Steps toward "useful" hydroclimatic scenarios for water resource management in the Murray-Darling Basin

Anthony S. Kiem[1] and Danielle C. Verdon-Kidd[1]

Received 29 July 2010; revised 8 February 2011; accepted 21 March 2011; published 16 June 2011.

[1] There is currently a distinct gap between what climate science can provide and information that is practically useful for (and needed by) natural resource managers. Improved understanding, and model representations, of interactions between the various climate drivers (both regional and global scale), combined with increased knowledge about the interactions between climate processes and hydrological processes at the regional scale, is necessary for improved attribution of climate change impacts, forecasting at a range of temporal scales and extreme event risk profiling (e.g., flood, drought, and bushfire). It is clear that the science has a long way to go in closing these research gaps; however, in the meantime water resource managers in the Murray-Darling Basin, and elsewhere, require hydroclimatic projections (i.e., seasonal to multidecadal future scenarios) that are regionally specific and, importantly, take into account the impacts, and associated uncertainties, of both natural climate variability and anthropogenic change. The strengths and weaknesses of various approaches for supplying this information are discussed in this paper.

Citation: Kiem, A. S., and D. C. Verdon-Kidd (2011), Steps toward "useful" hydroclimatic scenarios for water resource management in the Murray-Darling Basin, *Water Resour. Res.*, *47*, W00G06, doi:10.1029/2010WR009803.

1. Introduction

[2] Traditionally, water resource managers have used empirical methods that assume stationarity to estimate the risk of climate-related extremes (e.g., droughts, floods, and bushfires) that impact on water quantity, water quality, and/or water resource–related infrastructure and management decisions. In other words, the observed history of climate extremes is analyzed under the assumption that the chance of an extreme event occurring is the same from one year to the next and that the future will look like the past (i.e., the stationary climate assumption). This assumption is flawed given that the physical mechanisms that actually deliver climate extremes have been ignored and also given that the impacts associated with anthropogenic climate change are not considered [e.g., *Franks and Kuczera*, 2002; *Kiem et al.*, 2003, 2006; *Milly et al.*, 2008, *Verdon-Kidd and Kiem*, 2010]. Also ignored is the observed multiyear to multidecadal epochs of enhanced or reduced extreme event risk across eastern Australia, including the Murray-Darling Basin (MDB, Figure 1) [e.g., *Franks and Kuczera*, 2002; *Kiem et al.*, 2003, 2006; *Kiem and Franks*, 2004; *Verdon et al.*, 2004a, 2004b]. That is, the observations clearly show that the chance of drought or flood or bushfire is not the same from one year to the next. These studies demonstrate that the first step in any climate-driven extreme risk assessment should be to understand the climate mechanisms that actually drive the periods of elevated risk. For example, numerous studies (refer to *Diaz and Markgraf* [2000, and references therein]) have shown that strong relationships exist between eastern Australian rainfall and streamflow and the global-scale ocean-atmospheric circulation process known as the El Niño–Southern Oscillation (ENSO). Previous work has also shown that, while ENSO is important, other climate phenomena also influence Australian climate on interannual to multidecadal timescales [e.g., *Nicholls*, 1989; *Power et al.*, 1999; *Kiem et al.*, 2003, 2006; *Kiem and Franks*, 2004; *Verdon et al.*, 2004a, 2004b; *Verdon and Franks*, 2005; *Hendon et al.*, 2007; *Meneghini et al.*, 2007; *Kiem and Verdon-Kidd*, 2009, 2010; *Kirono et al.*, 2010]. On the basis of this research there is a clear need for an improved understanding into the multiple interactions between large- and local-scale climate drivers and their influence on climate related risk [*Murphy and Timbal*, 2008; *Risbey et al.*, 2009; A. J. E. Gallant et al., Understanding climate processes in the Murray-Darling Basin: Utility and limitations for natural resources management, submitted to *Water Resources Research*, 2011].

[3] Compounding the influence of natural climate variability, and the problems associated with the brevity (in climatological terms) of instrumental hydroclimatological records [e.g., *Verdon and Franks*, 2006, 2007], there is also serious concern about how human-induced climate change may increase the frequency and severity of extreme events, including droughts and floods, in the future [e.g., *Pittock*, 2003; *Parry et al.*, 2007]. Accordingly, there have been attempts to utilize climate model outputs to determine how anthropogenic climate change may affect water resources and, on the basis of this information, to develop water resource management strategies to deal with the projected risks. However, the uncertainty associated with

[1]Environmental and Climate Change Research Group, School of Environmental and Life Sciences, Faculty of Science and Information Technology, University of Newcastle, Callaghan, New South Wales, Australia.

0043-1397/11/2010WR009803

Figure 1. Location of the Murray-Darling Basin (~24°S–36°S, 140°E–150°E) (source: Discover Murray River, www.murrayriver.com.au).

future climate projections is known to be significant [e.g., *Parry et al.*, 2007; *Randall et al.*, 2007] and is magnified further when attempting to make inferences at the regional (i.e., catchment) scale (e.g., differentiating between coastal and inland processes). This is especially the case for precipitation [e.g., *Lim and Roderick*, 2009]. The uncertainty is so high that projections of future drought risk, on either the short (seasonal up to 5 years) or long (more than 10 years into the future) term, currently have limited practical usefulness for water resource managers and/or government policy makers [*National Climate Change Adaptation Research Facility*, 2010].

[4] Water resource planning must account for both natural climate variation and human-induced climate change, since these factors will continue to influence Australia's climate, even if immediate action is taken to curtail greenhouse gas emissions. Such considerations are needed to avoid over-allocation of water resources and/or to ensure that economic activity based on utilization of water resources is not unnecessarily restricted. This paper aims to demonstrate the importance of understanding the hydroclimatic drivers that influence MDB water resources so that this information can be used to more realistically quantify climate-related risk. The current limitations of climate models and the potential dangers associated with using them for something they were

not designed for (i.e., regional-scale water resources management) will also be examined. Finally, recommendations are given as to the steps required to enable provision of hydroclimatic scenarios that are useful for water resource management in the MDB.

2. Major Drivers of Murray-Darling Basin Hydroclimatic Variability

2.1. Regional-Scale Synoptic Patterns

[5] Because of its size and relative location to the Pacific, Indian, and Southern Oceans, the MDB (see Figure 1) is influenced by a range of regional synoptic systems. Previous studies [e.g., *Wright*, 1989; *Pook et al.*, 2006; *Verdon-Kidd and Kiem*, 2009a] have identified regional synoptic patterns that are important for Victoria, much of New South Wales, and the southern parts of Queensland. Gallant et al. (submitted manuscript, 2011) reviewed this work and described in detail the regional synoptic features that influence rainfall in the MDB.

2.2. Large-Scale Climate Drivers

[6] The regional-scale synoptic processes that deliver rain to the MDB are modulated on intraseasonal and longer time scales by major modes of large-scale (global) climate variability [e.g., *Pook et al.*, 2008; *Verdon-Kidd and Kiem*, 2009a]. The large-scale ocean-atmospheric phenomena that are known to influence the MDB on interannual to multidecadal time scales include ENSO, ENSO Modoki, the Interdecadal Pacific Oscillation (IPO), Indian Ocean sea surface temperatures and the Indian Ocean Dipole (IOD), the Southern Annular Mode (SAM), the Madden-Julian Oscillation, the subtropical ridge, and atmospheric blocking. For a comprehensive review of these large-scale climate drivers and their impacts in the MDB refer to Gallant et al. (submitted manuscript, 2011).

2.3. Interactions Between Large-Scale Climate Drivers

[7] Assuming that the Earth's climate can be viewed as an integrated system, it is unlikely that the large-scale climate drivers influential to the MDB are independent of each other and/or act in isolation. Evidence of this is discussed in detail by Gallant et al. (submitted manuscript, 2011) and is summarized below.

[8] 1. The frequency and magnitude of ENSO impacts in Australia is dependent on the phase of the IPO [e.g., *Power et al.*, 1999; *Kiem et al.*, 2003; *Verdon and Franks*, 2006].

[9] 2. There is an ongoing scientific debate concerning the IOD and its existence or nonexistence and dependence or independence on or from ENSO [e.g., *Verdon and Franks*, 2005, and references therein].

[10] 3. *Meyers et al.* [2007] used a comprehensive, physically based classification process to demonstrate that the location and magnitude of Australia rainfall anomalies differ markedly depending on which of the nine possible ENSO-IOD phases was in existence.

[11] 4. *Risbey et al.* [2009] discuss links between atmospheric blocking and, at least, ENSO.

[12] 5. The recent papers on ENSO Modoki [e.g., *Ashok et al.*, 2009; *Cai and Cowan*, 2009; *Taschetto and England*, 2009; *Taschetto et al.*, 2009] suggest that central Pacific SSTs (i.e., the ENSO Modoki region) play some role in altering the location, timing, and intensity of ENSO impacts on Australia. *Cai and Cowan* [2009] also suggest that as with ENSO the ENSO Modoki is similarly modulated by IPO.

[13] 6. *Kiem and Verdon-Kidd* [2009, 2010] showed that dry conditions in autumn across southeast Australia are most likely if an El Niño event occurs in combination with a positive SAM. It was also found that unlike the majority of eastern Australia, a La Niña event is not necessarily always associated with above-average rainfall in southeast Australia. In fact, La Niña events occurring in conjunction with a positive SAM phase are often as dry as an El Niño event. These findings possibly explain why three recent La Niña events (1998–1999, 1999–2000, and 2007–2008) failed to result in significant rainfall across southeast Australia since the SAM was not in a negative phase during autumn for any of these events. The physical mechanism explaining how ENSO and SAM (and/or other large-scale processes) interact to either enhance or block rain-producing systems is yet to be fully understood.

[14] It is clear from the points highlighted above that a single-climate mode (such as ENSO) will not fully explain the variability experienced in such regions as the MDB. In fact, *Risbey et al.* [2009] showed that for most Australia regions individual large-scale drivers, when treated as a single process, account for less than 20% of monthly rainfall variability. To illustrate the importance of understanding and accounting for interactions between multiple climate drivers in a climate modeling or forecasting application, *Kiem and Verdon-Kidd* [2009] developed a seasonal rainfall forecasting approach that included ENSO, IOD, and SAM indices as predictors. Importantly, the scheme attempted to capture the interaction between drivers by including ENSO and IOD (Pacific and Indian Oceans); ENSO and SAM (Pacific and Southern Oceans); IOD and SAM (Indian and Southern Oceans); and ENSO, SAM, and IOD (three-ocean index (3OI)) as predictors. The forecasting methodology was applied to nine rainfall sites across Victoria (Figure 2), most of which are located in the southern MDB, and the "best" predictor for each lag (Table 1) and site (Table 2) was identified. The "best" predictor was defined as the predictor that produced rainfall hindcasts with the lowest root-mean-square error (RMSE) between the median of the forecast distribution and the observed data for the target station and month (i.e., the one that produced rainfall hindcasts that were closest to observations). Correlations for each month, lag, and station were calculated along with the RMSE. Correlations alone were not relied on to determine the best predictor as correlations do not account for a systemic underestimate or overestimate of rainfall (this is better accounted for by the RMSE). Table 1 shows the percentage of time each predictor is selected as the best for each site and month combination at lags 0–9 (note that lag 0 refers to predictor in month x forecasting rainfall in month x and lag 3 refers to predictor in month x forecasting rainfall in month $x + 3$). The percentages relate to a total of 108 occurrences (i.e., nine sites times 12 months), so a value of 100% in the lag 0–predictor 7 cell would indicate that, at lag 0, predictor 7 (i.e., the 3OI) was chosen as best for every site and every month (i.e., 108 times).

[15] Table 1 shows that the predictors associated with single indices (i.e., methods 1–3) are rarely selected as best; in fact, it is clear that the combined state of the three oceans surrounding Australia is what drives rainfall in the southern

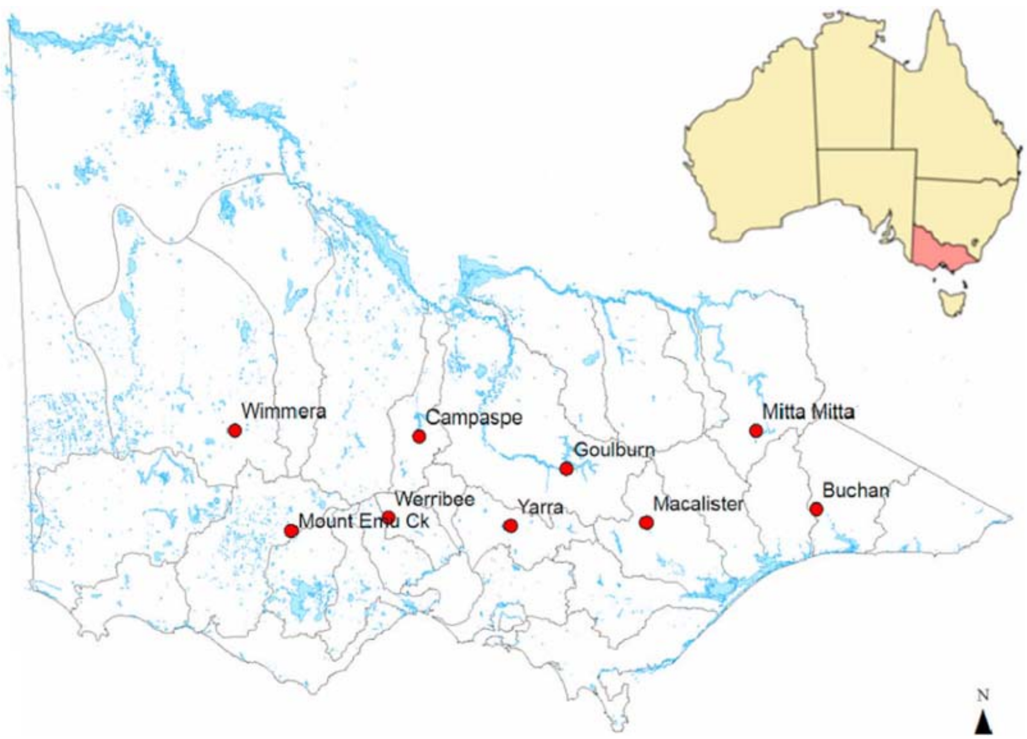

Figure 2. Location of selected catchments and their representative rainfall gauge [*Kiem and Verdon-Kidd*, 2009].

MDB. Therefore, any forecasting method that does not take into account interactions between multiple large-scale climate phenomena will perform poorly in, at least, the southern MDB. In addition, on the basis of the fact that predictors that include SAM (predictors 3, 5, 6, and 7) are selected as best at least 70% of the time (depending on lag), it is clear that, for southeast Australia, forecasting methods should include an index of SAM as a predictor (for a statistical method) or a realistic representation of SAM and how it interacts with ENSO and IOD (for a dynamic climate model).

[16] To demonstrate the spatial variability of predictor selection, Table 2 shows the percentage of time each predictor is selected as best for each site at lag 0 (note that only lag 0 is shown since Table 1 demonstrated that the predictors selected as best were consistent for lags 0 to 6). The percentages relate to a total of 12 occurrences (i.e., 12 months), so a value of 100% in the site 1–predictor 7 cell would indicate that at lag 0, predictor 7 was chosen as best for every month at site 1 (i.e., 12 times).

[17] The results in Table 2 demonstrate that there is some spatial variability in the best predictor selected. For example, on the basis of the results obtained using predictors 1, 4, and 5 (i.e., those containing ENSO), ENSO appears to have very little influence on the southwest corner of Victoria (i.e., sites 3, 6, and 7 (Mount Emu Creek, Wimmera, and Werribee)). This is consistent with research by *Folland et al.* [2002], who demonstrated how ENSO influences the location of the South Pacific Convergence Zone (SPCZ). The SPCZ is responsible for delivering rain-bearing cloud bands across eastern Australia in summer months. During El Niño (La Niña) events the SPCZ is located farther north (south) than usual, resulting in lower (higher) rainfall anomalies for much of eastern Australia. However, it appears that the

Table 1. Percentage of Time Each Predictor Is Selected as the "Best" for All Sites and Months at Lags 0–9[a]

	Lag									
	0	1	2	3	4	5	6	7	8	9
Predictor 1: ENSO	0.9	2.8	8.3	7.4	7.4	13.0	10.2	6.5	10.2	8.3
Predictor 2: IOD	9.3	4.6	6.5	4.6	6.5	5.6	12.0	10.2	8.3	6.5
Predictor 3: SAM	4.6	6.5	4.6	5.6	7.4	7.4	9.3	7.4	4.6	9.3
Predictor 4: P-I	17.6	11.1	13.9	20.4	13.0	19.4	9.3	11.1	13.0	14.8
Predictor 5: P-S	17.6	13.0	11.1	13.9	15.7	10.2	13.0	12.0	13.0	12.0
Predictor 6: I-S	10.2	19.4	12.0	15.7	8.3	8.3	8.3	13.9	13.9	13.9
Predictor 7: 3OI	39.8	42.6	43.5	32.4	41.7	36.1	38.0	38.9	37.0	35.2

[a]ENSO, El Niño–Southern Oscillation; IOD, Indian Ocean Dipole; SAM, Southern Annular Mode; P-I, Pacific and Indian Oceans; P-S, Pacific and Southern Oceans; 3OI, three-ocean index. See Figure 2 for location of sites.

Table 2. Percentage of Time Each Predictor Is Selected as the "Best" for Each Site at Lag 0[a]

	Site								
	1	2	3	4	5	6	7	8	9
Predictor 1: ENSO	0.0	8.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Predictor 2: IOD	8.3	0.0	25.0	8.3	0.0	8.3	8.3	8.3	16.7
Predictor 3: SAM	0.0	8.3	8.3	8.3	0.0	8.3	0.0	8.3	0.0
Predictor 4: P-I	8.3	25.0	0.0	16.7	50.0	0.0	16.7	16.7	25.0
Predictor 5: P-S	25.0	16.7	16.7	33.3	8.3	8.3	8.3	16.7	25.0
Predictor 6: I-S	16.7	0.0	0.0	8.3	8.3	16.7	25.0	16.7	0.0
Predictor 7: 3OI	41.7	41.7	50.0	25.0	33.3	58.3	41.7	33.3	33.3

[a]ENSO, El Niño–Southern Oscillation; IOD, Indian Ocean Dipole; SAM, Southern Annular Mode; P-I, Pacific and Indian Oceans; P-S, Pacific and Southern Oceans; 3OI, three-ocean index. Sites are 1, Buchan; 2 Macalister; 3, Mount Emu Creek; 4, Mitta Mitta; 5, Campaspe; 6, Wimmera; 7, Werribee; 8, Goulburn; 9, Yarra. See Figure 2 for location of sites.

Table 3. Observed Versus “Forecast” Rainfall for Yarra at Lags 0 and 3[a]

	Predictor 1: ENSO		Predictor 2: IOD		Predictor 3: SAM		Predictor 4: P-I		Predictor 5: P-S		Predictor 6: I-S		Predictor 7: 3OI	
Month	CC	I (%)	CC	I (%)	CC	I (%)	CC	I (%)	CC	I (%)	CC	I (%)	CC	I (%)
Lag 0														
1	0.13	0.3	**0.19**	**1.4**	−0.01	−1.2	0.03	−1.4	0.01	−1.8	0.14	1.1	0.16	1.1
2	−0.25	−0.8	**0.14**	**2.1**	0.01	1.2	0.06	1.3	−0.11	−0.5	0.08	1.6	0.10	1.6
3	−0.04	2.1	0.13	3.5	0.03	2.5	**0.23**	**5.0**	0.03	2.0	0.14	3.5	0.16	3.6
4	0.09	3.0	−0.14	0.9	0.22	4.4	−0.05	1.6	0.14	3.5	0.23	4.9	**0.26**	**6.3**
5	0.07	−0.3	−0.01	−1.8	0.26	2.1	0.12	0.3	0.21	1.5	0.27	2.7	**0.34**	**5.5**
6	0.17	1.5	0.12	0.8	0.09	0.6	0.10	0.9	**0.24**	**2.8**	0.18	2.1	0.21	2.5
7	0.19	0.7	−0.02	−3.9	0.21	1.1	0.03	−1.7	0.35	4.3	0.28	2.9	**0.36**	**5.9**
8	0.29	2.5	0.32	2.4	0.18	0.8	**0.39**	**5.4**	0.36	4.3	0.28	2.1	0.36	4.4
9	0.11	−0.9	0.12	−2.3	−0.08	−4.5	**0.19**	**0.2**	0.07	−2.9	0.11	−2.1	−0.01	−10.0
10	0.38	4.5	0.44	5.4	0.23	2.4	0.39	6.0	0.36	4.6	0.45	7.6	**0.45**	**10.4**
11	0.10	1.5	−0.17	−1.9	0.20	3.1	0.08	1.0	**0.31**	**5.0**	0.10	1.8	0.17	2.7
12	0.25	1.3	−0.29	−5.1	0.20	1.2	−0.21	−6.2	**0.30**	**2.5**	0.09	−0.4	0.21	1.6
Lag 3														
1	−0.03	−0.4	−0.06	−0.2	0.09	0.8	−0.01	−0.1	**0.14**	**1.5**	−0.11	−1.0	0.01	−1.1
2	−0.16	−0.5	0.13	0.9	−0.12	0.0	−0.21	−1.0	−0.01	0.2	−0.10	−0.2	**0.09**	**0.9**
3	0.11	2.9	−0.01	2.0	−0.01	2.1	−0.01	1.8	**0.16**	**3.3**	0.11	2.9	−0.01	0.0
4	0.20	4.0	−0.07	2.1	0.23	3.7	**0.29**	**5.4**	0.19	4.4	0.05	2.6	0.18	4.3
5	0.09	−0.1	−0.27	−2.4	0.01	−0.7	**0.12**	**0.4**	0.04	−1.0	0.01	−0.9	−0.06	−5.2
6	−0.12	−1.3	0.24	1.4	−0.05	0.0	−0.08	−1.6	**0.19**	**2.3**	0.22	2.1	0.14	1.2
7	−0.07	−2.9	0.18	−0.4	0.25	0.8	−0.02	−2.3	**0.19**	**1.0**	−0.13	−3.4	0.07	−3.4
8	0.18	0.7	0.02	−0.7	0.21	1.1	0.24	1.7	0.07	−1.0	**0.36**	**3.5**	0.25	1.9
9	0.17	0.0	0.04	−1.4	0.04	−1.0	0.28	1.7	0.03	−2.7	0.11	−0.5	**0.29**	**3.4**
10	−0.05	−0.9	0.12	0.8	0.05	0.4	−0.05	−1.4	0.24	2.5	−0.08	−1.6	**0.34**	**5.1**
11	−0.01	0.5	0.03	1.0	0.18	2.2	0.05	0.9	0.21	2.9	**0.34**	**4.2**	0.17	1.0
12	0.30	1.6	0.04	−0.8	0.01	−0.8	0.33	2.1	0.20	1.5	0.24	1.2	**0.38**	**6.3**

[a]CC, correlation coefficient; I, the improvement (i.e., RMSE reduction) when index-based forecasts are compared to climatology-based forecasts. Bold indicates the “best” (i.e., largest reduction in RMSE) index combination for each month. See Figure 2 for location of Yarra.

southwest corner of Victoria is beyond the influence of the SPCZ, and therefore no strong relationships exist with ENSO in this area. Similarly, sites 3, 5, 8, and 9 (Mount Emu Creek, Campaspe, Goulburn, and Yarra) appear to be strongly influenced by the IOD (usually in combination with ENSO and/or SAM). Again this is consistent with previous research that has identified strong links between the IOD and the northwest Australian cloud band [e.g., *Verdon and Franks*, 2005].

[18] Table 3 shows the level of improvement from using climatology alone that can be obtained (on the basis of correlation and RMSE) via incorporation of multiple climate drivers. Note that the results for only one site (Yarra) are shown; however, the results are similar across all study sites (although, as mentioned above, the stations located in the southwest of Victoria are less influenced by ENSO). Table 3 again demonstrates the importance of including the interactions between multiple large-scale climate phenomena in any forecasting scheme. For example, at lag 0, for the majority of months using multiple indices (i.e., predictors 4–7) this resulted in a greater improvement in rainfall forecast than what was achieved with any of the single-index predictors (e.g., during May, using ENSO alone results in no improvement on climatology, but by using all three indices a 5.5% improvement in the rainfall forecast was obtained). It should be noted that while this improvement is modest, this would translate to a larger improvement in streamflow forecasting (which is important for water resource management in the MDB, particularly in months where there is currently no forecasting skill). In addition, the scheme used here is fairly simplistic, and it is likely that much larger improvements could be gained using more sophisticated statistical or dynamical techniques if the same process of including the three ocean drivers were incorporated.

[19] The discussion above highlights the need for improved understanding and realistic model representations of regional and large-scale climate drivers important to eastern Australia, and therefore the MDB, in order to better understand (and prepare for) climate related risk; whether the climatic variability is naturally or anthropogenically induced is irrelevant. While the focus above was on seasonal forecasting, the insights gained are also applicable to long-term projections obtained using general circulation models (GCMs, also known as global climate models). Importantly, most, if not all, of the climate processes discussed in sections 2.1–2.3 are not realistically simulated by current climate models (either dynamical seasonal forecasting models (e.g., the Predictive Ocean Atmosphere Model for Australia (POAMA) used by the Australian Bureau of Meteorology) or GCMs [e.g., *Randall et al.*, 2007]. This represents a significant barrier to the provision of “useful” future hydroclimatic scenarios for MDB water resource management and is further discussed in section 3, with some potential ways forward presented in section 4.

2.4. Hydrological Drivers

[20] The important role that hydrological and/or land surface processes play in regulating climate variability across the MDB has also been demonstrated in previous studies [e.g., *Chiew et al.*, 1998; *Timbal et al.*, 2002; *Kiem and Verdon-Kidd*, 2009], with antecedent catchment conditions explaining an equivalent amount of streamflow variability as the individual large-scale climate drivers. *Commonwealth*

Scientific and Industrial Research Organisation (*CSIRO*) [2008a] also suggests that it is likely that after a prolonged dry period, there is less connectivity between the subsurface storage and the river system, and therefore significant amounts of rainfall and recharge are required to fill the storage before runoff can occur. In addition, it is plausible that extensive land clearance across the Australian continent has contributed to some long-term climatic trends [*Murphy and Timbal*, 2008].

[21] Further, rainfall in the MDB that comes from the west has traveled over land 2–4 days. Accordingly, MDB rainfall is sourced partly from evaporation off the Indian Ocean and partly from transpiration from vegetation upwind. The relative importance of transpiration is a function of deep soil moisture in the plant root zone, which itself is a function of previous rainfall. This rainfall recycling feedback (and the memory it has of previous rainfall) is poorly understood because the soil moisture–vegetation and soil-rainfall feedbacks are complex. However, it is believed to be important in determining downwind rainfall in continental areas such as inland Australia [*Koster et al.*, 2004; *Gimeno et al.*, 2010]. How such effects could be relevant to the more recent, and/or future, changes in MDB rainfall and runoff is currently unclear. Changes in land surface processes, including rainfall-runoff relationships, subsurface storage connectivity, and surface-atmosphere feedbacks, have the potential to significantly affect natural resources (especially water), and this is an area where considerable ongoing research is required, particularly if such processes are to be realistically incorporated in Earth system models and/or future projections of the impacts of anthropogenic climate change [e.g., *Koutsoyiannis et al.*, 2009].

[22] Recent drying in the MDB has also been associated with abnormally high temperatures [*Nicholls*, 2004; *Gallant and Karoly*, 2009], and it has been suggested that this explains the decrease in runoff and soil moisture that is not explained by the decrease in rainfall [*Cai and Cowan*, 2008; *Cai et al.*, 2009]. However, the physical mechanisms by which rising temperatures contribute to enhance a reduction in runoff or soil moisture are not clear, and this topic is the subject of ongoing debate [e.g., *Lockart et al.*, 2009; *Cai et al.*, 2010; *Donohue et al.*, 2010; *Franks et al.*, 2010] and an area where significant further research is required.

[23] As with the knowledge gaps identified relating to climatic drivers of MDB hydroclimatic variability, the unknowns relating to hydrological drivers also represent a significant barrier to the provision of useful future hydroclimatic scenarios for MDB water resource management (since these processes are not yet fully understood and therefore cannot be realistically simulated in the climate models).

3. Climate Modeling: How Useful Is It for Water Resource Management?

[24] Climate models, be they dynamical seasonal forecasting models (e.g., POAMA) or GCMs, theoretically simulate all ocean-atmospheric circulation patterns and their interactions. However, there are many limitations and uncertainties that exist with current climate models, including the following, that are particularly relevant to water resource management in at least the MDB.

[25] 1. *Blackmore and Goodwin* [2009] indicate that even our best climate models fail to simulate observed synoptic patterns that are known to drive rainfall extremes.

[26] 2. There are several large-scale physical processes known to be important for driving Australia rainfall variability (see section 2). Unfortunately, climate models do not satisfactorily simulate these processes or their impacts [*Randall et al.*, 2007], which is not surprising given the limited understanding into how the different phases of these large-scale processes initiate and evolve over time [e.g., *Kiem and Verdon-Kidd*, 2009, 2010; Gallant et al., submitted manuscript, 2011].

[27] 3. Very little is known about how the various climate drivers interact to drive MDB hydroclimatic variability (see section 2.3), and as a result these interactions, and their associated impacts, are also not realistically accounted for in current climate models.

[28] 4. *Lim and Roderick* [2009] show that when 20 climate models (i.e., the ones used in the Intergovernmental Panel on Climate Change 4th Assessment Report [*Parry et al.*, 2007; *Randall et al.*, 2007]) were used to produce 39 model runs of the 21st century for the MDB, 22 showed increases in annual average precipitation to the end of the 21st century, while 17 showed decreases. The uncertainty in the future rainfall projections is further demonstrated by Figure 3, which shows the percentage change in future mean annual rainfall (~2030 relative to ~1990) across the MDB as projected by 15 different climate models [*CSIRO*, 2008a; *Chiew et al.*, 2011]. Clearly, there is no consensus as to what will happen to MDB rainfall in the future; on the basis of this information should a water resource manager plan for a wetter or drier future?

[29] 5. None of the Intergovernmental Panel on Climate Change 4th Assessment Report [*Parry et al.*, 2007; *Randall et al.*, 2007] climate models, used in hindcast mode, reproduce the autumn drying trend that has occurred across southeast Australia since the mid-1990s (i.e., the "Big Dry") (e.g., *Verdon-Kidd and Kiem* [2009b] and publications from the South Eastern Australian Climate Initiative (SEACI), www.mdbc.gov.au/subs/seaci).

[30] 6. Climate model output is delivered in coarse grids (i.e., typically hundreds of kilometers in the horizontal and vertical), and as such, climate models are extremely limited in their ability to simulate regional-scale processes important for hydrology and MDB water resources management (particularly given the lack of topography and land surface–atmospheric feedbacks in current climate models) [e.g., *Milly et al.*, 2008]. For instance, GCMs are unable to distinguish the east Australian coastal strip from regions west of the Great Dividing Range, despite the known and marked differences in climate in these two places. Various downscaling methods (including limited-area models nested within GCMs) have been developed; however, limited research has been performed on the suitability of such downscaled output for hydrological applications. Further, the accuracy of the downscaled result is strongly dependent on the biases in the underlying GCM. This is a major concern given the work by *Pitman and Perkins* [2008], who conclude that the use of climate model data to explore sectors that are vulnerable to hydroclimatic extremes is strongly limited [see also *Koutsoyiannis et al.*, 2008].

[31] 7. Hydrological modeling requires daily (and subdaily) data, particularly for flood risk estimation. However,

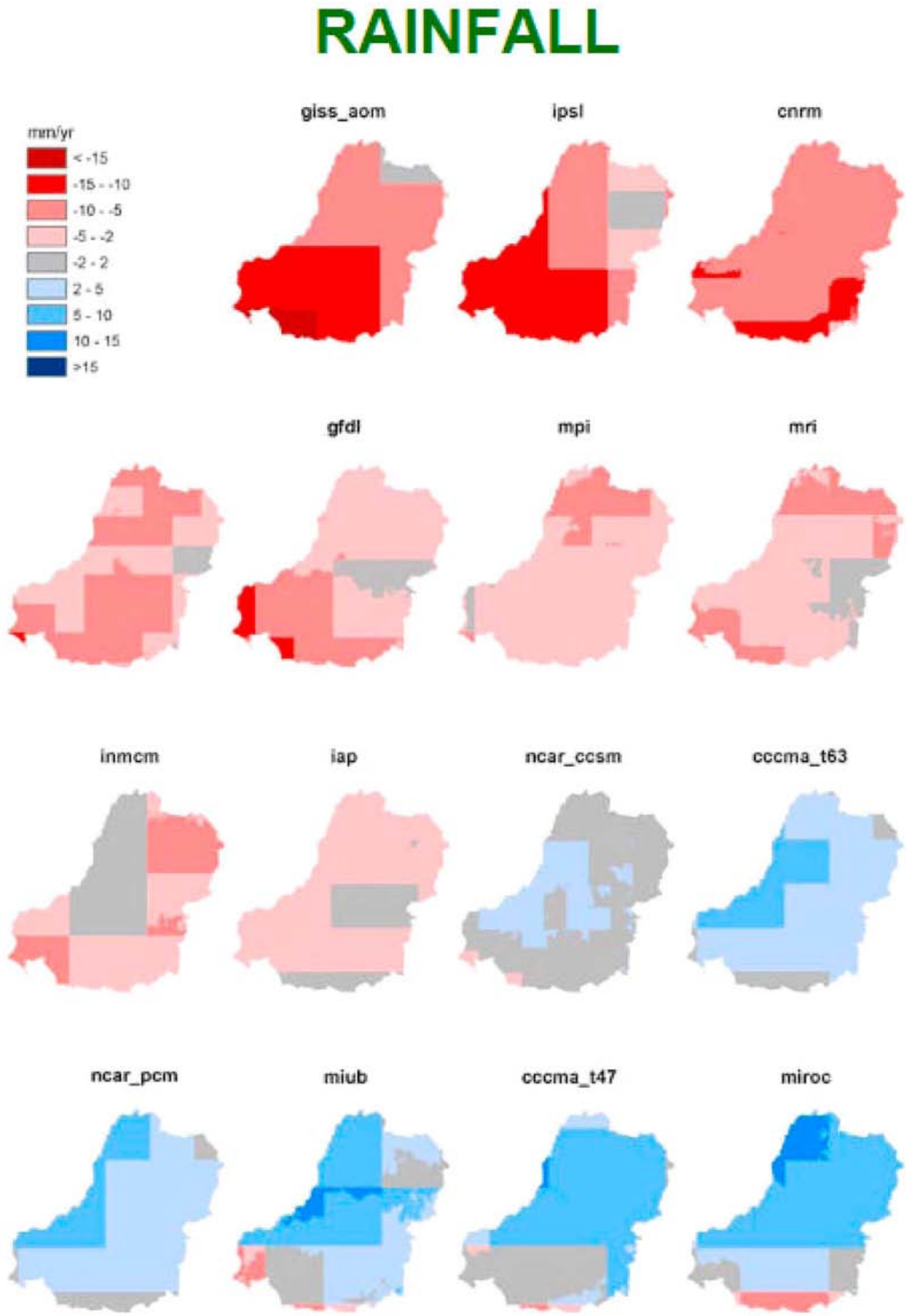

Figure 3. Percentage change in future mean annual rainfall (~2030 relative to ~1990) across the MDB as projected by 15 different climate models [*CSIRO*, 2008a; *Chiew et al.*, 2011].

Kiem et al. [2008] demonstrate that while climate models may do a reasonable job at replicating annual statistics (and in some cases seasonal statistics), climate model output at the monthly and submonthly scale, for precipitation in particular, is associated with significant biases, most likely due to the points raised above that observed synoptic scale patterns and known climate drivers are not well simulated by climate models. While it is true that various "bias correction" and "change factor" techniques (discussed further below) have been developed in an attempt to address this climate model inadequacy and to improve the spatial and temporal precision of climate model projections, these techniques actually introduce an additional layer of uncertainty and a degree of "false precision" that should not be confused with accuracy or reality.

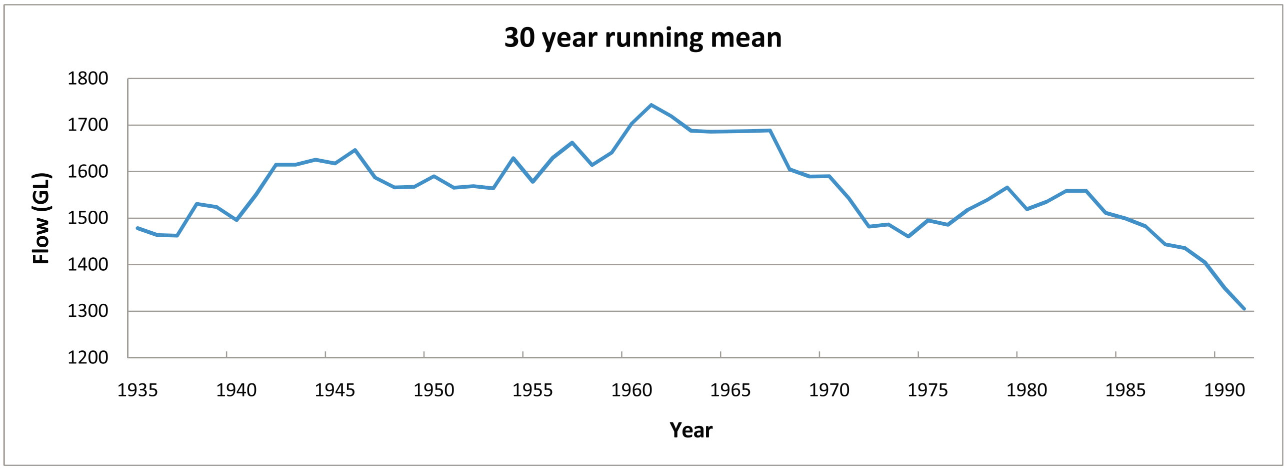

Figure 4. Variability of 30 year baselines for Goulburn (see Figure 2) as shown by a 30 year running mean of annual (January–December) flow totals.

[32] 8. Aerosols (both natural and from urban or industrial pollution) have been linked to the suppression of precipitation [e.g., *Rosenfeld*, 2000; *Randall et al.*, 2007] and to changes in the formation, composition, and albedo effect of clouds [e.g., *Roesler and Penner*, 2010]. However, aerosols, clouds, precipitation, weather, and climate are not yet studied or modeled as a holistic system, resulting in unclear projections as to the current and future relationships between aerosols, cloud processes, and precipitation [*Randall et al.*, 2007].

[33] In short, climate models are designed for testing theories about our understanding of global- or continental-scale climate processes, and undoubtedly, they are a useful tool for doing this. However, current climate models are not designed for application at the regional scale. Even with sophisticated downscaling or bias correction techniques, serious questions remain as to the applicability of climate model outputs to quantifying the risk of hydrological extremes (e.g., drought, flood, and bushfire) given that most of the critical factors that drive these extremes are not well simulated by the climate models. The fact that there is so much we do not yet understand about the numerous climatic drivers affecting the MDB, especially how they interact with one another, raises serious questions about the "realness" and accuracy of climate model output and its worth for water resource management: How can climate models be expected to satisfactorily simulate hydroclimatic process that we do not yet properly understand?

[34] Compounding this is our lack of understanding into the relationship between the climate (e.g., rainfall and temperature) and the hydroclimate (e.g., evaporation, runoff, streamflow, and soil moisture). For climate models to be useful for water resource management, they need to provide projections that simulate important land surface–ocean-atmosphere interactions which (1) are complex and imperfectly understood and (2) bring with them the added difficulties and computational limitations associated with integrating land surface models with climate models [e.g., *Randall et al.*, 2007; *Wei and Dirmeyer*, 2010].

[35] Attempts to overcome the limitations discussed above have involved using GCM output to quantify the rate of change in important climate variables and then applying the "change factor" to observed variables from an epoch that is assumed to represent "current" climate (i.e., the baseline) to obtain a climate change impacted "future" climate. This approach has the attraction that the climate change–impacted variables can be easily input into hydrological (or land surface) models to simulate climate change–impacted future water resource scenarios. However, this approach also has several limitations (along with the general limitations discussed for GCMs). The change factors obtained do not realistically account for natural climate variability as the important natural climate processes are not well simulated by the GCMs (as discussed above). The actual application of change factors also raises questions as to what statistical properties should change (e.g., the mean, the standard deviation, the skew, and the number of rain days) and by what rate (i.e., all the same or by differing amounts) and at what time step (e.g., annual, seasonal, or daily) [e.g., *Herron et al.*, 2010]. There are also questions associated with the fact that hydrological models are calibrated according to current climate conditions, and then it is assumed that this calibration will be valid under future climate conditions, but this may not be the case.

[36] An alternative approach that is often used to overcome the issues associated with unrealistic GCM outputs involves "bias correcting" GCM current climate output so it matches the spatial and temporal distribution of some observed climate baseline. The bias correction factors obtained are then applied to future GCM output, with the assumption being that the bias correction factors required to make the GCM current climate output match reality will be the same as that required in the future. The primary problem with this approach is that the bias corrections are assumed to be stationary over time, but clearly, there is a high probability that this will not be the case.

[37] Both the change factor and bias correction techniques involve the use of an observed reference climate baseline on which to compare the climate model outputs. Therefore, another important issue is the choice of climate "baseline" on which to apply the climate change factors or determine the bias corrections. Among the numerous possible criteria for selecting the baseline period, it should be representative of the present day (i.e., nonanthropogenic climate change–impacted) average climate in the study region and of sufficient duration to encompass a range of climatic variations,

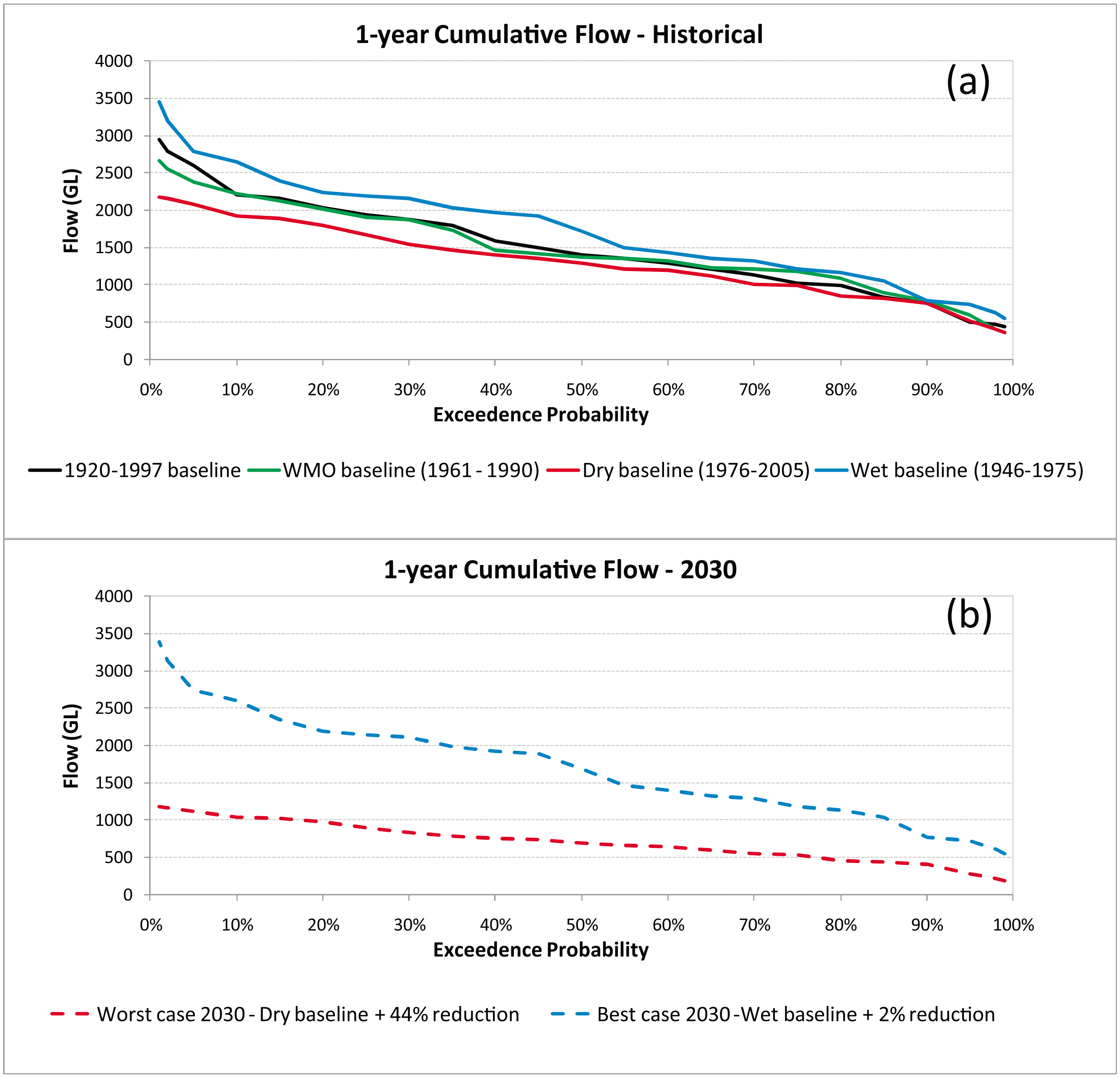

Figure 5. One year cumulative flow exceedance plot at Goulburn (see Figure 2) using a range of 30 year baselines (see Figure 3) under (a) historical conditions and (b) with best and worst case 2030 climate change conditions applied (2030 climate change projections obtained from *CSIRO* [2008b]).

including several significant weather anomalies (e.g., severe droughts or cool seasons). A popular climatological baseline period is a 30 year "normal" period, as defined by the World Meteorological Organization (WMO). The current WMO normal period is 1961–1990, which provides a standard reference for many impact studies (however, the suitability of this baseline for the MDB is particularly questionable given that this period does not capture either the worst flood or the worst drought on record in this region). Note also that many different baselines are currently being used, and this subjective choice of baseline can result in markedly different future scenarios (as illustrated in Figures 4, 5, and 6). Figure 4 shows, for Goulburn located in the MDB (Figure 2), the range in different 30 year baselines that could be used to represent current climate (as shown by a 30 year running mean of annual (January–December) flow totals). The range illustrated in Figure 4 takes into account only instrumental data (i.e., approximately the last 100 years) and does not account for paleoclimatological evidence that suggests that the majority of the 20th century may have been comparatively wet [e.g., *Verdon and Franks*, 2006] and that several droughts that were longer and more widespread than the major 20th century droughts (i.e., the Federation, World War II, and Big Dry or Millienium droughts) [*Verdon-Kidd and Kiem*, 2009b] have occurred previously.

[38] The uncertainty related to the subjective choice of baseline is further compounded by the range of different impacts projected by the models. For example, *CSIRO* [2008b] found that for 15 different climate models the

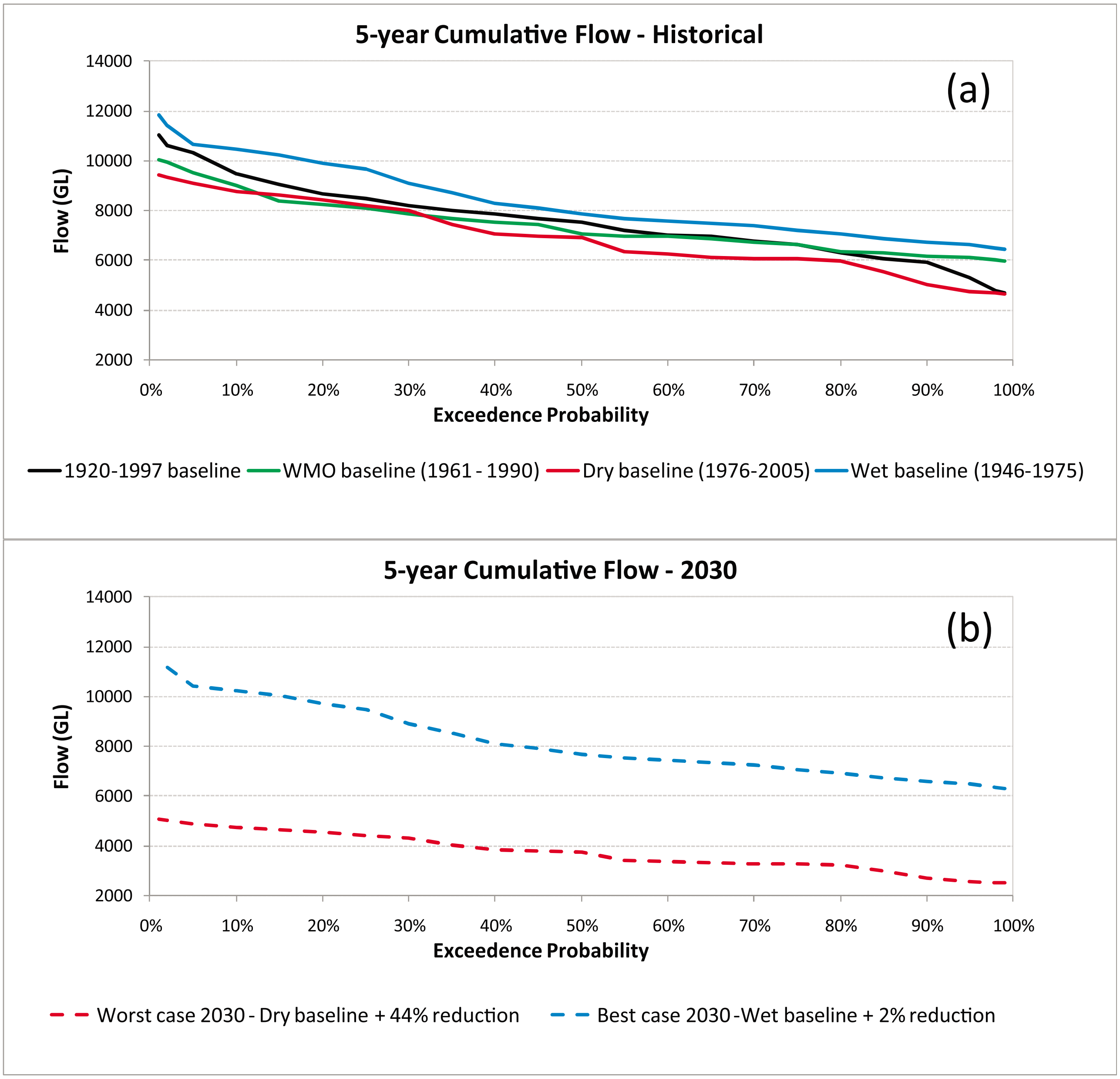

Figure 6. Five year cumulative flow exceedance plot at Goulburn (see Figure 2) using a range of 30 year baselines (see Figure 4) under (a) historical conditions and (b) with best and worst case 2030 climate change conditions applied (2030 climate change projections obtained from *CSIRO* [2008b]).

2030 projection for changes to annual streamflow at Goulburn ranged from a 44% reduction to a 2% reduction, with a best (i.e., median) estimate of a 13% reduction. Even though these climate change projections are based on one emissions scenario (when there are actually several that should be considered), the result is a range of different plausible scenarios (e.g., Figures 5b and 6b), so what should the water resource manager plan for?

4. A Way Forward: Steps Toward Hydroclimatic Scenarios That Are Useful for Water Resource Management

[39] There is currently a disconnect between what climate science is capable of providing and the needs of water resource managers. Indeed, a climate scientist's idea of a "successful" climate forecast is vastly different from what a hydrologist would consider satisfactory, which is different again from what a water resource manager (i.e., the practitioner) actually requires (R. Moran, senior hydrologist, Victorian Department of Sustainability and Environment, personal communication, 2010). Often water resource managers do not get the information they want or can readily use (i.e., sometimes the right information may exist but it is inaccessible for water resource managers because of time, expertise, and/or technological constraints). This problem, which is essentially a communication problem, needs to be addressed if we are to bridge the gap between climate science and the practically useful information that stakeholders require.

[40] Similarly, the issues raised in section 3 relating to the use of climate model output as a tool for water resource management are likely to take several years of research, significant climate model improvement, and advances in computational capability to address. Even if the issues mentioned are resolved, uncertainties in climate model projections will always be present, not simply because of observational uncertainty and chaotic variability but also because of the fact that different climate models with different model structures forced by different initial conditions and emissions scenarios will continue to project a range of future climates [e.g., *Stainforth et al.*, 2007; *Koutsoyiannis et al.*, 2008, 2009].

[41] However, water resource managers in the MDB, and elsewhere, cannot necessarily wait until all these issues are addressed; they require hydroclimatic projections (i.e., seasonal to multidecadal future scenarios) that are regionally specific and, importantly, quantify the impacts, and associated uncertainties, of both natural climate variability and anthropogenic change, and they need this information now. In fact, while there is a definite need for improved climate projections, the more urgent, and the more achievable, objective is to robustly quantify the uncertainties involved and to develop tools to support decision making under uncertainty. A suggested pathway that can be taken to achieve this is outlined below.

4.1. Step 1: Communication Between Climate Scientists, Hydrologists, and Water Resource Managers

[42] There needs to be increased dialogue between hydroclimate scientists and water resource managers as to what the definition of "practically useful" hydroclimatic scenarios is (and whether this is a realistic expectation given current scientific understanding) [e.g., *Koutsoyiannis et al.*, 2009; *Blöschl and Montanari*, 2010; *Montanari et al.*, 2010]. Water resource managers need to outline what information they need and climate scientists need to identify which needs can be met on the basis of current understanding and which require further research. For the areas that require further research, recommended research directions should be identified and addressed. For the areas that can be addressed now (or in the near future), the format of the output from the climate science needs to be agreed upon. This "communication" issue has been extensively investigated in climate change scenario development (e.g., the UK Climate Impacts Programme (www.ukcip.org.uk) and associated UK Climate Projections (http://ukclimateprojections.defra.gov.uk) and also the Climate Futures for Tasmania project (www.acecrc.org.au/drawpage.cgi?pid=climate_futures)). However, there is still a disconnect that needs to be addressed around what can be realistically expected from climate science (there is still some reluctance to act until the science is "certain" and, in some sectors, an expectation that skillful multiyear to multidecadal catchment-scale precipitation forecasts are just around the corner) and around the plausibility of the scenarios that eventuate (how much uncertainty is associated with the various steps used to produce the scenarios). This needs to be addressed in terms of not just what the projected changes are but also why (e.g., as per *Blöschl and Montanari* [2010], without understanding the reasons for the changes, the results of impact studies are of little value). Additionally, it is important to then determine what to do with the probabilistic scenarios and associated uncertainty (i.e., adaptation under uncertainty; see section 4.4).

4.2. Step 2: Quantify the Baseline Risk Associated With Natural Climate Variability

[43] The baseline (i.e., historical) risk needs to be properly quantified in the light of insights into the drivers of natural climate variability and the fact that the stationarity assumption, which is fundamental to existing hydrological risk estimates in the MDB, has been shown to be flawed [e.g., *Franks and Kuczera*, 2002; *Kiem et al.*, 2003; *Kiem and Franks*, 2004; *Milly et al.*, 2008]. We need to know, on the basis of instrumental and preinstrumental (paleo) evidence, the natural limitations as to how dry (and wet) it can get and for how long. This requires an understanding of the drivers of regional extreme event risk and long-term variability of the system. An example of how this may be achieved has been described by *Verdon-Kidd and Kiem* [2010], who reconcile paleodata with instrumental data, climate variability insights, and a stochastic framework [e.g., *Verdon and Franks*, 2006, 2007; *Koutsoyiannis et al.*, 2008] to robustly quantify uncertainty levels and to ensure that the entire range of variability is considered rather than just the one climate realization that the instrumental record represents.

4.3. Step 3: Incorporate the Projected Impacts of Anthropogenic Change

[44] As per *Verdon-Kidd and Kiem* [2010], if we want to know how the MDB hydroclimate will change (under natural and anthropogenic forcings), then we need to be reasonably confident that models on which the future scenarios are based realistically account for the governing physical processes. This requires a three-step process: (1) identify and understand the physical processes driving the MDB hydroclimate, (2) identify (or if needed develop) climate models that adequately simulate the key physical processes, and (3) from the "adequate" climate models determine how the climate driving processes will change in the future and apply these changes to the baseline assessment (section 4.2) in a stochastic framework to obtain future hydroclimatic scenarios that incorporate both the full range of instrumental and preinstrumental natural variability and also projected anthropogenic climate change impacts. These three steps are necessary to ensure that future climate scenarios are plausible and not simply artifacts of the climate model(s), which is especially important if the models underestimate the impacts of anthropogenic climate change [e.g., *Koutsoyiannis et al.*, 2009]. It should also be noted that while the accuracy of the projected anthropogenic climate change impacts may improve as the climate science and climate models improve, it is naïve to hope that uncertainties associated with climate model projections will ever be insignificant [e.g., *Stainforth et al.*, 2007; *Koutsoyiannis et al.*, 2008, 2009], particularly for catchment-scale precipitation and especially for extremes [e.g., *Blöschl and Montanari*, 2010]. Hence, there is a need for a stochastic approach that makes it possible to account for climate model, and other sources of, uncertainty [e.g., *Preston and Jones*, 2008; *Koutsoyiannis et al.*, 2008, 2009; *Milly et al.*, 2008; *Verdon-Kidd and Kiem*, 2010].

4.4. Step 4: Develop Appropriate Adaptation Strategies

[45] Adaptation strategies need to be developed to make the most of favorable conditions and to decrease our vulnerability to unfavorable conditions [e.g., *Di Baldassarre et al.*, 2010]. As discussed in sections 4.1–4.3, in order to achieve this, reliable probabilistic quantification of uncertainties are required to inform risk-based water resource management decisions [e.g., *Koutsoyiannis et al.*, 2008, 2009; *Milly et al.*, 2008; *Chiew et al.*, 2011; *Verdon-Kidd and Kiem*, 2010]. Improved hydroclimatic projections that account for natural variability and anthropogenic change (as outlined in section 4.3) would obviously assist this process but only if the projections can be demonstrated to be plausible; currently, with climate model–reliant projections, this is not the case. In any case, for improved adaptation, urgent research is required into the robust quantification of uncertainties associated with climate projections and the development of "win-win" adaptation strategies that consider multiple plausible climate futures and that are flexible enough to cope with inherent natural variability and the possibility that things might be better or worse than expected [e.g., *Kabat et al.*, 2005; *Blöschl and Montanari*, 2010].

4.5. Step 5: Ongoing Communication

[46] Communication between hydroclimate scientists and water resource managers is needed to identify knowledge gaps, practical issues associated with implementation of the scenarios, and any areas for improvement. Improved communication requires more than just addressing the issues identified in section 4.1 (i.e., differences in language, expectations, and temporal or spatial reference frames); it is also about the ways of communication, its intensity, its time span, and its frequency. Holding regular workshops involving people from mixed backgrounds brought together to identify problems, knowledge gaps, and possible solutions or research directions is one strategy that has recently proven successful in the Climate Futures for Tasmania project (www.acecrc.org.au/drawpage.cgi?pid=climate_futures).

[47] The five-step process outlined in sections 4.1–4.5 is an advance on current approaches to account for climate change in water resources management, which typically account for either natural variability or anthropogenic climate change but rarely both. Indeed, the majority of climate change assessment and adaptation planning carried out in Australia omits steps 1, 2, and 5 and does not satisfactorily carry out step 3, which makes step 4 extremely difficult (if not impossible). One of the major problems is the tendency to subjectively "choose" the level of baseline risk and assume stationarity (i.e., that the hydroclimatic risk during the subjectively chosen baseline period is the same as it was at every other point in time). It is clear that we need to move beyond this flawed method of assessment, which results in climate scientists working to different objectives than hydrologists and water resource managers (and vice versa).

5. Conclusion

[48] Water resource managers are now realizing the necessity of planning for climate change and are turning to climate models for direction on what to plan for. However, while climate models may represent the "best available science" in terms of our understanding into global climate processes, it does not necessarily follow that climate model outputs represent the best available science with respect to provision of useful scenarios for sustainable water resources management. This is hardly surprising given that climate models were not designed, or intended to be used as, a tool for water resource management. Given the limitations of climate models mentioned in sections 3 and 4, is it sensible to continue carrying out studies that simply take climate model outputs, which we know are flawed, apply this to an arbitrarily chosen baseline, and via factoring or some other approach, use this information in hydrological models to obtain climate change impacted scenarios? Further, is it wise to then make management, strategic planning, and infrastructure development decisions on the basis of "blind faith" in the outputs of such studies? Although this sounds very negative, it is the intention here to highlight concerns about what seems to have become standard practice in Australian climate impact and adaptation projects (perhaps due to a lack of communication), when there are better ways to generate information for such a purpose (as described in section 4) and superior "codes of practice" that have been suggested [e.g., *Koutsoyiannis et al.*, 2008, 2009; *Blöschl and Montanari*, 2010; *Montanari et al.*, 2010; *Verdon-Kidd and Kiem*, 2010], and in our opinion should be followed.

[49] Other possibilities do exist for water resource managers to quantify risks associated with climate variability and/or change that do not rely solely on climate model outputs [e.g., *McMahon et al.*, 2008; *Koutsoyiannis et al.*, 2008, 2009; *Verdon-Kidd and Kiem*, 2010]. Knowledge gaps and research directions have also been identified above and elsewhere [e.g., *Koutsoyiannis et al.*, 2009; *Milly et al.*, 2008; *Verdon-Kidd and Kiem*, 2010] that, if investigated, could improve our understanding of climate-related risk and at the same time improve the capabilities of climate models and their applicability to water resource management. Until climate models can be shown to satisfactorily simulate the physical mechanisms we know are important for regional scale hydrology, their outputs should be used with caution as there is the danger that the "worst-case scenario" projected by current climate models may not actually be the worst case possible for water resource managers in terms of extreme events, particularly if the baseline is inappropriately assessed [e.g., *Verdon-Kidd and Kiem*, 2010]. This has been recently demonstrated in eastern Australia with the December 2010 and January 2011 flooding and prior to that with the Big Dry drought, which lasted more than a decade; both of these events were far more severe than anything projected by any climate models under even the worst emissions scenarios and out to at least 2070.

[50] We recommend further research into the knowledge gaps mentioned and a focus on development of climate-informed (but not climate model–reliant), regionally specific, practically useful scenarios that incorporate impacts associated with both natural climate variability and anthropogenic climate change, along with robustly quantified uncertainty estimates. Effort should also be focused on the continued improvement and verification of climate models, but, with the understanding that, given that they are models, their outputs will never be perfect and that skillful prediction of an unknown future is not simply a matter of time. Alternative methods aimed at quantifying current and future

uncertainties and ensuring robust water resource management under a changing climate should also be explored.

[51] **Acknowledgments.** The authors would like to thank Jason Alexandra and the Murray-Darling Basin Authority for commissioning the research and reports that formed the basis for this paper. We also thank the two anonymous reviewers and Associate Editor Alberto Montanari for their review comments, which have improved the paper significantly.

References

Ashok, K., C.-Y. Tam, and W.-J. Lee (2009), ENSO Modoki impact on the Southern Hemisphere storm track activity during extended austral winter, *Geophys. Res. Lett.*, *36*, L12705, doi:10.1029/2009GL038847.

Blackmore, K. L., and I. D. Goodwin (2009), Climate change impact for the Hunter, lower north coast and central coast region of NSW, *Rep. 3*, Hunter and Cent. Coast Reg. Environ. Strategy, Thornton, N. S. W., Australia.

Blöschl, G., and A. Montanari (2010), Climate change impacts—Throwing the dice?, *Hydrol. Processes*, *24*, 374–381, doi:10.1002/hyp.7574.

Cai, W., and T. Cowan (2008), Evidence of impacts from rising temperature on inflows to the Murray-Darling Basin, *Geophys. Res. Lett.*, *35*, L07701, doi:10.1029/2008GL033390.

Cai, W., and T. Cowan (2009), La Niña Modoki impacts Australia autumn rainfall variability, *Geophys. Res. Lett.*, *36*, L12805, doi:10.1029/2009GL037885.

Cai, W., T. Cowan, P. Briggs, and M. Raupach (2009), Rising temperature depletes soil moisture and exacerbates severe drought across southeast Australia, *Geophys. Res. Lett.*, *36*, L21709, doi:10.1029/2009GL040334.

Cai, W., T. Cowan, K. Braganza, D. A. Jones, and J. S. Risbey (2010), Comment on "On the recent warming in the Murray-Darling Basin: Land surface interactions misunderstood" by Lockart et al., *Geophys. Res. Lett.*, *37*, L10706, doi:10.1029/2009GL042254.

Chiew, F. H. S., T. C. Piechota, J. A. Dracup, and T. A. McMahon (1998), El Niño Southern Oscillation and Australian rainfall, streamflow and drought: Links and potential for forecasting, *J. Hydrol.*, *204*(1–4), 138–149, doi:10.1016/S0022-1694(97)00121-2.

Chiew, F. H. S., W. J. Young, W. Cai, and J. Teng (2011), Current drought and future hydroclimate projections in southeast Australia and implications for water resources management, *Stochastic Environ. Res. Risk Assess.*, *25*, 601–612, doi:10.1007/s00477-010-0424-x.

Commonwealth Scientific and Industrial Research Organisation (CSIRO) (2008a), Water availability in the Murray-Darling Basin, 67 pp., Clayton South, Victoria, Australia.

Commonwealth Scientific and Industrial Research Organisation (CSIRO) (2008b), Water availability in the Goulburn-Broken, 12 pp., Clayton South, Victoria, Australia.

Diaz, H. F., and V. Markgraf (Eds.) (2000), *El Niño and the Southern Oscillation: Multiscale Variability and Global and Regional Impacts*, doi:10.1017/CBO9780511573125, Cambridge Univ. Press, Cambridge, U. K.

Di Baldassarre, G., A. Montanari, H. Lins, D. Koutsoyiannis, L. Brandimarte, and G. Blöschl (2010), Flood fatalities in Africa: From diagnosis to mitigation, *Geophys. Res. Lett.*, *37*, L22402, doi:10.1029/2010GL045467.

Donohue, R. J., T. R. McVicar, and M. L. Roderick (2010), Assessing the ability of potential evaporation formulations to capture the dynamics in evaporative demand within a changing climate, *J. Hydrol.*, *386*, 186–197, doi:10.1016/j.jhydrol.2010.03.020.

Folland, C. K., J. A. Renwick, M. J. Salinger, and A. B. Mullan (2002), Relative influences of the Interdecadal Pacific Oscillation and ENSO on the South Pacific Convergence Zone, *Geophys. Res. Lett.*, *29*(13), 1643, doi:10.1029/2001GL014201.

Franks, S. W., and G. Kuczera (2002), Flood frequency analysis: Evidence and implications of secular climate variability, New South Wales, *Water Resour. Res.*, *38*(5), 1062, doi:10.1029/2001WR000232.

Franks, S. W., D. Kavetski, and L. N. Lockart (2010), Reply to the comment of Cai et al. on the paper "On the recent warming in the Murray-Darling Basin: Land surface interactions misunderstood" by Lockart et al., *Geophys. Res. Lett.*, *37*, L10403, doi:10.1029/2010GL043615.

Gallant, A. J. E., and D. J. Karoly (2009), The atypical influence of the 2007 La Niña on rainfall and temperature in southeastern Australia, *Geophys. Res. Lett.*, *36*, L14707, doi:10.1029/2009GL039026.

Gimeno, L., A. Drumond, R. Nieto, R. M. Trigo, and A. Stohl (2010), On the origin of continental precipitation, *Geophys. Res. Lett.*, *37*, L13804, doi:10.1029/2010GL043712.

Hendon, H. H., D. W. J. Thompson, and M. C. Wheeler (2007), Australian rainfall and surface temperature variations associated with the Southern Hemisphere Annular Mode, *J. Clim.*, *20*(11), 2452–2467, doi:10.1175/JCLI4134.1.

Herron, A., A. S. Kiem, and M. C. Peel (2010), Projecting impacts of climate change on future water resources: How and what to change?, paper presented at Practical Responses to Climate Change National Conference, Victoria Water Eng. Branch, Natl. Comm. On Water Eng., Eng. Aust., Melbourne, Victoria, Australia, 29 Sept. to 1 Oct.

Kabat, P., W. van Vierssen, J. Veraart, P. Vellinga, and J. Aerts (2005), Climate proofing the Netherlands, *Nature*, *438*, 283–284, doi:10.1038/438283a.

Kiem, A. S., and S. W. Franks (2004), Multi-decadal variability of drought risk, eastern Australia, *Hydrol. Processes*, *18*(11), 2039–2050, doi:10.1002/hyp.1460.

Kiem, A. S., and D. C. Verdon-Kidd (2009), Climatic drivers of Victorian streamflow: Is ENSO the dominant influence?, *Aust. J. Water Resour.*, *13*(1), 17–30.

Kiem, A. S., and D. C. Verdon-Kidd (2010), Towards understanding hydroclimatic change in Victoria, Australia–preliminary insights into the "Big Dry," *Hydrol. Earth Syst. Sci.*, *14*, 433–445, doi:10.5194/hess-14-433-2010.

Kiem, A. S., S. W. Franks, and G. Kuczera (2003), Multi-decadal variability of flood risk, *Geophys. Res. Lett.*, *30*(2), 1035, doi:10.1029/2002GL015992.

Kiem, A. S., S. W. Franks, and D. C. Verdon (2006), Climate variability in the land of fire and flooding rain, *Aust. J. Emerg. Manage.*, *21*(2), 52–56.

Kiem, A. S., H. Ishidaira, H. P. Hapuarachchi, M. C. Zhou, Y. Hirabayashi, and K. Takeuchi (2008), Future hydroclimatology of the Mekong River basin under climate change simulated using the high resolution Japan Meteorological Agency (JMA) AGCM, *Hydrol. Processes*, *22*(9), 1382–1394, doi:10.1002/hyp.6947.

Kirono, D. G. C., F. H. S. Chiew, and D. M. Kent (2010), Identification of best predictors for forecasting seasonal rainfall and runoff in Australia, *Hydrol. Processes*, *24*(10), 1237–1247.

Koster, R. D., et al. (2004), Regions of strong coupling between soil moisture and precipitation, *Science*, *305*, 1138–1140, doi:10.1126/science.1100217.

Koutsoyiannis, D., A. Efstratiadis, N. Mamassis, and A. Christofides (2008), On the credibility of climate predictions, *Hydrol. Sci. J.*, *53*(4), 671–684, doi:10.1623/hysj.53.4.671.

Koutsoyiannis, D., A. Montanari, H. F. Lins, and T. A. Cohn (2009), Climate, hydrology and freshwater: Towards an interactive incorporation of hydrological experience into climate research, *Hydrol. Sci. J.*, *54*(2), 394–405, doi:10.1623/hysj.54.2.394.

Lim, W. H., and M. L. Roderick (2009), *An Atlas of the Global Water Cycle Based on the IPCC AR4 Climate Models*, ANU E Press, Canberra.

Lockart, N., D. Kavetski, and S. W. Franks (2009), On the recent warming in the Murray-Darling Basin: Land surface interactions misunderstood, *Geophys. Res. Lett.*, *36*, L24405, doi:10.1029/2009GL040598.

McMahon, T. A., A. S. Kiem, M. C. Peel, P. W. Jordan, and G. G. S. Pegram (2008), A new approach to stochastically generating six-monthly rainfall sequences based on empirical model decomposition, *J. Hydrometeorol.*, *9*, 1377–1389, doi:10.1175/2008JHM991.1.

Meneghini, B., I. Simmonds, and I. N. Smith (2007), Association between Australian rainfall and the Southern Annular Mode, *Int. J. Climatol.*, *27*, 109–121, doi:10.1002/joc.1370.

Meyers, G., P. McIntosh, L. Pigot, and M. Pook (2007), The years of El Niño, La Niña, and interactions with the tropical Indian Ocean, *J. Clim.*, *20*, 2872–2880, doi:10.1175/JCLI4152.1.

Milly, P. C. D., J. Betancourt, M. Falkenmark, R. M. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer (2008), Stationarity is dead: Whither water management?, *Science*, *319*, 573–574, doi:10.1126/science.1151915.

Montanari, A., G. Blöschl, M. Sivapalan, and H. Savenije (2010), Getting on target, *Public Serv. Rev. Sci. Technol.*, *7*, 167–169.

Murphy, B. F., and B. Timbal (2008), A review of recent climate variability and climate change in southeastern Australia, *Int. J. Climatol.*, *28*(7), 859–879, doi:10.1002/joc.1627.

National Climate Change Adaptation Research Facility (2010), National climate change adaptation research plan: Water resources and freshwater biodiversity, Southport, Queensland, Australia. [Available at www.nccarf.edu.au/national-adaptation-research-plan-water-resources-freshwater-biodiversity.]

Nicholls, N. (1989), Sea surface temperatures and Australian winter rainfall, *J. Clim.*, *2*, 965–973, doi:10.1175/1520-0442(1989)002<0965:SSTAAW>2.0.CO;2.

Nicholls, N. (2004), The changing nature of Australian droughts, *Clim. Change*, *63*, 323–336, doi:10.1023/B:CLIM.0000018515.46344.6d.

Parry, M. L., O. F. Canziani, J. P. Palutikof, P. J. van der Linden, and C. E. Hanson (Eds.) (2007), *Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge Univ. Press, Cambridge, U. K.

Pitman, A. J., and S. E. Perkins (2008), Regional projections of future seasonal and annual changes in rainfall and temperature over Australia based on skill-selected AR4 models, *Earth Interact.*, *12*, 1–50, doi:10.1175/2008EI260.1.

Pittock, B. (Ed.) (2003), *Climate Change: An Australian Guide to the Science and Potential Impacts*, Aust. Greenhouse Off., Canberra.

Pook, M., P. McIntosh, and G. Meyers (2006), The synoptic decomposition of cool season rainfall in the south-eastern Australian cropping region, *J. Appl. Meteorol.*, *45*(8), 1156–1170, doi:10.1175/JAM2394.1.

Pook, M., S. Lisson, J. Risbey, C. Ummenhofer, P. McIntosh, and M. Rebbeck (2008), The autumn break for cropping in southeast Australia: Trends, synoptic influences and impacts on wheat yield, *Int. J. Climatol.*, *29*(13), 2012–2026, doi:10.1002/joc.1833.

Power, S., T. Casey, C. Folland, A. Colman, and V. Mehta (1999), Interdecadal modulation of the impact of ENSO on Australia, *Clim. Dyn.*, *15*(5), 319–324, doi:10.1007/s003820050284.

Preston, B. L., and R. N. Jones (2008), Evaluating sources of uncertainty in Australian runoff projections, *Adv. Water Resour.*, *31*(5), 758–775, doi:10.1016/j.advwatres.2008.01.006.

Randall, D. A., et al. (2007), Climate models and their evaluation, in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by S. Solomon et al., chap. 8, pp. 589–662, Cambridge Univ. Press, Cambridge, U. K.

Risbey, J. S., M. J. Pook, P. C. McIntosh, M. C. Wheeler, and H. H. Hendon (2009), On the remote drivers of rainfall variability in Australia, *Mon. Weather Rev.*, *137*, 3233–3253, doi:10.1175/2009MWR2861.1.

Roesler, E. L., and J. E. Penner (2010), Can global models ignore the chemical composition of aerosols?, *Geophys. Res. Lett.*, *37*, L24809, doi:10.1029/2010GL044282.

Rosenfeld, D. (2000), Suppression of rain and snow by urban and industrial air pollution, *Science*, *287*, 1793–1796, doi:10.1126/science.287.5459.1793.

Stainforth, D. A., M. R. Allen, E. R. Tredger, and L. A. Smith (2007), Confidence, uncertainty and decision-support relevance in climate predictions, *Philos. Trans. R. Soc. A*, *365*, 2145–2161, doi:10.1098/rsta.2007.2074.

Taschetto, A. S., and M. H. England (2009), El Niño Modoki impacts on Australian rainfall, *J. Clim.*, *22*, 3167–3174, doi:10.1175/2008JCLI2589.1.

Taschetto, A. S., C. C. Ummenhofer, A. Sen Gupta, and M. H. England (2009), Effect of anomalous warming in the central Pacific on the Australian monsoon, *Geophys. Res. Lett.*, *36*, L12704, doi:10.1029/2009GL038416.

Timbal, B., S. Power, R. Colman, J. Viviand, and S. Lirola (2002), Does soil moisture influence climate variability and predictability over Australia?, *J. Clim.*, *15*, 1230–1238, doi:10.1175/1520-0442(2002)015<1230:DSMICV>2.0.CO;2.

Verdon, D. C., and S. W. Franks (2005), Indian Ocean sea surface temperature variability and winter rainfall: Eastern Australia, *Water Resour. Res.*, *41*, W09413, doi:10.1029/2004WR003845.

Verdon, D. C., and S. W. Franks (2006), Long-term behaviour of ENSO: Interactions with the PDO over the past 400 years inferred from paleoclimate records, *Geophys. Res. Lett.*, *33*, L06712, doi:10.1029/2005GL025052.

Verdon, D. C., and S. W. Franks (2007), Long term drought risk assessment in the Lachlan River Valley–A paleoclimate perspective, *Aust. J. Water Resour.*, *11*(2), 145–152.

Verdon, D. C., A. S. Kiem, and S. W. Franks (2004a), Multidecadal variability of forest fire risk: Eastern Australia, *Int. J. Wildland Fire*, *13*(2), 165–171, doi:10.1071/WF03034.

Verdon, D. C., A. M. Wyatt, A. S. Kiem, and S. W. Franks (2004b), Multidecadal variability of rainfall and streamflow: Eastern Australia, *Water Resour. Res.*, *40*, W10201, doi:10.1029/2004WR003234.

Verdon-Kidd, D. C., and A. S. Kiem (2009a), On the relationship between large-scale climate modes and regional synoptic patterns that drive Victorian rainfall, *Hydrol. Earth Syst. Sci.*, *13*, 467–479, doi:10.5194/hess-13-467-2009.

Verdon-Kidd, D. C., and A. S. Kiem (2009b), Nature and causes of protracted droughts in Southeast Australia: Comparison between the Federation, WWII and Big Dry droughts, *Geophys. Res. Lett.*, *36*, L22707, doi:10.1029/2009GL041067.

Verdon-Kidd, D. C., and A. S. Kiem (2010), Quantifying drought risk in a non-stationary climate, *J. Hydrometeorol.*, *11*(4), 1019–1031, doi:10.1175/2010JHM1215.1.

Wei, J., and P. A. Dirmeyer (2010), Toward understanding the large-scale land-atmosphere coupling in the models: Roles of different processes, *Geophys. Res. Lett.*, *37*, L19707, doi:10.1029/2010GL044769.

Wright, W. J. (1989), A synoptic climatological classification of winter precipitation in Victoria, *Aust. Meteorol. Mag.*, *37*, 217–229.

A. S. Kiem and D. C. Verdon-Kidd, Environmental and Climate Change Research Group, School of Environmental and Life Sciences, Faculty of Science and Information Technology, University of Newcastle, Callaghan, NSW 2308, Australia. (anthony.kiem@newcastle.edu.au)