins, M., Tom, L., Hall, A., Hawkins, E., Johnson, N.C., Cassou, C., 2014. Towards predictive understanding of regional climate change: issues and opportunities for progress. Nat. Publ. Gr 5, 1–29. http://dx.doi.org/10.1038/nclimate2689.
Zhang, X.C., 2013. Verifying a temporal disaggregation method for generating daily precipitation of potentially non-stationary climate change for site-specific impact assessment. Int. J. Climatol. 33, 326–342. http://dx.doi.org/10.1002/joc.3425.
Zweig, C.L., Kitchens, W.M., 2009. Multi-state succession in wetlands: a novel use of state and transition models. Ecology 90, 1900–1909. http://dx.doi.org/10.1890/08-1392.1.