David Adamson and Adam Loch

Overcoming deterministic limits to robustness tests of decision-making given incomplete information: the state contingent analysis approach

Water Economics and Policy, 2022; 8(4): 2240011

Electronic version of an article published as Water Economics and Policy, 2022; 8(4): 2240011. DOI: http://dx.doi.org/10.1142/S2382624X22400112

Overcoming deterministic limits to robustness tests of decision-making given incomplete information: the state contingent analysis approach

Adamson, David[†] and Loch, Adam[†*]

[†] Centre for Global Food and Resources, The University of Adelaide, Adelaide, South Australia, 5005

[*] Corresponding author: Adam Loch adam.loch@adelaide.edu.au | P: +61 8 8313 9131

ORCID: David Adamson (0000-0003-1616-968X); Adam Loch (0000-0002-1436-8768)

Abstract

Incomplete information may result in multiple factors combining to jointly affect the consequences of decision-making. The typical response to incomplete information has been tests of robustness and a fixed decisions' capacity to withstand a wide variety of future conditions. But what of reversed contexts, where the revealed future alters decision-making via experience, learning and innovation such that the decision itself changes? In this paper we contrast a commonly applied expected value robustness metric to state contingent analysis which allows for learning and innovation. State contingent analysis views robustness as how decision-makers achieve profits across all future states by reallocating resources *ex post* to maximize payoffs and/or minimize losses via outputs that are conditionally specific. Consequently, the state-contingent approach enables researchers to identify the benefits and constraints of resource reallocation—rather than fixed decision-making—over plausible scenarios. Within SCA, scenarios can thus be uncoupled from the historical averages to explore rare events, even if never before experienced, including thin- and fat-tailed probability distribution outcomes and their impact on decision-making, innovation and future solutions. A case study assessment of water resource management in a large river basin provides the basis for our comparison. We find that expected value models mask innovation and adaptation reactions by decision-makers in response to external stimuli (e.g., increased droughts) and under-represent water reallocation outcomes. Conversely, state contingent models represent and report decision-maker reactions that can be more readily interpreted and linked to stimuli including policy interventions, expanding the study of complex human-water systems.

Key words: state contingent, robustness tests, decision-making, water, risk

JEL codes: D81, Q25, Q54

Key Points:

- Current robustness tests of decision-making do not allow for feedback meaning innovation and modelling adaptation responses are constrained
- Adaptation to climate change under policy design, assessment and modification requires effective modelling approaches reflecting innovation/non-deterministic pathways
- We suggest state contingent analysis as a modelling alternative which better illustrates learning and the need for decoupled plausible scenarios in the climate and water policy space

Acknowledgments, Samples, and Data

- There are no conflicts of interest to declare. Thanks are extended to Nikki Dumbrell and Liam Wagner for helpful comments during the preparation of this work. Collaborative funding for this paper was provided by an ARC DECRA Grant DE160100213 *Optimising National Benefits from Restoring Environmental Water Flows*, and an ARC DECRA Grant DE150100328 *Transaction costs in Murray-Darling Basin water reform*. Full datasets are available online at http://www.uq.edu.au/rsmg/

Declarations: None applicable

Introduction

In the long-run everything changes but how that will occur, and how individual decision-makers with flexible options may respond to change options, is yet to be revealed. Climate change is a prime example (Kandlikar, Risbey, & Dessai, 2005) where future water resources will change based on probabilistic (risky) and non-probabilistic (uncertain) outcomes that may be difficult to accurately define and quantify for relevant scientific and social factors from a global to local scale. Where incomplete information is part of the quantitative calculation researchers have come to rely on expected outcomes to system changes as a basis for decision-making (McPhail et al., 2018). However, over long time horizons (e.g. 70-100 years) our capacity to combine multiple factors is especially challenging (Maier et al., 2016). This has led researchers to adopt processes capable of identifying *plausible* future scenarios without necessarily ranking their likelihood (Döll & Romero-Lankao, 2017). As pointed out by several studies (see for example Herman, Reed, Zeff, & Characklis, 2015; Kwakkel, Eker, & Pruyt, 2016), this approach has resulted in tests of decision robustness in the face of incomplete information via alternative metrics, such that the chosen solution will withstand a wide variety of outcomes (i.e., robustness or resilience to change). However, this represents non-adaptation to emerging realities. In other words, a decision-maker maintains their adopted solution no matter the realized future outcomes. While applicable for some large-scale investments, this approach may not represent how *individuals* with flexible choices respond to protect their capital.

Robustness metric calculation involves specifying alternative solutions (e.g. policy options), performance outcomes (e.g. minimum cost), and plausible future conditions/scenarios under which the solution/performance interaction will occur. While iterative processes to redesign a solution may be undertaken to improve robustness, it will be conditional upon how the future unfolds. But the ultimate aim is to define and test how expected consequences related to the selected solution and/or to minimize any undesirable outcomes (Kwakkel et al., 2016). Robustness metrics commonly applied include i) expected values of performance across a range of scenarios, ii) satisficing scenarios with acceptable performance relative to thresholds, iii) regret-based differentials between selected option performance given plausible future outcomes and the best possible option for those conditions, and iv) higher-order moments such as variance and skewness that inform performance across multiple scenarios. All of these metrics reflect varied levels of risk aversion, and differ in how they define and deal with robustness (McPhail et al., 2018).

However, when decision-makers respond to incomplete information via adopting flexible management solutions surely this differs from existing fixed-solution choice robustness metric calculations. That is, where revealed states of nature affect decision-making via feedback or adaptation at local/small-scale levels, Ben-Tal et al.'s (2009) deterministic and set-based factors which define the state of the world must also change. Any movement away from set paths and historic values increases the complexity of factors to derive metrics for, and incorporate into, robustness tests. This is because complex systems may react to external stimuli, especially when decision innovation is supported over routine choices (Jean-Paul Chavas & Nauges, 2020; Dow, 2020). In such contexts learning and innovation is not only expected for traditional perspectives of robustness or resilience, it is also more likely where decision-makers regularly adapt (e.g. operational or strategic choices versus long-term infrastructure or hydrological investments). Learning and adaption will also depend on individual experience and recognition by each state of nature (Goldstein & Gigerenzer, 2002). A critical example of these adaptation concepts is water use and management given common variability in supply/demand and a significant connection to human and natural systems. Thus, where information on complex economic, social and physical environments is incomplete we may need to study human-water systems in more general and alternative ways to improve our explanatory and scenario development capability (Sivapalan et al., 2014).

This is because complex interrelated systems provide scope for unintended consequences to both public and private decision-making (Dow, 2020). For example, Pindyck (2011) and Quiggin (2019) describe the relevance of correctly identifying and describing impacts of thin- or fat-tailed probability distributions which drive different decision solutions and performance objectives—and ultimately a cumulative risk-sharing utility (Quiggin, 1982). In such cases, information about distribution tails for key variables should be quantified or assigned a level of confidence (Mastrandrea et al., 2010) to ensure the data is taken into account (e.g. separately defined drought states) including measures that separate dispersion and means to provide valuable trade-off information (Kwakkel et al., 2016). Thus, when modelling new pathways that stem from innovation to decision-maker routines it will be necessary that the role of institutions, policy-makers and any firm/household decision-makers be included (Quiggin, 2019) such that public/private investment decisions can be pivoted to effectively target, mitigate, prevent or adapt to future climate change shocks (Mazzucato, 2013); currently the tails of the distribution.

In this paper we examine an additional robustness metric model that allows the study of reversed interactions between revealed states of nature and altered decisions; the state contingent analysis (SCA) approach. The key to SCA is that it separates the future state signal from the response to that future state, allowing for profit maximizing/loss minimizing outcomes to be determined from alternative individual management responses (i.e. reallocation of inputs). SCA assumes that we can completely describe plausible futures into a set of mutually exclusive states of nature. For example, in the case of this paper we know that future water supply can either be what we have expected over the long run (i.e. normal), greater than anticipated (i.e. wet); or less than we require (i.e. dry). While the decision-maker may have some awareness of the frequency of each state of nature, they do not have the ability to influence which state occurs However, for each state of nature, we can describe a set of management options that require a set of inputs, and each management strategy provides a state-described outcome. Therefore, once the state is revealed, decision-makers have complete information on how to respond (Chambers and Quiggin 2000).

In SCA modelling robustness is viewed as how decision-makers adapt to conditions by reallocating resources, maximizing payoffs (or minimizing losses) in response to state outcomes due to inductive reasoning, or experiencing the failure of existing routines and a need to innovate in response (Grant & Quiggin, 2012). When we understand the payoffs over different states of nature we are better placed to identify the benefits over the plausible scenarios (Arrow, 1953) and can incorporate states of nature based on thin- or fat-tailed conditions. We then have the capacity to explore how management solutions can be designed to respond to known state of nature frequencies, and explore how new solution decisions change in response to external stimuli and altered reallocation or payoffs. This capacity then also allows for the payoff of current and future strategies to be explored when states alter, or new states that have not been previously experienced come to fruition. Following Goldstein and Gigerenzer (2002), learning is state dependent and representable through the introduction of an error term defining a stochastic range. As experience increases, we can reduce the size of the error term, and this represents learning and adaption.

Having detailed the SCA approach we then compare its results to that of a common robustness metric in the literature, the expected value (EV) method, and evaluate the insights these alternative approaches provide for state of nature drivers on learning/innovation outcomes in decision-making. This process allows us to answer three questions. First, is it possible to adapt the perfect foresight SCA model used by Adamson et al. (2009) through an incorporation of stochastic bounds to represent incomplete information problems such as climate change adaptation, and test robust decision-making? Second, if this is possible, what can we learn from comparing stochastic bounded SCA model results to perfect foresight EV models of how decision-makers' may innovate/learn to reallocate water resources in response to future climate change? Third, what do these results suggest for robust metric modelling of decision-making in complex interrelated system settings under incomplete information? Decision-making and innovation/learning insights from comparing these modelling approaches is based on a case study of agricultural production and land/water use reallocation choices in Australia's Murray–Darling Basin (MDB). Climate change in the MDB illustrates a need to shift from routine to innovative choices where future outcomes may be known (e.g., decreased rainfall), but the full set of choices (both allowing and motivating innovative adaptation) remains incomplete. We begin with a description of the MDB and its production/water systems as a basis for the model data before shifting to an explanation of the two analytical approaches.

2 Study context: Australia's MDB

In Australia's Murray-Darling Basin (MDB) water resources are over-allocated. On average the MDB has 25,467GL (gigalitres or one billion litres) of conjunctive water resources (runoff rather than river or storage inflows) that contributes to annual allocable water resources shared between users. This volume is primarily derived from rainfall (23,925GL) and groundwater aquifers (1,424GL), while 1,118GL are transferred into the MDB from the Snowy Basin (Adamson, Quiggin, & Quiggin, 2011). However, averages are misleading when dealing with water resources. The MDB has the second most variable water flows in the world (McMahon & Finlayson, 1991) and the Darling River is the most variable river system globally (Khan, 2008). To access these resources approximately 19,300GL of water right entitlements have been issued, but the annual conjunctive and allocable water resources average around 11,000GL per annum (BoM, 2020). This over-allocation creates conflict between economic, social and environmental users, and climate change is expected to reduce the future volume of water available exacerbating that conflict. Critically for the purposes of our case study, any misallocation of water resources will increase fragility of economic, social and environmental systems and lower their capacity to respond effectively.

As stated above, a prime example of plausible future states of nature in the MDB is climate change which is expected to increase the frequency of MDB extreme flood and drought events. Both extreme events will be triggered by altered spatial and temporal patterns of rainfall, but the general consensus for Australia is that droughts will become more frequent and more severe (IPCC, 2018). As 88 per cent of irrigation supplies in the Basin are derived from surface flows (Adamson et al., 2011) understanding future rainfall and runoff patterns is critical. However, outcome predictions are bounded by the complexities involved in upscaling and downscaling climate models (Berrocal, Craigmile, & Guttorp, 2012; Whetton, Grose, & Hennessy, 2016). This scaling issue creates confusion and considerable incomplete information for local and smaller-scaled decision-makers, as well as those charged with managing the resources at basin scale. For example, if we use proportional downscaling models based on an assumption that four per cent of MDB rainfall becomes surface runoff (Australian Bureau of Statistics, 2008) we could assume a linear relationship between rainfall to runoff. However, Austin et al. (2010) found that this relationship is not linear. The spatial and temporal nature of rainfall and the landscape rainfall-runoff attributes incur an elasticity of two to three-times (i.e., a 10% decline in rainfall equates up to a 20 to 30% reduction in runoff), making future natural variability predictions and the identification of viable economic, social and environmental solutions difficult. This problem statement may be served by the plausible future robustness metrics described above.

But new plausible futures will shape the bio-physical characteristics of surface runoff and soil moisture and possibly fall outside past or current decision-making experience. Further, where decision-makers fail to correctly identify and parameterize these future production inputs (e.g., water) and outputs (i.e., changing comparative advantage) then economic, social and environmental capital will all be similarly exposed (Kingwell & Farre, 2009). To prevent capital loss Jodha (1991) argues decision-makers must incorporate flexibility into their decision systems and rapidly innovate based on past and new information when signals are 'ecologically rational' (Goldstein & Gigerenzer, 2002). However, as Mallawaarachchi and Foster (2009) and Loch et al. (2012) discuss, any adaptation to climate signals is dependent on the flexibility of institutional frameworks and available solutions (e.g., capacity to trade water), the decision-maker's cognitive capacity (e.g., bounded rationality or attitude to learning), and existing production system constraints (e.g., perennial versus annual cropping systems)—issues not typically represented by or incorporated into the traditional robustness metrics described earlier. In this paper we argue that by explicitly representing what we understand about plausible future states, alternative public/private capacity to recognize those states, and incomplete (non-deterministic) response sets applicable to these settings we can identify when/how institutional or decision-maker solutions fail—and innovative decisions with increased adaptive flexibility (robustness). This flexibility should theoretically lead to robust outcomes which not only adapt to past and new plausible scenarios, but also provide greater capacity to respond to future events.

3 Modelling incomplete information and resource (re)allocation

With this context in mind and, given our focus on robustness tests, we next detail the EV and SCA approaches used in our comparisons. Each approach involves a deterministic (complete information) and stochastic (plausible) model specification. To frame our resource reallocation analysis—which is a focus of traditional economic study—we begin with a general discussion of how economic modelling deals with incomplete information.

3.1 Traditional production economics approaches

Incomplete information in economics is typically modelled via sensitivity analysis to explore the mean and variance of probability distributions that positively/negatively impact costs/benefits (Merrifield, 1997). However, in such analyses the decision-maker remains passive to external stimuli and incapable of innovation/learning or operating within nonlinear parameters. Downside risk has motivated economic researchers to expand beyond mean-variance approaches (e.g., by including skewness) to explore innovation/technology adoption impacts on our thin- or fat-tailed payoff distributions (Jean-Paul Chavas & Nauges, 2020). For example, in production economic applications, modelling resource reallocation often involves a passive decision-making response based upon the mean and an error term. This formed the basis of Just & Pope's (1978) critical review of stochastic production functions where the general form of their model is:

$$\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{X}, \boldsymbol{\varepsilon}). \tag{1}$$

The error term (ε) provides a stochastic description of final output based on set combinations of inputs (X). However, the error term is frequently based on past data where known mean and variance parameterize a probability distribution function. Monte-Carlo simulations allow for a series of outcome-runs to determine the likelihood of investment decisions making a return, given expected pricing outcomes. Taking these issues into account, Just and Pope concluded that while the generalized function is appropriate for empirical work, it remains unsatisfactory for dealing with plausible futures. Prior to this, Rothschild & Stiglitz (1970, 1971) noted the limitations of relying on mean-variance by illustrating the results of choosing between variables with the same expected value, but different distributions. A critical limitation, commonly known as *Mean Preserving Spread,* identifies how alternative weights in the distribution of tails can result in investors choosing riskier rather than safer investments by assuming the decision-maker remains passive to signals provided. As discussed, Pindyck (2011) argues climate change events can have thin- or fat-tailed outcomes and may transition between these two outcomes; possibly within short time frames due to the complex systems involved. Thus, modelling which fails to account for these plausible outcomes may represent a decision-maker (e.g., farmer) as one who refuses to adapt in the face of required change no matter the signal; which as discussed is unrealistic given different approaches to innovation/learning. Despite this conclusion, the use of stochastic production functions is common within the literature when dealing with production decisions under incomplete information. We detail a common modelling approach below.

3.2 Expected value modelling approaches

In expected value (EV) models future economic return $E[Y]$ is calculated by multiplying each possible outcome by the likelihood it will occur and then summing those values to provide a long-run average or mean. In a simple application/equation, deterministic parameters are used. For example, agricultural decision-makers will maximize returns with respect to available area A of production systems (δ).[1] Final returns are subject to yield Q, market prices P and production costs C (Equation 2):

$$\boldsymbol{E}[\boldsymbol{Y}] = \textstyle\sum_{\boldsymbol{\delta}}\left[\boldsymbol{A}^{\boldsymbol{\delta}} \times \boldsymbol{Q}^{\boldsymbol{\delta}} \times (\boldsymbol{P}-\boldsymbol{C})^{\boldsymbol{\delta}}\right] \tag{2}$$

This then provides a single point estimate of an outcome (Figure 1a). In such a world we are modelling complete information. However, we can relax the deterministic equation above and adapt it to climate change problems—as an example of incomplete information—by incorporating stochastic representations via the addition of an error term ε (as in Figure 1b) to describe final outputs based on random combinations of inputs, and to represent plausible futures (Equation 3). We keep P constant to minimise multiplicative uncertainty to explore how the availability and demand for water alters decision-making between different models:

$$\boldsymbol{E}[\boldsymbol{Y}\boldsymbol{\varepsilon}] = \textstyle\sum_{\boldsymbol{\delta}}\left[\boldsymbol{A}_{\boldsymbol{\varepsilon}}^{\boldsymbol{\delta}} \times \boldsymbol{Q}_{\boldsymbol{\varepsilon}}^{\boldsymbol{\delta}} \times \left(\boldsymbol{P}^{\boldsymbol{\delta}} - \boldsymbol{C}_{\boldsymbol{\varepsilon}}^{\boldsymbol{\delta}}\right)\right] \tag{3}$$

Recall that stochastic representations acknowledge the inherent natural variability within a system but also assume decision-makers do not innovate/learn in response to external stimuli, thereby potentially misallocating resources (Chambers & Quiggin, 2000; Chavas, Chambers, & Pope, 2010). However, this version of the model is more comparable to alternative SCA approaches for determining how decision-makers may reallocate resources in response to a changing climate.

3.3 State contingent analysis modelling approaches

Early SCA studies used the term ‘states of nature’ when discussing the assessment of production choices under exogenous plausible futures. SCA allows for active decision-making

---

[1] For the models three terms are critical: 21 production system (δ) choices in total for state contingent modelling; for each production system there is a defined commodity (M) dependent on states that defines the inputs and outputs by that state; and 16 production systems for the EV modelling which are based on normal state production systems only. See Table 2 which describes these systems and the adaptation contrast between SCA and EV.

responses to revealed or anticipated future states of nature (e.g., climate change impacts such as increased frequency of drought events). It therefore reduces problems of incomplete information and resource misallocation that could be driven by applications of a stochastic EV model (Just & Pope, 1978).

The earliest work was undertaken by Arrow (1953) and Debreu (1959), providing capacity to represent how decision-makers respond to realized and/or plausible future states (e.g., drought/flood events). Graham (1981) used this approach to explore farmers' willingness to pay for a public dam project that provided water supply in dry states of nature, and flood mitigation in wet states. However, it was Hirshleifer's (1965, 1966)[2] work that articulated clear differences between dominant mean-variance approaches and state of nature representations of incomplete information risk. According to Hirshleifer (1965), state of nature approaches remove the "vagueness" (pg. 534) associated with some robustness test methodologies, as it allows the decision-maker to precisely identify both the natural endowments provided in a given state and the factors of production required to obtain an output in that state of nature. This finding has been reiterated in more recent studies (e.g. Adamson & Loch, 2021; Hildebrandt & Knoke, 2011).

Chambers and Quiggin (2000) subsequently extended the state of nature approach by merging it with dual optimisation to illustrate how resource allocations represent adjusting input use in all states by time, place and type (Rasmussen, 2003)[3]. Following this work, the state of nature approach became the SCA approach. In the SCA approach, nature $(\boldsymbol{\Omega})$ defines the state space that can be divided into a series of states of nature (s) to define real and mutually-exclusive sets (S) describing plausible futures $(\boldsymbol{\Omega} = \{1, 2, \dots, s, \dots, S\})$. Importantly the decision-maker has no ability to influence which s occurs; s is determined exogenously (Figure 1c where triangles represent distribution by dry, normal and wet states). Further, the decision-maker's subjective belief about the frequency $(\boldsymbol{\pi})$ of each s occurring is a probability vector described by $(\boldsymbol{\pi} = \pi_1, \dots, \pi_s)$. However, for each s the decision-maker has a set of solutions giving rise to alternative commodity options (*M*) dependent on the state outcome—see Table 1 for details. This can be represented (Equation 4) by a "continuous input correspondence, $\boldsymbol{X}: \boldsymbol{\Re}_+^{\boldsymbol{S}} \to \boldsymbol{\Re}_+^{\boldsymbol{N}}$, which maps state-contingent inputs into output sets that are capable of producing that state-contingent output vector" (Chambers & Quiggin, 2002, pg. 514):

$$\boldsymbol{X}(\mathbf{z}) = \{\boldsymbol{x} \in \boldsymbol{\Re}_+^{\boldsymbol{N}}: \mathbf{x\ can\ produce\ z}\}. \tag{4}$$

The basic form of the state contingent approach to model production risk and incomplete information is:

$$\mathbf{y_S} = \boldsymbol{f}(\mathbf{x}_s) \ \ \mathbf{s} \in \boldsymbol{\Omega} = \{\mathbf{1}, \dots, \mathbf{S}\} \tag{5}$$

where output (y) is described from a specific crop (x) produced within a single state of nature (s). Rasmussen (2006) argues that outcomes (i.e., yields and prices) arise from states of nature, implying the use of stochastic functions. Chavas (2008) used this concept to illustrate the output from a decision when inputs had to be allocated before the state was fully realized, in line with traditional robustness tests outlined above. By highlighting the reliability of state conditions or what we expect within a state (e.g., quantity of rainfall in a drought) we can illustrate production heterogeneity within the model (i.e., variable yields in a given state of nature), the amount of input required by state (i.e., water requirements for a state commodity choice) and importantly

---

[2] Note Hirshleifer (1965) uses the term 'state-preference' rather than Arrow's (1953) states of nature.

[3] Refers to three input types: i) ***non-state-specific (or state-general)*** inputs that must be allocated *ex-ante* to the s being realized, and which influence z in all s; ii) ***state-specific inputs*** that are applied *ex-post* to the realisation of s, and which influence z in only that s; and iii) ***state allocable (flexible) inputs*** that are applied *ex-ante* to s being realized, but where benefits accrue once s is realized.

the solution response to extant conditions (i.e., variation with a state decreases through time via learning). Now climate change can also be represented by altering the states' variance. This can be written as:

$$\mathbf{y_S} = \boldsymbol{f}(\boldsymbol{x_s}\,, \boldsymbol{\varepsilon_s})\ \mathbf{s} \in \boldsymbol{\Omega} = \{\mathbf{1}, \dots, \mathbf{S}\}. \tag{6}$$

This sets climate variability and resource reallocation by placing boundaries on incomplete information about future states, and illustrating a decision-makers' capacity to learn and apply appropriate contingency measures. When the re-introduction of stochastic errors are applied independently to either the state of nature, the state specific inputs requirements, or the state described outputs, then the environmental signal and the response to that signal can be separated. This separation minimizes multiplicative and additive uncertainty found in approaches with multiple stochastic functions. Applications of this approach can either follow Chavas' (2008) two stage decision model (i.e., fixed inputs allocated before the state was revealed) or mimic capacity to reallocate resources once the state is revealed and learning or innovation occurs. The concept of a two-stage decision is analogous to describing the error term from Equation 6 to simulate the solution using a Monte-Carlo simulation (Liddle & Monahan, 1988). For our paper this is referred to as the simulated or *ex-ante* (i.e., before the state is revealed) solution. The second approach occurs when decision-makers can reallocate resources after the state reveals itself. This is analogous to having perfect awareness and is modelled through Monte-Carlo optimisation using Equation 6 where new data is drawn from the deterministic distribution. In this paper, we label this the *ex-post* (complete information) solution. A triangular distribution has been used to set hard bounds (Equation 7). As the distance between bounds increases the fuzziness proportionally increases:

$$y_s = \begin{cases} \frac{2(y_s - a_s)}{(c_s - a_s)(b_s - a_s)} \text{ if } a_s \leq y_s \leq c_s \\ \frac{2(b_s - y_s)}{(b_s - c_s)(b_s - a_s)} \text{ if } c_s \leq y_s \leq b_s \end{cases} \tag{7}$$

Note that in our study the state of nature is a special case in this formula. River flow can only be $a_s \geq 0$ but the minimum and maximum water supply is confined by other state of nature mean flows and must not exceed c of the proceeding and subsequent states of nature. For example, if state 1 = dry, state 2 = normal, and state 3 = wet then $c_1 \leq b_2 \leq \ c_2$. This prevents obscuring the signal.

In our SCA models, a complete set of states explicitly internalizes plausible futures and allows for deterministic approaches using complete information to be estimated for a 10-year investment horizon. This specification means that individual decision-makers have perfect awareness about all future states of nature (i.e., a dry state is always identical through time), any commodity always requires the same volume of irrigation water (and other inputs) in each state of nature, and outputs through time are constant within each state. This equation can be expanded to mimic the stochastic EV model specification above, where the probability of state occurrence π, production systems, state commodity selections, yields, market prices and costs are all state specific (Equation 8):

$$\boldsymbol{E}[\boldsymbol{Y}] = \sum_{\boldsymbol{\delta}} \sum_{\boldsymbol{S}} \boldsymbol{\pi_S} \left[\boldsymbol{A^\delta} \times \boldsymbol{Q_S^\delta} \times \ (\boldsymbol{P} - \boldsymbol{C})_S^\delta\right] \tag{8}$$

This version of the model is aligned to a perfect knowledge outcome, where all probabilities are known in advance. Chambers and Quiggin (2000) argue that representing perfect foresight problems within a state contingent approach allows for solutions to be generated using standard optimisation techniques applied to problems not involving incomplete information. For example, using a perfect foresight model, Adamson et al. (2009) illustrated how SCA can encapsulate economic, environmental and social objectives while predicting how irrigators respond to climatic variability and change. By explicitly representing water variability by state (i.e., dry, normal and wet), and decision responses to that state (change in inputs or production system), they determined that changes in the frequency of dry states was a greater factor in decision-maker allocation of capital than the reduction in water supply by state outcome. However, they concluded that when optimising with complete deterministic awareness while the theoretical optimum may be obtained the solution will be inflexible, as any natural variability in the description of the state and the inputs required in each state is ignored. Further, in that case, as the solution was derived from a directed river flow/network model any incomplete information would violate the optimisation constraints and ultimately result not only in misallocated resources but in solutions that could compound negative externalities.

To counter these outcomes, an uncoupled determination and incorporation of probability outcomes in the model may be achieved via a stochastic SCA version. To model an agricultural production problem under incomplete information the model must incorporate a stochastic representation of either the state of nature (e.g., dry) and/or those inputs required by each state of nature (e.g., additional water resources). Examining each commodity option separately prevents the environmental signal and the response to that signal from being misinterpreted. Importantly, relaxation of the deterministic values permits decision-makers to innovate/learn in response to new signals within defined bounds. Further, a stochastic representation of outputs by state of nature is not needed as the ultimate constraint is the total future volume of water to share between all users. State described output is a function of the state and the inputs available as below:

$$\boldsymbol{E}[\boldsymbol{Y_\varepsilon}] = \sum_{\delta} \sum_{\boldsymbol{S}} \boldsymbol{\pi_S} \left[\boldsymbol{A^\delta} \times \boldsymbol{Q_S^\delta} \times (\boldsymbol{P} - \boldsymbol{C})_S^\delta\right]. \tag{9}$$

As π_S is the probability of the state occurring, $\sum \pi_S = 1$ (i.e., every state is identified), where $0 < \pi \leq 1$ (i.e., the states must have a chance of occurring). Here the frequency of state occurrence π 1 to 3 = (0.2, 0.5, 0.3). Within those frequencies, the volume of water that is available, based on expected long term average inflows derived from MDBC (2006) is dry (0.6 x Normal Inflows), and wet (1.2 x Normal Inflows). Decision-makers are expected to respond to these state outcomes by reallocating output. By altering the volume available in normal states we can then explore the impact of climate change (see below).

3.4 Additional model specification requirements

Returning to our MDB case study, climate change compounds externalities associated with over-allocated and ill-defined water property rights (Young & McColl, 2009). These negative externalities include loss of natural capital (Kingsford, 2000), high salinity (Keating et al., 2002; Yaron & Bresler, 1970), urban water quality reduction (Adamson, Schrobback, & Quiggin, 2008) and the inability of the irrigation network to deliver water to all users when required (Robertson & Wang, 2004). Consequently, to deal with inequitable resource reallocations, future shares of water in the MDB are constrained by environmental and social objectives to internalize these externalities (Commonwealth of Australia, 2008). We account for these issues with extensions to the model specification, as below. The model aims to maximize economic return (Equations 2, 3, 8 and 9) from using water for irrigation in a spatially explicit representation of regional comparative advantage in production by state of nature (S = dry, normal and wet). Commodity options δ equal 16 in the EV models and 21 in the SCA models. This difference is due to the SCA model's capacity to transition in and out of return-generating activity Y by state of nature. The river system is modelled as an undeveloped network with natural inflows and salt loads by state of nature. As water is extracted for irrigation the return flows transport salt back into the river network, thereby highlighting the opportunity cost of water use by location. The models are optimized from a national good perspective (i.e., a benevolent individual controlling all resources to maximize returns across catchments subject to environmental needs and social requirements for salinity levels in water). This then mimics the complex interrelated system described at the beginning of the paper.

For each model specification the relevant equations are summarized in Table 2. Maximized economic return is always subject to maintaining the City of Adelaide's water quality at less than 800 electrical conductivity (EC) in each state of nature, in at least 95% of years. The measurement of salinity in milligrams per litre (σ) is converted into EC by dividing it by 0.64 (Equations 10-13). The volume of water used in the basin must also always be less than the Cap[4] on average (i.e., as long as the average Cap is not violated you may use up to the Cap in a given state of nature) as specified in Equations 14-17. In the model extractions described for the urban and dryland use under the Cap, all catchments apart from Adelaide are removed from inflow before the model is optimized to ensure that they received their water allocations. The Cap has been transformed simply into diversions for irrigation purposes. Equations 18-21 ensure that water use in a catchment must be less than or equal to the flow in that catchment, while Equations 22-25 state that the area dedicated to horticulture in any catchment must be less than or equal to the horticultural constraint in that area. Equations 26-29 ensure that the total area dedicated to irrigation in any region must be less than the total area available in that region. Finally, Equations 30-33 ensure that there is sufficient operator labour to undertake the irrigation activity mix in a region (r).

The costs for producing one hectare of state-dependent commodity M for each catchment K in each state S can be written as the sum of capital costs (i.e., capital costs do not change by state of nature and are modelled as an annual cost), plus operator labour costs LC (i.e., hours L is multiplied by a constant price LP), plus variable costs VC (Equation 38). Finally, Equation 39 details the variable production costs which are derived from the sum of casual labour CL (i.e., hours multiplied by a constant price), contractor costs Con, machinery costs Ma, chemical costs Ch, plus water use W multiplied by water price Wp and the sum of any other costs Ot.

$$\mathrm{R_{ks}} = \sum (\mathrm{CC_k} + \mathrm{LC_{ks}} + \mathrm{VC_{ks}}) \tag{38}$$

$$\mathrm{VC_{ks}} = \sum (\mathrm{CL_{ks}} + \mathrm{Con_{ks}} + \mathrm{Ma_{ks}} + \mathrm{Ch_{ks}} + (\mathrm{W_{ks}} \times \mathrm{Wp_{ks}}) + \mathrm{Ot_{ks}}) \tag{39}$$

Once again, Equations 30-33 in Table 2 deal with the amount of operator labour L required to produce $\Sigma\,\delta$ in K. Here we ensure that the amount of labour in a region derived from ABS (2004) data and based on number of farms multiplied by two people by 2,500 hours/person is adequate to meet the needs of the chosen production systems.

3.5 Models and data

The models were developed in Microsoft Excel using the Risk Solver Platform from Frontline Systems v.12. In line with our earlier definitions of ex-ante and ex-post models the platform uses a Monte-Carlo approach in two different ways—again, as depicted in Figure 1. First, for all ex-ante models the solution is optimized once (i.e. production systems are held constant) and then the robustness of that model is tested 1,000 times by exploring either a stochastic representation of water input requirements (i.e. ex-ante inputs) or the description of

[4] The Cap refers the 1997 limit on long term diversions. Here the term Cap is interchangeable with the economic consumptive diversion limit (CDL) or environmental sustainable diversion limit (SDL) depending on which scenario is run.

the state of nature (i.e. total water supply, ex-ante state). Under this constraint, simulating water requirements for the production systems we see change to water quality (e.g., salt levels), water flows and the hard environmental targets (i.e. flows to the Coorong). We recognize that under this approach the environment is forced to assume all risk, which is unrealistic, but simplifies things. As shown in Appendix Table A3, ex-ante water input model runs are depicted in Runs 2, 7, 12, 17 and 22 while ex-ante state are Runs 4, 9, 14, 19 and 24. These runs allow us to see how either the water requirements or water supply impact on water quality (Equations 10 and 12) and water flow constraints (Equation 18 and 21).

Second, the ex-post models are optimized 1,000 times with a complete description of either the inputs required by state of nature (i.e. ex-post inputs Runs 3, 8, 13, 18 and 23) or the state of nature total water supply (i.e. ex-post state Runs 5, 10, 15, 20 and 25). For input requirements we can then see how production systems are optimized while meeting salinity constraints (Equation 11 and 13) and flow constraints (Equations 19 and 21). By altering one variable at a time we minimize multiplicative uncertainty and determine whether it is the description of the inputs or the states that have the largest impact on reallocating land between production systems, farm profit, water use, residual flow and water quality outcomes. Logically, the ex-post with complete information is the theoretically maximum allocation of resources. This approach follows Adamson et al. (2007).

The optimization algorithm used was the Large Scale SQP Engine to deal with the non-linearity of river flow. Each of the models uses a conjunctive approach to water resources as described above. Consequently, total water inflows are dependent upon surface supplies, ground water supplies and inter-basin transfers. The model uses a directed flow network where the Basin is divided into 21 catchments consisting of the 19 irrigation areas plus the City of Adelaide and the Coorong (default flow to sea). Production area by catchment K is a matrix of commodity choices dependent of the state outcome $(K \times \delta) \times \mathrm{S}$ (Table 1). There are 23 production systems consisting of state commodity choices, the City of Adelaide's water supply, and a dryland production system. Catchments (e.g., the Condamine as described in Table 3 and further detailed in Appendix Table A1) are based on disaggregated Catchment Management Regions to help model the directed flow network (water and salt). Water flows (*fks*) out of a given catchment are equal to inflows (net of evaporation and seepage) less extractions (net of return flows). Extractions are determined endogenously by land use decisions as described below, subject to limits imposed by the availability of both surface and groundwater (Equations 34-37, Table 2). This structure allows for the determination of total irrigation use, flow to the Coorong, and water quality arriving at the City of Adelaide.

The second critical factor in describing A is the matrix δ where the state contingent production systems are defined. Each state of nature outcome drives an independent commodity representation of yields Q, prices P, costs of production C and input requirements N such that each matrix has a form of (21 x 23). This data is based on a series of regional gross margin budgets that provide the data for the five inputs modelled (*N* = water, land, labour, capital and cash input). The agricultural systems are derived from $(\mathrm{K} \times \mathrm{M}) \times \mathrm{S}$, where in this case *M* represents commodities. A commodity is a single enterprise under a given state in a given catchment. This version of the model has 15 distinct commodities (*M*) plus urban water for the City of Adelaide and water for the Coorong. Consequently, there are (M+2) x S distinct state-contingent commodities. Yield Q has a dimension of $(\mathrm{K} \times \mathrm{M}) \times S$ which represents the output derived for that state of nature. Net return per hectare is described in the model as (*P*-*C*). Price P paid for output has a matrix of $(\mathrm{M} \times \mathrm{S})$. For simplicity it has been assumed that the price paid in all regions for each commodity is uniform by state of nature.

Because the model is solved on an annual basis, the process of capital investment is modelled as an annuity representing the amortized value of the capital costs over the 10-year lifespan of the development activity. This allows us to model a range of pricing rules for capital, and to represent the imposition of appropriate constraints on adjustment to derive both short-run and long-run solutions. The state contingent approach also allows for discontinuous environmental and production functions to be classified as alternatives within each state of nature. This specification of environmental, urban or private requirement by state of nature helps determine the type and number of water property rights needed to meet that demand. For all scenarios examined in this paper, Equations 34-37 apply only to those scenarios that specify a minimum flow of 1,000 GL reaching the Coorong. Alternative studies could incorporate environmental targets along the river system to stipulate river flow constraints along the system as either flow targets by each state of nature (i.e., dry, normal or wet) or on average over the states of nature. Finally, climate change is represented in our models as the difference between i) current state conditions (experienced) and ii) two alternative climate scenarios (plausible) where average atmospheric carbon levels reach 550 parts per million (ppm) under constant state frequencies (Runs 11-15 and 16-20 in Appendix Table A3) for the EV and SCA models, and a second where climate change is represented as an increase in the frequency of dry states under current climate conditions (Runs 21-25 in Appendix Table A3). .The second scenario is only run in the SCA model because the EV does not explore tails. This approach builds on Quiggin et al. (2010), and is incorporated in the ex-ante/ex-post runs. For a complete set of model outputs please refer to the Appendix materials Tables A3 to A5 online.

4 Results

Recall that our first research question queried if it is possible to represent incomplete information problems via stochastic bounds across the model types. In simple terms this is possible, and our results suggest that deterministic (complete information) EV models align well to stochastic (plausible future) SCA model specifications. This can be illustrated via a consideration of how land and water resources are reallocated across the MDB in response to different event outcomes (Table 4). EV modelled economic returns during dry and wet events, even when modelled by input or state, are non-existent. By contrast, the deterministic, input and state SCA models return more nuanced results across all states for both current and future climate conditions. Note though that both salinity and Coorong flow results are differentiated between the deterministic and input/state EV models, where wet and dry condition outcomes drive some reallocation above zero values. This suggests that the ex-post inputs model, and both the ex-ante and ex-post state EV models, have some capacity to respond to stochastic events with respect to those model constraints—but not others. Thus, the deterministic EV models appear to ignore (not represent) environmental signals.

Note also the water use results in Table 4. In both current and future climate conditions water use in dry and wet conditions falls to zero across the full set of EV models, with only the mean (normal) values being reported. While all models have the same bounds, the capacity of the SCA models to capture and report differences in the frequency of state events allows for kinks in the available water supply in gigalitres (Figure 2). Akin to thinking by Guttman et al. (2006), differences between rational experience, informed decision-making and discontinuities arising from innovation or learning may appear as kinks. Their work finds no evidence of smoothing in financial markets; why then would we expect to find it in complex natural systems? In our models, changes in event frequency (e.g., more drought) causes decision kinks to move inversely. In the EV models these might be interpreted as noise, rather than adaptation decisions in response to altered state outcomes, and be ignored as such.

Production reallocation decision results are also interesting across the commodity model runs, especially for horticulture crops between the EV and SCA models (Table 5). Note what happens in the area by state of nature. Under increasing climate change, the EV model is unable to respond to the extreme tails in the distribution, sticking instead to mean values. This shrinks the total area dedicated to irrigation and fundamentally alters the institutional characteristics of the system. By contrast, the SCA model reallocates land under production during good seasons to offset lower returns in the drought (e.g., wheat/cotton). In this situation we see the SCA model reallocates water away from those commodities that always use water towards those that stop irrigating in dry years (e.g. Flex cotton and Flex Rice)—and as opposed to those that crop every year in a fixed pattern. Opportunistic irrigation will only occur in wet years (Dryland Cotton and Dryland Wheat)[5], when the frequency of dry states increases. See the Appendix for further elaboration on this complex process which represents decision-maker adaptation to the plausible future signals provided, and model capacity to represent innovation/learning over adherence to familiar decision pathways based on experience (i.e., routines).

The requirement for models to take state of nature tails into consideration—and prompt innovation or learning (note the change in area between SCA State, ex-ante and SCA State ex-post between Rice Flex and Wheat Dryland)—is also borne out in predicted water flows by state which enables us to look more closely at the importance of variability. Under the deterministic EV and SCA models demand will quickly outstrip supply in dry states, threatening river system shutdown. But, equally, the models will fail to report decision-makers' willingness to use abundant water resources during wet periods. Model solutions that fail to account properly, or at all, for system bounds and the full extent of outcome variance ultimately fail. Figure 3 puts this into perspective across the model runs. The EV model data range for both deterministic and stochastic representations of inputs falls within the estimated bounds of the deterministic SCA model. This suggests that the EV model cannot progress past the range of the deterministic (deterministic or historic data-coupled) SCA, is constrained by the tails, and suggests decision-makers cannot learn to adapt or innovate to change. This is unrealistic as we have discussed above. Further, differences between the ex-ante (plausible) and ex-post (complete information) models also illustrate the positive benefits of innovation/learning by decision-makers.

As both Quiggin (2019) and Pindyck (2011) have noted, tails in the distribution have serious implications for understanding climate change, and rare events often have far greater consequence than we give them credit for. Thus, any approach that cannot represent both the possible impact and solution consequences to rare events may lead to a serious underinvestment in flexible or adaptive responses leading to long term economic, environmental or social losses. Considering the time required to optimize between a deterministic model and a stochastic model and the outcomes from the model, a deterministic SCA model provides significant insights for minimal time.

These findings provide insights for our second research question about why models of decision-making must be capable of representing innovation or learning in response to future uncertain events (e.g., climate change). Logically, as inputs change and the comparative advantage of commodity choices alter, decisions should alter as well. For example, as complete information about the future significance of dry states increase (ex-ante) the need to transition away from perennial commodities that require water in all states (i.e., horticulture) will increase. As Adamson and Loch (2021) show, insufficient water for horticulture crops across all state outcomes may result in irreversible capital losses (i.e., root stock loss). Models that do not take

[5] Remember Table 3 where water use by SCA production system is produced. Rice is not grown in the Condamine so appears as 0 ML/Ha in all states.

irreversible outcomes into account are invalid in agricultural (and other) decision contexts comprising horticulture and may skew the interpretation or full set of public/private decision options. As plausible future events impose input shocks this will require public/private goals, institutions or behaviour decision sets to innovate and adapt in order to achieve long-run resilience; and models of robustness tests must appropriately capture and reflect such learning and innovation.

Figure 4 illustrates this requirement using Coorong flow results as a test of model robustness. The deterministic SCA model provides a stable flow of water that is consistent with policy and system constraints (i.e., realistic). The three EV model runs transfer an increasing volume of water to Coorong flows as water is transitioned away from production under mean (normal condition) use assumptions that, in reality, are unsustainable. Importantly, in Figure 4 we see that even with three EV models we cannot represent a change in the frequency of alternative states of nature (or bad events occurring) as the current climate and frequency runs are close to identical. In other words, again it appears as noise in the outcomes. Thus, even the deterministic SCA model provides greater capacity to deal with changes to incomplete information over time.

This finding is contrary to that of Adamson et al. (2009) where the frequency of bad states had greater impacts on reallocating investments than a proportional mean reduction in average inflows. In those earlier models, production area decreased but the investment decisions remained constant. Thus, the EV model is incapable of seeing the difference in state frequencies and generates the same results for current and future climate; even once the climate has altered (i.e., EV state, ex-post frequency). If the model is representing a mean-reduction in water availability (i.e., the 550 ex-post run), then a difference in the EV results will appear. This is a problem for drought policy. If we model future climate adaptation as an increase in the frequency of bad events, an EV model will not represent change. This also links back to our Figure 1 representations of the model differences and supports the expected model outcomes.

Finally, we compared all model representations of drought water flows to the Coorong Wetlands, as shown in Figure 5. It is clear that the deterministic EV and ex-ante EV results lead to situations where no flow to the Coorong occurs, as those models fail to understand the risk to the conjunctive resource base. In essence the EV model then places bounds around the analysis and would create a completely unknown/unexpected outcome. Any failure to consider water demand upstream could lead to the collapse of the Coorong; a key management flow target with irreversible loss implications. In reality, basin managers might allocate less water to irrigation which could in turn lead to a solution choice creating irreversible private capital losses.

By acknowledging that alternative states of nature exist, the SCA model constraints are achieved in the deterministic and the ex-post input evaluation. The deterministic model (i.e., SCA, Inputs ex-ante results) would be expected to fail in 50% of years and not 5% of years; violating a key salinity performance objective for the river system. This suggests that production/commodity system choices must transition away from always requiring water in each state of nature (i.e., reduction in perennial crops), as detailed by Loch, Adamson, and Auricht (2020). Critically, the difference between the deterministic and ex-post SCA model occurs as the ex-post model actively reallocates resources towards opportunistically irrigating with substantial shifts towards “dryland cotton” and “dryland wheat” as illustrated in Table 2.

5 Concluding Comments

We have shown that climate change problems are well characterized as incomplete information events with some ambiguity in the set of performance objectives and the full set of appropriate solutions in response. Our comparison suggests that SCA modelling of land and water reallocation more robustly represents and evaluates public policy and private investment decisions than deterministic/stochastic EV models which is the more commonly adopted approach for economic and robust metrics modelling of incomplete information with respect to plausible futures. This is based on our findings that applications of state contingent analysis using deterministic data allows for an improved representation and understanding of plausible future events (i.e., adverse and positive states of nature) together with model recognition that—once incomplete information is addressed—decision-makers innovate/learn consistent with Marshallian views. Stochastic SCA models also facilitate assessment of policy or investment goals so that they can be tested for fragility, unrealistic conclusions, and/or irreversible loss outcomes.

Applications of the stochastic SCA model description and its bounds allows for an exploration of the level of risk associated with state-described input use, thus overcoming issues associated with thin- or fat-tailed event distributions and non-linear climate change events (Rosser, 2011). This is not possible using EV model approaches. By comparing ex-ante and ex-post results we are able to identify the value of being prepared for future adverse events, and selecting adaptation/investment choices in response to preserve capital (i.e., natural, economic, social, cultural etc.) Further, deterministic SCA models provide better outcomes than stochastic EV models due to the above-stated capacity to represent solution responses to thin- or fat-tailed outcomes. This conclusion is supported by the SCA model's capacity to clearly separate the signal from the individual's decision response, and thus inform how distribution tails contribute to reallocation choices. This separation helps identify the importance of tail events and helps identify where existing knowledge, technology and known management responses fail—even where plausible future scenarios do not reflect states of nature previously experienced. We could further apply such analysis and undertake sensitivity testing to determine when systems may fail and/or enter the active set of possibilities, and this would provide lessons for on-going management adaptation at both private and public levels. Future research paths and questions will be informed by an increased awareness of the full set of contingencies that may/may not be applicable under future climate change. Such research will enhance future innovation and adaptation and tests of robustness in the literature given the call to explore complex inter-relationships in human-water systems. However, in practice, the success of those choices will still be constrained by decision-maker bounds to awareness, and any truly Knightian uncertain events that may arise.

References

Adamson, D., & Loch, A. (2021). Incorporating uncertainty in the economic evaluation of capital investments for water use efficiency improvements. *Land Economics, 97*(3), 655-671.

Adamson, D., Mallawaarachchi, T., & Quiggin, J. (2007). Water use and salinity in the Murray-Darling Basin: A state-contingent model. *Australian Journal of Agricultural and Resource Economics, 51*(3), 263-281.

Adamson, D., Mallawaarachchi, T., & Quiggin, J. (2009). Declining inflows and more frequent droughts in the Murray–Darling Basin: climate change, impacts and adaptation. *Australian Journal of Agricultural and Resource Economics, 53*(3), 345-366. doi: 10.1111/j.1467-8489.2009.00451.x

Adamson, D., Quiggin, J., & Quiggin, D. (2011). *Water Supply Variability & Sustainable Diversions Limits: Issues to Consider in Developing the Murray-Darling Basin Plan* Brisbane.

Adamson, D., Schrobback, P., & Quiggin, J. (2008). *Options for managing salinity in the Murray-Darling Basin under reduced rainfall*. Paper presented at the 2nd International Salinity Forum: Salinity, water and society—global issues Adelaide Convention Centre, South Australia.

Arrow, K. J. (1953). Le rôle des valeurs boursières pour la répartition la meilleure des risques, Econométrie, 41–47, CNRS, Paris; translated as The role of securities in the optimal allocation of risk bearing,. *The Review of Economic Studies*, *31*(2), 91-96. doi: 10.2307/2296188

Austin, J., Zhang, L., Jones, R. N., Durack, P., Dawes, W., & Hairsine, P. (2010). Climate change impact on water and salt balances: an assessment of the impact of climate change on catchment salt and water balances in the Murray-Darling Basin, Australia. *Climatic Change, 100*(3-4), 607-631.

Australian Bureau of Statistics. (2008). *Water and the Murray-Darling Basin - A Statistical Profile Australia 2000–01 to 2005–06: ABS Catalogue No. 4610.0.55.007* Canberra, Australia: A. B. o. Statistics.

Ben-Tal, A., El Ghaoui, L., & Nemirovski, A. (2009). *Robust optimization*: Princeton university press.

Berrocal, V. J., Craigmile, P. F., & Guttorp, P. (2012). Regional climate model assessment using statistical upscaling and downscaling techniques. *Environmetrics, 23*(5), 482-492. doi: 10.1002/env.2145

BoM. (2020). Water Information - Water Dashboards. Retrieved 12 February, 2020, from http://www.bom.gov.au/water/dashboards/#/water-storages/summary/state

Chambers, R. G., & Quiggin, J. (2000). *Uncertainty, production, choice, and agency: The state-contingent approach*. New York: Cambridge University Press.

Chambers, R. G., & Quiggin, J. (2002). The state-contingent properties of stochastic production functions. *American Journal of Agricultural Economics, 84*(2), 513-526. doi: 10.2307/1244969

Chavas, J.-P. (2008). A Cost Approach to Economic Analysis Under State-Contingent Production Uncertainty. *American Journal of Agricultural Economics, 90*(2), 435-446.

Chavas, J.-P., Chambers, R. G., & Pope, R. D. (2010). Production Economics and Farm Management: A Century of Contributions. *American Journal of Agricultural Economics, 92*(2), 356-375. doi: 10.1093/ajae/aaq004

Chavas, J.-P., & Nauges, C. (2020). Uncertainty, learning and technology adoption in agriculture. *Applied Economic Perspectives and Policy, 42*(1), 42-53.

Commonwealth of Australia. (2008). *Water Act 2007* Canberra: Office of Legislative Drafting and Publishing, Canberra.
Debreu, G. (1959). *The Theory of Value*. New York: Wiley.
Döll, P., & Romero-Lankao, P. (2017). How to embrace uncertainty in participatory climate change risk management—A roadmap. *Earth's Future, 5*(1), 18-36.
Dow, S. (2020). *Alfred Marshall, evolutionary economics and climate change*. Paper presented at the Fourth Annual Tiziano Raffaelli Lecture, STOREP Conference, Rome.
Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review, 109*(1), 75-90. doi: 10.1037/0033-295X.109.1.75
Graham, D. A. (1981). Cost-Benefit Analysis Under Uncertainty. *The American Economic Review, 71*(4), 715-725.
Grant, S., & Quiggin, J. (2012). Induction reasoning about unawareness. *Economic Theory*, 1-39. doi: 10.1007/s00199-012-0734-y
Guttman, I., Kadan, O., & Kandel, E. (2006). A Rational Expectations Theory of Kinks in Financial Reporting. *The Accounting Review, 81*(4), 811-848.
Herman, J. D., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015). How should robustness be defined for water systems planning under change? *Journal of Water Resources Planning and Management, 141*(10), 04015012.
Hildebrandt, P., & Knoke, T. (2011). Investment decisions under uncertainty—a methodological review on forest science studies. *Forest Policy and Economics, 13*(1), 1-15.
Hirshleifer, J. (1965). Investment Decision under Uncertainty: Choice—Theoretic Approaches. *The Quarterly Journal of Economics, 79*(4), 509-536. doi: 10.2307/1880650
Hirshleifer, J. (1966). Investment Decision Under Uncertainty: Applications of the State-Preference Approach. *The Quarterly Journal of Economics, 80*(2), 252-277. doi: 10.2307/1880692
IPCC. (2018). *Global Warming of 1.5°C, an IPCC special report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty* Geneva. Retrieved from http://www.ipcc.ch/report/sr15/.
Jodha, N. S. (1991). Sustainable Agriculture in Fragile Resource Zones: Technological Imperatives. *Economic and Political Weekly, 26*(13), A15-A26. doi: 10.2307/4397463
Just, R. E., & Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of Econometrics, 7*(1), 67-86. doi: http://dx.doi.org/10.1016/0304-4076(78)90006-4
Kandlikar, M., Risbey, J., & Dessai, S. (2005). Representing and communicating deep uncertainty in climate-change assessments. *Comptes Rendus Geoscience, 337*(4), 443-455. doi: https://doi.org/10.1016/j.crte.2004.10.010
Keating, B. A., Gaydon, D., Huth, N., Probert, M., Verburg, K., Smith, C., & Bond, W. (2002). Use of modelling to explore the water balance of dryland farming systems in the Murray-Darling Basin, Australia. *European Journal of Agronomy, 18*(1-2), 159–169.
Khan, S. (2008). Managing climate risks in Australia: options for water policy and irrigation management. *Australian Journal of Experimental Agriculture, 48*, 265-273.
Kingsford, R. T. (2000). Ecological impacts of dams, water diversions and river management on floodplain wetlands in Australia. *Austral Ecology, 25*(2), 109-127. doi: 10.1046/j.1442-9993.2000.01036.x
Kingwell, R., & Farre, I. (2009). Climate change impacts on investment in crop sowing machinery. [Article]. *Australian Journal of Agricultural and Resource Economics, 53*(2), 265-284. doi: 10.1111/j.1467-8489.2007.00441.x

Kwakkel, J. H., Eker, S., & Pruyt, E. (2016). How robust is a robust policy? Comparing alternative robustness metrics for robust decision-making. In *Robustness analysis in decision aiding, optimization, and analytics* (pp. 221-237): Springer.

Liddle, R. F., & Monahan, J. F. (1988). A stationary stochastic approximation method. *Journal of Econometrics, 38*(1–2), 91-102. doi: 10.1016/0304-4076(88)90028-0

Loch, A., Adamson, D., & Auricht, C. (2020). (g)etting to the point: The problem with water risk and uncertainty. *Water Resources and Economics, 32*, 100154. doi: https://doi.org/10.1016/j.wre.2019.100154

Loch, A., Bjornlund, H., Wheeler, S., & Connor, J. (2012). Allocation trade in Australia: a qualitative understanding of irrigator motives and behaviour. *Australian Journal of Agricultural and Resource Economics, 56*(1), 42-60. doi: 10.1111/j.1467-8489.2011.00575.x

Maier, H. R., Guillaume, J. H., van Delden, H., Riddell, G. A., Haasnoot, M., & Kwakkel, J. H. (2016). An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? *Environmental Modelling & Software, 81*, 154-164.

Mallawaarachchi, T., & Foster, A. (2009). *Dealing with irrigation drought: the role of water trading in adapting to water shortages in 2007-08 in the southern Murray-Darling Basin* Canberra, Australia. Retrieved from http://adl.brs.gov.au/data/warehouse/pe_abarebrs99001593/rr09.6_irrigation_drought_report.pdf.

Mastrandrea, M. D., Field, C. B., Stocker, T. F., Edenhofer, O., Ebi, K. L., Frame, D. J., . . . Matschoss, P. R. (2010). Guidance note for lead authors of the IPCC fifth assessment report on consistent treatment of uncertainties.

Mazzucato, M. (2013). *The Entrepreneurial State - Debunking Public vs. Private Sector Myths*. London UK: Anthem Press.

McMahon, T. A., & Finlayson, B. L. (1991, 27-29 November 1991). *Australian surface and groundwater hydrology - regional characteristics and implications.* Paper presented at the Water allocation for the environment: Proceedings of an International Workshop, Armidale.

McPhail, C., Maier, H., Kwakkel, J., Giuliani, M., Castelletti, A., & Westra, S. (2018). Robustness metrics: How are they calculated, when should they be used and why do they give different results? *Earth's Future, 6*(2), 169-191.

MDBC. (2006). Murray-Darling Basin Water Resources Fact Sheet. *Murray Darling Basin Commisson, July 2006.* Retrieved from http://www2.mdbc.gov.au/__data/page/20/MDB-WaterResources-FactSheet-July2006.pdf

Merrifield, J. (1997). Sensitivity Analysis in Benefit Cost Analysis: A Key To Increased Use and Acceptance. *Contemporary Economic Policy, 15*(3), 82-92. doi: doi:10.1111/j.1465-7287.1997.tb00480.x

Pindyck, R. S. (2011). Fat Tails, Thin Tails, and Climate Change Policy. *Review of Environmental Economics and Policy, 5*(2), 258-274. doi: 10.1093/reep/rer005

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization, 3*(4), 323-343.

Quiggin, J. (2019). *Economics in two lessons: Why markets work so well, and why they can fail so badly*. Princeton NJ: Princeton University Press.

Quiggin, J., Adamson, D., Chambers, S., & Schrobback, P. (2010). Climate Change, Uncertainty, and Adaptation: The Case of Irrigated Agriculture in the Murray–Darling Basin in Australia. *Canadian Journal of Agricultural Economics, 58*(Special Issue: Water in the 21st Century [4]), 531-554.

Rasmussen, S. (2003). Criteria for optimal production under uncertainty. The state-contingent approach. *Australian Journal of Agricultural and Resource Economics, 47*(4), 447-476.

Rasmussen, S. (2006). Optimising Production using the State-Contingent Approach versus the EV Approach. [19/06/2012]. *FOI Working Papers no. 03/2007, Institute of Food and Resource Economics, Department of Economics, University of Copenhagen*. Retrieved from http://www.foi.life.ku.dk/Publikationer/~/media/migration%20folder/upload/foi/docs/publikationer/working%20papers/2007/working%20paper%20no%2003-%202007.pdf.ashx

Robertson, D., & Wang, Q. J. (2004). Bayesian networks for decision analyses - an application to irrigation system selection. *Australian Journal of Experimental Agriculture, 44*(2), 145-150.

Rosser, J. B. (2011). How Nonlinear Dynamics Complicate the Issue of Global Warming. In *Complex Evolutionary Dynamics in Urban-Regional and Ecologic-Economic Systems* (pp. 197-211): Springer New York.

Rothschild, M., & Stiglitz, J. E. (1970). Increasing risk: I. A definition. *Journal of Economic Theory, 2*(3), 225-243. doi: http://dx.doi.org/10.1016/0022-0531(70)90038-4

Rothschild, M., & Stiglitz, J. E. (1971). Increasing risk II: Its economic consequences. *Journal of Economic Theory, 3*(1), 66-84. doi: http://dx.doi.org/10.1016/0022-0531(71)90034-2

Sivapalan, M., Konar, M., Srinivasan, V., Chhatre, A., Wutich, A., Scott, C., . . . Rodríguez‐Iturbe, I. (2014). Socio‐hydrology: Use‐inspired water sustainability science for the Anthropocene. *Earth's Future, 2*(4), 225-230.

Whetton, P., Grose, M., & Hennessy, K. J. (2016). A short history of the future: Australian climate projections 1987-2015. *Climate Services, 2-3*, 1-14.

Yaron, D., & Bresler, E. (1970). A Model for the Economic Evaluation of Water Quality in Irrigation. *Australian Journal of Agricultural Economics, 14*(1), 53-62.

Young, M. D., & McColl, J. C. (2009). Double trouble: the importance of accounting for and defining water entitlements consistent with hydrological realities. *Australian Journal of Agricultural and Resource Economics, 53*(1), 19-35. doi: 10.1111/j.1467-8489.2007.00422.x

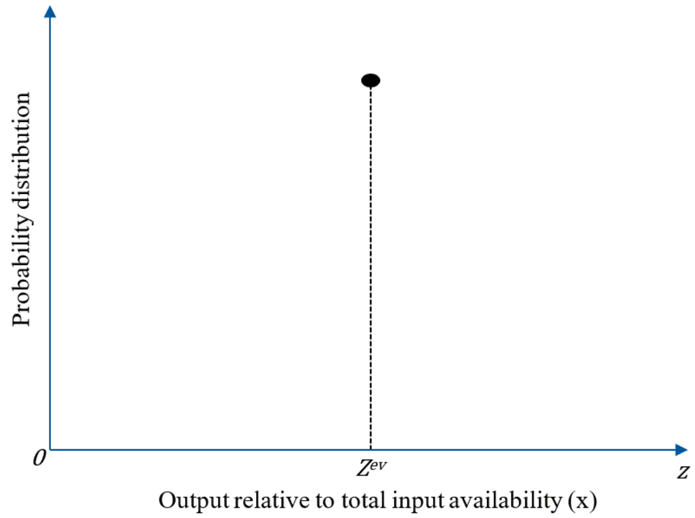

Figure 1a: Deterministic EV state outcome representation.

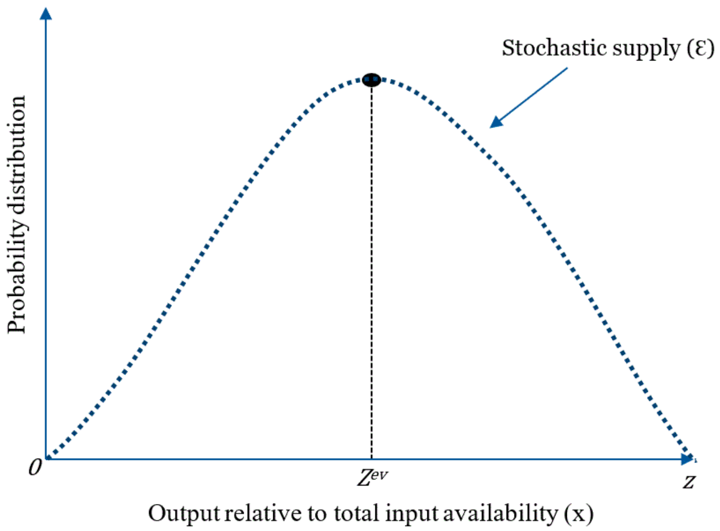

Figure 1b: Deterministic EV state outcome representation with error terms.

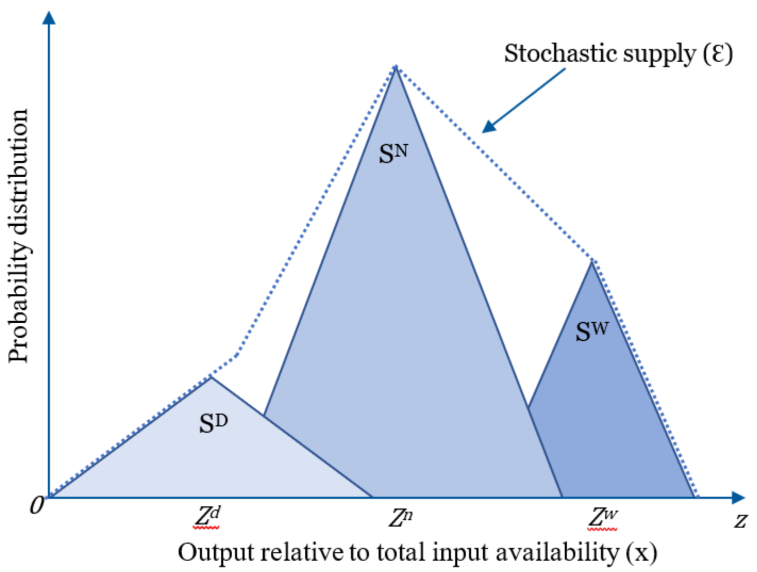

Figure 1c: SCA deterministic state-described outcomes (D = dry, N = normal, W = wet) within the stochastic frontier.

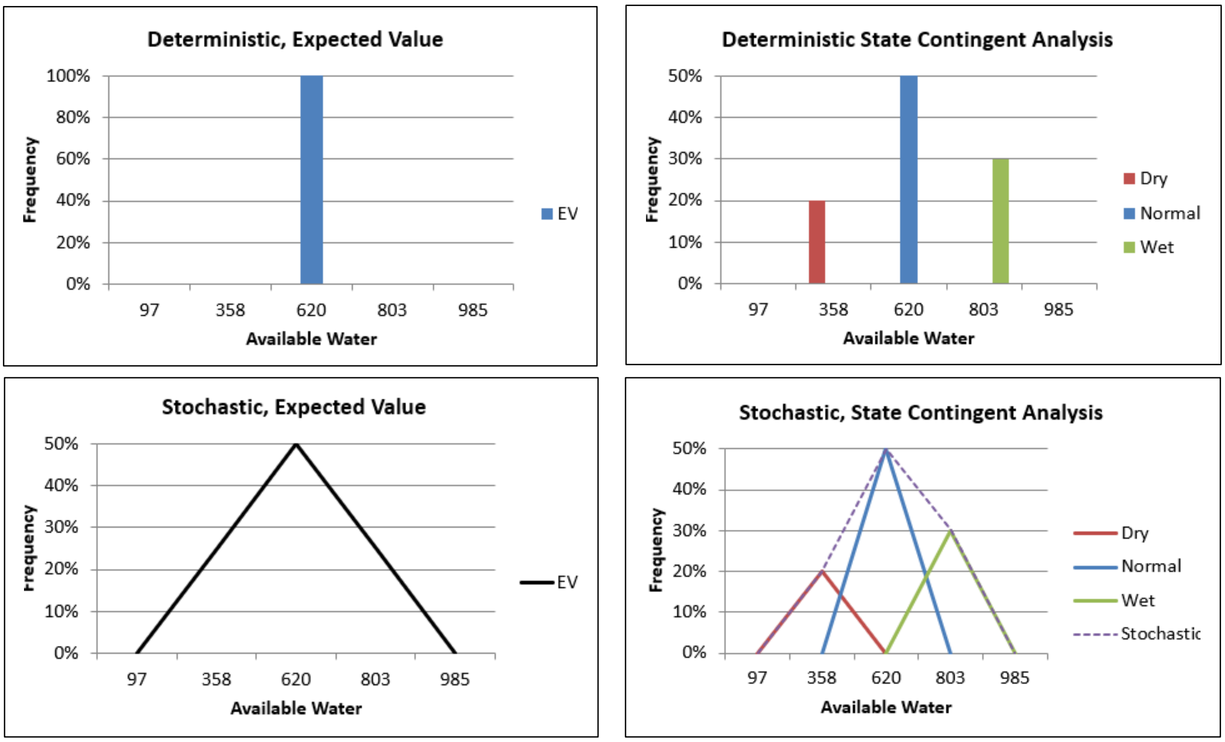

Figure 2: Charts of water use derived from the alternative modelling approaches

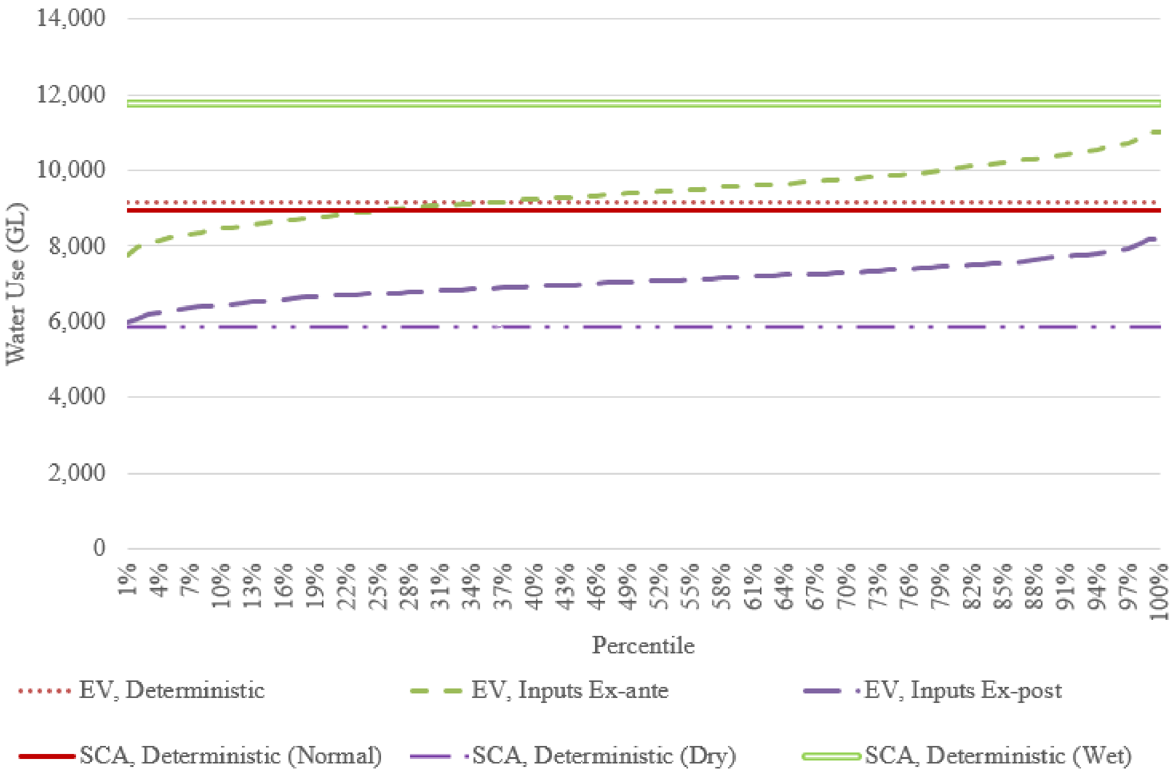

Figure 3: Water use (GL) results

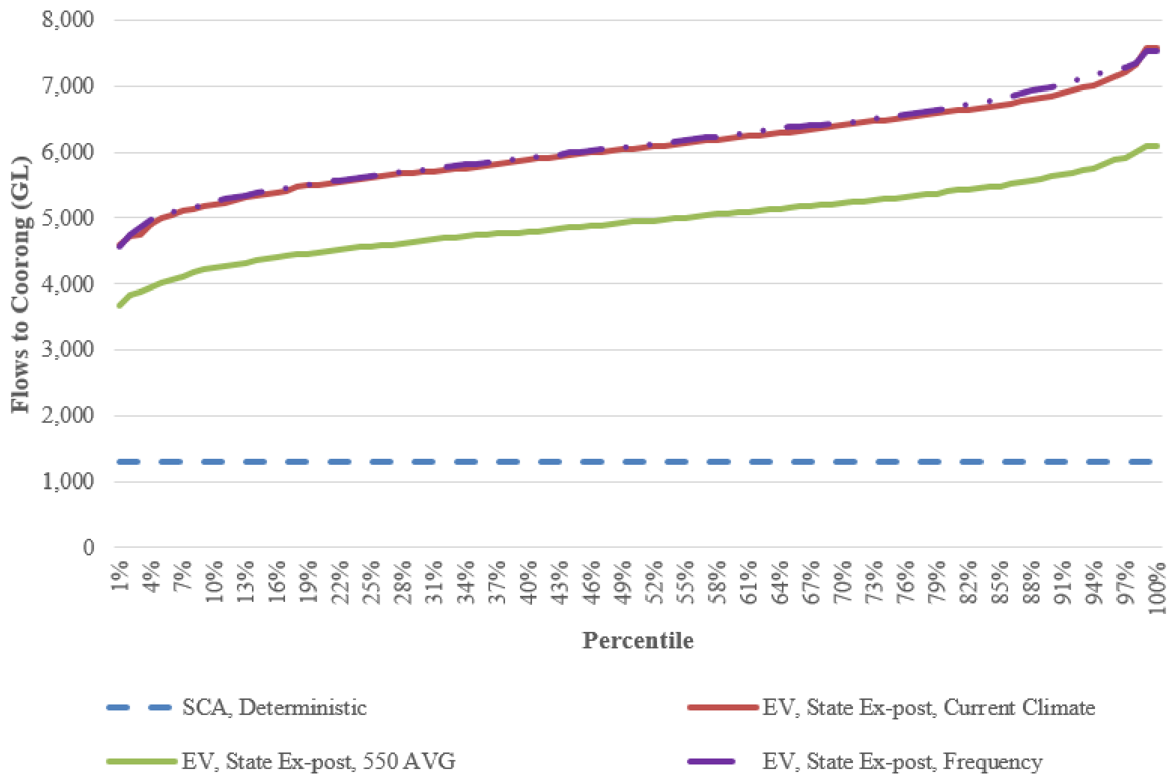

Figure 4: Coorong flow results under dry conditions by EV/SCA model (ex-post)

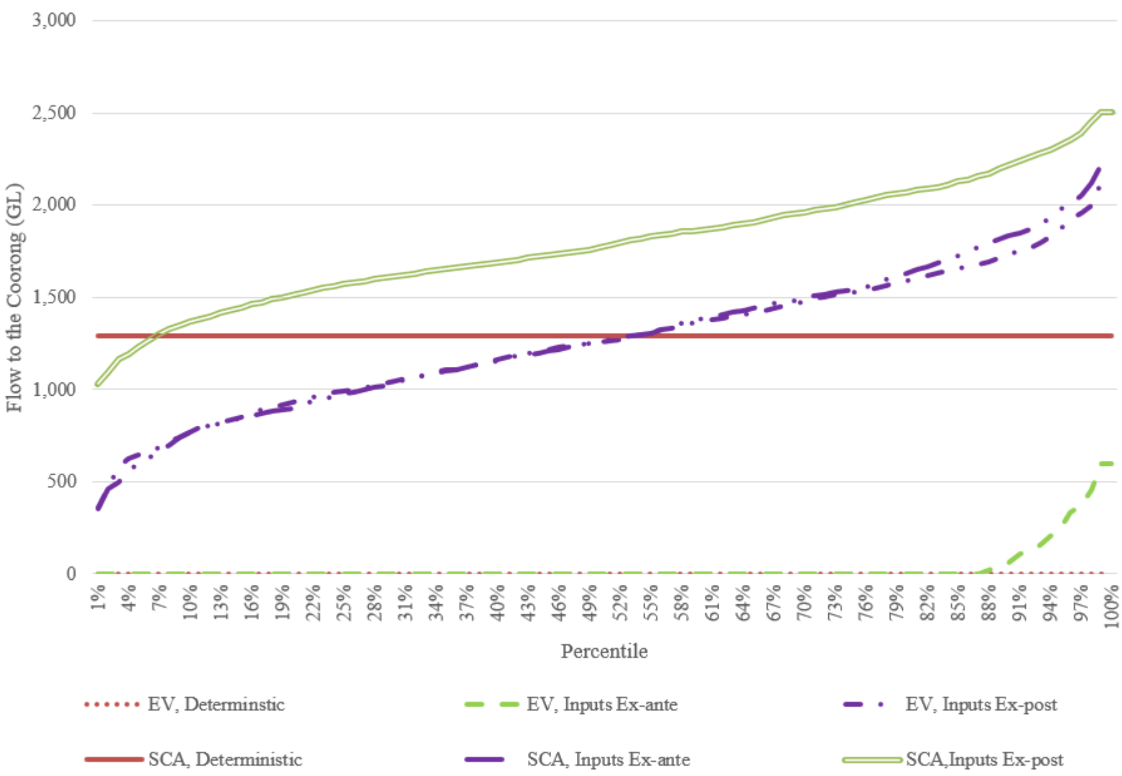

Figure 5: Comparison of EV and SCA results on environmental dry flows to Coorong

Table 1: Production System by EV and SCA models

Production System (δ)	State Contingent Approach: Commodity (M)			EV Approach
	Dry	**Normal**	**Wet**	
Citrus-H	Citrus-H	Citrus-H	Citrus-H	Citrus-H
Citrus-L	Citrus-L	Citrus-L	Citrus-L	Citrus-L
Grapes	Grapes	Grapes	Grapes	Grapes
Stone Fruit-H	Stone Fruit-H	Stone Fruit-H	Stone Fruit-H	Stone Fruit-H
Stone Fruit-L	Stone Fruit-L	Stone Fruit-L	Stone Fruit-L	Stone Fruit-L
Pome Fruit	Pome Fruit	Pome Fruit	Pome Fruit	Pome Fruit
Vegetables	Melons	Vegetables	Fresh Tomatoes	Vegetables
Cotton Flex	Dryland Cotton	Cotton Flex	Cotton	
Cotton Fixed	Cotton Fixed	Cotton Fixed	Cotton Fixed	Cotton Fixed
Cotton/Chickpea	Chickpea	Cotton Flex	Cotton	
Cotton Wet	Dryland Cotton	Dryland Cotton	Cotton	
Rice PSN	Rice PSD	Rice PSN	Rice PSW	Rice PSN
Rice Flex	Dryland Wheat	Rice PSN	Rice PSW	
Rice Wet	Dryland Wheat	Dryland Wheat	Rice PSW	
Wheat	Wheat	Wheat	Wheat	Wheat
Wheat Legume	Wheat Legume PSD	Wheat Legume PSN	Wheat Legume PSW	Wheat Legume
Sorghum	Sorghum	Sorghum	Sorghum	Sorghum
Oilseeds	Oilseeds	Oilseeds	Oilseeds	Oilseeds
Sheep Wheat	Sheep Wheat PSD	Sheep Wheat PSN	Sheep Wheat PSW	Sheep Wheat
Dairy-H	Dairy-H	Dairy-H	Dairy-H	Dairy-H
Dairy-L	Dairy-L	Dairy-L	Dairy-L	Dairy-L

Notes: The EV model has less production systems available as the ability to alter production systems by state of nature is not considered.
H = intensive irrigation capital (i.e., drip lines)
L = low irrigation capital (i.e., furrows)
Flex = production systems that may alter from year to year
Fixed = production system that are employed every year
PSD = production system, dry conditions
PSN = production system, normal conditions
PSW = production system, wet conditions

Table 2: Summary of the full model specification, by approach and deterministic/stochastic setting

EV	**Eq.**	**EV, Stochastic**	**Eq.**	**SCA**	**Eq.**	**SCA, Stochastic**	**Eq.**
$E[Y] = \sum_{\delta}\left[A^{\delta} \times Q^{\delta} \times (P - C)^{\delta}\right]$	(2)	$E[Y_{\varepsilon}] = \sum_{\delta}\left[\boldsymbol{A_{\varepsilon}^{\delta}} \times \boldsymbol{Q_{\varepsilon}^{\delta}} \times \left(\boldsymbol{P^{\delta}} - \boldsymbol{C_{\varepsilon}^{\delta}}\right)\right]$	(3)	$E[Y] = \sum_{\delta}\sum_{S}\pi_S\left[A^{\delta} \times Q_S^{\delta} \times (P_S^{\delta} - C_S^{\delta})\right]$	(8)	$E[Y_{\varepsilon}] = \sum_{\delta}\sum_{S}\pi_S\left[\boldsymbol{A_{\varepsilon}^{\delta}} \times \boldsymbol{Q_{s\varepsilon}^{\delta}} \times \left(\boldsymbol{P_s^{\delta}} - \boldsymbol{C_{s\varepsilon}^{\delta}}\right)\right]$	(9)
Subject to:							
$\sigma^{20}/0.64 \leq 800\ EC$	(10)	$VaR_{0.95}\left(\sigma^{20}/0.64 \leq 800\ EC\right)$	(11)	$\sigma_s^{20}/0.64 \leq 800\ EC$	(12)	$VaR_{0.95}\,(\sigma_s^{20}/0.64 \leq 800\ EC)$	(10)
$\sum K \leq CAP$	(14)	$\sum K \leq CAP$	(15)	$\sum K_s\pi_s \leq CAP$	(16)	$\sum K_s\pi_s \leq CAP$	(11)
$wk \leq fk$	(18)	$Va\delta_{0.95}\,(wk_{\varepsilon} \leq fk_{\varepsilon})$	(19)	$wk_S \leq fk_S$	(20)	$Va\delta_{0.95}\,(wk_{S\varepsilon} \leq fk_{s\epsilon})$	(21)
$A_k\delta_{1..5} \leq AHort_k$	(22)	$A_k\delta_{1..5} \leq AHort_k$	(23)	$A_k\delta_{1..5} \leq AHort_k$	(24)	$A_k\delta_{1..5} \leq AHort_k$	(25)
$A_k\delta_{1..16} \leq Atotal_k$	(26)	$A_k\delta_{1..16} \leq Atotal_k$	(27)	$A_k\delta_{1..22} \leq Atotal_k$	(28)	$A_k\delta_{1..22} \leq Atotal_k$	(29)
$\sum L_{rk} \leq L_k$	(30)	$\sum L_{rk} \leq L_k$	(31)	$\sum L_{rk} \leq L_k$	(32)	$\sum L_{rk} \leq L_k$	(33)
$fk^{21} \geq 1{,}000\ GL$	(34)	$Va\delta_{0.95}\,(fk^{21} \geq 1{,}000\ GL)$	(35)	$fk_s^{21} \geq 1{,}000\ GL$	(36)	$Va\delta_{0.95}\,(fk_{s\varepsilon}^{21} \geq 1{,}000\ GL)$	(37)

Table 3: Water Use by State of Nature (ML): Condamine catchment example only

Production System	**State Contingent Water Use**			**Normal (EV)**
	Dry	**Normal**	**Wet**	
Citrus-H	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
Citrus-L	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
Grapes	(2.5, 5, 7.5)	(2.5, 5.0, 7.5)	(3.0, 6.0, 9.0)	(2.5, 5, 7.5)
Stone Fruit-H	(1.7, 3.3, 5)	(1.7, 3.33, 5.0)	(2.0, 4.0, 6.0)	(1.7, 3.3, 5.0)
Stone Fruit-L	(3.2, 6.4, 9.7)	(3.2, 6.4, 9.7)	(3.9, 7.7, 11.6)	(3.2, 6.4, 9.7)
Pome Fruit	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
Vegetables	(0, 0, 0)	(2.0, 4.0, 6.0)	(3.0, 6.0, 9.0)	(0, 0, 0)
Cotton Flex	(0, 0, 0)	(2.5, 5.0, 7.5)	(2.5, 5, 7.5)	
Cotton Fixed	(2.5, 5.0, 7.5)	(2.5, 5.0, 7.5)	(2.5, 5, 7.5)	(2.5, 5.0, 7.5)
Cotton/Chickpea	(1.9, 3.8, 5.6)	(2.5, 5.0, 7.5)	(2.5, 5, 7.5)	
Cotton Wet	(0, 0, 0)	(0, 0, 0)	(3.0, 6.0, 9.0)	
Rice PSN	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
Rice Flex	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	
Rice Wet	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	
Wheat	(0.8, 1.5, 2.3)	(0.8, 1.5, 2.3)	(0.9, 1.8, 2.7)	(0.8, 1.5, 2.3)
Wheat Legume	(0.8, 1.7, 2.5)	(1.3, 2.6, 3.9)	(1.6, 3.2, 4.7)	(0.8, 1.7, 2.5)
Sorghum	(2.0, 4.0, 6.0)	(2.0, 4.0, 6.0)	(2.4, 4.8, 7.2)	(2.0, 4.0, 6.0)
Oilseeds	(2.0, 4.0, 6.0)	(2.0, 4.0, 6.0)	(2.0, 4.0, 6.0)	(2.0, 4.0, 6.0)
Sheep Wheat	(3.7, 7.4, 11.0)	(2.4, 4.8, 7.1)	(1.7, 3.5, 5.2)	(3.7, 7.4, 11.0)
Dairy-H	(3.2, 6.3, 9.5)	(4.5, 9.0, 13.5)	(5.4, 10.8, 16.2)	(3.2, 6.3, 9.5)
Dairy-L	(3.0, 6.0, 9.0)	(5.0, 10.0, 15.0)	(6.0, 12, 18)	(3.0, 6.0, 9.0)

Notes: For both the state-contingent and expected value the deterministic data is always the middle number. If all values 0 then the commodity is not grown in that region. If the values are 0 in states and >0 in others it means that the production system has transitioned from dryland to irrigated. If the cell is blank for the EV that production system is not possible in the EV model.
H = intensive irrigation capital (i.e., drip lines)
L = low irrigation capital (i.e., furrows)
Flex = production systems that may alter from year to year
Fixed = production system that are employed every year
PSN = production system, normal conditions

Table 4: Comparison of model runs by current climate, 550 ppm Climate Change and shifts to increased dry frequency, see Appendix A3 for details. Results shown for estimated water use (GL), the flow to the terminal node (Coorong), the salinity (Water Quality) at Morgan (the offtake for Adelaide's potable supplies), and the economic return from land allocation (Table 5). Data for stochastic runs is the 50th Percentile.

	Model Run	**Water Use (GL)**				**Coorong Flow (GL)**				**Salinity (EC)**				**Economic Return (AU$'m)**			
		Dry	Normal	Wet	Avg	Dry	Normal	Wet	Avg	Dry	Normal	Wet	Avg	Dry	Normal	Wet	Avg
Current climate	**EV, Deterministic**	0	9,162	0	9,162	0	6,221	11,753	6,221	0	228	222	228	$0	$2,591	$0	$2,591
	EV, Inputs Ex-ante	0	9,412	0	9,412	0	6,191	11,746	6,191	0	231	223	231	$0	$2,644	$0	$2,644
	EV, Inputs Ex-post	0	7,065	0	7,065	1,256	7,833	13,475	7,833	380	158	166	158	$0	$2,270	$0	$2,270
	EV, State Ex-ante	0	9,368	0	9,368	3,858	760	11,755	760	203	1,045	222	1,045	$0	$2,591	$0	$2,591
	EV, State Ex-post	0	6,792	0	6,792	6,056	2,572	13,606	2,572	94	407	161	407	$0	$2,013	$0	$2,013
	SCA, Deterministic	5,849	8,930	11,757	9,162	1,287	6,383	10,482	6,594	288	235	285	260	$1,085	$2,644	$3,872	$2,701
	SCA, Input Ex-ante	6,092	9,116	11,994	9,374	1,254	6,398	10,461	6,588	295	234	286	262	$1,085	$2,644	$3,871	$2,701
	SCA Input Ex-post	5,517	8,013	10,763	8,339	1,772	7,170	11,323	7,336	214	190	243	211	$1,026	$2,396	$3,590	$2,480
	SCA, State Ex-ante	6,055	9,136	11,963	9,368	5,771	880	10,478	4,738	91	1,061	285	634	$1,085	$2,644	$3,872	$2,701
	SCA, State Ex-post	5,516	6,829	14,146	8,762	6,212	2,465	8,956	5,161	70	409	342	321	$901	$2,084	$3,663	$2,321
New climate RCP 550 Avg.*	**EV, Deterministic**	0	9,000	0	9,000	0	3,756	8,117	3,756	0	350	311	350	$0	$2,502	$0	$2,502
	EV, Inputs Ex-ante	0	9,228	0	9,228	0	3,740	8,109	3,740	0	350	312	350	$0	$2,348	$0	$2,348
	EV, Inputs Ex-post	0	7,853	0	7,853	0	4,703	9,119	4,703	0	262	253	262	$0	$2,292	$0	$2,292
	EV, State Ex-ante	0	9,206	0	9,206	1,627	0	8,136	0	411	1,305	310	1,305	$0	$2,502	$0	$2,502
	EV, State Ex-post	0	5,311	0	5,311	4,962	2,079	10,980	2,079	133	656	210	656	$0	$1,852	$0	$1,852
	SCA, Deterministic	4,632	9,179	12,154	9,162	1,000	3,630	6,430	3,944	266	374	445	374	$1,075	$2,578	$3,752	$2,629
	SCA, Input Ex-ante	4,842	9,392	12,369	9,375	997	3,625	6,424	3,939	268	375	445	374	$959	$2,348	$3,447	$2,400
	SCA Input Ex-post	4,396	8,636	10,752	8,422	1,398	4,155	7,556	4,624	183	315	347	298	$884	$2,116	$3,242	$2,208
	SCA, State Ex-ante	4,838	9,385	12,360	9,368	4,583	0	6,449	2,851	86	0	444	150	$1,075	$2,578	$3,752	$2,629
	SCA, State Ex-post	3,687	5,293	15,032	7,894	5,641	2,097	4,570	3,548	51	440	664	429	$869	$1,853	$3,472	$2,142
Frequency	**SCA, Deterministic**	3,492	10,535	14,234	9,162	3,409	5,260	8,748	5,402	87	297	367	248	$1,279	$2,809	$3,786	$2,546
	SCA, Input Ex-ante	3,682	10,752	14,447	9,370	3,423	5,253	8,743	5,402	86	296	367	247	$1,192	$2,546	$3,431	$2,317
	SCA Input Ex-post	3,194	9,599	12,919	8,342	3,863	6,059	9,813	6,151	62	247	308	204	$1,048	$2,355	$3,281	$2,148
	SCA, State Ex-ante	3,698	10,741	14,440	9,368	7,866	0	8,745	4,109	42	1,538	368	855	$1,279	$2,809	$3,786	$2,546
	SCA, State Ex-post	4,640	7,074	17,575	8,444	7,079	2,396	6,558	4,634	55	436	528	340	$1,009	$2,126	$3,694	$2,104

Notes: Avg = Average. Shaded areas show what occurs when EV allocations (i.e. average flows) are utilized as a basis for the SCA model to explore wat would occur if 'other' states eventuated. This highlights surplus flows that would be available and reallocated by the SCA model, and the adaptation that takes place. Average in the EV are therefore the 'Normal Values' to make the table easier to read.

Ex-ante is the plausible future solution. Ex-post is the complete information solution. Input is the quantity of water inputs required. State is the description of water supply.

0 salinity = as there was no water flowing there was no salinity. For 0 values for water use and economic return, the EV models do not generate these values

* The RCP 550 Average scenario denotes a 550 parts-per-million CO_2 representative concentration pathway, or a relatively high level of future climate change impact.

Table 5: Production system by state commodity ('000 hectares)

		Citrus-H	Citrus-L	Grapes	Stone Fruit-L	Pome Fruit	Veg	Cotton Flex	Cotton Fixed	Cotton Wet	Rice PSN	Rice Flex	Rice Wet	Wheat	Dairy-H	Dairy-L
Current climate	**EV, Deterministic**	9	127	14	4	7	57	0	390	0	403	0	0	229	0	195
	EV, Inputs Ex-ante	9	127	14	4	7	57	0	390	0	403	0	0	229	0	195
	EV, Inputs Ex-post	9	127	14	4	7	57	0	253	0	240	0	0	301	0	144
	EV, State Ex-ante	9	127	14	4	7	57	0	390	0	403	0	0	229	0	195
	EV, State Ex-post	9	127	14	4	7	57	0	132	0	238	0	0	275	0	191
	SCA, Deterministic	0	136	72	4	7	0	438	0	243	392	0	0	33	24	186
	SCA, Input Ex-ante	0	136	72	4	7	0	438	0	243	392	0	0	33	24	186
	SCA Input Ex-post	0	136	72	4	7	0	304	41	240	314	39	0	67	24	139
	SCA, State Ex-ante	0	136	72	4	7	0	438	0	243	392	0	0	33	24	186
	SCA, State Ex-post	0	136	72	4	7	0	167	0	378	389	0	435	150	24	57
Climate change 550 Avg.*	**EV, Deterministic**	9	127	14	4	7	57	0	335	0	456	0	0	280	0	155
	EV, Inputs Ex-ante	9	127	14	4	7	57	0	335	0	456	0	0	280	0	155
	EV, Inputs Ex-post	9	127	14	4	7	57	0	269	0	364	0	0	313	0	115
	EV, State Ex-ante	9	127	14	4	7	57	0	335	0	456	0	0	280	0	155
	EV, State Ex-post	9	127	14	4	7	57	0	104	0	158	0	0	204	0	122
	SCA, Deterministic	0	135	72	4	7	0	423	0	244	253	213	0	33	24	147
	SCA, Input Ex-ante	0	135	72	4	7	0	423	0	244	253	213	0	33	24	147
	SCA Input Ex-post	0	136	72	4	7	0	315	0	129	188	271	0	164	24	108
	SCA, State Ex-ante	0	135	72	4	7	0	423	0	244	253	213	0	33	24	147
	SCA, State Ex-post	0	136	72	4	7	0	117	0	309	0	0	755	116	24	234
Frequency	**SCA, Deterministic**	0	136	72	4	7	0	443	57	230	0	528	0	122	24	186
	SCA, Input Ex-ante	0	136	72	4	7	0	443	57	230	0	528	0	122	24	186
	SCA Input Ex-post	0	136	72	4	7	0	414	0	205	0	488	0	157	24	141
	SCA, State Ex-ante	0	136	72	4	7	0	443	57	230	0	528	0	122	24	186
	SCA, State Ex-post	0	136	72	4	7	0	124	43	422	29	61	694	154	36	300

* The 550 Average scenario denotes a 550 parts-per-million CO^2 representative conceptration pathway, or a relatively high level of future climate change impact.

Appendix Material

Table A1: Illustrative Water Resource Data for Condamine only ('000 GL) Current Climate)

Description		State of Nature	
	Dry	Normal	Wet
Deterministic Normal		620	
Stochastic Normal Triangular Distribution (a, b, c)		(97, 620, 985)	
Deterministic SCA	359	620	802
Stochastic SCA Triangular Distribution (a, b, c)	(97,358,620)	(359,620,803)	(620,803,985)

Table A2: Water Resource Data for Condamine only ('000 GL) Climate Change (550 Avg, 2050)

Description		State of Nature	
	Dry	Normal	Wet
Deterministic		564	
Stochastic Triangular Distribution (a, b, c)		(88, 564, 896)	
Deterministic SCA	326	564	730
Stochastic SCA Triangular Distribution (a, b, c)	(88,326,564)	(326,564,730)	(564,730,896)

There is constant water reduction in each corresponding cell. Full data sets available on request.

Table A3: Analysis Summary

Run	Description	Climate	State of Nature Frequency		
			Dry	Normal	Wet
1	EV, Deterministic	Current		1.0	
2	EV, Inputs Ex-ante	Current		1.0	
3	EV, Inputs Ex-post	Current		1.0	
4	EV, State Ex-ante	Current		1.0	
5	EV, State Ex-post	Current		1.0	
6	SCA, Deterministic	Current	0.2	0.5	0.3
7	SCA, Input Ex-ante	Current	0.2	0.5	0.3
8	SCA Input Ex-post	Current	0.2	0.5	0.3
9	SCA, State Ex-ante	Current	0.2	0.5	0.3
10	SCA, State Ex-post	Current	0.2	0.5	0.3
11	EV, Deterministic	550 Avg		1.0	
12	EV, Inputs Ex-ante	550 Avg		1.0	
13	EV, Inputs Ex-post	550 Avg		1.0	
14	EV, State Ex-ante	550 Avg		1.0	
15	EV, State Ex-post	550 Avg		1.0	
16	SCA, Deterministic	550 Avg	0.2	0.5	0.3
17	SCA, Input Ex-ante	550 Avg	0.2	0.5	0.3
18	SCA Input Ex-post	550 Avg	0.2	0.5	0.3
19	SCA, State Ex-ante	550 Avg	0.2	0.5	0.3
20	SCA, State Ex-post	550 Avg	0.2	0.5	0.3
21	SCA, Deterministic	Current	0.3	0.5	0.2
22	SCA, Input Ex-ante	Current	0.3	0.5	0.2
23	SCA Input Ex-post	Current	0.3	0.5	0.2
24	SCA, State Ex-ante	Current	0.3	0.5	0.2
25	SCA, State Ex-post	Current	0.3	0.5	0.2

EV= expected value
SCA = State contingent analysis
Current climate = historical values
550 Avg = forecasted climate in 2050 under 550 ppm of carbon
State of Nature = examines the implication of how a state of nature is described
Inputs by state = describes the volume of water required to produce a state specific commodity

Table A4 Area Irrigated By State of Nature

	Description	State of Nature		
		Dry	**Normal**	**Wet**
Current climate	**EV, Deterministic**		1,435	
	EV, Inputs Ex-ante		1,435	
	EV, Inputs Ex-post		1,156	
	EV, State Ex-ante		1,435	
	EV, State Ex-post		1,053	
	SCA, Deterministic	853	1,290	1,533
	SCA, Input Ex-ante	853	1,290	1,533
	SCA Input Ex-post	802	1,145	1,385
	SCA, State Ex-ante	853	1,290	1,533
	SCA, State Ex-post	838	1,005	1,818
Climate change 550 Avg.	**EV, Deterministic**		1,444	
	EV, Inputs Ex-ante		1,444	
	EV, Inputs Ex-post		1,279	
	EV, State Ex-ante		1,444	
	EV, State Ex-post		805	
	SCA, Deterministic	673	1,309	1,553
	SCA, Input Ex-ante	673	1,309	1,553
	SCA Input Ex-post	702	1,288	1,417
	SCA, State Ex-ante	673	1,309	1,553
	SCA, State Ex-post	591	708	1,772
Frequency	**SCA, Deterministic**	607	1,577	1,808
	SCA, Input Ex-ante	607	1,577	1,808
	SCA Input Ex-post	539	1,440	1,645
	SCA, State Ex-ante	607	1,577	1,808
	SCA, State Ex-post	780	965	2,081

Table A5 Compare Deterministic v Stochastic & Climate Change (Ex-post)

	Description		State of Nature		
		Model	Dry	Normal	Wet
Deterministic	Current Climate	EV	0	1,435	0
	Current Climate	SCA	853	1,290	1,533
	New climate RCP 550 Avg	EV	0	1,444	0
	New climate RCP 550 Avg	SCA	673	1,309	1,553
	Frequency	SCA	607	1,577	1,808
Inputs	Current Climate	EV	0	1,156	0
	Current Climate	SCA	802	1,145	1,385
	New climate RCP 550 Avg	EV	0	1,279	0
	New climate RCP 550 Avg	SCA	702	1,288	1,417
	Frequency	SCA	539	1,440	1,645
State	Current Climate	EV	0	1,053	0
	Current Climate	SCA	838	1,005	1,818
	New climate RCP 550 Avg	EV	0	805	0
	New climate RCP 550 Avg	SCA	591	708	1,772
	Frequency	SCA	780	965	2,081

SCA production systems note to the model

The state-contingent approach examines how the state of nature (e.g. droughts and floods) influences the management strategy to alter the inputs used to produce state specific outputs. For example, shiraz grapes produced in periods of low water supply have more smaller berries than grapes produced with normal water supply. Smaller berries then increase the grape skin to moisture ratio and can produce a higher quality wine.

The transformation of commodities into SCA production systems allows for irrigation management practices to be reflected both within and between states of nature. As similar state of natures, with identical outcomes, can be combined to keep the state space small, the model has merged similar commodities with similar management strategies into generic production systems (see Citrus below) to reduce the model size.

The description of each of the 22 state-contingent production systems x is documented below and Table illustrates how the state-contingent production systems alter the inputs used and outputs obtained by state of nature. In Table , the multiplier for Z alters output, the term 'water' is a multiple for the water used and the heading 'VC' either increases or decreases the variable costs per Ha by the described dollar value. The Citrus production system is used to illustrate, how the variables Z, 'water' and 'VC' are used to transform the normal states production data to production data for the dry and wet state of nature.

The Horticultural State-Contingent Production Systems:

Citrus
The citrus production system is designed to reflect strategies used by grapefruit, lemon, lime, mandarin and orange producers to deal with changing states of water availability. Producers can utilize either –H or –L irrigation technology to produce citrus crops.

When compared to the normal state of nature, a Citrus-H producer operating in a dry state of nature, will allocate the same volume of water but receive a 20% reduction in output and face increased variable costs of $20/Ha (Table). When the wet state of nature is experienced, the producer increases water consumption by 120%, in part to help flush salt away from the root zone. Yield is expected to increase by 20% per Ha in a wet state of nature and this then requires an additional expenditure of $20/Ha to manage and harvest the crop (Table).

The state-contingent production systems reflect this via the reduction in output experienced in the dry state of nature. When compared to the normal state of nature, Citrus-L and Citrus-H output declines by 10% and 20% respectively when compared to the normal sate of nature.

Grapes
The grape production system reflects the changes in output (i.e. tons of grapes), water used and variable costs experienced by table and wine grape producers as they adapt to alternative states of nature.

Table A6 Data for the State-Contingent Productions

X	Production System Name	Dry Multipliers and Costs				Normal	Wet Multipliers and Costs			
		Commodity	*Z*	Water	VC	Commodity	Commodity	*Z*	Water	VC
$x1$	Citrus-H	Citrus-H	0.8	1.0	\$20	Citrus-H	Citrus-H	1.2	1.2	\$20
$x2$	Citrus-L	Citrus-L	0.9	1.0	\$0	Citrus-L	Citrus-L	1.2	1.2	\$100
$x3$	Grapes	Grapes	0.9	1.0	\$20	Grapes	Grapes	1.2	1.2	\$20
$x4$	Stone Fruit-H	Stone Fruit-H	0.8	1.0	\$20	Stone Fruit-H	Stone Fruit-H	1.2	1.2	\$20
$x5$	Stone Fruit-L	Stone Fruit-L	0.9	1.0	\$0	Stone Fruit-L	Stone Fruit-L	1.2	1.2	\$100
$x6$	Pome Fruit	Pome Fruit	0.9	1.0	\$20	Pome Fruit	Pome Fruit	1.2	1.2	\$20
$x7$	Vegetables	Melons	1.0	1.0	\$0	Vegetables	Fresh Tomatoes	1.0	1.0	\$0
$x8$	Cotton Flex	Dryland Cotton	1.0	1.0	\$0	Cotton Flex	Cotton	1.0	1.0	\$100
$x9$	Cotton Fixed	Cotton Fixed	1.0	1.0	\$0	Cotton Fixed	Cotton Fixed	1.0	1.0	\$0
$x10$	Cotton/Chickpea	Chickpea	1.0	1.0	\$0	Cotton Flex	Cotton	1.0	1.0	\$100
$x11$	Cotton Wet	Dryland Cotton	0.8	1.0	\$0	Dryland Cotton	Cotton	0.9	1.2	\$100
$x12$	Rice PS	Rice PSD	1.0	1.0	\$0	Rice PSN	Rice PSW	1.1	1.1	\$0
$x13$	Rice Flex	Dryland Wheat	1.0	1.0	\$0	Rice PSN	Rice PSW	1.0	1.2	\$100
$x14$	Rice Wet	Dryland Wheat	1.0	1.0	\$0	Dryland Wheat	Rice PSW	0.95	1.2	\$100
$x15$	Wheat	Wheat	0.8	1.0	\$0	Wheat	Wheat	1.1	1.2	\$50
$x16$	Wheat Legume	Wheat Legume PSD	1.0	1.0	\$0	Wheat Legume PSN	Wheat Legume PSW	1.0	1.0	\$0
$x17$	Sorghum	Sorghum	0.8	1.0	\$0	Sorghum	Sorghum	1.1	1.2	\$100
$x18$	Oilseeds	Oilseeds	0.8	1.0	\$0	Oilseeds	Oilseeds	1.1	1.0	\$0
$x19$	Sheep Wheat	Sheep Wheat PSD	1.0	1.0	\$50	Sheep Wheat PSN	Sheep Wheat PSW	1.0	1.0	\$0
$x20$	Dairy-H	Dairy-H	0.9	0.7	\$300	Dairy-H	Dairy-H	1.5	1.2	\$0
$x21$	Dairy-L	Dairy-L	0.8	0.6	\$300	Dairy-L	Dairy-L	1.2	1.2	\$0
$x22$	Dryland	Dryland	1.0	1.0	\$0	Dryland	Dryland	1.0	1.0	\$0

H= intensive irrigation capital (e.g. drip lines).
L = low irrigation capital (e.g. furrows).

Stone fruit
Stone fruit production systems reflect the management systems used by apricot, cherry, nectarine, peach and plum producers as they alter their inputs by state of nature.

Pome Fruit
The pome fruit state-contingent production system detail changes in inputs and outputs by state of nature, for the apple and pear industry in the MDB.

Vegetables
The term vegetables is used to describe a range of regional irrigated vegetable production alternatives, including asparagus, beetroot, broccoli, cabbage, capsicum, carrot, cauliflower, eggplant, garlic, lettuce, onion, potato, pumpkin, rockmelon, sweet corn, tomato, watermelon and zucchini.

> "In the normal state, the vegetable production activity is represented by an average return from a range of alternative irrigated vegetable crops. In the dry state, water resources are conserved by planting only a dryland rockmelon crop. In the wet state, all resources are transferred to producing tomatoes for the fresh market" (Quiggin et al. 2010, p. 542).

Broadacre commodities:

Cotton (Fixed Rotation) or Cotton Fixed

> "To assist pest management, and sustain soil fertility, cotton is produced on a rotation system, represented here as allowing for two years of irrigated cotton production and one year of dryland agriculture over a three-year cycle. The simplest way of managing such a system is a three-field rotation, in which one-third of the land area is rotated out of irrigation each year" (Adamson, Mallawaarachchi & Quiggin 2007, p. 270).

Cotton (Flexible Rotation) of Cotton Flex

> "We also model an alternative rotation system in which the entire land area is allocated to dryland agriculture in dry years, and to cotton production in wet years. Since this activity requires more active management it incurs a cost penalty relative to the Fixed Rotation activity which has the same average yield. However, if producers face variable state-contingent prices for water (or variable shadow prices associated with constraints), they may choose to adopt this activity" (Adamson, Mallawaarachchi & Quiggin 2007, p. 270).

Cotton/Chickpea
The cotton/chickpea state-contingent production system mimics the 'Cotton Flex' production option but instead of allocating resources to a dryland crop in the dry state of nature, inputs are allocated towards an irrigated chickpea crop.

Cotton Wet
The 'cotton wet' production system is designed to model opportunistic irrigation practices that occur in the NMDB when supplementary property rights are most secure in the wet state of nature (Section **Error! Reference source not found.**). For this production system…

> "[t]he producer produces an irrigated cotton crop only in the wet state of nature. In other states of nature, dryland grain cropping is undertaken.(Quiggin et al. 2010, p. 542).

Rice PSN
The Rice PSN was designed to illustrate how rice is produced in the Southern Murray-Darling Basin (SMDB) and is similar in design to the cotton fixed rotation. This production system divides each Ha of Rice PSN, into 1/3 of the area planted to rice and the remaining 2/3 grows wheat, to reflect industry

practices. In a normal state of nature, once the rice crop is harvested, farmers take advantage of residual soil moisture by producing a vegetable crop, and 10% of this production is assumed to be derived from the Rice PSN. In the dry state (Rice PSD) this vegetable crop cannot be produced and in the wet state of nature (Rice PSW), 15% of vegetable returns are due to the rice crop.

Rice Flex

The 'Rice Flex' production system was designed to mimic the 'Cotton Flex' system for the rice industry as it allows producers to allocate resources towards producing a dryland wheat crop in the dry state of nature.

Rice Wet

The 'Rice Wet' provides the opportunity for the rice industry to respond to years when water is plentiful. Like the 'Cotton Wet' system, irrigation only occurs in the wet state of nature and in all other states of nature a dryland wheat crop is produced. To reflect this opportunistic behavior by non-specialist producers, a yield penalty of 5% has been applied (Table).

Wheat

The wheat system produces an irrigated crop of wheat in every state of nature.

Wheat/Legume

Rotation cropping practices provide output benefits and greater efficiency of input use; as each crop in the rotation requires different bundles of inputs, adaption to a state can be inferred if resources are reallocated. To represent this management option the Wheat/Legumes production system was created and 'Legume' is a default commodity derived from the available legume crops each k, which includes adzuki bean, chickpea, fava bean, mungbean, navy bean, peanut and soybean.

The farmer's adaption to water availability is represented by altering the percentage of land dedicated to the wheat and legume crop in each Ha and to reflect the benefits of investing in rotation wheat output is increased by 10% in each state of nature. Land allocation between wheat and legumes occurs at a rate of 50/50, 100/0 and 30/70 for the normal, dry and wet state of nature respectively.

Oil Seeds

The oil seed production system provides the opportunity for irrigators to invest in producing canola and/or sunflowers, depending on what can be produced in each k.

Sheep/Wheat

> "This production activity represents a state-contingent production plan where producers allocate resources between sheep and wheat production in response to climatic conditions and market forces. The production mix between the two outputs is 50% wheat and 50% sheep in the normal state, 90% sheep and 10%wheat in the dry state, and 30% sheep and 70%wheat in the wet state. Effort is placed in keeping the breeding stock alive during the dry state while in wet states there is plenty of fodder available on the non-irrigated pasture, and irrigated land can be allocated to wheat production"(Quiggin et al. 2010, p. 542).

Dairy

During the Millennium drought one adaption strategy employed by dairy producers was the trading of water to purchase feed. The 'Dairy' production system modelled here does not include the capacity to trade water in the dry state but rather assumes that all water is used on farm to reflect the ability of dairy producers to respond to water supplies by increasing or decreasing the total area irrigated within a property and compensating feed deficiencies by purchasing feed. The data used to construct Chart A1 to describe the changing area irrigated is for illustration purposes only.

A dairy producer has the choice of producing dryland or irrigated pasture on their farm. To represent the decision maker's response to the availability of water, the proportion of each Ha that is irrigated alters by state of nature. Using the data for Dairy- H (Table), the water multiplier for the dry and wet state of nature is 0.7 and 1.2, respectively. The impact of this state described water multiplier then means that in a dry state of nature only 40% of each Ha is irrigated, in the normal state of nature 80% of the Ha is irrigated and in the wet state of nature the entire Ha is irrigated (Chart A1). To compensate for the lack of feed in the dry state of nature, an additional $300 is spent per Ha purchasing supplements (Table) but despite feeding cattle, output decreases by 10%. But in a wet state of nature, no additional feed is required and output increases by 50%.

Chart A1 Proportion of a Hectare Irrigated by State of Nature (%)