Assessing the Risk of Climate Change on the Water Resources of the Macquarie River Catchment

R.N. Jones and C.M. Page

CSIRO Atmospheric Research, Private Bag 1, Aspendale VIC 3915, Australia (roger.jones@dar.csiro.au)

Abstract: The uncertainty surrounding climate change is a major obstacle facing the sustainable management of water resources in Australia. We describe a modelling system built to analyse the risk of climate change using results obtained from water resource modelling of the Macquarie River catchment in NSW. Scenarios of climate change in 2030 and 2070, selected from the outputs of nine climate models, were used to perturb a long-term historical daily climate of rainfall (P) and potential evaporation (Ep). Relationships for δP and δEp with water storage, Macquarie Marsh environmental flows and irrigation allocations were established and probability distribution functions (PDFs) constructed using Monte Carlo sampling. Critical thresholds for irrigation allocation and environmental flows were established. Decadal variability affecting rainfall was also investigated and found to vary baseline results by ±20% from the long-term mean. These critical thresholds are exceeded if streamflow reduces from the long-term mean by >10% in a drought-dominated climate, >20% in a normal climate and >30% in a flood-dominated climate. Uncertainty analysis shows that global warming provides 25% of total uncertainty due to climate change, rainfall change contributes 64% and potential evaporation change contributes 12%. Understanding climate change in terms of local rainfall change will contribute significantly to narrowing uncertainty. However, Bayesian analysis shows that the risk of threshold exceedance is little changed after altering the input assumptions for rainfall or global warming that either expand uncertainty or alter its prior distribution. The most likely changes to mean annual Burrendong Dam storage, Macquarie Marsh inflows and irrigation allocations are 0% to −15% in 2030 and −0% to −35% in 2070. Flow increases have only a 5% probability of occurring in 2030 and 2070 under most assumptions. In 2030, under a drought-dominated rainfall regime, the risk of critical threshold exceedance occurs in 20–30% of climates. This risk decreases to <1% in a normal climate and to <<1% in a flood-dominated climate. In 2070, these risks of exceedance are 70–80%, 35–50% and 10–20%. Considerable hardship would be experienced before these thresholds are crossed. The most optimal strategies are hedging risk through the preparation of adaptation strategies to manage the most likely range of outcomes, and monitoring climate to determine whether changes are likely to result in critical threshold exceedance.

Keywords: Climate change; Hydrology; Risk assessment; Uncertainty

1. INTRODUCTION

Assessing the risk of climate change requires knowledge of the likelihoods of both climate change and of its consequences. Within climate change studies, high uncertainty requires the use of scenarios that are plausible but have no probability attached [Carter and La Rovere, 2001]. For example, if greenhouse gas emission scenarios and climate change scenarios are plausible with no further likelihood, then the consequences of those scenarios in terms of impacts have the same limitations. This leads to a growing cascade of uncertainties associated with a chain of consequences limited by the least predictable link [Jones, 2000].

However, although individual scenarios have no probability, they define a population that does have a probability distribution, which is unknown. By understanding how the component ranges of uncertainty contribute to the range of outcomes, and how different formulations of those component uncertainties affect its probability distribution, we can determine which assumptions are robust and which are sensitive.

The water sector has postponed adaptation due to climate change uncertainty. Although there is wide acceptance that water resources are sensitive to climate change, managers have delayed accounting for climate change in their planning until the risks are better known.

Assuming that the risk of climate change to a particular activity is a function of probability × hazard, two methods of managing uncertainty suggest a way past this impasse. (1) Developing ranges of uncertainty for key drivers of change, such as greenhouse gas emissions, climate sensitivity and regional climate change and using Bayesian methods of analysis to explore these ranges. (2) Developing critical thresholds that mark an unacceptable level of change beyond the current coping range for a particular activity.

We aim to show how the limitations of individual scenarios can be overcome by combining these two methods to estimate the probability of exceeding a given critical threshold. This paper illustrates these methods using results from an assessment of climate change on water resources in the Macquarie River Catchment [Jones et al., 2001]. We present two critical thresholds based on environmental flows and annual irrigation allocations, carry out an uncertainty analysis and apply a Bayesian analysis to assess the likelihood of those thresholds being exceeded in 2030 and 2070.

2. MODEL STRUCTURE

CSIRO's climate scenario generator, OzClim, was coupled to the Integrated Quality Quantity Model (IQQM) for the Macquarie River developed by the NSW Department of Land and Water Conservation (DLWC). IQQM consists of the Sacramento rainfall-runoff model and river routing, water demand and allocation routines to simulate river flow, environmental flows to the Macquarie Marshes and urban and irrigation water supply.

High quality scenarios of regional change as a function of global warming (percent change per °C of global warming) for potential evaporation (Ep) and precipitation (P) were prepared from nine global and regional climate models and applied to OzClim. These were scaled by estimates of global warming that take into account different rates of greenhouse gas emissions and climate model sensitivity for 2030 and 2070. Daily records of P and Ep within IQQM were then modified according to these scenarios, providing a record of climate variability from 1890–1996. This series includes a drought-dominated period (1890–1947) and a flood-dominated period (1948–1996) allowing different modes of decadal variability to also be assessed. Multiple scenarios for 2030 and 2070 were applied to IQQM in batch mode to explore the full range of uncertainty projected by the Intergovernmental Panel on Climate Change [IPCC, 2001] and CSIRO [CSIRO, 2001] for climate change. The method of coupling is described by Page and Jones [2001].

Three types of output were considered for risk assessment: storage in the Burrendong Dam (the major water storage), environmental flows to the Macquarie Marshes (nesting events for the breeding of colonial waterbirds), and proportion of irrigation allocations met over time.

3. MODEL RESULTS

3.1. Climate Model Runs

Multiple climate change simulations were run:

- For 2030 based on the IS92a–f greenhouse gas emissions scenarios, IPCC [1996] warmings, nine climate models at low, moderate and high climate sensitivity, for a total of 27 simulations.

- For 2070 based on the SRES greenhouse gas emission scenarios, IPCC [2001] warmings, nine climate models at low, moderate (2) and high climate sensitivity for a total of 36 simulations.

The results produced changes to mean annual storage in Burrendong Dam ranging from +1% to −22% in 2030 and +6% to −55% in 2070. Allowing for the higher IPCC [2001] warmings compared to IPCC [1996], the updated results for 2030 are +1% to −30%. Changes to flows into the Macquarie Marshes are slightly more sensitive and irrigation allocations are slightly less sensitive.

If we follow the definition of a scenario as being plausible with no further probability we are restricted to communicating these results as follows: *By incorporating the major input uncertainties that can readily be quantified into the analysis, changes to mean annual storage range from 0% to −30% in 2030 and +5 to −55% in 2070.*

3.2. Transfer Functions

Uncertainty and risk analysis was carried out using Monte Carlo random sampling, requiring a method of rapid analysis. The simulations detailed above supplied input data for regression relationships relating P and Ep change (δEp and δP) with streamflow. Results from eight models providing 56 samples were used (one model was rejected due to errors affecting Ep calculations for June and July). A non-linear inverse tangent function produced the best physically realistic fit for the distribution:

$$\delta\text{flow} = a \times (\text{atan} (\delta\text{Ep} / \delta\text{P}) - b) \qquad (1)$$

where δEp and δP were measured in mm yr^{-1} and δflow in GL yr^{-1} and percent, and a and b are constants. The results have a standard error ranging from 1 to 2% (Table 1).

Table 1. Regression relationships for Burrendong Dam storage and Macquarie Marsh inflows in GL and irrigation allocations in percent.

Output	a	b	R^2	SE (%)
Burrendong storage (GL)	-98.96	80.10	0.98	1.75
Macquarie Marshes inflows (GL)	-48.00	79.78	0.98	2.10
Irrigation allocations (change in %)	-6.17	81.15	0.98	1.19

3.3. Probability Distributions

According to the central limit theorem of statistics, if multiple ranges of uncertainty are combined, then the central tendencies are favoured at the expense of the extremes [e.g. Wigley and Raper, 2001]. Three ranges of uncertainty contributed to the analysis: global warming and regional δP and δEp. Monte Carlo methods (repeated random sampling) were used to sample the IPCC [2001] range of global warming for 2030 and 2070. These were then used to scale a range of change per °C of global warming on a quarterly basis for P, sampling Ep using a regression relationship established for the Macquarie catchment [Jones et al., 2001]. The quarterly changes for P and Ep were then totalled to determine annual δP and δEp. The transfer function in Equation 1 was used to estimate the probability distribution for Burrendong Dam storage, Macquarie Marshes inflows and irrigation allocations in 2030 and 2070.

The following assumptions were applied:

- The range of global warming in 2030 was 0.55–1.27°C with a uniform distribution. The range of change in 2070 was 1.16–3.02°C.

- Changes in P were taken from the full range of change for each quarter from the sample of nine climate models.

- Changes in P for each quarter were assumed to be independent of each other (seasonally dependent changes between seasons could not be found).

- The difference between samples in any consecutive quarter could not exceed the largest difference observed in the sample of nine climate models.

- Ep was partially dependent on P ($\delta Ep = 5.75 - 0.53\delta P$, standard error = 2.00, randomly sampled using a Gaussian distribution, units in percent change).

Figure 1 shows the results for 2030 where the probability distribution is tallied from wettest (best) to driest (worst) outcomes. Although there is an increased flood risk with increases, the drier outcomes are considered worse in terms of lost productivity and environmental function. The driest and wettest outcomes are less likely than the central outcomes where the line is steepest. The most likely outcomes range from about 0% to −15% in 2030 and −0% to −35% in 2070 (not shown).
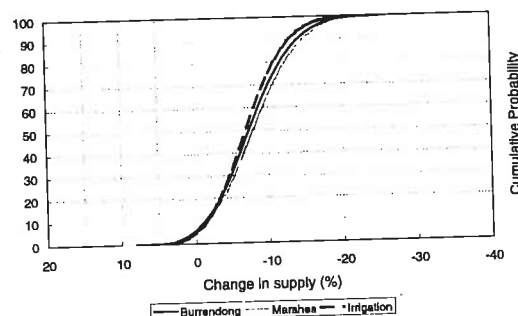

Figure 1. Probability distribution for changes to mean annual Burrendong Dam storage, Macquarie Marsh inflows and irrigation allocations based on Monte Carlo sampling of input ranges of global warming, δP and δEp in 2030.

Critical thresholds

A critical threshold marks the point at which an activity or system faces an unacceptable level of harm [Jones, 2001]. It delineates the coping range of climate (i.e. the range of climate variability that is considered normal and is easily managed) from that part of the range where an activity is vulnerable, providing a criterion or hazard by which to measure risk. If a critical threshold can be expressed in climatic terms and quantified under climate change, it then becomes possible to estimate risk if a probability distribution for the climate inputs can be determined. Two critical thresholds were established:

1. Bird breeding events in the Macquarie Marshes, taken as 10 consecutive years of inflows below 350 GL.

2. Irrigation allocations falling below a level of 50% for five consecutive years.

Both thresholds are a measure of accumulated stress rather than a single extreme event.

From the sample of runs described in section 3.1, both thresholds were exceeded if mean annual flows fell below 10% in a drought-dominated climate, 20% in a normal climate and 30% in a flood-dominated climate.

Table 2. Results of uncertainty analysis for water storage in Burrendong Dam in 2030 and 2070. The ranges shown are in percent change from mean annual storage in Burrendong Dam.

2030	Limits of Range	Range	Contribution to Uncertainty
All	+10.3 to −28.4	38.7	
Constant global warming	+7.7 to −21.4	29.1	25%
Constant P	−1.9 to −15.9	14.0	64%
Constant Ep	7.2 to −26.7	33.9	12%
			101%
2070			
All	+23.8 to −60.1	83.9	
Constant global warming	+17.3 to −45.8	63.1	25%
Constant P	−4.6 to −34.0	29.4	65%
Constant Ep	16.3 to −57.7	74.0	12%
			102%

4. UNCERTAINTY ANALYSIS

Uncertainty analysis was carried out to understand how the component uncertainties contributed to the range of outcomes. Three ranges of input uncertainty, global warming and local changes in P and Ep, were assessed by keeping each input constant within a Monte Carlo assessment while allowing the others free play, consistent with Visser et al. [2000]. Global warming was held at 0.91°C in 2030 and 2.09°C in 2070. δP was taken as the average of the nine models in percent change per °C global warming for each quarter. δEp was linearly regressed from δP, omitting the sampling of a standard deviation. In both 2030 and 2070, δP provides almost two-thirds of the total uncertainty, global warming about 25% and δEp just over 10% (Table 2).

The key climate change uncertainty for water supply is δP as a function of global warming. Therefore, the direction and magnitude of rainfall change is the important climate uncertainty for water resources. The rate of global warming itself is secondary and δEp as a function of both P and global warming is least important. However, given that δEp is likely to be easier than δP to diagnose due to its reduced variability, the rate of Ep change may provide some indication of P change through the inverse modelling of the co-dependent P and Ep relationship.

5. BAYESIAN ANALYSIS

Bayesian analysis involves testing of input assumptions on the resulting probabilities [e.g. New and Hulme, 2000]. Two different sets of assumptions were tested. δP was sampled on a six-monthly and annual basis to determine whether the independent sampling of rainfall changes on a quarterly basis affected the results.

The effect of different probability distributions for the input uncertainties was also tested.

Figure 2 shows the impact of quarterly, six monthly and annual sampling on the probability distribution for changes to mean annual Burrendong storage in 2030. Also shown are the individual scenarios, which are given equal probability of occurring. The resultant probability distributions for six-monthly and annual sampling produce higher flows, but the results do not change by more than 10% from the standard in most cases. The probability distribution function is relatively insensitive to changed seasonal sampling strategies for P and Ep.

The next test was to determine this impact of a non-uniform distribution of global warming, compared to the uniform distribution used in Section 3, on the results. Wigley and Raper [2001] produced non-linear PDFs for global warming in 2030 and 2070 based on input uncertainties for the SRES emissions scenarios, radiative uncertainties for greenhouse gases and sulphate aerosol, atmospheric greenhouse gas modelling and climate sensitivity with each range having a log normal distribution. We applied those ranges in 2030 and 2070 (Figures 3 and 4).

Altering the input PDF for global warming has little effect on the results. This is consistent with global warming forming only 25% of the input uncertainties. Only very large changes in the range or distribution of global warming would be expected to significantly affect the outcome.

We also tested the effect of altered distributions of rainfall change by applying cubic polynomial regressions to the range provided by the nine models, counting the lowest and highest sample as the 10th and 90th percentile respectively (thereby extending the range of rainfall change). These were added to the non-linear Wigley and Raper

PDFs for global warming and are also shown in Figures 3 and 4. Although the total ranges have increased by 2% and 31% in 2030 and 20% and 55% in 2070 for the "W&R warming" and "All" cases (Table 2), the PDFs remain fairly similar for the major part of the range.
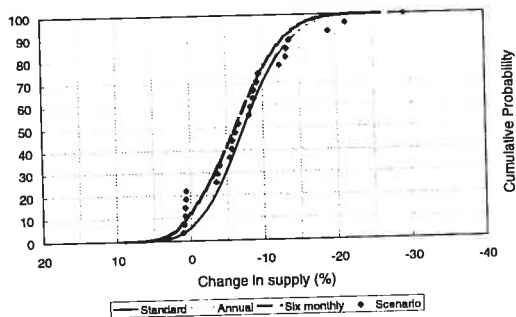

Figure 2. Impact of scenario-based, quarterly (Standard), six monthly and annual sampling of δP and δEp on the probability distribution for changes to mean annual Burrendong storage in 2030.
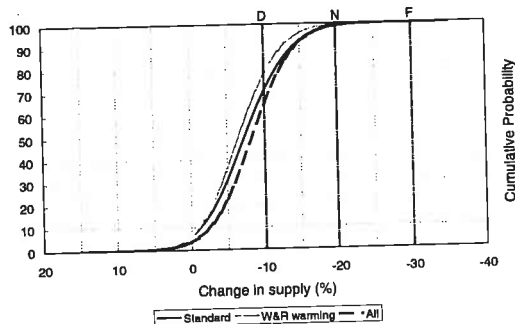

Figure 3. Impact of the standard approach, non-linear sampling of global warming [Wigley and Raper, 2001] and non-linear sampling of rainfall change (All) on the probability distribution for changes to mean annual Burrendong storage in 2030. Critical thresholds under a drought-dominated climate (D), flood-dominate climate (F) and normal climate (N) are also shown.
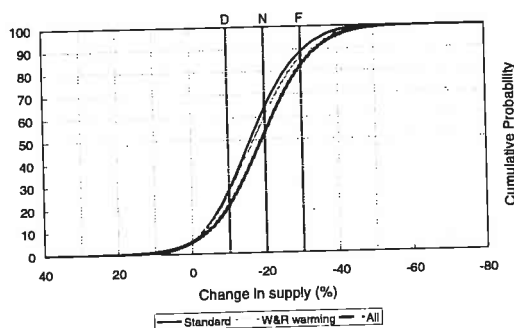

Figure 4. Impact of the standard approach, non-linear sampling of global warming [Wigley and Raper, 2001] and non-linear sampling of rainfall change (All) on the probability distribution for changes to mean annual Burrendong storage in 2070. Critical thresholds under a drought-

dominated climate (D), flood-dominate climate (F) and normal climate (N) are also shown.

These results show that the "most likely" parts of the ranges are not greatly expanded by increasing the ranges of uncertainty by the amounts here. The input ranges of uncertainty for rainfall for the Macquarie catchment are about ±4% per degree of global warming [Jones et al., 2001]. These would have to be expanded considerably to alter the risk to water supply.

6. CONCLUSIONS

In this study, we applied scenarios from a sample of nine climate models to the IQQM for the Macquarie River catchment, scaling a long-term historical daily climate of P and Ep (1890–1996) by a range of climate changes in 2030 and 2070 consistent with IPCC projections [2001]. Relationships for δP and δEp with Burrendong Dam storage, Macquarie Marsh inflows and irrigation allocations were established using 54 samples from 2030 and 2070. Monte Carlo sampling has then allowed PDFs for these outputs for 2030 and 2070 to be established.

Uncertainty analysis on the range of outcomes in terms of flow changes are 25% for global warming, 64% in terms of δP per °C global warming and 12% of δEp per °C global warming. Therefore, attribution of climate change in terms of local rainfall change as a function of global warming is the most important issue for narrowing the range of uncertainty with regard to the risk posed by climate change to water resources.

However, changes to decadal variability are equally as important but are very poorly understood in terms of dynamics and diagnosis. Critical thresholds for both irrigation and environmental flows occur are exceeded with mean changes in flow of −10% in a drought-dominated climate, −20% in a normal climate and −30% in a flood-dominated climate (Figures 3 and 4).

Bayesian analysis showed that the risk of threshold exceedance is not changed greatly by altering the input assumptions for rainfall or global warming. The "best bet" changes to Burrendong Dam storage, Macquarie Marsh inflows and irrigation allocations in 2030 are 0% to −15%, and in 2070 are 0% to −35%. However, in 2030 critical thresholds are likely to be exceeded by 20–30% in a drought-dominated climate, <1% in a normal climate and <<1% in a flood-dominated climate. In 2070, these risks are 70–80%, 35–50% and 10–20% respectively. Considerable hardship would be experienced before these thresholds are crossed. The most

optimal strategies are hedging risk through the preparation of adaptation strategies to manage the most likely range of outcomes, and monitoring climate to determine whether changes are likely to result in critical threshold exceedance.

7. ACKNOWLEDGEMENTS

8. REFERENCES

Carter, T.R. and La Rovere, E.L., Developing and applying scenarios. In: McCarthy, J.J., Canziani, O.F., Leary, N.A., Dokken, D.J. and White, K.S. (eds.) *Climate Change 2001: Impacts, Adaptation, and Vulnerability*, Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, 145–190, 2001.

CSIRO, Climate Change Projections for Australia, CSIRO Atmospheric Research, Melbourne, 8 pp, 2001.

IPCC, Technical Summary. In: Houghton, J.T., Meira Filho, L.G., Callander, B.A., Harris, N., Kattenberg, A. and Maskell, K. (eds.), *Climate Change 1995: The Science of Climate Change*, Contribution of Working Group I to the second assessment report of the IPCC, Cambridge University Press, Cambridge, 9–49, 1996.

IPCC, Summary for Policymakers. In: Houghton, J.T., Ding, Y., Griggs, D.J., Noguer, M., Van Der Linden, P. and Xiaosu, D. (eds.) *Climate Change 2001: The Scientific Basis*, Cambridge University Press, Cambridge, 1–20, 2001.

Jones, R.N., Analysing the risk of climate change using an irrigation demand model, *Climate Research*, 14, 89–100, 2000.

Jones, R.N., An environmental risk assessment/ management framework for climate change impact assessments, *Nat. Hazards*, 23, 197–230, 2001.

Jones, R.N. et al., Applying a climate scenario generator to water resource policy issues, CSIRO Atmospheric Research Technical Paper, 50 pp (in press), 2001.

New, M. and Hulme, M., Representing uncertainty in climate change scenarios: a Bayesian Monte-Carlo approach, *Integrated Assessment*, 1, 203–213, 2000.

Page, C.M. and Jones, R.N. [2001] Coupling a climate scenario generator with impact models using OzClim. In: Proceedings of the MODSIM Congress Canberra, 2001.

Visser H., Folkert R.J.M., Hoekstra J., de Wolff J.J., Identifying key sources of uncertainty in climate change projections, *Clim. Change*, 45, 421–457, 2000.

Wigley, T.M.L. and Raper, S.C.B., Interpretation of high projections for global-mean warming, *Science*, 293, 451–454, 2001.