Role of Sectoral Transformation in the Evolution of Water Management Norms in Agricultural Catchments
A Sociohydrologic Modeling Analysis

Roobavannan, M; Kandasamy, J; Pande, S.; Vigneswaran, S; Sivapalan, M.

DOI
10.1002/2017WR020671

Publication date
2017

Document Version
Final published version

Published in
Water Resources Research

AGU PUBLICATIONS

Water Resources Research

RESEARCH ARTICLE

10.1002/2017WR020671

Special Section:
Socio-hydrology: Spatial and Temporal Dynamics of Coupled Human-Water Systems

Key Points:
- Water allocation in the Murrumbidgee, Australia exhibited a "pendulum swing" from agricultural expansion to environmental restoration
- Pendulum swing was a result of a change of community sentiment, from a focus on economic livelihood toward environmental health
- Economic diversification and sectoral transformation swung the community's sensitivity in favor of environmental protection

Supporting Information:
- Supporting Information S1

Correspondence to:
J. Kandasamy,
jaya.kandasamy@uts.edu.au

Citation:
Roobavannan, M., Kandasamy, J., Pande, S., Vigneswaran, S., & Sivapalan, M. (2017). Role of sectoral transformation in the evolution of water management norms in agricultural catchments: A sociohydrologic modeling analysis. *Water Resources Research*, *53*, 8344–8365. https://doi.org/10.1002/2017WR020671

Received 28 FEB 2017
Accepted 6 SEP 2017
Accepted article online 17 SEP 2017
Published online 17 OCT 2017

Role of Sectoral Transformation in the Evolution of Water Management Norms in Agricultural Catchments: A Sociohydrologic Modeling Analysis

M. Roobavannan[1], J. Kandasamy[1], S. Pande[2], S. Vigneswaran[1], and M. Sivapalan[3,4]

[1]School of Civil and Environmental Engineering, University of Technology Sydney, Sydney, NSW, Australia, [2]Department of Water Management, Delft University of Technology, Delft, Netherlands, [3]Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, USA, [4]Department of Geography and Geographic Information Science, University of Illinois at Urbana-Champaign, Urbana, IL, USA

Abstract This study is focused on the water-agriculture-environment nexus as it played out in the Murrumbidgee River Basin, eastern Australia, and how coevolution of society and water management actually transpired. Over 100 years of agricultural development the Murrumbidgee Basin experienced a "pendulum swing" in terms of water allocation, initially exclusively for agriculture production changing over to reallocation back to the environment. In this paper, we hypothesize that in the competition for water between economic livelihood and environmental wellbeing, economic diversification was the key to swinging community sentiment in favor of environmental protection, and triggering policy action that resulted in more water allocation to the environment. To test this hypothesis, we developed a socio-hydrology model to link the dynamics of the whole economy (both agriculture and industry composed of manufacturing and services) to the community's sensitivity toward the environment. Changing community sensitivity influenced how water was allocated and governed and how the agricultural sector grew relative to the industrial sector (composed of manufacturing and services sectors). In this way, we show that economic diversification played a key role in influencing the community's values and preferences with respect to the environment and economic growth. Without diversification, model simulations show that the community would not have been sufficiently sensitive and willing enough to act to restore the environment, highlighting the key role of sectoral transformation in achieving the goal of sustainable agricultural development.

1. Introduction

The coevolution of humans and water, in the presence of multiple feedback loops, has the power to produce emergent dynamics (Sivapalan & Blöschl, 2015). In the Murrumbidgee River Basin in eastern Australia, Kandasamy et al. (2014) reported such emergent dynamics in water management, which they called "pendulum swing." This was attributed to a change in community sentiment toward the environment. At the initial stage of development in the basin in the early 1900s, the focus was on economic development and the use of water for productive purposes only. Later degradation of ecosystems became evident due to the reduction of the share of water to the environment, which progressively got worse. As this took hold, broader community concern over environmental degradation was raised over subsequent decades (Kandasamy et al., 2014; van Emmerik et al., 2014), putting pressure on the government and managers to reallocate water back to the environment and thus restore ecosystem services.

In the Murrumbidgee, agriculture has long been an important source of employment and wealth generation (MJA, 2010; Swainson et al., 2011). There were naturally concerns in the community that any changes to water management to reallocate water back to the environment would inevitably shrink the agricultural economy and contribute to increased unemployment (Bark et al., 2014; MJA, 2010). Water policy in the Murrumbidgee Basin therefore had to mediate the conflicting concerns for the environment and for the economic well-being of basin inhabitants. In the event, the concerns for the environment did prevail and water was indeed reallocated back to the environment as part of several successful initiatives to restore ecosystem services (Kandasamy et al., 2014). Such conflicting concerns are not just limited to the Murrumbidgee basin, they have emerged, and will continue to emerge, in other parts of the world such as Tarim river basin in China (Liu et al., 2014), Lake Toolbin catchment in western Australia (Elshafei et al., 2015). To replicate the successful outcome of the Murrumbidgee story in other circumstances, and to learn the lessons from its experience, it is important to understand the mechanisms behind the transformation of water management in the Murrumbidgee Basin. This is the motivation for this paper.

Paradoxically, the reallocation of water to the environment, when it actually happened, did not adversely affect the overall employment in the basin. In fact, total employment increased and the unemployment rate decreased in spite of a shrinking agricultural economy. The causes of this *unemployment paradox* were explored by Roobavannan et al. (2017). Their study indicated that before the onset of water reallocation, growth of agriculture was accompanied by a diversification of the economy, with parallel growth of industrial (manufacturing and service) sectors of the economy. Over time, the industrial and service sectors grew big enough and helped the basin economy to reduce its dependence on agriculture, with the latter constituting just 10% of the total basin economy by the time reallocation of water back to the environment was introduced. It has been argued before that the now much reduced contribution of agriculture to the basin GDP due to the increasing diversification of the economy, as well as (and not just) the aforementioned degradation of the environment (Elshafei et al., 2014; Kandasamy et al., 2014) were the impetus of the observed pendulum swing.

Roobavannan et al. (2017) showed that employment in agriculture was impacted by the reallocation of water to the environment. For example, Figure 8b in Roobavannan et al. (2017) shows that the employment in the agriculture sector started to plateau and then fall around mid-1990s which was when reallocation was implemented [see also Figure 4 in Roobavannan et al. (2017) showing irrigated land area]. However, the presence of a diversified economy helped to mitigate the resulting economic stress, since workers who became unemployed in the agricultural sector as a result of water reallocation were able to find employment in the expanding industry sector. This ability of the basin economy to absorb the contraction of agriculture sector resulting from water reallocation, through a sectoral transformation, mitigated the negative impacts of water reallocation on the economic well-being of basin residents. Roobavannan et al. (2017) took changes to irrigated land area (as a surrogate for the amount of water allocated to agriculture) as an exogenous variable, i.e., externally prescribed driver of the system that "forced" the changes in water allocation within the Murrumbidgee. For this reason, the study stopped short of explaining *why* or *how* the change in water allocation was triggered, how it was linked to both increased community concerns about environmental degradation, and to the ability of a diversified economy to mitigate the negative impacts of the change on economic well-being. This is the subject matter of the present study.

Societal preference of how water is allocated and used (e.g., between agriculture and the environment) and how water is managed are interlinked (Elshafei et al., 2014; Kandasamy et al., 2014; van Emmerik et al., 2014). The amount of land that is under irrigation emerges as an important variable that both triggers and consequently responds to changing community sensitivity toward more water for the environment. Our hypothesis is that in the competition for water between economic well-being and environmental health, diversification of the economy, and sectoral transformation swung the community's sensitivity in favor of environmental protection. The pattern of rise and fall of irrigated land area emerged as one of the observed phenomena. The resulting change of community focus triggered policy action to reallocate water back to the environment and tipped the balance in favor of environment restoration. The diversified economy played a critical role in successful transformation of water management norms. In other words, a lower level of economic diversification could have meant that basin residents would not have valued the environment as much and the shift of water allocation to the environment may not have occurred.

In order to test this hypothesis, we built a sociohydrological model that links the dynamics of the whole economy (agriculture and industry) to a community sensitivity state variable that is responsive to environmental degradation, as well as to the state of the diversified economy. The community sensitivity feeds back to the economy through the management responses it triggers, e.g., water allocation and release of more environmental flows, that impacts on the basin economy in terms of how the agriculture sector grows relative to the industry sector, and in this way, drives sectoral transformation. By doing so, the model fills a major gap in our understanding of the basin's sociohydrology, with the advantage that the resulting modeling framework is more suitable for transfer to other basins in the world, albeit with minor adaptations.

The paper is organized as follows: the next section briefly describes the study area, i.e., the Murrumbidgee river basin. This is followed by a detailed description of the sociohydrological model, which links the dynamics of the basin economy and its economic structure to the community's sensitivity toward the environment. Model robustness is then tested, along with a discussion of the approach used for model calibration and cross validation, followed by an interpretation of observed dynamics through model simulations. In particular, the important role that sectoral transformation played in changing community sensitivity and transforming the basin economy is discussed. We conclude with key lessons learned from the study, including opportunities for future extensions of this research. The accompanying supporting information contains more details on the model, its configuration and further evidence for the robustness of its predictions.

2. Data and Methodology

2.1. Study Area

The study is centered on the Murrumbidgee River Basin (MRB), which is located in the south-east of the Murray Darling Basin (MDB) in eastern Australia, with a population of over 540,000. Although only representing approximately 8% of the Murray Darling Basin's (MDB) land mass (Figure 1), the Murrumbidgee basin accounts for 22% of the surface water diverted for irrigation and urban use within the MDB (Kandasamy et al., 2014). Agricultural production within the Murrumbidgee basin is valued at over $A1.9 billion annually (ABS, 2012). A history of agricultural development within the Murrumbidgee basin over the past century is given in Kandasamy et al. (2014).

2.2. Model and Parameterization

The human-water dynamics is explored using a conceptual model that utilizes a sociohydrology framework, with explicit inclusion of the associated two-way feedbacks. The sociohydrological model is developed with particular attention to our central hypothesis: that diversification of the basin economy played a key role in changing human values and preferences within the MRB in favor of the environment that eventually led to a change in water policy favoring increased environmental flows. The model presented involved a major extension of an earlier simpler model developed by Roobavannan et al. (2017) that simulates the diversification of the basin economy and dynamics of human migration. In the new model presented here, changes to the irrigation area are no longer externally prescribed [as in Roobavannan et al. (2017)], but endogenously modeled as part of the model in response to changing community sensitivity. The latter is simulated

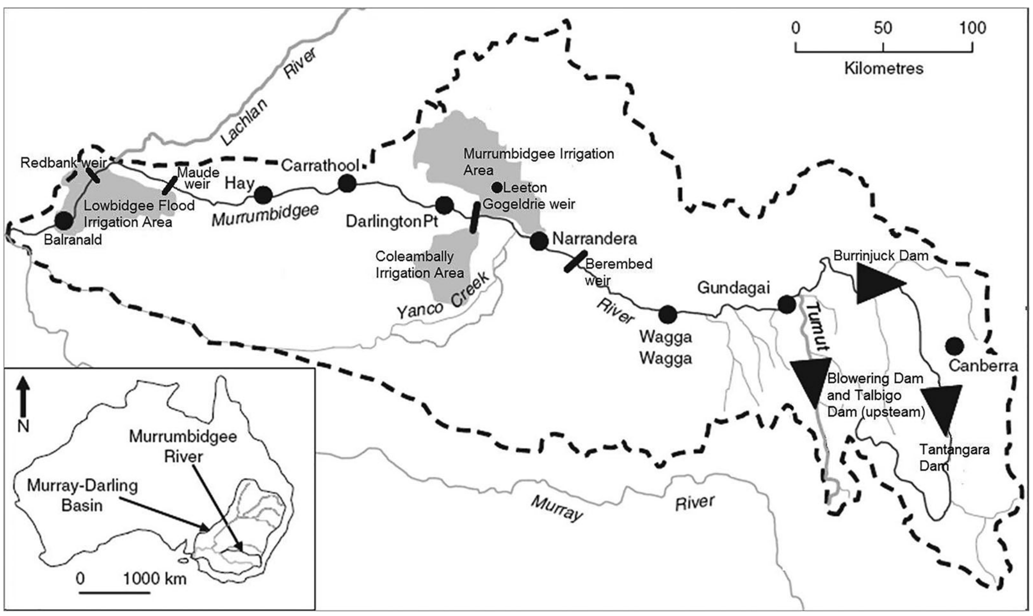

Figure 1. Murrumbidgee Catchment within the Murray Darling Basin (adapted from Kandasamy et al., 2014). The Murrumbidgee Irrigation Area incorporates the Yanco Irrigation Area, Mirrool Irrigation Area, Wah Wah Irrigation District, Benerembah Irrigation District, and Tabbita Irrigation District.

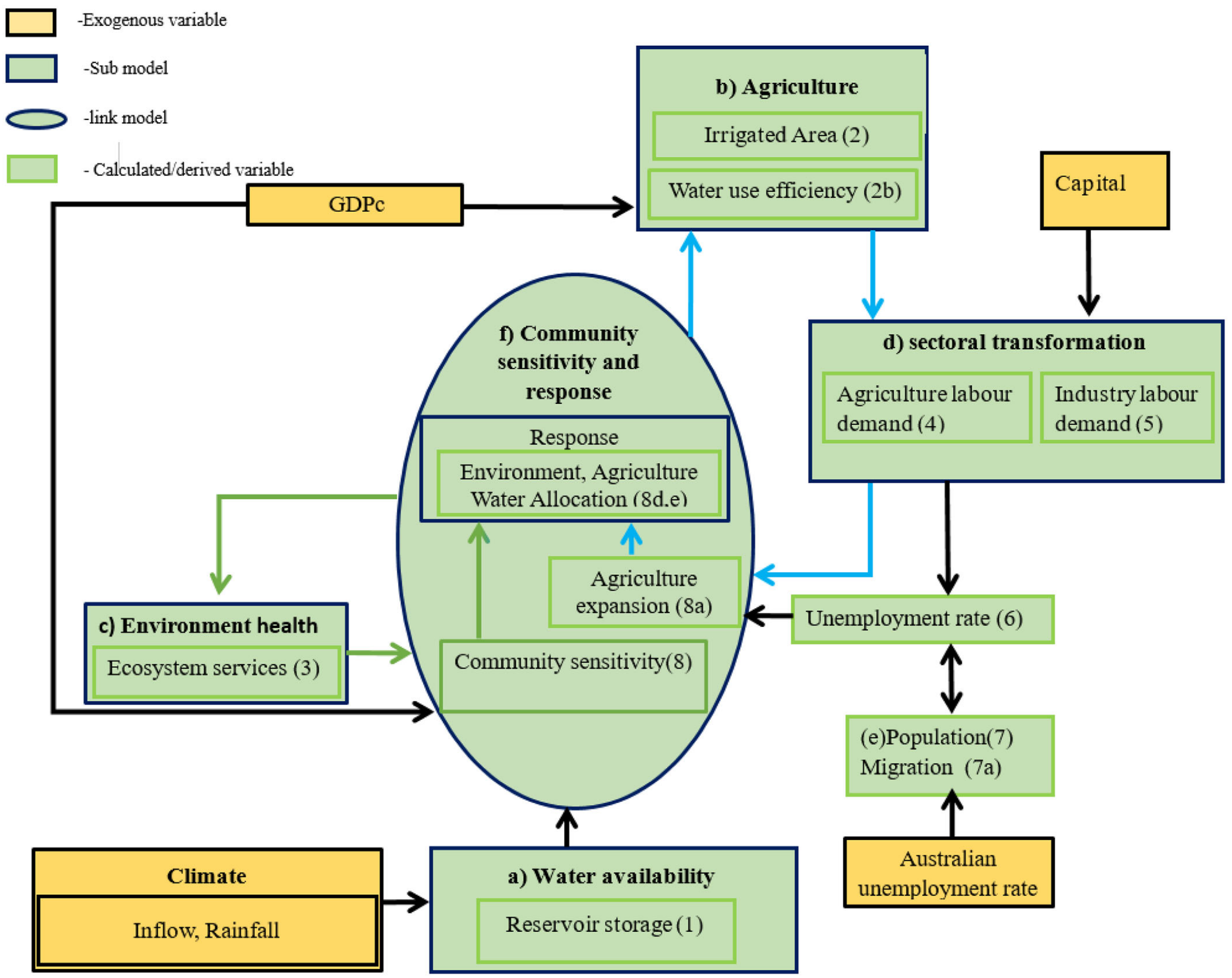

Figure 2. Sociohydrology conceptual framework populated with variables, used to study the dynamics of Murrumbidgee catchment. A yellow-filled box indicate exogenous variables. Green arrows indicate restorative loop and blue arrows indicate productive loop. A link-model is oval shaped and filled green. A submodel is rectangular shaped filled green.

by the community sensitivity and response framework proposed by Elshafei et al. (2014) and is used to account for the changing focus of water management.

The new sociohydrological model (Figure 2) consists of the following submodels: (a) water availability (labeled "a" in Figure 2); (b) agriculture; (c) environment health; (d) sectoral transformation; and (e) population. The sub-models are coupled to each other to mimic their coevolution over time. The coevolution is facilitated by a link-model described below.

The community sensitivity and response (CSR) (f in Figure 2) is a link-model, which is used to influence the functioning of other submodels. The link-model has additional functions for comparing state variables from other submodels, and depending on their relative values, direct a course of action in terms of the amount of water allocated to the environment relative to the agriculture sector (cf. section 2.2.7). In this way, the link-model connects the state variables associated with various subsystems and facilitates the feedbacks between them.

2.2.1. Feedback Loops

The operations of the CSR link-model create feedback loops between the submodels and conceptualize the coevolution of associated state variables. Figure 2 shows the two different colored feedback loops (blue and green) and how the submodels are coupled. In Figure 2, the green feedback loop couples water availability to environment health. Economic benefits, which are obtained by diverting water to agriculture ("productive" loop), when excessive, cause environmental degradation and a decline in ecosystem health. Over time, this creates awareness about the state of the environment in the community, and gives rise to the restorative feedback. Humans are conflicted by the restorative and productive feedbacks and *might* cut back on water allocation to agriculture in order to improve the health of the environment (e.g., by changing water policy in favor of the environment), or vice versa.

The agriculture production loop, shown in blue in Figure 2, shows the productive feedback to the economy, which in part is driven by the global economy and in part responds to availability of resources (land, water, and human). In times of increasing prosperity, economic benefits drive landholders and farmers to expand production through increased cropped land area, leading to increased water consumption (Kandasamy et al., 2014). The competing demands for water by the environment (green feedback loop) and agriculture (blue feedback loop) are in the end arbitrated through the community's sensitivity and response (CSR) link-model.

Agriculture expansion with increasing agriculture production and labor demand in the basin increases the prosperity of the residents and attracts additional people (migrants) to the basin from outside the basin. In this study, we use a human migration behavior state variable called *attractiveness* (see population section) to simulate migration to/from the basin and into or away from agriculture (Roobavannan et al., 2017). Note that the sociohydrological model presented here simulates the entire basin as a "lumped" system. The submodels of the framework are now described in greater detail.

2.2.2. Water Availability: Figure 2 Submodel a

The water availability submodel estimates the total amount of water available for the environment, irrigated agriculture, and other users such as town water supply, industry water, etc. Water allocation is determined based on water available in the storage of the dams (Burrinjuck and Blowering, see Figure 2). A simple water balance model is used to determine water availability:

$$\dot{S}=\max\left(0, I - Q_A - Q_E - Q_T - Q_O - Q_m\right) \tag{1}$$

where S is the storage in the dams, $\dot{S}=\frac{dS}{dt}$, and I is the inflow to the dams (an external driver or an exogenous variable of the system). Q_A is the water withdrawn for agriculture and Q_E is the environment water delivered to cater for ecosystem services. In the Murrumbidgee, and elsewhere in Australia, the environment (wetlands and other ecosystem) has the legal right for access to water. The environment is provided an entitlement to water, in the same way as farmers are, in order to enhance ecosystem services. Both are arbitrated by the CSR link-model (see section 2.2.7). The town water supply (Q_T) depends on the basin population (P) and a constant domestic water use per capita (w_p) (ABS, 2016a):

$$Q_T = w_p P \tag{1a}$$

Overflows over dam (Q_O) occurs when the storage capacity (S_c) is exceeded.

$$Q_O=\begin{cases} 0 & S < S_c \\ K_q\left(S-S_c\right)^{1.5} & S > S_c \end{cases} \tag{1b}$$

where K_q is an overflow parameter obtained through calibration. A minimum flow (Q_m) is released to fulfill the end of system flow requirement (DPI Water, 2016) if the inflow is greater than 2000 GL/yr. This maintained channel connectivity and prevents saltwater intrusion and reduces mixing with seawater in downstream estuaries. Otherwise a fraction of that is released based on the dam inflow:

$$Q_m=\begin{cases} \mathrm{wm}, & I > 2000 \\ \mathrm{wm}\dfrac{I}{2000}, & I < 2000 \end{cases} \tag{1c}$$

where w_m is minimum flow requirement when the inflow is greater than 2000 GL/yr.

2.2.3. Agriculture: Figure 2, Submodel b

This models the evolution of irrigated land area, L_A. Agriculture in the Murrumbidgee has been driven by availability of water for cultivation (Kandasamy et al., 2014; O'Gorman, 2013). Production has fluctuated with the volume of water that is available for agriculture. Farmers do maximize their profit from agricultural production by optimizing choices with regards to labor, physical capital, and cropping pattern under given levels of water supply, technology, and market prices of labor and output (Debertin, 2012). Our model is lumped and currently considers farm level optimization behavior with respect to labor. Thus, the irrigated land area depends on the water withdrawn for agriculture (Q_A), average water required for irrigation per hectare (ψ (Singh et al., 2005)) which is assumed to be constant and the efficiency of water usage (E_f) :

$$L_A = Q_A \frac{E_f}{\Psi} \tag{2}$$

From Equation (2), changes in irrigated land area are given by;

$$\frac{\dot{L_a}}{L_a} = \frac{\dot{Q_A}}{Q_A} + \frac{\dot{E_f}}{E_f} \tag{2a}$$

A higher efficiency of water use lowers the amount of water required to irrigate land. The efficiency of water usage naturally improves with development in technology (irrigation technology, farm practices, etc.).

Water use efficiency was assumed to follow the trend in technological development. The number of patents has often been used as an indicator of technological development. Since the number of patents are found to strongly correlate with economic growth, we empirically derive a relationship between water use efficiency and the Australian *GDP* per capita to model technological innovations in water use efficiency (Equation (2b)) (see supporting information Figure A1):

$$E_f = \alpha_1 GDPc + \alpha_0 \tag{2b}$$

where *GDPc* is the gross domestic product per capita and α_1 and α_0 are regression coefficients estimated based on an established relationship between water use efficiency, number of patents (technology), and *GDPc*. Note that water use efficiency increased from 0.69 to 0.72 from 1997 to 2005 (Meyer, 2005).

In this paper, for simplicity, technology growth is modeled exogenously by relating it to GDPc. It should be noted that it has been modeled endogenously in previous work published in van Emmerik et al. (2014). However, it is not endogenized in the present study because this would have meant additional parameters to calibrate, which would have increased the risk of over parameterizing the model.

2.2.4. Environment Health: Figure 2, Submodel c

This sub-model estimates the health of the ecosystem and its state of degradation. In this study, human perception of ecosystem health is captured through a sensitivity state variable (V) as one of the driving variables, which accounts for lifestyle-related ecosystem services (E_s) (Equation (9)) (Elshafei et al., 2014). E_s feeds back to the CSR link-model and influences the bias toward the restoration of the environment through reallocation of water. Here ecological degradation is accounted for by using a proxy index for the state of the ecosystem. The ecosystem service provided by the environment is measured using a 7 year moving average of the Fish Species Richness (FSR) index (Yoshikawa et al., 2014) given by the following exponential equation:

$$E_s = \beta_0 {Q_B}^{\beta_1} \tag{3}$$

Here Q_B is the flow in the river downstream of the irrigation area, i.e., $Q_B = Q_E + Q_O + Q_m + Q_r$ and β_0 and β_1 are parameters of the FSR index (Yoshikawa et al., 2014). Apart from environment water (Q_E), excess flows over dams (Q_o), minimum flow (Q_m), and catchment runoff (Q_r) downstream of the dam can also contribute to ecosystem health. Catchment runoff downstream of the dam is given by:

$$Q_r = R_f C_a \beta_r \tag{4}$$

where R_f is annual total rainfall; C_a is catchment area between the dams and Carrathool; β_r is annual runoff coefficient (CSIRO, 2008).

2.2.5. Sectoral Employment: Figure 2, Submodel d

The sectoral employment submodel translates cuts to water allocation and the consequent impact on agriculture in the basin to the remainder of the basin's economic sectors, i.e., how the reduction in water allocation to agriculture affects employment within each economic sector and the total unemployment within the basin. For simplicity, we aggregate the basin economic activities into two sectors, agriculture and industry (the latter comprising manufacturing and service subsectors). The changes in employment rates in the two sectors of the economy, agriculture, and industry, are based on the Cobb-Douglas production function model (Bah, 2009; Gollin, 2002; Ngai & Pissarides, 2004), which incorporates growth rates of the total factor of productivity and of capital, and changes in wage rates.

Based on profit maximization conditions, Roobavannan et al. (2017) showed that the rate of change in labor demand in the agriculture sector depends on the rates of change of land area under irrigation, technology and wage, i.e.:

$$\frac{\dot{D}_a}{D_a}=\frac{\dot{L}_a}{L_a}+\frac{\gamma_a}{\alpha}-\frac{\gamma_w}{\alpha} \tag{5}$$

where $\frac{\dot{L}_a}{L_a}$ is the rate of change in irrigated area, γ_a is the growth rate of the total factor of productivity (TFP) in agriculture, γ_w is the wage growth rate (ABS, 2015), α is the productivity share of land in agricultural output. Similarly, labor demand in the industry sector (D_i) has been shown to depend on capital growth rate (γ_c), growth rate of TFP in industry (γ_i) and γ_w and is given by (Roobavannan et al., 2017):

$$\frac{\dot{D}_i}{D_i}=-\frac{\gamma_w}{\theta}+\gamma_c+\frac{\gamma_i}{\theta} \tag{6}$$

where θ is the productivity share of capital in industrial output.

The rate of unemployment (U_b) in the basin depends on the employment demand in each sector of the economy and the labor force in the basin. Roobavannan et al. (2017) estimated it by:

$$U_b=\max\left(0,\frac{P\phi-(D_a+D_i)}{P\phi}.100\right) \tag{7}$$

where P is population size and ϕ is labor portion in the population.

2.2.6. Population: Figure 2, Submodel e

The change of population within the basin may be influenced by factors such as natural growth (births and deaths) and economic migration. The change in population (P) is estimated by:

$$\frac{\dot{P}}{P}=\varsigma-\Omega+M \tag{8}$$

where ς is the annual birth rate; Ω is annual mortality rate; and M is the annual net economic migration rate. This study focuses on internal migration within Australia, driven by economic well-being. However, the attractiveness of the basin to human migration can also be influenced by other factors such as social well-being, climate, environment, and political or security related issues.

Following Roobavannan et al. (2017), economic migration to/from basin is modeled based on an assumption that it is driven by the potential for economic well-being. Economic migration to/from the Murrumbidgee basin is modeled in terms of the gradient between unemployment rates within and outside the basin (within Australia):

$$M=\nu\,(U_A-U_b) \tag{8a}$$

where U_A is unemployment rate of Australia and ν is a constant.

2.2.7. Community Sensitivity and Response (CSR): Figure 2, Link-Model f

The CSR link-model simulates changes in human perceptions regarding ecosystem health and degradation and how it in turn drives changes to water management. Decisions on water management are made at a basin scale with extensive community participation and consultation being an essential component (MDBA, 2017). In this way, local community sensitivity and response become essential input to policy changes at basin scale. The submodel aims to capture this effect, i.e., how changes in society's values and preference drive changes in water allocation at basin scale.

Community Sensitivity. Elshafei et al. (2014) proposed a generic model using the concept of *community sensitivity*. The rationale behind this model is discussed in detail in Elshafei et al. (2014, 2015). It is based on vulnerability and resilience theories and conceptualizes community sentiment as a trade-off of environmental well-being relative to their economic well-being.

The trade-off depends upon the extent to which the community is dependent on environmental water for their economic well-being. Since the community is heterogeneous in terms of income, education, and social and political alignment, all of which impact its collective behavior/action (Magnani, 2001), we assume that community sensitivity is influenced by the relative positions of individuals within the basin and in context of this heterogeneity. This effect of heterogeneity on community sensitivity is modeled using an exponential probability distribution function, i.e., $1-\exp\left(-\gamma_g \frac{D_a}{D_a+D_i}\right)$, where γ_g is the inverse of the scale parameter of the distribution function. Then the probability of an individual within a community supporting water consumptive agriculture growth over industrial growth is higher when the community depends on agriculture economy more than on industrial economy. Equation (9) translates this effect of the heterogeneity to lower sensitivity of the entire community to the environment. The change in the community sensitivity ($\dot{V}=\frac{dV}{dt}$) is given by,

$$\dot{V}=\gamma_v\left[\left(-\widetilde{E_s}-\widetilde{I_c}\quad\left(1-\exp\left(-\gamma_g\frac{D_a}{D_a+D_i}\right)\right)\right)\right]V \tag{9}$$

where γ_v is a parameter reflecting the time scale of community sensitivity which could be influenced by outside social, economic, and political factors (Elshafei et al., 2014). Communities with longer time scales are slower in changing their attitude toward the environment. $\widetilde{E_s}=\Delta Es/\overline{E_s}$ is the relative change in ecosystem services of the catchment with $\overline{E_s}$ being the average ecosystem services over past 5 years. I_c is income per capita and $\widetilde{I_c}=\ \Delta Ic/\overline{I_c}$ is relative change in income per capita for the basin population with $\overline{I_c}$ being the average over past 5 years. Even though I_c is expected to depend upon the gross basin product per capita (GBPc) as the indicator of mean household income, we chose Australian GDP per capita because of the strong correlation between median household income of the basin and Australian GDP per capita (Roobavannan et al., 2017).

In this paper, governance structure was not separately modeled, and was included in the community sensitivity framework implicitly in a lumped way. This was able to capture the intended dynamics (i.e., influence of diversification on changing value and preference) and was deemed adequate for this study. Extension of the model to explicitly include the role of governance institutions is left for further study (see Yu et al., 2017, for an example).

Inducement for Agricultural Expansion (D_e). The inducement for agricultural expansion reflects community's aspiration for future economic well-being. D_e, which is dimensionless, is influenced by the population growth ($\frac{\dot{P}}{P}$) and unemployment rate (U_b) and stimulates the demand for agriculture expansion. Agriculture development will be limited by the extent to which critical natural resources within the basin have been utilized or by resources capacity factors which are ratios of utilized land and water to what is available, namely land (L_A/L_m) and water (R_e/S_c) resources (Elshafei et al., 2014). The capacity usage (L_m (DWE, 2008) and S_c is included since management decisions are progressively less likely to acquiesce to expansion pressures as usage levels approach the capacity (Elshafei et al., 2014).

$$D_e\quad=\left[\frac{\dot{P}}{P}+\mathrm{Ub}\quad\right]\left(1-\frac{L_a}{L_m}\right)\left(1-\frac{R_e}{S_c}\right) \tag{9a}$$

where R_e is total committed water that may be extracted, such as irrigation and town water supply. In the past, when farms were established in the Murrumbidgee, farmers were given access to water for agriculture through licenses or entitlements (MJA et al., 2010). The entitlements provide legal basis to extract prescribed amounts water from river. R_e is cumulative of entitlements for agriculture and town water supply. Each year, water managers have an obligation to service farmers' entitlements, and to ensure the undisturbed supply of committed water but only if there is enough water to do so. L_m is the maximum land available for agriculture and S_c is the reservoir capacity of the Blowering and Burrinjuck dams.

2.2.7.1. Community Response

Community Sentiment. At the initial stage of development in the basin in the early 1900s, the focus was on economic development and the use of water for productive purposes only. Later the extraction of water for irrigated agriculture led to environmental degradation, including the drying and contraction of the riparian and floodplain wetlands, loss of native fish species and reduced biodiversity, extended periods of low flows, altering of natural discharge patterns, and river and land salinity (Kandasamy et al., 2014). While all these are serious environmental problems, land salinity more easily communicates the stark nature of the environmental problems faced in the Murrumbidgee and how ecosystem stress was felt by the basin community. Excessive irrigation caused water tables to rise bringing up with it salts that were present underground. Land salinity impacted both farm and town communities (Kandasamy et al., 2014) and made farms unproductive. In towns, salinity caused severe structural damage to infrastructure (roads, water, and sewer) and residential and other buildings and was extensive. Economic losses were at the personal level as farming households could lose their single largest asset, which is a means for income and the nest-egg for retirement (Murray-Darling Basin Commission (MDBC), 2001). Town residents suffered damage to their homes, and their sensitivity was heightened given that their livelihood was not directly sourced from agriculture. Mitigation of land salinity (e.g., pumping to lower ground water) was not sustainable, costly and had only a localized impact (Pannell, 2001). River salinity, caused by saline groundwater flowing into rivers, was as bad and at elevated levels could make river flow unusable for agriculture and for town water supply. Wetlands, aquatic flora and fauna and the riparian environment had degraded to very poor conditions and were visually ever-present. All these environmental issues made the local community aware (both farm and town) of the excessive extraction and use of water for agriculture. It galvanized local communities and generated community sentiment toward environmental remediation (Kandasamy et al., 2014). By the early 1990s there was consensus for action. This directly led the introduction of a temporary "cap" (no further licenses issued to extract water) which was made permanent in 1997. Subsequently action was taken to divert more water to the environment (Kandasamy et al., 2014).

Conceptualizing Community Response. The above narrative is conceptualized as follows. When a community is highly sensitive to environmental degradation, which overrides the inducement for agricultural expansion (De), it triggers management action to divert water away from agriculture and reallocate it to the environment. This trigger is modeled through a response function X. Water reallocation to the environment occurs when X is positive and exceeds a certain critical sensitivity threshold V_c*.

The response function (X) determines community action (i.e., action to change how water is allocated) based on two competing feedback loops, positive (agriculture "blue" loop in Figure 2) and negative (environment "green" loop) feedback loops. The competition between the two feedback loops are captured by the tension between induced demand for agriculture expansion (D_e) (blue loop, Figure 2) to increase the socioeconomic well-being and community sensitivity (V) (green loop, Figure 2) (Elshafei et al., 2015, 2014) to the environment degradation, respectively. The model determines the overall degree and direction of action by resolving the tension between community sensitivity (V) to the environment and the inducement for agricultural expansion (D_e) (Elshafei et al., 2014) and is conceptualized as,

$$\mathrm{X} = \begin{cases} -K_d De \ , \ F(V) < V_c^* \\ F(V) \quad -K_d De \ , \ F(V) \geq V_c^* \end{cases} \tag{9b}$$

where K_d is scaling factor, V_c^* is the critical community sensitivity and $F(V)$ is normalized sensitivity estimated as,

$$F(V) = \frac{\dot{V}}{V_m - V} \tag{9c}$$

where V_m is a constant reflecting the maximum sensitivity of the particular community (Elshafei et al., 2014). The term V_m-V scales the incremental change in sensitivity to increase as the baseline sensitivity approaches the maximum, i.e., normalized sensitivity becomes more sensitive to increases in environment sensitivity as the latter approaches to its maximum.

From Community Response to Water Policy Action. The response function is transformed through translation functions (Elshafei et al., 2014), adapted to the Murrumbidgee, into water management action or water allocation for agriculture and water allocation for the environment.

Water for Agriculture. Water withdrawn for agriculture (Q_A) depends on the community response (X) and water allocation (W_A). A simple formulation for water withdrawal for agriculture (Q_A) is defined below, following Di Baldassarre et al. (2013) and Elshafei et al. (2015):

$$\dot{Q}_A = \begin{cases} \eta_E \dfrac{\dot{W}_A}{W_A} Q_A, \ \mathrm{X} > 0 \\ -\eta_A \ \mathrm{X} + \eta_E \frac{\dot{W}_A}{W_A} Q_A \ , \ \mathrm{X} \leq 0 \end{cases} \tag{9d}$$

where $\eta_{A,} \ \eta_E$ are translation parameters estimated through calibration. Water allocation (W_A) depends on water use and climate and it displays a linear relationship with storage (S) (see supporting information

Figure A2). We assume this linear relationship between W_A and S. The change in water withdrawn for agriculture is then given by:

$$\dot{Q}_A = \begin{cases} \eta_E \frac{\dot{S}}{S} \; Q_A, \; X \; > 0 \\ -\eta_A \; X \; + \eta_E \frac{\dot{S}}{S} \; Q_A \; , \; X \; \leq 0 \end{cases} \tag{9e}$$

Water for the Environment. Similarly, assuming that there is an function that obeys a similar formulation as Equation (9e), the environment water delivered in response to the environment stress is given by:

$$\dot{Q}_E = \begin{cases} \eta_E \frac{\dot{S}}{S} \; Q_E, \; X \; < 0 \\ \eta_A \; X \; + \eta_E \frac{\dot{S}}{S} \; Q_E \; , \; X \; \geq 0 \end{cases} \tag{9f}$$

where $\dot{Q}_E$ is the change in the amount of water delivered to the environment. Equations (9e) and (9f) are such that the following restrictions hold:

1. If X is 0, then Q_E and Q_A are proportional to storage (S), which enforces a restriction that flows to the environment and to agriculture are proportional to water storage. There is no change in policy action, i.e., *status quo*, and
2. If the change in storage ($\dot{S}$) is 0, then the sum of $\dot{Q}_E$ and $\dot{Q}_A$ is 0. Any change (positive or negative) in environmental flow is at the expense of flow directed for agricultural use.

2.2.8. Model Input Data and Setting

External Drivers. The external drivers of the model relate to climate and the Australian economy (Figure 3). The input data used in the model are summarized in Table 1. Hydroclimatic drivers of the model are inflow to the dams (Blowering and Burrinjuck Dams) and annual rainfall over the catchment. The economic drivers of system are gross domestic product per capita of Australia (*GDPc*) and the national unemployment rate (U_A).

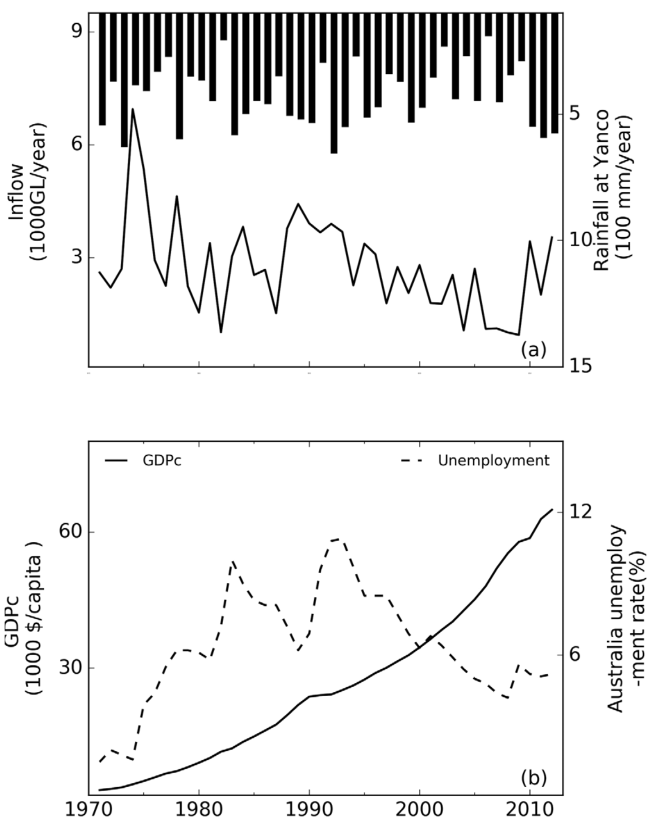

Figure 3. External drivers used in the model study; (a) yearly total inflow to the dams and annual rainfall at Yanco; (b) Australia's gross domestic product per capita (*GDPc*) and nationwide unemployment rate.

Coefficients, Parameters, Initial Data, and Variables. The coefficients, parameters, initial values, and variables used in the model are summarized in Appendix 1. Coefficients are constant values, which are derived from data or based on the literature (see supporting information Table A1). Parameters are variables that are calibrated and used in the governing equations of the various submodels (Figure 2). In total, *seven parameters* needed to be calibrated. Initial estimates for the calibrated parameters, which explain the dynamics reasonably well, are first obtained manually. Following that, 100,000 random samples of parameters (uniform sampling) that lie within the range of 50–150% of the initial values are obtained. Model simulations are then carried out using these random parameters sets, selecting those "behavioral" parameter values for which the performance of the model is deemed "acceptable" (Beven & Binley, 1992) (see further in section 3.1). The results of this simulation are given in section 3.1.

Initial values are the values of variables at the first time step. As mentioned before, these are obtained from the literature (shown in supporting information Table A2) and are used to initiate the model computations. Values at subsequent time steps are updated based on model calculations.

Simulation Period and Time Steps. Model simulation period is from 1971 to 2012. The availability of detailed data sets for external drivers limited the simulations to this period. The model was run on time steps of one year. Data that are used to calibrate and cross validate the model are available on an annual basis. Simulations are done using the PyDStool module (Clewley, 2012) in Python.

Table 1
Summary of Data Used in Model

Input data	Function	Submodel	Time step	Reference
Climate data				
Inflow to the dam	External driver	Water availability, (a) in Figure 2	Yearly	Water NSW (2014)
Rainfall at Yanco	External driver	Environment health, (c) in Figure 2	Yearly	BOM (2016)
Discharge	Calibration/validation	Water availability, (a) in Figure 2	Yearly	Water NSW (2014)
Economic data				
Australia's unemployment rate	External driver	Population, (f) in Figure 2	Yearly	World Bank (2014)
GDP per capita	External driver	CSR, (f) in Figure 2	Yearly	World Bank (2014)
Basin's unemployment rate	Calibration/validation	Population, (f) in Figure 2	Yearly	ABS (2009)
Employment in each sector	Calibration/validation	ST, (e) in Figure 2	5 year	ABS (2014)
Population	Calibration/validation	Population, (f) in Figure 2	5 year	ABS (2014)
Total irrigated area	Calibration/validation	Agriculture, (b) in Figure 2	Yearly	ABS (2016b, 2016c), Dunlop (2001), Hope and Wright (2003), and Meyer (2005)
Water allocation for agriculture	Calibration/validation	Agriculture, (b) in Figure 2	Yearly	Office of Water (2014)

2.3. Model Assumptions

In summary, the model assumes the following:

1. Basin economy is an open economy and the political system is a democratic political system (Elshafei et al., 2014).
2. Agriculture in the Murrumbidgee has been driven by availability of water for cultivation (Kandasamy et al., 2014; O'Gorman, 2013). Thus, the irrigated land area depends on the water withdrawn for agriculture (Q_A).
3. Water allocation for agriculture is related to storage in the dams (Office of Water, 2014).
4. Water use efficiency was assumed to follow the trend in technological development as measured by the number of patents each year (Meyer, 2005).
5. Water withdrawals from river for agriculture purposes have been decided based on fixed water use per hectare (ψ), which in reality is influenced by the types of crops grown and the climatic conditions.
6. The health of ecosystem could be surrogated by the richness of fish species (Yoshikawa et al., 2014).
7. Basin scale water policies emerge from decisions taken by within basin stakeholders in a participatory manner (MDBA, 2017).
8. Changes in societal value and preference influence within basin participatory politics (Sivapalan & Blöschl, 2015).
9. Storage capacity constrains the water utilization for human use (Elshafei et al., 2014).
10. Production in agriculture and industry obey the Cobb-Douglas production function (Cobb & Douglas, 1928; ABS, 2010).
11. Catchment economy follows the same trend as the economy outside the basin (Roobavannan et al., 2017).
12. Producers in the agriculture and industry primarily maximize their profits with respect to labor and take cultivated land area and invested capital respectively as given (Bah, 2009).
13. Migration to/from basin is driven by the potential for economic well-being (Roobavannan et al., 2017).
14. Society responded to ecosystem degradation mainly by diverting the water from agriculture to the environment while continuing to increase the water use efficiency and save water (Kandasamy et al., 2014).

3. Model Calibration and Validation

Calibration and validation of coupled sociohydrological models are extremely challenging (Pande & Sivapalan, 2016; Troy et al., 2015) due to changes of intangible variables, such as community sensitivity, over long periods (Kandasamy et al., 2014). This often leads to equifinality in terms of model structure and corresponding parameters.

On the Formulation of Community Sensitivity. The uncertainty about functional relationships adds to the uncertainty in the interpretation of an observed sociohydrological phenomenon (Pande & Sivapalan, 2016;

Troy et al., 2015). In this study, we tested different formulations for community sensitivity and compared the model performances (two such formulations are compared in supporting information Table A3: Comparison of different formulations of community sensitivity) to arrive at an acceptable formulation given in Equation (9) (see section 2.2.7). The results of these simulations are given in section 3.1.

3.1. Calibration and Cross Validation

The model was calibrated and cross validated in order to check the robustness of the model and build confidence in the chosen parameter values. This calibration and cross validation is similar to the twofold cross-validation method (Stone, 1973), which is extensively used in data analytics. Here a model is first calibrated on one portion of the data (subsample) and tested on the remaining portion and then this process is repeated (crossed) by calibrating on the second portion and validating on the first. In our calibration, the difference is that instead of using portions of data of the same variable, entire datasets of *subsets of variables* are used one at a time for calibration and *the remaining subset of variables* for validation. That is, in CV1 (see Figure 4), irrigated land area and delivered environment water is used for *calibration* and the model is validated on the remaining other variable, i.e., observed discharge at the upstream and at downstream ends of the irrigation area. Then to *cross validate*, the variables are switched. In CV2 (see Figure 4) observed discharge at upstream and at downstream of the irrigation area are used for calibration and the model is validated on irrigated land area and the delivered environment water.

When calibrating (CV1) on observed irrigated land area and delivered environment water data, a parameter value is deemed acceptable when the Nash-Sutcliffe efficiency (Houska et al., 2014) of simulated irrigated land area (L_A) relative to the observed data is greater than 0.2 and when R^2 of simulated environment water delivered with respect to the observed (Q_E) is greater than 0.2. These define the limits of accepting parameter values of the model (Beven, 2006). Model performance for simulating irrigated land area for the selected parameter range is presented in the supporting information (see supporting information Figure A3).

Figures 4a and 4b show the calibrated irrigated land area and delivered environment water. Model results are reported using the median value of the "behavioral" parameter sets, which are obtained through calibration of the model. The shaded area in figures showing the model results indicate 90% confidence intervals of model simulations, corresponding to the behavioral parameter sets, which accounts for the uncertainty in the chosen parameter values. The coefficient of determination (R^2) between observed and simulated irrigated area and delivered environment water are 0.35 and 0.22, respectively, while the Nash-Sutcliffe efficiency scores are 0.28 and -0.85, respectively, for the selected median parameter set.

Figures 4c and 4d show validation results based on the comparison between observed and simulated yearly discharges at Gundagai (upstream of irrigation area, see Figure 1) and Carrathool (downstream), respectively. The difference between discharges at these locations accounts for the extraction of water for irrigation. The correlation coefficient between recorded and simulated annual discharge at Gundagai and Carrathool is $R^2 = 0.82$ and 0.8, respectively. The modeled discharge is underestimated because irrigation water requirement is assumed to be fixed (ψ). We note that irrigation water requirement is affected by rainfall, evapotranspiration and the type of crop cultivated but here the model was kept simple. This is because the main objective was to understand the dominant sociohydrological dynamics and trends in water management, and in particular to understand the role of community sensitivity in triggering a shift in water policy toward allocation of more water to the environment. Additional model complexity such as incorporating the dynamics of crop diversification is left for future work. Nevertheless, despite these limitations, the accuracy of the modeled discharges presented in Figure 4 is deemed adequate for the purposes of this modeling exercise.

For cross validation, we calibrate (CV2) the model with observed discharge data at the upstream and downstream ends of the irrigation area and then validate with observed irrigated land area and delivered environment water. In order to carry out the validation, we selected the parameters for which the coefficient of determination (R^2) of simulated discharges at the upstream and downstream of irrigation area, relative to the observed data, is greater than 0.8. Figures 4e and 4g show the calibrated annual discharge at Gundagai and Carrathool. The coefficient of determination between observed and simulated discharge at Gundagai and Carrathool is 0.83, 0.81, respectively, while Nash-Sutcliffe efficiency is 0.51, 0.42, respectively, for the chosen median parameter set.

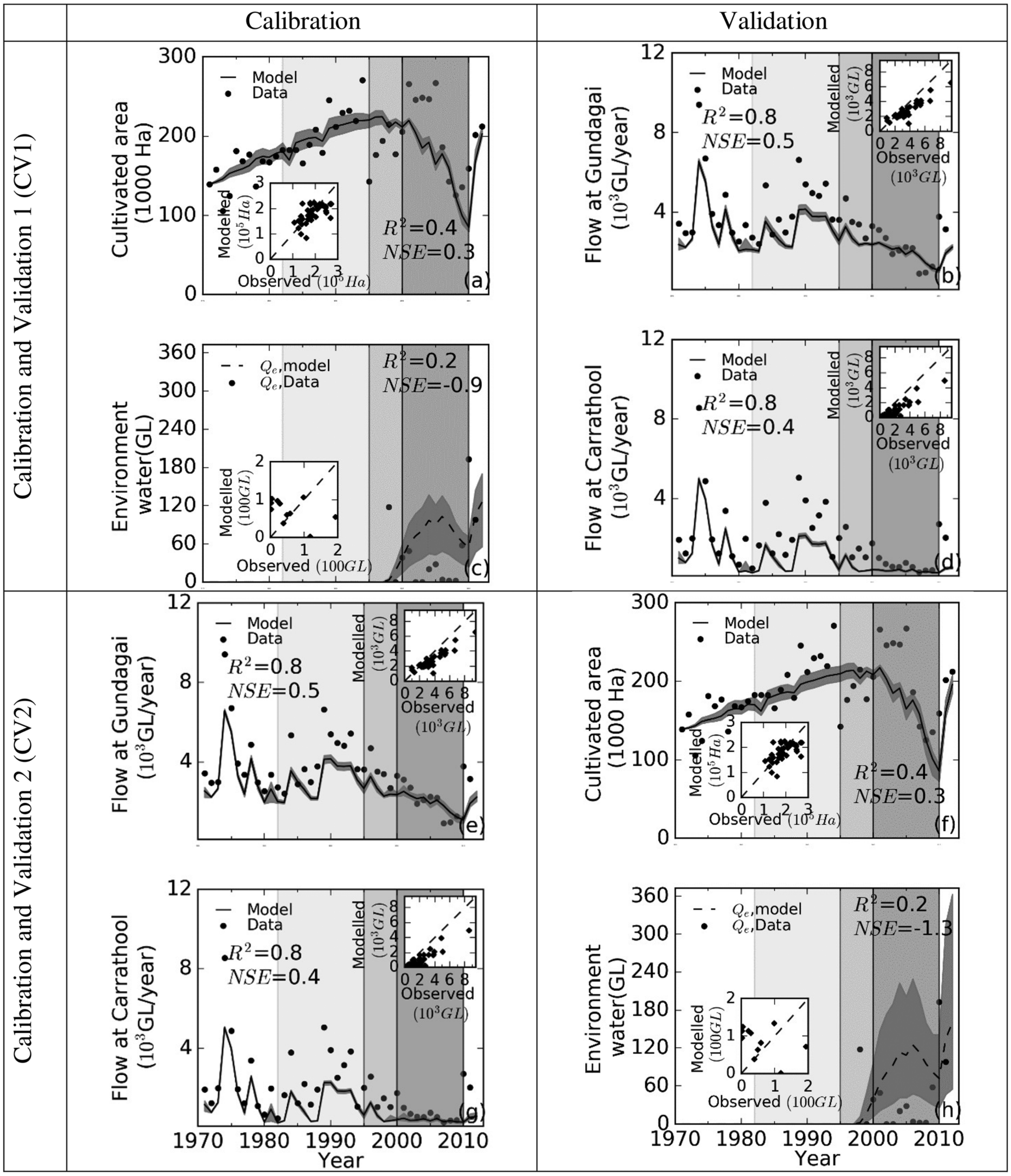

Figure 4. Cross calibration and validation of model CV1 and CV2. Comparison between observed and calibrated (CV1); (a) irrigated land area; (c) delivered environment water. Comparison between observed and validated (b) discharge at Gundagai (downstream of dams); and (d) discharge at Carrathool (downstream of irrigation districts). Comparison between observed and calibrated (CV2); (e) discharge at Gundagai (downstream of dams); and (g) discharge at Carrathool (downstream of irrigation districts). Comparison between observed and validated; (f) irrigated land area; (h) delivered environment water. Shaded area indicates 90% confidence interval. The line corresponds to the simulation using the median value of the uncertainty range for calibrated parameters. Cross validation increases the confidence on model robustness. Different columns of shaded areas indicate major events in water management from left to right: water reform began in 1982; cap was introduced in 1995; drought started in 2000; and drought broke in 2010.

Table 2
Model Performance Statistics for Calibration and Cross Validation

		CV1: When calibrating with irrigated land area and delivered environment water				CV2: When calibrating with discharge at upstream and downstream of irrigation area		
	Figure	RMSE	R^2	NSE	Figure	RMSE	R^2	NSE
Irrigated land	4a	34661.62 ha	0.37	0.29	4e	35589.45 ha	0.38	0.25
Environment water	4c	727.14 GL	0.24	−0.64	4g	896.54 GL	0.16	−1.50
Discharge at Gundagai	4b	1130.37 GL	0.82	0.50	4f	1124.01GL	0.83	0.51
Discharge at Carrathool	4d	1284.81GL	0.80	0.35	4h	1207.18 GL	0.81	0.43
Labor in agriculture	5b	2037.54	0.65	−3.93	NS	1607.20	0.74	−2.07
Labor in industry	5b	394.25	0.99	0.99	NS	394.25	0.99	0.99
Population	5d	1401.68	0.97	0.96	NS	217.83	0.96	0.90

Note. The gray correspond to the variables used for validation.
[a]NS—not shown.

Figures 4d and 4f show the validation results based on the comparison between observed and simulated irrigated land area and delivered environment water, respectively. The coefficient of determination between recorded and simulated irrigated land area and delivered environment water is $R^2 = 0.38$ and 0.17, respectively. Statistics of model performance of the chosen median parameter set are given in Table 2 for cross calibration and validation.

The performance of the model in the two steps of calibration and cross validation on simulated variables such as irrigated land area, delivered environment water, discharges at the upstream and downstream ends of the irrigation area are reported in Table 2. In addition, Table 2 reports on model performance for simulating labor in agriculture and industry sectors and the basin population. These are shown in Figure 5 and discussed in the next section. Model performance statistics, see also Table 2, for variables when the model is calibrated with irrigated land area, delivered environment water are close to the performance statics for the variables when it is calibrated on discharge at upstream and downstream of irrigation area (also considering the performance scores on validation variables shown in gray in Table 2). The fit with recorded population data were $R^2 = 0.96$, 0.97 in both cases. The correlation of model simulation with observed data on employment in agriculture and industry sectors is 0.66, 0.99 and 0.74, 0.99, respectively, in calibration and cross validation. This, in addition to model calibration and cross validation, demonstrates that model is not overparameterized. The model therefore provides a robust interpretation of the underlying sociohydrological dynamics. The calibration and cross validation on complementary information demonstrates that in spite of the seven parameters and complex closure relationships, the model does not overfit the data and in that sense, it is robust. Thus, even though the explanation of the underlying sociohydrological processes is simplified, the model is reliable. The performance of the model is similar to those in other sociohydrology modeling studies for different catchments (Lake Toolbin, Kissimmee River Basin) such as in Elshafei et al. (2015) and Chen et al. (2016).

3.2. Model Interpretation of the Unemployment and Population Dynamics

The set of parameters which gave better overall performance (CV1) was used to obtain Figure 5. Figure 5a shows that water allocation predominantly favored irrigated agriculture until the mid-1990s before it began an overall decline. This turn occurred as government policy “capped” water allocations (1995–1997) and began to buy back water entitlements (Kandasamy et al., 2014). It decreased further during the prolonged drought that occurred in the 2000–2010 period. During the period of cuts to the amount of water for agriculture (1995–2010), sectoral transformation occurred from the agriculture sector to the industrial sector (manufacturing and service sectors) (Figures 5b and 5c). Here the sectoral transformation (i.e., decreasing dependence on agriculture relative to other sectors) is demonstrated by the growth in employment in the industry sector (composed of manufacturing and service subsectors) and the post-1995 decline in agriculture. Figure 5b shows the number of employees in the agricultural sector, and in the industry sector. Figure 5c shows the employment share in the agricultural sector and the industry sector.

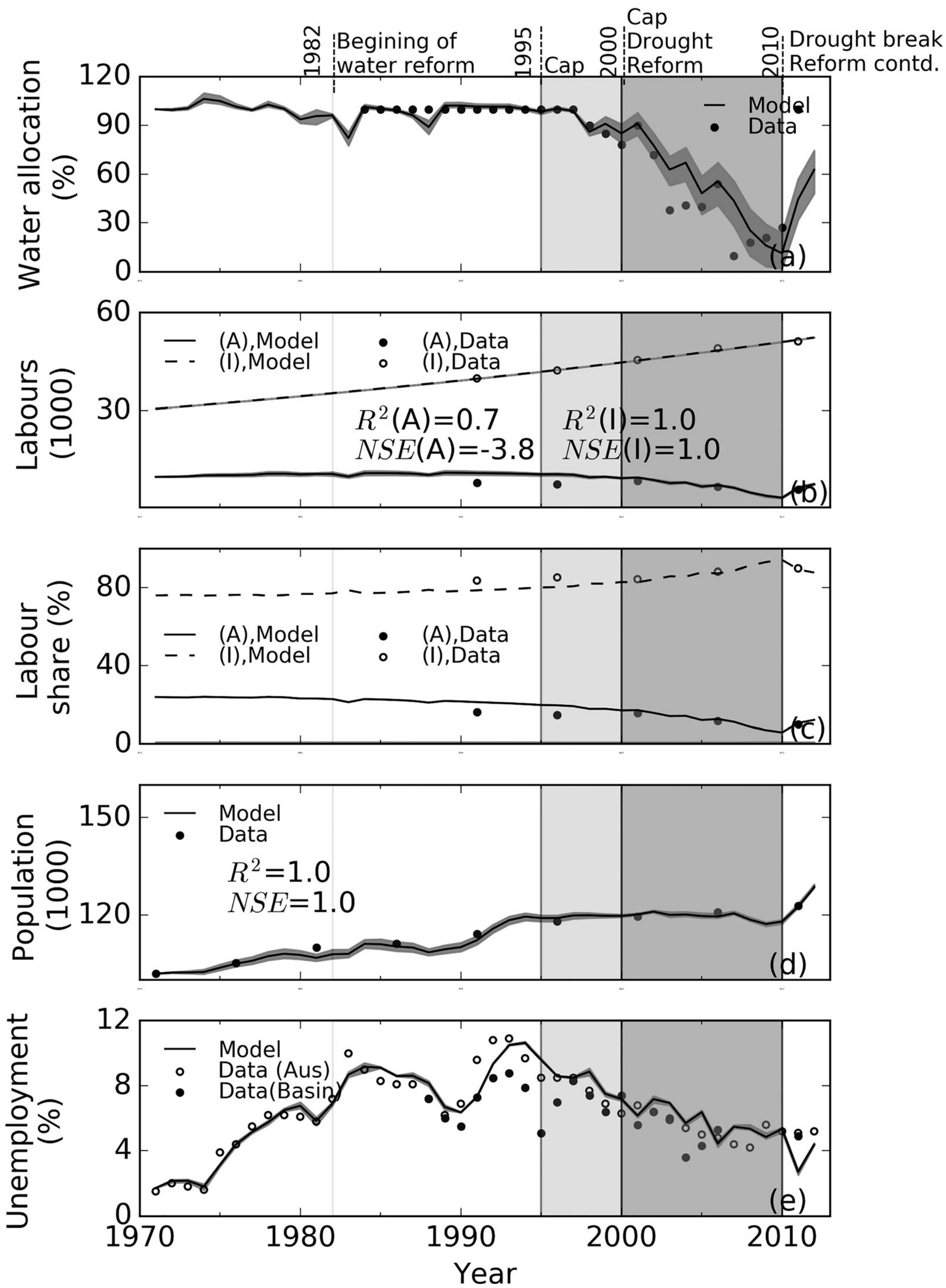

Figure 5. (a) Observed water allocation at the start of July and simulated average water allocation in Murrumbidgee basin; (b) observed and modeled employment in agriculture (A) and industry (I) sector; and (c) observed and modeled labor share in the agriculture (A) sector and industry (I) sector; (d) basin population (modeled and observed) of Murrumbidgee basin; and (e) unemployment rate (modeled and observed) in the basin and in Australia. Line and dots represent the model output and observed data respectively. Different columns of shaded areas indicate the major events in water management from left to right: water reform began in 1982; cap was introduced in 1995; drought started in 2000; and drought broke in 2010.

The employment in agriculture was primarily influenced by land area under cultivation (Bah, 2009), which in general has been found to be strongly influenced by the volume of water allocated to the agriculture sector (UN Water, 2016). The sectoral transformation was occurring even before 1995. Figure 5b shows that the growth in employment in the industry sector was faster than the decline in the agriculture sector (Figure 5b). The growth in the industry sector fueled by the growth in capital investments was the impetus for growth of employment in the industry sector. Meanwhile, diminishing availability of land and water resources constrained the growth of employment in the agriculture sector. Employment was further impacted by improved agricultural practices (i.e., mechanization, technology improvements, corporate farming practices, etc.).

Post-1995, the Murrumbidgee economy continued to transform and employment in the industry sector continued to grow while the employment in the agriculture sector declined (Figures 5b and 5c). This growth of employment and associated growth in production in the industrial sector supported the viability of the basin economy during a period of contraction of the agricultural sector. More water was available after 2010 as the Millennium Drought (which occurred between 2001 and 2010 period) receded, which resulted in a rise in agriculture employment. Nonetheless, the dependency of the basin economy on agriculture continued to decrease as the community became increasingly dependent on the industry sector.

Figure 5d shows a continuous increase in population between 1976 and 1995, before slowing down in the late 2000s. Basin population changed by natural causes (i.e., births, deaths) and by migration. When the water allocation to the agriculture sector decreased, employment in the agriculture sector dropped. Ordinarily this would have given rise to unemployment in the basin. However, this was not the case. Figure 5e shows that the unemployment in the Murrumbidgee dropped when water was allocated away from the agricultural sector. Workers that lost employment in the agriculture sector, moved to the industry sector and some even migrated out of the basin. This corroborates the conclusion drawn in Roobavannan et al. (2017) regarding how sectoral transformation and migration reduced the adverse impact of reallocation of agricultural water to the environment on the livelihoods of the MRB community.

3.3. Model Interpretation of Community Sensitivity

Community sensitivity closely follows the independent narratives of how community sentiment changed over time given in Kandasamy et al. (2014). Normalized community sensitivity (F(V)) passed the threshold level and showed peaks in the 1980s, 1997–2006, and 2008–2010 (see supporting information Figure B5(c) type1). At these times the community concern over environment degradation was high and the community sought actions to alleviate the issue.

The peaks of F(V) in 1980s did not translate to water diversion to the environment. Modeling shows the response function (X) was less than 0. Nonetheless the peaks in X identify periods of escalated community sentiment and concern (supporting information Figure B5(d) type1) that drove government policy reforms and funding that favored the environment. In 1982, coinciding with the first series of peaks, the Government commenced policy changes in response to widespread environmental degradation (salt intrusion, salinity, algal blooms, etc.; Kandasamy et al., 2014) culminating in 1987 when the Murray-Darling Basin Commission (MDBC) was given wider powers over the basin's natural resources. Despite this, agriculture water allocation remained high and serious ecological degradation persisted (loss of wetlands, native fish and birds; Kandasamy et al., 2014).

The widespread community concern (coinciding with peaks in X in 1997 and beyond which were greater than 0) provided the impetus for further policy reform to control the water usage such as water reform legislation, separation of water rights from land holding titles, temporary cap to water allocations in 1995 made permanent in 1997. In 2004, Federal and South Australian governments announced a package of measures aimed at reducing salinity, improving water quality and protecting biodiversity in the Murray-Darling region under the National Action Plan for Salinity and Water Quality and National Heritage Trust. Coinciding with the 2008 peak, the Water Act (2007) was passed in the Federal parliament, the Murray-Darling Basin Authority was established and the Prime Minister announced the AUD$10 billion basin plan for sustainable river management (Kandasamy et al., 2014).

The modeling over the simulation period (1971–2012) showed a turn-around from agricultural development and food production to community inspired reallocation of water back to the environment or "pendulum swing" (Kandasamy et al., 2014). Recently, Wei et al. (2017) showed using newspaper content analysis on water management issues that societal preference swung toward environmental sustainability after

1981(see Figure A4 in supporting information (SI) for comparison). Their results provide additional support to the interpretation of community sensitivity presented here.

4. Role of Sectoral Transformation in Changing Community Sensitivity and Water Reallocation

Recalibration Without Diversification. In order to understand the influence of economic diversification (or sectoral transformation) on community sensitivity and to test the hypothesis that diversification influenced community sensitivity to trigger environmental flow, we omit the term $\left(1-\exp\left(-\gamma_g\frac{D_a}{D_a+D_i}\right)\right)$ in Equation (9) (see section 2.2.7). The term accounts for the effect of the heterogeneity of society on community sensitivity arising from economic diversification. The equation, which we use to demonstrate the role of the diversification term, by its omission, now becomes:

$$\dot{V}=\gamma_v\left[\left(-\widetilde{E_s}-\widetilde{I_c}\right)\right]V \qquad (10)$$

Using this formulation of community sensitivity the model simulation was rerun with 100,000 random samples of parameters (uniform sampling) that lie within the parameter range obtained by the original analysis (see section 2.2.8). In all runs, the total delivered environment water (Q_E) is found to be 0. This shows that the normalized community sensitivity never passed the critical threshold to trigger environmental flows when the effect of diversification is absent or omitted. The model simulation shows that the hypothesis that economic transformation *did not* play a key role in swinging community sensitivity in favor of environmental protection is not supported. This indicates that the term $\left(1-\exp\left(-\gamma_g\frac{D_a}{D_a+D_i}\right)\right)$ in the model, which accounts for economic diversification, simulates the influence of sectoral transformation on community sensitivity in a representative manner. It appears that the basin community, over time, became increasingly favorably disposed toward the environment relative to economic growth, as the basin economy diversified toward an expanded industry sector and decreased its dependence on agriculture.

Sensitivity Test. This section presents results of further model runs, in the form of sensitivity analyses, to elucidate the effect of sectoral transformation on water reallocation and basin population growth. The labor force employed in agriculture in 1971 was increased in a series of model runs, from 0% (all industrial sector) to 100% (all agriculture sector), in order to understand the impact of sectoral transformation on community sensitivity, water allocation, and population. Other factors, such as initial number employed in the labor force, population, land area, and water, were kept the same.

Figure 6 shows how the total amount of environment water delivered over the model simulation period (1971–2012) changes when the initial agriculture labor share (in 1971) is increased. It shows how delivered environment water gradually decreased to 0 GL as initial agriculture labor share was increased to a case where 60% of the labor in 1971 was employed in agriculture. This demonstrates how a community that is more engaged and highly dependent on agriculture is less likely to acquiesce to a larger allocation of water back to the environment.

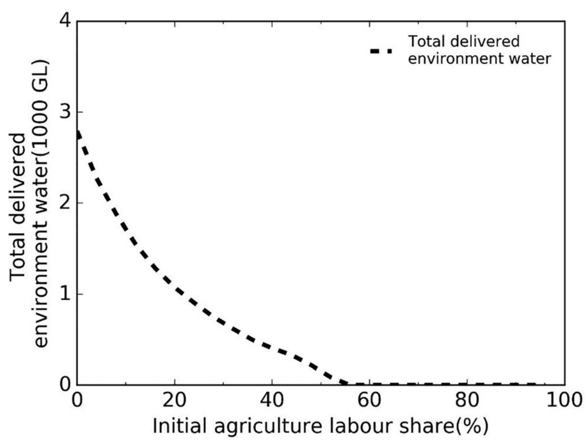

Figure 6. Total amount environment water delivered over the model simulation period (42 years); when the initial agriculture labor share in 1971 was increased from 0% (full industrial labor force) to 100% (full agricultural labor force).

This is further explained in Figure 7 which presents the internal dynamics of coupled system for different dependency of society on agriculture. Figures 7a and 7b show the ecosystem service (E_s) provided by the environment when the agriculture labor share in 1971 was 24% (which was actually the case for the Murrumbidgee basin in 1971) and 60% (a hypothetical scenario), respectively. Ecosystem mostly declined as agriculture extraction is increased. The two peaks in E_s coincide with periods of floods and periods of high annual discharges in the Murrumbidgee. A comparison of Figures 7a and 7b shows that when a higher percentage of the population is employed by agriculture and depends on it for their livelihood, ecosystem services degrade more. Despite this, Figure 7d shows that community sensitivity (V) remained low when agricultural labor share in 1971 was set to 60% (scenario case), despite environmental degradation being much higher. The community sentiment was less affected despite environmental concerns. By contrast Figure 7c shows that the community sensitivity rose over

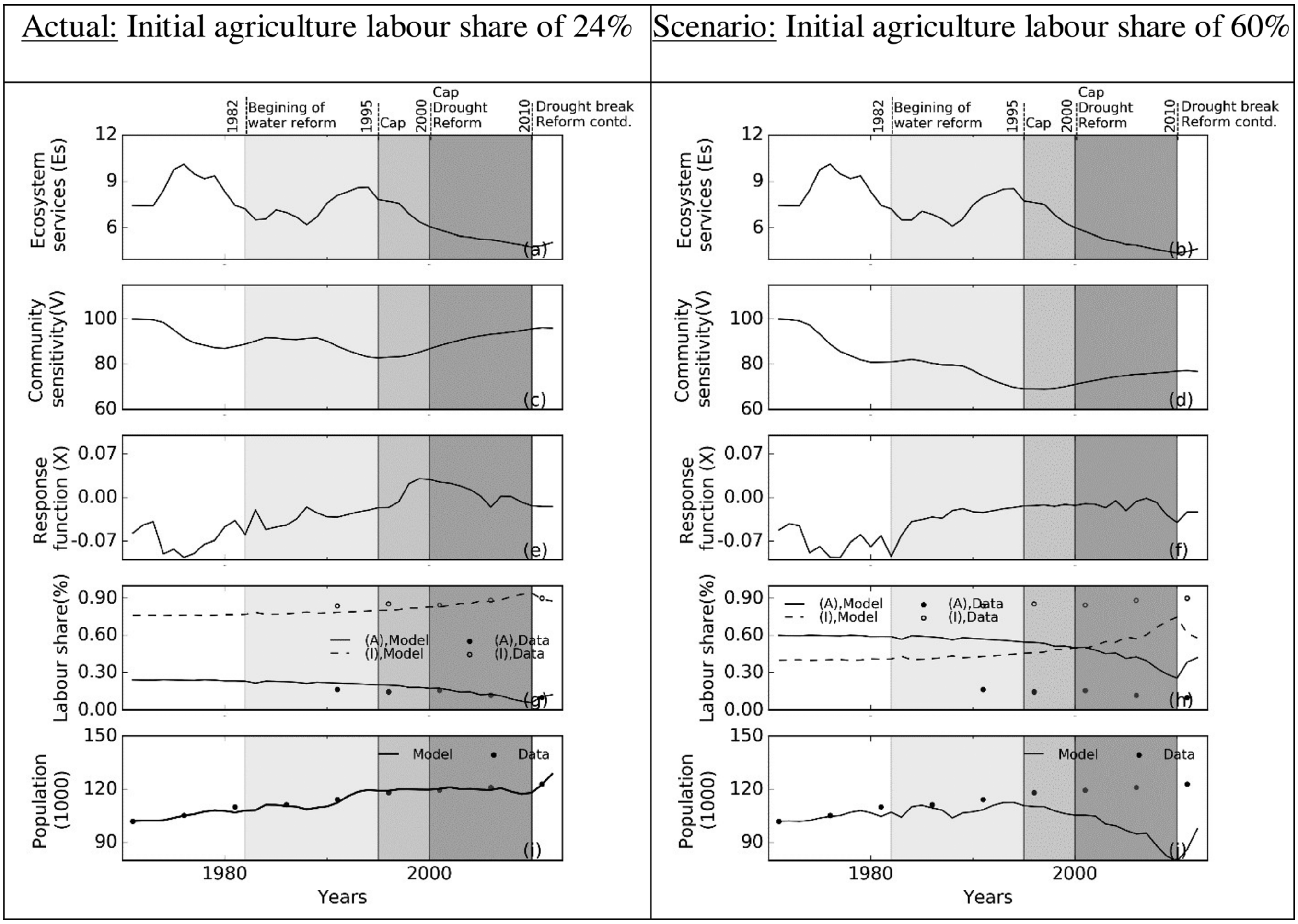

Figure 7. Simulated coupled dynamics of Murrumbidgee basin; (a and b) Ecosystem services (E_s); (c and d) community sensitivity (V); (e and f) response function (X); (g and h) agriculture labor share; (i and j) population. Plots (a, c, e, g, and i) show the dynamics in the actual case when initial agriculture share is 24%. Plots (b, d, f, h, and j) show the dynamics in the scenario when initial agriculture share is 60%. Economic diversification influenced community sensitivity. Different columns of shaded area indicate major events in water management from left to right: water reform began in 1982; cap was introduced in 1995; drought started in 2000; and drought broke in 2010.

the simulation period as the environment degraded when initial agriculture labor share was 24% (actual case).

The response function (X) models the overall degree and direction of action resulting from the competition between community sensitivity (V) to the environment and the demand for agricultural expansion (D_e) (see Equations (9a) and (9b)). X did not pass the zero level in the scenario (60%) indicating that throughout this period the community favored economic production over environmental protection. This meant that water reallocation to the environment was not triggered. In the actual case (24%), the response function is triggered whenever X was more than 0, leading to environmental water allocation (see Figure 4h).

In the scenario (60%), during the drought period (2000–2010) the share of labor engaged in agriculture dropped (Figures 7g and 7h), due to lack of water in the system. During this period labor in the agriculture sector lost employment and as a result unemployment rate increased. When a larger portion of the population depends on agriculture, more people become unemployed, translating into higher unemployment. In part, this impact is mitigated somewhat since some basin residents would migrate out of the basin, attracted by a better economy elsewhere outside the basin. This is seen in Figure 7i. The basin population over the period of drought decreased. This scenario demonstrates how a community can be prone to high economic stress, at a time when the climate is adverse (drought) and a greater portion of the population depends on the agriculture. By contrast for the case when the agricultural labor share in 1971 was 24%

(actual case in Murrumbidgee), Figure 7i shows that the population actually grew. Unemployed agriculture workers in the basin had the opportunity to obtain employment in the industrial sectors which grew strongly (Figure 7g). Meanwhile, in the scenario (60%) the growth in the industrial sector was not large enough to take all workers that were becoming employed in the agriculture sector. This led to higher out-migration and population decline.

The modeling over the simulation period (1971–2012) shows a turn-around from agricultural development and food production to community inspired reallocation of water back to the environment or what has been described as a "pendulum swing" (Kandasamy et al., 2014). The above narrative thus demonstrates that the CSR link-model that accounts for diversification provides an interpretation of the pendulum swing that is consistent with what had historically happened in the Murrumbidgee Basin (section 3.4) and robustly captures the dynamics and thresholds of the pendulum swing.

Discussion. Roobavannan et al. (2017) showed how the basin economy and the population size were impacted by the reallocation of water away from agriculture and how sectoral diversification and population movements reduced the impact of economic stress on the community. Their study used irrigated land area as an exogenous variable to drive changes in water allocation. This study extended the model further by demonstrating that the sectoral transformation made community more sensitive to the environment relative to the agriculture sector, consequently triggering a release of water to the environment at the cost of reduced allocation to the agricultural sector. The latter in turn fed back to reducing the irrigated land under cultivation, making this variable *endogenous*. The model simulated this change through the CSR link-model, which influenced the balance between the state of ecosystem services and GBP (Gross Basin Product) generated by all economic sectors of the basin. Sectoral transformation changed the Murrumbidgee society's values toward higher preference for the environment (relative to economic growth) over time and ultimately led to policy action that favored environmental restoration and protection. Essentially, sectoral transformation played a crucial role in facilitating environmental action in the Murrumbidgee. This is the first study that included the role of the broader economy (industry. i.e., manufacturing and services, together with agriculture), and its influence on community sentiment and the allocation of water. Previous studies included only the agriculture sector.

This study gives insights into the dynamics between agriculture and industrial sectors in a community and how the basin community was impacted by economic diversification. A similar dynamics was reported in the Kissimmee River basin, Florida (Chen et al., 2016) where the population's relative preferences for and between flood protection and ecosystem restoration was affected by the relative sizes and influences of the population between upstream and downstream parts of the basin, whose values about the environment and their own well-being were different.

5. Conclusions

This paper focused on the water-agriculture-environment nexus that has played out in the Murrumbidgee River Basin located in south-eastern Australia. A sociohydrological model, which included bidirectional feedbacks between human and water systems, was used to explore how the competition for water between humans and the environment was mediated in the basin, guided by endogenous changes in the community's preferences on water use. The model captured the feedbacks, internal dynamics, including threshold processes that resulted from changes in water management. It was tested using available data in a robust manner based on calibration and cross validation on complementary variables such as irrigated area, environmental flow, as well as measured streamflows.

Agriculture within the Murrumbidgee initially exhibited continued expansion when abundant land and water resources were available. The resulting growth in prosperity and accumulation of wealth (capital) paralleled the strong growth of the industry sector due to strong Australian economy. On the other hand, the expansion of agriculture by harnessing more water and land inevitably degraded the environment. As a result, community sensitivity to the degradation of the environment increased. This triggered community action to restore the environment through reallocation of water away from the agriculture and toward the environment. In our sociohydrological model, the Community Sensitivity Response (CSR) link-model mimicked the impetus for action toward environment-centric measures, i.e., reallocation of water back to the environment, when community sensitivity crossed a critical threshold. The model successfully captured the dynamics of community sensitivity, which initially favored agriculture expansion, only to reverse later in response to the deterioration of environmental health. This subsequently triggered changes in water management in favor of environmental degradation, leading to the decline of agriculture, and thus was able to simulate the occurrence of the pendulum swing.

Model simulations demonstrated that sectoral transformation played a crucial role in sensitizing the community about the environment. Model simulations indicated that sectoral transformation essentially changed the community's values toward higher preference for the environment, which ultimately led to policy action that directed the water back to the environment. Sensitivity analyses further corroborated it by demonstrating that a more diversified economy amplified the bias toward the environment.

The insights gained from this study provide a deeper explanation for the outcomes of our previous study (Roobavannan et al., 2017), which was limited to studying the roles of sectoral transformation and population migration in reducing the basin economic stress resulting from reduced water allocation to the agriculture sector. In this paper, instead of prescribing the reduced water allocation to the agriculture sector and its consequences for basin economy, we provided explanations for the sociohydrological mechanisms that contributed to the water reallocation to the environment.

The place-based sociohydrology model developed here is a useful tool that can be used to predict future trajectories of system behavior under changing hydroclimatic and/or socioeconomic conditions. More such place-based studies are needed for other human-water systems in different hydroclimatic, social, and economic regions to learn and identify what is unique and what is generally applicable. This will assist toward development of more generic human-water system models for application across different places. Generic sociohydrology models can then be used to answer diverse puzzles, such as how and why human values change and what are its effects, and to understand, interpret or explain phenomena, such as possible lock-ins (e.g., water ownership in the western United States, Sivapalan & Blöschl, 2015) and system collapses (e.g., Aral Sea, Maya civilization), including the circumstances under which these might happen (Pande & Sivapalan, 2016).

In stating this, we acknowledge that the structure of the sociohydrological model used here is very much tailored to the Murrumbidgee Basin in terms of type of economy, role of government, type of administration and level of support, the role of the community and how much it values the environment. Some limitations of the proposed model are: (1) water withdrawals from river for agriculture purposes have been decided based on fixed water use per hectare, which in reality is influenced by the types of crops grown and the climatic conditions; (2) an index based on the richness of fish species has been used as a surrogate for the provision of ecosystem services; and (3) catchment economy follows the same trend as the economy outside the basin. These simplifying assumptions can be relaxed in the future, e.g., by including an economic submodel that estimates production from the various economic sectors in the basin as well as outside the basin, capital formation and the gross basin product, which entails adding more and more complexity to the model to improve the realism of the model. These extensions are left to future research.

Acknowledgments
This paper falls within the framework of the Panta-Rhei Research Initiative of the International Association of Hydrological Sciences (IAHS). We would like to acknowledge the US National Science Foundation's Socio-Environmental Synthesis Center (SESYNC; NSF award DBI-1052875) for their support of the project "Toward Sociohydrologic Synthesis: Modeling the Co-evolutionary Dynamics of Coupled Human, Water, and Ecological System." M. Roobavannan acknowledges PhD funding provided by Australian Postgraduate Award. The paper benefited from constructive criticisms and suggestions from three anonymous reviewers for which we are grateful. Model data used in this study is deposited at 10.6084/m9.figshare.5120275.

References

ABS (2009, September 1987–October 2007), *6291.0.55.001 Labour Force, Australia, Detailed—Electronic delivery, Table 16A. Labour force status by regions and sex*). Retrieved from http://www.abs. gov.au/

ABS (2010), *Cat. No. 5260.0.55.002 Experimental estimates of industry multifactor productivity, Australia: Detailed productivity estimates*. Retrieved from http://www.abs.gov.au/

ABS (2012), *Gross value of irrigated agricultural production, 2000–01 to 2009–10, (4610.0.55.008*). Retrieved from http://www.abs.gov.au/ausstats/abs@.nsf/Products/4610.0.55.008 ∼2000-01+to+2009-10

ABS (2014), *Census*. Retrieved from http://www.abs.gov.au/census

ABS (2015), *6345.0 Wage Price Index, Australia,Table 9a. Ordinary hourly rates of pay excluding bonuses: Sector by industry, original (financial year index numbers for year ended june quarter)*. Retrieved from http://www.abs.gov.au

ABS (2016a). *4610.0—Water account for Australia, 1993–94 to 1996–97*. Retrieved from http://www.abs.gov.au/AUSSTATS/abs@.nsf/allprimarymainfeatures/56B72BBB0A118C6ECA256E980079E261?opendocument

ABS (2016b), *4618.0—Water use on Australian farms*. Retrieved from http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/4618.02014-15?OpenDocument

ABS (2016c), *1300.1—New South Wales year book*. Retrieved from http://www.abs.gov.au/ausstats/abs@.nsf/mf/1300.1/

Bah, E. M. (2009). *A three-sector model of structural transformation and economic* (Working Paper, pp. 1–38). Auckland, New Zealand: University of Auckland.

Bark, R., Kirby, M., Connor, J. D., & Crossman, N. D. (2014). Water allocation reform to meet environmental uses while sustaining irrigation: A case study of the Murray–Darling Basin, Australia. *Water Policy*, *16*, 739–754. https://doi.org/doi:10.2166/wp.2014.128

Beven, K. (2006). A manifesto for the equifinality thesis. *Journal of Hydrology*, *320*, 18–36. https://doi.org/doi:10.1016/j.jhydrol.2005.07.007
Beven, K., & Binley, A. (1992). The future of distributed models: Model calibration and uncertainty prediction. *Hydrological Processes*, *6*, 279–298. https://doi.org/doi:10.1002/hyp.3360060305
BOM (2016). Climate Data Online. Retrieved from http://www.bom.gov.au/climate/data/stations/
Chen, X., Wang, D., Tian, F., & Sivapalan, M. (2016). From channelization to restoration: Sociohydrologic modeling with changing community preferences in the Kissimmee River Basin, Florida. *Water Resources Research*, *52*, 1227–1244. https://doi.org/doi:10.1002/2015WR018194
Clewley, R. (2012). Hybrid models and biological model reduction with PyDSTool. *PLoS Computational Biology*, *8*(8), e1002628. https://doi.org/10.1371/journal.pcbi.1002628.
Cobb, C., & Douglas, P. (1928). A theory of production. *American Economic Review*, *18*, 139–165.
CSIRO (2008). Water availability in the Murrumbidgee: Summary of a report to the Australian Government from the CSIRO Murray-Darling Basin Sustainable Yields Project (pp. 1–12). Sydney, Australia.
Debertin, D. L. (2012). *Agricultural production economics* (2nd ed., pp. 1–431). New York: Macmillan Publishing Company.
Di Baldassarre, G., Kooy, M., Kemerink, J. S., & Brandimarte, L. (2013). Towards understanding the dynamic behaviour of floodplains as human-water systems. *Hydrology and Earth System Sciences*, *17*, 3235–3244. https://doi.org/doi:10.5194/hess-17-3235-2013
DPI water (2016). *Water alloaction statement-Murrumbidgee Valley-15-July-2016* (pp. 1–3). Sydney, Australia: NSW Department of Primary Industries Water.
Dunlop, M. (2001, 1 March). *Australian water use statistics: Report II of IV in a series on Australian Water Futures* (pp. 1–160). Canberra, Australia: CSIRO Sustainable Ecosystems.
DWE (2008). *Instream salinity models of NSW tributaries in the Murray-Darling Basin Volume 6—Murrumbidgee river salinity integrated quantity and quality model* (pp. 1–98). Sydney, Australia: Department of Water and Energy, NSW Government.
Elshafei, Y., Coletti, J. Z., Sivapalan, M., & Hipsey, M. R. (2015). A model of the socio-hydrologic dynamics in a semiarid catchment: Isolating feedbacks in the coupled human-hydrology system. *Water Resources Research*, *51*, 6442–6471. https://doi.org/10.1002/2015WR017048
Elshafei, Y., Sivapalan, M., Tonts, M., & Hipsey, M. R. (2014). A prototype framework for models of socio-hydrology: Identification of key feedback loops and parameterisation approach. *Hydrology and Earth System Sciences*, *18*, 2141–2166. https://doi.org/10.5194/hess-18-2141-2014
Gollin, D. (2002). Getting income shares right. *Journal of Political Economy*, *110*, 458–474.
Hope, M., & Wright, M. (2003). *Murrumbidgee catchment irrigation profile* (pp. 1–154). Dubbo, Australia: NSW Agriculture-NSW.
Houska, T., Multsch, S., Kraft, P., Frede, H.-G., & Breuer, L. (2014). Monte Carlo based calibration and uncertainty analysis of a coupled plant growth and hydrological model. *Biogeosciences*, *11*(2007), 2069–2082. https://doi.org/10.5194/bgd-10-19509-2013
Kandasamy, J., Sounthararajah, D., Sivabalan, P., Chanan, A., Vigneswaran, S., & Sivapalan, M. (2014). Socio-hydrologic drivers of the pendulum swing between agricultural development and environmental health: A case study from Murrumbidgee River basin, Australia. *Hydrology and Earth System Sciences*, *18*, 1027–1041. https://doi.org/doi:10.5194/hess-18-1027-2014
Liu, Y., Tian, F., Hu, H., & Sivapalan, M. (2014). Socio-hydrologic perspectives of the co-evolution of humans and water in the Tarim River basin, Western China: The Taiji-Tire model. *Hydrology and Earth System Sciences*, *18*, 1289–1303. https://doi.org/doi:10.5194/hess-18-1289-2014
Magnani, E. (2001). The Environmental Kuznets Curve: Development path or policy result?. *Environmental Modelling and Software*, *16*, 157–165. https://doi.org/doi:10.1016/S1364-8152(00)00079-7
Meyer, W. S. (2005). *The irrigation industry in the Murray and Murrumbidgee basins* (Tech. Rep. 03/05, pp. 1–137). Australia: CRC for Irrigation Futures, CSIRO.
MDBA (2017). MDBA-governance. Retrieved from https://www.mdba.gov.au/about-us/governance
MJA (2010), *Delivering the basin plan-economic and social profiles and impact assessments in the Murray-Darling basin-synthesis report* (pp. 1–244). Canberra, Australia.
MJA, RMCG, Consultants, E., Consultants, D., University, A.N., McLeod, G., Cummins, T., (2010). *Economic and social profiles and Darling basin plan: Synthesis report* (pp. 1–244). Melbourne, Australia.
Murray-Darling Basin Commission (2001), *Dryland Salinity in the Murrumbidgee Region What is it costing you?* (pp. 1–2), Australia.
Ngai, L. R., & Pissarides, C. A. (2004). Structural change in a multi-sector model of growth centre for economic performance (CEP Discussion Pap. 627, pp. 1–36). London, UK: London School of Economics and Political Science.
Office of Water (2014), *New South Wales Department of Primary Industries, Office of Water*. Retrieved from www.water.nsw.gov.au/Water-management/Water-availability/Water-accounting/default.aspx
O'Gorman, E. (2013). Growing rice on the Murrumbidgee River: Cultures, politics, and practices of food production and water use, 1900 to 2012. *Journal of Australian Studies*, *37*, 96–115. https://doi.org/doi:10.1080/14443058.2012.748673
Pannell, D. J. (2001). Dryland salinity: Economic, scientific, social and policy dimensions. *Australian Journal of Agricultural and Resources Economics*, *45*, 517–546. https:doi.org/10.1111/1467-8489.00156
Pande, S., & Sivapalan, M. (2016). Progress in socio-hydrology: A meta-analysis of challenges and opportunities. *WIREs Water*, *4*, c1193. https://doi.org/doi:10.1002/wat2.1193
Roobavannan, M., Kandasamy, J., Pande, S., Vigneswaran, S., & Sivapalan, M. (2017). Allocating environmental water and impact on basin unemployment: Role of a diversified economy. *Ecological Economics*, *136*, 178–188. https://doi.org/10.1016/j.ecolecon.2017.02.006
Singh, R. P., Mullen, J., & Jayasuriya, R. (2005). Farming systems in the Murrumbidgee irrigation area of NSW: An economic analysis (Econ. Res. Rep. 10, pp. 1–5). Yanco, Australia: NSW Department of Primary Industries. Retrieved from http://www.agric.nsw.gov.au/reader/10550
Sivapalan, M., & Blöschl, G. (2015). Time scale interactions and the coevolution of humans and water. *Water Resources Research*, *51*, 6988–7022. https://doi.org/doi:10.1002/2015WR017896
Stone, M. (1973). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society: Series B*, *36*, 111–147.
Swainson, B., Loë, R. D., & Kreutzwiser, R. (2011). Sharing water with nature: Insights on environmental water allocation from a case study of the Murrumbidgee catchment, Australia. *Water Alternatives*, *4*, 15–34.
Troy, T. J., Pavao-Zuckerman, M., & Evans, T. P. (2015). Debates-Perspectives on socio-hydrology: Socio-hydrologic modeling: Tradeoffs, hypothesis testing, and validation. *Water Resources Research*, *51*, 4806–4814. https://doi.org/doi:10.1002/2015WR017046
UN Water (2016). *WWAP (United Nations World Water Assessment Programme) (2016)* (pp. 1–148). Paris, France: The United Nations World Water Development Report 2016: Water and Jobs.

van Emmerik, T. H. M., Li, Z., Sivapalan, M., Pande, S., Kandasamy, J., Savenije, H. H. G., . . . Vigneswaran, S. (2014). Socio-hydrologic modeling to understand and mediate the competition for water between agriculture development and environmental health: Murrumbidgee River Basin, Australia. *Hydrology and Earth System Sciences*, *18*, 4239–4259. https://doi.org/doi:10.5194/hess-18-4239-2014

Water NSW (2014). *Water NSW*. Retrieved from http://waterinfo.nsw.gov.au/about/data.shtml

Water Act (2007), *An Act to make provision for the management of the water resources of the Murray-Darling Basin, and to make provision for other matters of national interest in relation to water and water information, and for related purposes*. Australia: Federal Register of Legislation. Retrieved from www.legislation.gov.au/Details/C2017C00151, assessed 6 October 2017

Wei, J., Wei, Y., & Western, A. (2017). Evolution of the societal value of water resources for economic development versus environmental sustainability in Australia from 1843 to 2011. *Global Environmental Change*, *42*, 82–92. https://doi.org/doi:10.1016/j.gloenvcha.2016.12.005

World Bank (2014), *Wold Bank indicators*. Retrieved from http://data.worldbank.org/indicator

Yoshikawa, S., Yanagawa, A., Iwasaki, Y., Sui, P., Koirala, S., Hirano, K., . . . Kanae, S. (2014). Illustrating a new global-scale approach to estimating potential reduction in fish species richness due to flow alteration. *Hydrology and Earth System Sciences*, *18*, 621–630. https://doi.org/doi:10.5194/hess-18-621-2014

Yu, D. J., Sangwan, N., Sung, K., Chen, X., & Merwade, V. (2017). Incorporating institutions and collective action into a sociohydrological model of flood resilience. *Water Resources Research*, *53*, 1336–1353. https://doi.org/doi:10.1002/2016WR019746