A Bayesian Approach to Assessing Regional Climate Change Pressures on Natural Resource Conditions in the Central West of NSW, Australia

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EXTENDED ABSTRACT

Climate change is now being acknowledged in environmental planning strategies in Australia. However, there are still difficulties in linking strategic level responses to climate change with local impacts. To date, only limited research has been conducted in predicting the effects climate change may have on meeting natural resource condition targets at regional and local levels. Recently, Catchment Action Plans (CAPs) have been developed by Catchment Management Authorities in NSW. These identify a range of natural resource management targets that are seen as achievable within the next ten years. However, the implications of climate change in meeting these targets have not yet been considered by the CMAs.

In this paper, we describe a modelling approach that we have used to develop a Decision Support System (DSS) for the Central West Catchment Management Authority (CMA) in NSW. The DSS will assist the Central West Catchment Management Authority (CMA) of NSW in assessing the likelihood of meeting their existing natural resource condition targets in the context of several climate change scenarios. CAP targets in the Central West region of NSW refer to both water dependent agricultural systems and high value ecological assets that are susceptible to climate change.

We use a Bayesian network (BN) modelling approach in this work for several reasons. Firstly, a BN incorporates uncertainties by modelling probabilities of variable responses. Secondly, a BN can be built using quantitative and qualitative data and is easily updated with additional information, such as outputs from other models. Thirdly, BNs can be developed in a modular and somewhat spatially explicit fashion, which makes revision of the model easier, and outputs more relevant to the local scale.

In consultation with stakeholders, we developed a conceptual model of the system with regionalised climate change scenarios as system drivers. This system representation forms the basis of the BN that integrates regional and local information sources into the DSS. Using average rainfall changes as an example, we show how the uncertainties in global and regional climate projections can be incorporated into probabilistic indications of regional climate change. We also show how this approach can be used to identify areas that are less vulnerable to impacts of climate change.

In addition, we provide examples of model outputs that relate to the Central West CMA natural resource condition targets, and show how these can be interpreted. The importance of documenting within the DSS the assumptions and information sources used in modelling is emphasised in the interpretation of model outputs. We also give an example of how sensitivity analysis can be used to inform further development of the BN underlying the DSS. We do this by showing how a river flow model component has more influence over a model endpoint than some model components that are directly linked to that endpoint, and by discussing the limitations of the information used to populate the river flow model component.

The BN used in this approach is designed to be updated and revised in an iterative fashion as more information becomes available, and the impacts of climate change on system responses are further researched.

1. INTRODUCTION

Climate change is a topical research area, but there is still only limited information on the impacts of climate change at regional and local levels. This is partly due to the uncertainties in climate predictions, and the difficulties in quantifying system responses to any predicted change. However, climate change may have a large impact on the condition of natural resources, and it needs to be accounted for when local and regional natural resource management targets are set.

The Central West region of NSW, and in particular the Macquarie River area, contains agricultural industries and high value environmental assets (including the internationally significant Macquarie Marshes) that depend upon water availability and acceptable climatic conditions (Hassall and Associates Pty Ltd. 1998). Research has been undertaken in this area to determine system responses to water flows or aspects of climate, but most of the studies to date have only focused on one or two system attributes (e.g. Kidson et al. 2000). Different studies have also used different climate change projections, which makes it difficult to relate the findings of one study to another. This makes it very hard for managers, such as the Central West Catchment Management Authority (CMA), to assess research and evaluate how climate change may impact on their local natural resource assets.

Decision Support Systems (DSS) provide a popular and useful means for collating and presenting information in a user-friendly fashion, as well as integrating information in a modelling environment. DSSs are problem-based and can be effective vehicles for knowledge sharing as well as integrated assessment and modelling. If appropriate modelling, such as a Bayesian network (BN), is also used, the uncertainties in the climate projections as well as the system responses can be assessed. Exploring and quantifying uncertainties like this is very important when a range of possible changes can occur (such as a range of projected rainfall changes), each with a different possible impact on the system.

In this paper we present an overview of a climate change related BN that has been developed for the Central West CMA in NSW. This BN has been developed in the context of a DSS, and it indicates some likely effects of climate change on the regional and local natural resource targets that the CMA has set as management goals. We show how our approach can incorporate several climate scenarios at once, and how the uncertainties in climate change projections can be assessed using such a probabilistic model. We illustrate this through the interpretation of some of the DSS outputs.

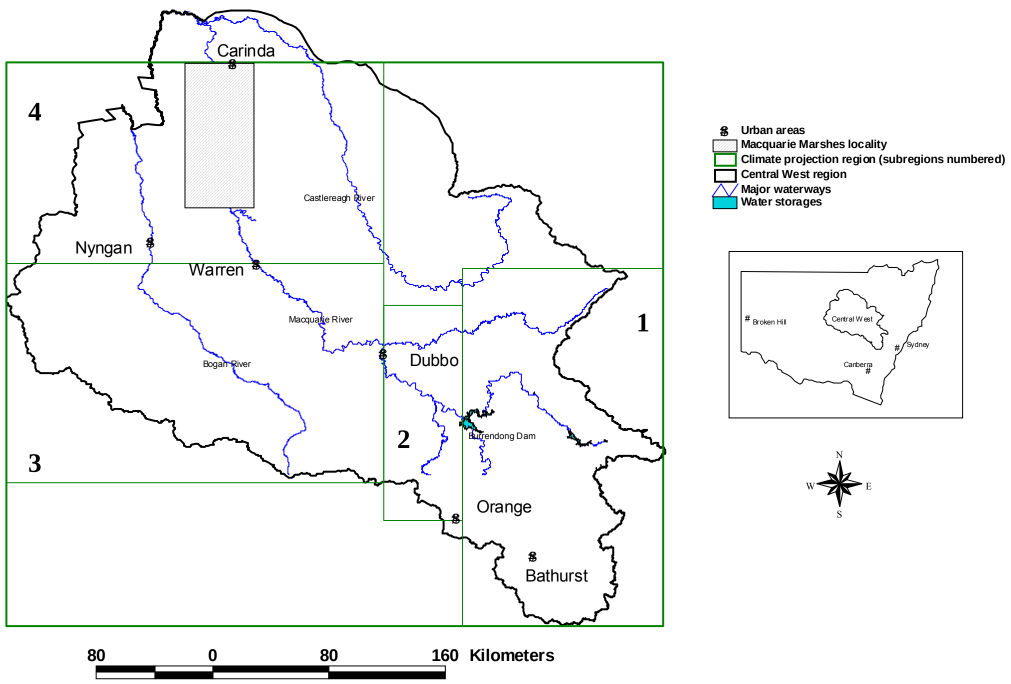

Figure 1. The Central West of NSW showing regions that relate to the Macquarie River Valley that OzClim projections were calculated for. 1 = Upper catchment, 2 = Burrendong Dam to Dubbo, 3 = Dubbo to Warren, 4 = Warren to Carinda.

2. THE MODELLING APPROACH

We chose a Bayesian Network approach for this project for several reasons. BNs present findings as probabilities, and they deal well with the uncertainty inherent in environmental systems. BNs can use a range of information when modelling a system, ranging from data to expert opinion (Borsuk et al. 2004). BNs can be developed in a modular fashion. Small causal networks can be developed for parts of the system where information is available. These can be linked together or linked to a larger network, and they can be copied and modified as more information becomes available (Borsuk et al. 2004). This modular approach can also be used to make the BN spatially explicit. For example, water quality data from one monitoring point on a river can be used to build a sub-network that relates to that point. When monitoring data becomes available for another site, the sub-network can be used as a template and the model can be extended. Making the model adaptable in this way may increase its longevity.

3. METHODS

3.1. The Bayesian network

A preliminary conceptual model of the system was developed with stakeholders. Owing to time and data constraints, the BN that we developed from the conceptual model was limited to the aquatic system of the Macquarie River downstream of Burrendong Dam and:

- two projection time frames; 2015 and 2070 (with a baseline of 1990 climate as 'current conditions'); and
- indicators and outputs that relate to natural resource condition targets that have been developed by the Central West CMA (Central West CMA 2005). We selected a subset of the possible indicators based on the availability of information and by consulting with stakeholders.

The BN derived from the conceptual model is summarised in Figure 2. It was developed in Netica version 3.19 (Norsys 2007). Despite having constrained the scope of the BN, development was still hampered by a lack of data. In particular, information about the relationships between system components and climate changes was lacking. We used river flow as a surrogate measure of climate impacts on many variables. Given the focus on the focus on the Macquarie Marshes, where flows and flooding are the dominant climate related effects on the system, we considered this an acceptable concession. In addition, river flow is represented using nodes that are based on the location of gauging stations along the Macquarie River, making it more spatially explicit. This structure is summarised in Figure 2 as the 'River flow sub-network'.

Probability tables in the BN were populated using case file learning where data was available (using Netica version 3.19. Where this type of information was not available, relationships between variables were determined by reviewing regional studies and literature, or by using expert opinion. Where none of these methods were available, we used generic qualitative assumptions (Figure 2) to populate probability tables.

3.2. Climate scenarios as model input

The type of information we used in the different network components is indicated in Figure 2. For climate projections, we utilised the regional output options available in OzClim version 2.0.1, the Australian Climate Scenario Generator (Page and Jones 2001). Our aim was to capture the uncertainties across a range of common models (vetted by CSIRO, Hennessy et al. 2004) and global climate projections. We chose three of the SRES marker scenarios that gave us the widest range of global temperature change at each time frame (Table 1). This allowed us to include 'worst' and 'best' case climate change projections in the DSS (in the context of the commonly used SRES scenarios), which gives the CMA the most flexibility in exploring and understanding the possible impacts of climate change in the future. For the scenarios we chose, we used the results of all eight global climate models available in OzClim to generate temperature change (°C), average change in rainfall (as % change from baseline), and average change in point potential evaporation (as % change from baseline) for the Central West on a monthly basis for each chosen time frame (expressed as an average monthly result within each season). The baseline was the 1990 long term climate averages provided in OzClim. We generated the projections for the whole region and for sub-regions that approximate different areas of the Central West while focusing on the Macquarie River area (Figure 1).

3.3. Reviewing and assessing the model

Like most BNs, the one summarised in Figure 2 is a 'work in progress', in that the data used to populate the probability tables is incomplete and of varying quality. Identifying these knowledge gaps, and working out how they affect model outputs is very important. The model is only valid if the impact of these knowledge gaps is taken into account. As the model is designed to be re-assessed and updated, we see the most appropriate form of model validation as the use and review of the BN (and the DSS) by the end-users. In this case, the end-user is the Central West CMA, and their assessment should be done in the context of the stated aim of the model (to inform the CMA as to possible climate change impacts on selected condition targets).

In addition to end-user model review, sensitivity analysis can aid identification of knowledge gaps in the model. Full sensitivity analysis of the BN is beyond the scope of this paper, but an example is presented in regards to the qualitative model end-point of 'Health of the Macquarie Marshes', using the measure of mutual information available in Netica (Norsys 2007). Mutual information is an indication of the amount of influence one model component has on another (Korb and Nicholson 2003). A value of one indicates a perfect causal relationship, while zero indicates no influence between model components. Typically, model components that are direct inputs to the interrogated component have higher mutual information values, compared to components that are not direct inputs. However, mutual information is a relative measure and is interpreted as such.

3.4. The DSS

We incorporated the model in Figure 2 into a prototype DSS that was developed in ICMS (Reed et al. 2000)). The DSS provides a user friendly interface for selecting scenarios and viewing model outputs, and includes extensive documentation of assumptions and information sources as context for the interpretation of model results. This packaging of information helps the end-user in reviewing and interpreting the model outputs. Further details of the DSS are not provided here.

3.5. Example scenarios

Numerous scenario combinations can be explored in the DSS. To illustrate the outputs of the DSS (and BN), we use:

- average rainfall (% change from baseline)

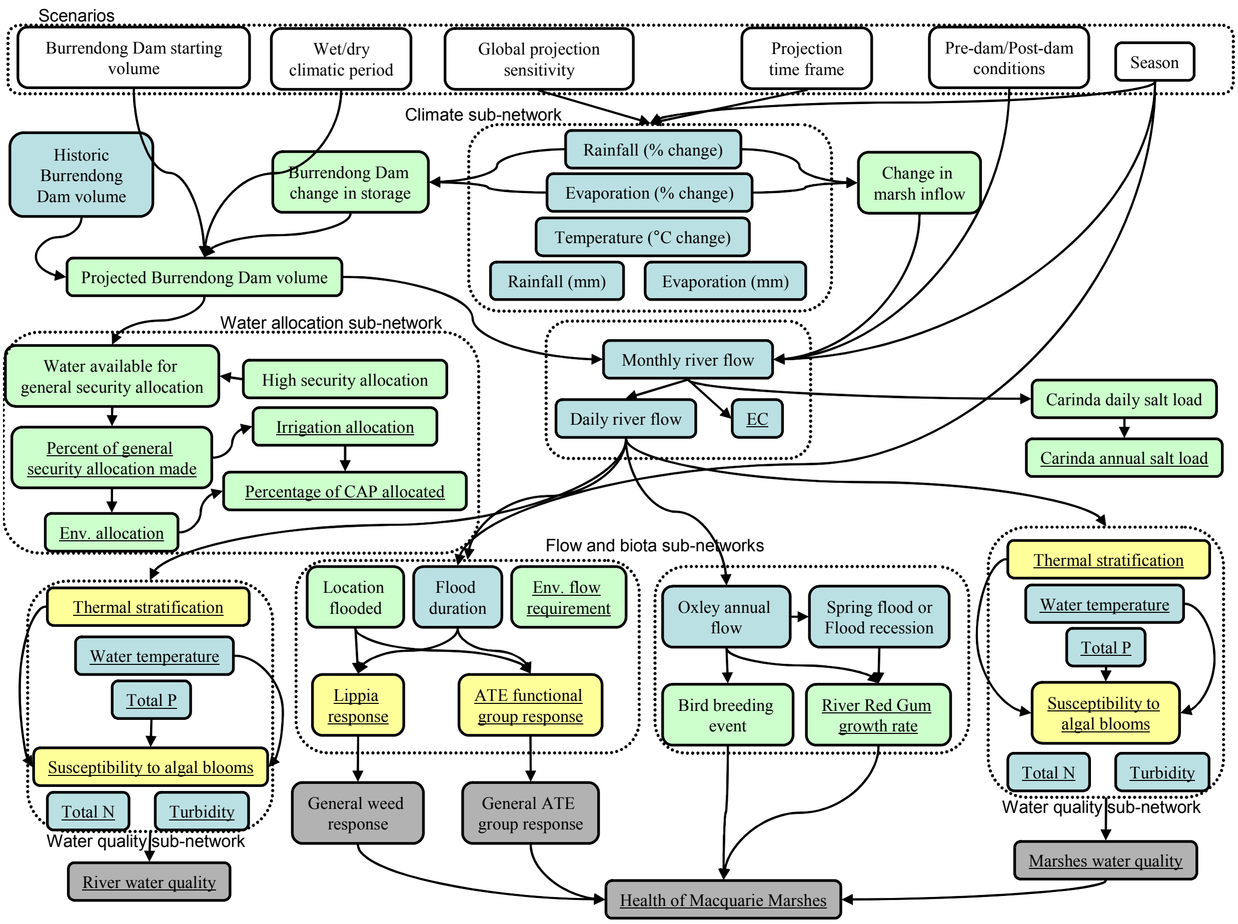

Figure 2. A summary of the BN of climate impacts on chosen aspects of the Macquarie River and Marshes in the Central West of NSW. Dashed outlines indicate sub-networks or modules. Some linkages within sub-networks have been omitted for clarity. Blue = historical data or multiple model outputs, green = empirical relationship from literature or data, yellow = qualitative relationship from literature, grey = qualitative assumptions. Underlined = related to CMA targets.

across the region in a winter month, 2070 with high global temperature sensitivity (Table 1). This scenario combination represents a plausible projected change in an important agricultural rainfall season; and

- outputs for some water quality and water flow indicators - now (in a winter month) and for the 2070 climate scenario already described (Figure 3). Other scenario choices in the BN (Figure 2) for these model runs were arbitrary and were selected to represent current conditions and a Burrendong Dam Volume that would result in the most conservative changes in river flows (i.e. 100 % dam volume).

Table 1. Global scenarios and temperature change projections used to inform the BN.

Timeframe	SRES marker scenario	Temperature increase (°C)		
		low	Moderate	High
2015	A1B	0.30	0.40	0.50
	A1T	0.42	0.55	0.66
	A1F		Not modeled	
	B1	0.33	0.45	0.54
2070	A1B	1.68	2.30	2.87
	A1T		Not modeled	
	A1F	2.30	3.10	3.77
	B1	1.17	1.64	2.08

4. RESULTS AND DISCUSSION

4.1. Climate outputs

For the climate scenario we have used (winter, 2070), Table 2 shows some large variations the regional climate impacts across the Central West, with predicted changes in rainfall of -70% to + 60%.

This variation is impossible to present in a single deterministic assessment of climate change. An important finding is that despite the uncertainty (arising from eight climate models) the probability of decreases in rainfall (> 5 % decrease) across the region is significant (Table 2). There are also large seasonal differences in the projected rainfall changes. For instance, there is an increase in the probability of higher average rainfall (a positive change from baseline conditions) during a summer month of 2070 compared to a winter month (data not shown).

In the scenario detailed in Table 2, there is also a large probability (48.1 %) of there being no obvious change in average rainfall in the region between Burrendong Dam and Dubbo. This trend persists across seasons (43 % for summer months). This may indicate that this area is less vulnerable to climate change than other areas. However, this is difficult to say with certainty without further investigation of OzClim and the underlying climate models, and how their projections are interpolated across small areas.

Table 2. Probability of average rainfall changes for the study area and sub-regions from Figure 1, using the example scenario of winter, 2070.

	Probability of average rainfall (% change from baseline)				
	-70 to -20	-20 to -5	-5 to 5	5 to 20	20 to 60
Whole region	19.8	27.2	30.9	14.8	7.41
Upper catchment[12]	17.9	26.8	34.2	15.2	5.17
Burrendong Dam to Dubbo[1]	8.78	23.4	48.1	14.8	4.92
Dubbo to Warren[1]	18.4	27.9	32.4	13.9	7.40
Warren to Carinda	19.8	25.2	33.2	12.8	9.01

[1] Lowest state for this subregion -65 to -20
[2] Highest state for this subregion 20 to 65

4.2. Indicators

Figure 3 presents the paired results for 3 outputs of the DSS. These relate to the water theme of the Central West CMA CAP, and each has been chosen to illustrate some of the interpretations, and the limitations, of the initial modelling. All of the comparisons are limited to the example scenario combination already described (i.e. a winter month 'now' and in 2070).

Figure 3a shows changes in the probability of meeting the daily environmental flow requirement at the Marebone flow gauging station upstream of the Macquarie Marshes. There is an increase in the probability of the daily flow at this location falling below the environmental flow requirement, when winter 'now' is compared to 2070 (56 compared to 65 %). Interpreting this result requires the user to be aware of the data limitations within the model. In this case, the probabilities were developed using the relationship between monthly and daily flow volumes at the Marebone station. The assumption here is that while the distribution of monthly and daily flow volumes may change under the influence of climate change, the relationship between them will stay the same.

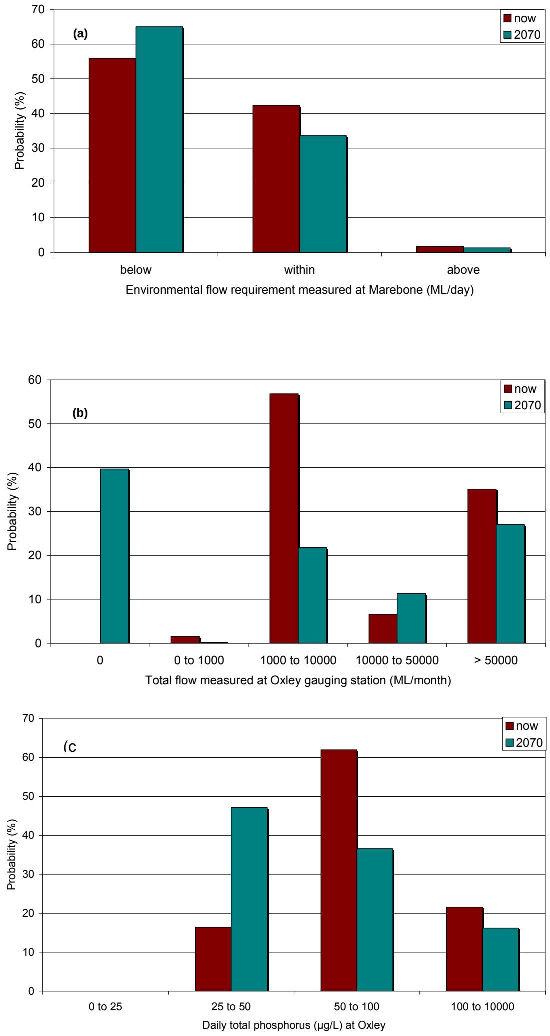

Figure 3. Probabilities of; meeting environmental flow requirements (a), total flow measured at Oxley gauging station (b), total phosphorus (µg L^{-1}) at Oxley gauging station (c) for now and 2070.

Figure 3b is based on a summarised relationship derived from an older coupling of rainfall-runoff modelling with OzClim outputs (Jones et al. 2002). This shows a 40 % increase in the probability of zero total monthly river flows at Oxley stream gauging station (taken as an inflow point to the Macquarie Marshes) when winter 'now' is compared to 2070. Again, this result needs to be interpreted in light of the assumptions used in the modelling. These probabilities are based on past IQQM modelling (Jones and Page 2001), which incorporates older water sharing and allocation rules than are currently in use. However, the modelled changes are so large that even when the assumptions are considered, Figure 3b still indicates that there may be large decreases or stoppages in marsh inflows due to climate change. These changes are also strongly seasonal (23 % probability of zero total monthly flow in an autumn month in 2070, 50 % in a spring month).

Figure 3c shows that there is an increase in the probability of lower daily total phosphorus concentrations measured at Oxley (i.e. there an increase in probability of the 25 to 50 µg L^{-1} state occurring). The relationship between river flow and phosphorus concentrations that was used to produce these probabilities was based on historical water quality data. This data shows a trend of decreasing phosphorus with decreasing river flow. This reflects the assumption that the trend of decreasing phosphorus concentration with decreasing river flows (evident in historical data), will continue under the influence of climate change. Thus, it is too simplistic to say that water quality may increase (in regards to total P, at least) under climate change, if this assumption is valid and the river flows at that location also decrease (Figure 3b).

The examples above show how interpretation of the BN outputs should be done while considering the data and assumptions that have informed the modelling. An assumption that does not appear to be valid probably indicates a knowledge gap that needs to be addressed. One of the roles of the DSS is to provide details of information sources and the related assumptions to the user.

4.3. Sensitivity analysis

A summary of a sensitivity analysis for the model end-point 'Health of the Macquarie Marshes' is shown in Table 3, using the scenario of a winter month in 2070. We only display the mutual information for a subset of model components to illustrate the use of sensitivity analysis in reviewing the model.

In Table 3, 'Red Gum growth rate', 'Bird breeding event', and 'Marshes water quality' are direct inputs into 'Marsh health' (see Figure 2). These have a strong influence on 'Marsh health' as indicated by the relatively high mutual information values in Table 3. However, the river flow components in Table 3 also have a strong influence on 'Marsh health', even though they are not direct inputs (relatively high mutual information values). This indicates that these are important model components, but as already discussed, they are based on past modelling efforts or historical data. The key assumption (particularly with the use of historical data) is that the relationships that have been determined can be extrapolated into a future that is influenced by climate change. This is a large and unverified assumption. Thus, we can regard the influence of climate on flow (particularly at gauging station locations near the Marshes) as a knowledge gap, where the limited information could be strengthened with more detailed modelling.

Table 3. Indicative sensitivity analysis for 'Marsh health', showing mutual information contained in model components.

Model component	**Mutual information**
Red Gum growth rate	0.081
Annual flow at Oxley	0.060
Bird breeding event	0.060
Total marsh inflow (at Oxley)	0.056
Total monthly river flow at Marebone	0.052
Daily flow at Oxley	0.046
Oxley total phosphorus	0.031
Marshes water quality	0.014

5. CONCLUSIONS

Even though climate change research is topical, limited information is available on the regional and local effects of global climate change, and subsequently there is considerable uncertainty involved in determining the impacts on environmental assets at this scale. The approach we have used amalgamates some of the existing sources of information on climate projections and system responses into a single modelling framework. Adopting a modular BN approach allows us to examine the uncertainty and probabilities of climate change across the sub-regions of the Central West, as well as making updating and modifying the BN easier.

We have also shown how some of the outputs of the BN should be interpreted in conjunction with the data that has been used to produce the model. In particular, we have shown how some aspects of the model (such as river flow relationships) have been based upon historical information and that the model assumes these relationships are unaffected by possible climate change. The relative importance of these relationships is shown using an example of a sensitivity analysis, which indicates that this is one knowledge gap that should be the focus of further research.

6. ACKNOWLEDGEMENTS

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