An integrated dynamic modeling framework for investigating the impact of climate change and variability on irrigated agriculture

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[1] Many hydrologic systems are likely to be affected by climate change. This is of particular importance given that agricultural production systems are inextricably linked to the hydrologic systems they rely upon. Although irrigation is often employed as a method to dampen the effect of short-term variation in climatic inputs to agricultural production, sources of irrigation water are not immune to long-term climatic change. Irrigation water use decisions are most often made at the farm level. It is at this scale that the economic and social impacts of climate change will be manifest. This paper presents an integrated stochastic dynamic modeling framework that can be used to investigate the viability of irrigated farms under alternative climate change scenarios. The framework is applied to a theoretical farm in the Murray Darling Basin, Australia, under four potential future climate scenarios. It is found that neglecting interannual variability in climatic inputs to agriculture consistently underestimates the reduction in farm viability caused by climate change and that multiyear sequences of climate states strongly influence estimates of farm profitability.

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1. Introduction

[2] Agricultural production and hydrologic systems are inextricably linked. Natural variability in climatic processes, such as rainfall and potential evapotranspiration, drive changes in both these systems and, as such, adds significant complexity to this nexus. In regions where this natural variability in climate processes would severely limit agricultural output, irrigation is commonly used to increase productivity. The long-term viability of irrigated agricultural production depends on cost-effective access to sources of irrigation water that can reliably meet seasonal shortfalls in crop water requirements on an ongoing basis. The typically lagged response of irrigation water sources to system change is what gives them their appeal. Regardless, these water resources are not immune from ongoing changes to the hydrological cycle.

[3] Although the hydrological impacts of climate change cannot be predicted with certainty, successive reports from the Intergovernmental Panel on Climate Change (IPCC) have painted a clearer and more stark image of the type of climate that might be expected in decades to come [*IPCC*, 1996, 2001, 2007]. In regions where agricultural production is already reliant upon irrigation, changes to both the magnitude and temporal variability of climatic inputs to agricultural and hydrologic systems could threaten the viability of agricultural production [*Easterling and Apps*, 2005]. There are several key drivers to these potential changes: first, irrigation requirements are likely to increase because of enhanced evapotranspiration, reduced natural rainfall, and, in some areas, longer growing seasons; second, long-term sustainable yield of water resources might be reduced by decreased resource replenishment over the longer term; third, increased temporal variability of climatic drivers to both agricultural and hydrologic systems may severely compromise the reliability with which crop water requirements can be met, thus undermining the ongoing viability of crop production.

[4] Estimating the combined impact of these three effects is not trivial, and most modeling approaches struggle to explicitly account for the uncertainty present in the temporal dimension of a naturally stochastic climate. This shortcoming is of particular importance when modeling irrigated agriculture because investments in irrigation infrastructure and perennial crop plantings are expensive and are made on the basis that incurred costs will be recovered over a relatively long period. While it has been common for previous studies (such as the one by *Carey and Zilberman* [2002]) to assume investment in irrigation technology or permanent plantings to be irreversible, *Baerenklau and Knapp* [2007] showed that this is not strictly the case and that this assumption leads to overestimated trigger prices for investment. *Baerenklau and Knapp* [2007] do, however, show that reversing investments is still costly. Uncertainty about future conditions makes decisions on these investments difficult to evaluate and optimize.

[5] The literature on this topic can be considered in terms of a few predominant methodological approaches, each of which has its limitations. Econometric regression models, for example, Ricardian models [e.g., *Mendelsohn*

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et al., 1994], describe how the complex relationships between historical climate, hydrology, and crop production decisions result in observable spatial variation in farm value. The approach of *Mendelsohn et al.* [1994] has been applied in many regions as diverse as the United States [*Polsky*, 2004], China [*Liu et al.*, 2004], Europe [*Lang*, 2007; *Reidsma et al.*, 2007], and Africa [*Benhin*, 2008; *Kabubo-Mariara and Karanja*, 2007], as well as being adapted for applications that do not fit the traditional land market–based approach [*Deschênes and Greenstone*, 2007; *Polsky*, 2004; *Schlenker et al.*, 2005]. Because such studies rely on historical data and an assumed relationship between historical spatial variation and future temporal changes, they cannot provide much more than a general indication of the impact of climate at the regional scale. The very nature of the regression approach means they do not consider the fundamental processes that drive farm profitability. As a consequence of this shortcoming, these models are able to explain very little about climate change impacts outside the range of past events, including system behavior under new management policies.

[6] Process-based mathematical optimization models allow for representation of both crop production dynamics and farmer decision-making behavior, most often using a comparative static approach. Most of these models do not account for the natural variability present in climatic inputs to farming, but rather assess the impact of known changes to average values of variables such as reductions in rainfall and irrigation water availability and increased potential evapotranspiration [*Audsley et al.*, 2008; *Elbakidze*, 2006]. There have been several attempts to consider irrigator response to climate-induced changes that incorporate uncertainty in climate processes [*Connor et al.*, 2009; *McCarl et al.*, 1999]. These models assign probability distribution functions to stochastic climate variables, and farmers have perfect knowledge of these distributions. This knowledge is used to inform farmer decisions, with farmers considering the probability of each climatic state occurring in any single year. As a consequence of their static architecture, these models lack the ability to represent critical events resulting from a sequence of similar climatic states, such as droughts, which have the potential to impact farm profitability far more severely than intermittently occurring individual years or short sequences of dry cropping seasons.

[7] By including the temporal dimension and using a stock and flow model architecture, dynamic models improve the representation of environmental variability as a driver of system dynamics. *Booker et al.* [2005] applied this approach at the basin scale to optimize water allocation in a regulated hydrologic system in the Rio Grande Basin, United States, and *Letcher et al.* [2004] use an integrated hydrological-economic framework approach for their model used to assess allocation options in the Namoi River catchment, Australia. While this approach enables the hydrological dynamics of a regulated river system to be represented as a sequence of states, basin-scale (or even subbasin scale, in the case of *Letcher et al.* [2004]) models necessitate the aggregation of both long- and short-run decision processes that occur at the level of the water user, therefore making it difficult to accurately represent the nature of irrigation and crop capital stock investment decisions that, in reality, occur at the farm level.

[8] Representing farms as individual decision-making units allows the outcomes of previous water use and investment decisions to influence the farm state at any point in time. While not explicitly modeling climate impacts on farm investment behavior, *Baerenklau and Knapp* [2007] apply a stochastic dynamic programming approach to a singular farm household to investigate price conditions under which farmers' would switch irrigation technology. Modeling at this scale allows for a more representative model of farmer decision-making behavior; however, the optimization approach of dynamic programming (which was also used by *Letcher et al*. [2004], albeit at a subbasin, not household, scale) can only provide a single output representing the expected value of the objective, even when uncertainty in states of nature are taken into account in the optimization process. This type of output does not provide any indication of the possible range of outcomes and the likelihood of any potential outcome occurring.

[9] Agent-based models (ABMs) aim to represent multiple actors at the farm level with a more realistic model of decision-making behavior and have been applied to water resources management [*Feuillette et al.*, 2003; *Happe et al.*, 2006; *Perez et al.*, 2002] and, more specifically, in the context of climate change impacts on crop production [*Bharwani et al.*, 2005]. As dynamic recursive models, they too allow sequencing effects that influence the system state to be considered; however, their main focus is on investigating the complex social processes present in multiactor systems. The dynamic complex network structure of ABMs can make handling uncertainty difficult, and data requirements for describing this complexity are intense. *Iglesias et al.* [2003] modeled drought impacts at the farm level by simplifying the ABM approach to consider farms on an individual basis, rather than as a complex network. Like most dynamic simulation models, the objective of their study is to estimate the impacts of drought rather than climate change in general, and it is therefore only run over a short period of historical data.

[10] While drought and climate change are closely related in most areas that currently rely upon irrigation, using historical data sequences describing singular drought events does not allow the modeler to draw any conclusions on the basis of long-term impacts of climate change. At any point in time the future sequence of climatic states is uncertain, and the nature of this uncertainty means climate change impact models should investigate the range of probable outcomes for a generalized case, rather than the likely outcome from a single event that is assumed to be critical. Short model runs over sequences of historical data cannot do this as they do not represent the relationship between farm investment decisions (the outcome of which is realized over decades) and important aspects of climate change like increased drought frequency.

[11] Regardless of model structure and whether or not uncertainty of future climate states is accounted for in decision-making processes, few farm models are able to generate probabilistic outputs, and those that do [e.g., *Gibbons and Ramsden,* 2005] neglect the importance of sequences in both climatic events and crop production decisions.

[12] This paper presents a generic framework for creating an integrated model of irrigated agricultural production at the farm scale that acknowledges that climate processes

are one of the key drivers of farm profitability. The model framework explicitly accounts for sequencing effects present in naturally variable climate parameters and is specifically designed to incorporate uncertainty and thus model a general, uncertain climate future by using Monte Carlo simulation methods. The framework is used to create a model to estimate the impact of climate change on the underlying financial viability of farms already reliant on irrigation technology and to test the often implicitly made assumption that ignoring climatic sequences does not systematically underestimate the costs of climate change for irrigated agriculture.

[13] The rest of this paper proceeds as follows. The proposed model framework is described in section 2 along with a novel representation of farmer decision-making behavior. Section 3 describes an application of the model framework to a case study in the Murray-Darling Basin, Australia, to create a model that is used to assess the benefits of this methodology. Section 4 presents a discussion of the results of this application, focusing on the importance of probabilistic output and sequencing effects in stochastic climate variables, while section 5 gives a summary and concludes the paper.

2. Model Framework

2.1. Overview

[14] The integrated environmental-economic system represented by the proposed model framework is shown in Figure 1. The conceptual framework represents an irrigated agricultural production system from the point of view of an individual farmer by separating the system into three subsystems representing environmental processes, markets the farmer interacts with, and the farm itself. Figure 1 illustrates how individual processes within each of these sectors are disaggregated to component models that are linked through flows of resources (solid arrows) and information (dashed arrows).

[15] Central to the modeled system is the farmer. In general terms, the farmer utilizes resources provided by the environment sector (e.g., rainfall and irrigation water) to produce a crop and engages the market sector to realize economic gain from this activity. The farmer model consists of both a short-run decision model that optimizes annual profit given the known climatic state of the current cropping season and other constraints on production and a long-run model that attempts to maximize future profits given expected future climatic states. Constraints on these decisions are dynamic and are a function of the farmer's stock of financial capital, which is itself a function of past farm decisions.

[16] The farmer's access to irrigation water in any year varies and is a function of the volume of water entitlement the farmer owns (a long-run variable) and the degree to which water allocations will fulfill the entitlement in any year. Seasonal allocation levels vary from season to season and are a fraction of the farmer's water entitlement ranging from 0 to 100%. They are determined in the model by a set of allocation rules that are implemented by the river regulator in response to information describing climatic state and result in the regulator controlling the degree of access the farmer has to irrigation water.

[17] To effectively utilize each growing season's climatic state and available water to generate marketable goods, the farmer relies on his knowledge of how to best employ his own farm capital. This farm capital includes perennial crops, typical farm machinery, production infrastructure, and irrigation equipment, which together compose the field component model. The productivity of the field varies in time as a result of both the state of maturity of the crop and changes in the efficiency of irrigation infrastructure that occur with age. Therefore, the long-run decision must take into account the temporal aspect of both climate variability and field productivity.

[18] The model created using the framework is a dynamic simulation model with an annual time step. Execution of

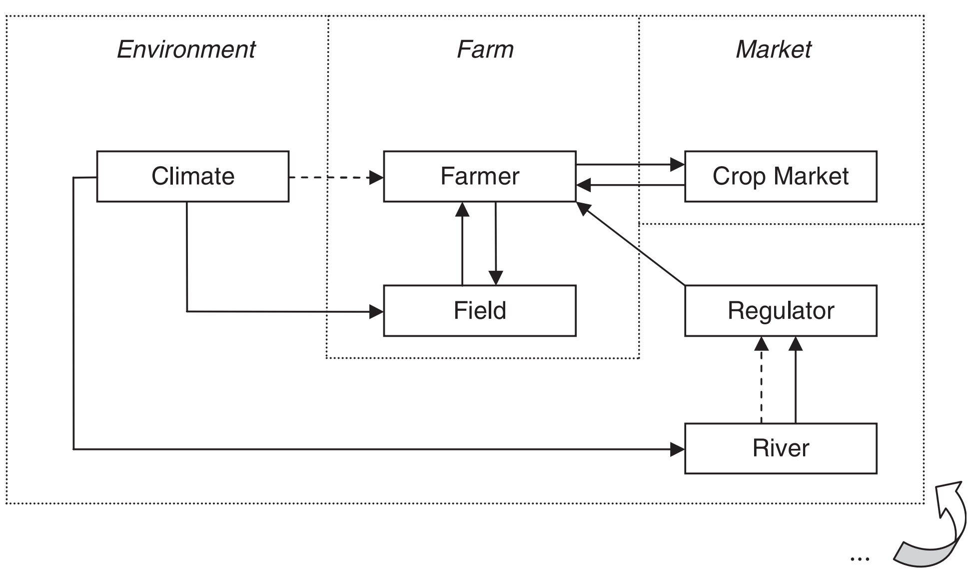

Figure 1. Proposed integrated simulation model framework.

each time step involves first updating stocks of stochastic environmental variables (i.e., drivers outside the actor sector as defined in Figure 1) and execution of the farmer decision and field production models.

2.2. Model Framework Structure

2.2.1. Environment Sector

[19] The environment sector comprises processes that affect crop water requirements (potential evapotranspiration), irrigation water requirements (rainfall), and irrigation water availability (state of irrigation water source). Together, these models provide the farmer sector with a set of random variables that describe the environmental state at any point in time and are therefore key inputs to the farmer decision-making models. It is this representation of the stochastic nature of environmental processes, coupled with the dynamic model structure, that allows the model framework to represent sequencing effects that result from interannual variability in climatic state.

2.2.2. Market Sector

[20] The market sector provides the farmer model with price information for inputs to and outputs from crop production. This framework considers crop production as the sole farm output.

2.2.3. Farm Sector

2.2.3.1. Field Model

[21] The field component model describes physical crop production processes occurring on the farm, which are driven by climatic inputs and farmer decisions. More specifically, the field model describes the crop water yield response as a function of current climatic state (potential evapotranspiration and rainfall) and farmer short-run inputs (applied irrigation water) and as a consequence of preceding farmer long-run decisions (crop and irrigation infrastructure type and age). Following from *Baerenklau and Knapp* [2007], this model includes vintage effects resulting from the reduction in the efficiency of irrigation systems as they age. This model extends Baerenklau and Knapp's approach by also including crop age effects relating to the different phases of productivity typical of perennial crops. This approach allows the model to represent a key dynamic of long-run investments in irrigated perennial crops, which typically exhibit an initial period of low productivity after planting due to crop immaturity, a period of peak productivity, and a subsequent gradual decrease in productivity due to aging effects. The temporal dynamics of farm productivity is accounted for by including a yield reduction factor that combines the effects of both crop maturity and irrigation infrastructure age on farm productivity and that varies in time. Figure 2 gives a conceptual example of how the combined effects of crop and irrigation infrastructure age affect the productivity of the farm in terms of maximum attainable relative yield. Inclusion of this temporal aspect of farm productivity within the field model contributes to the ability of the framework to account for sequencing effects of long-run decisions.

[22] The field component model has two functions within the model framework. First, the dynamics of the crop water relationship described by the field model informs the farmer short-run decision model (described in section 2.2.3.2), and second, the model is used to determine crop production in any season as a result of farmer decisions.

2.2.3.2. Farmer Model

[23] Traditional models that use a single objective function for both long- and short-run decisions tend to use the discounted sum of all farm profits over a fixed planning horizon to evaluate decision options. This net present value approach to investment analysis ignores the potential value to the farmer of retaining the option to make long-run investments at some point in the future by delaying investment decisions [*Dixit and Pindyck*, 1995]. The true value of delaying long-run investments should be evaluated on the basis of expected return over the whole productive life of the investment once it is made. This is important when considering climate change impacts, as modeling a generalized case involves long simulation runs where the age-productivity relationship described in section 2.2.3.1 is a driver of long-run investment decisions. Options involving delayed investment require a dynamic assessment horizon to ensure that decisions are not made on the consideration of only a portion of the expected life of an investment and that costs associated with reversing an investment are captured.

[24] To account for this important dynamic, the model represents the farmer decision-making process using two objective functions, one explicitly representing short-run water use decisions and the other representing long-run investment decisions in farm capital comprising irrigation

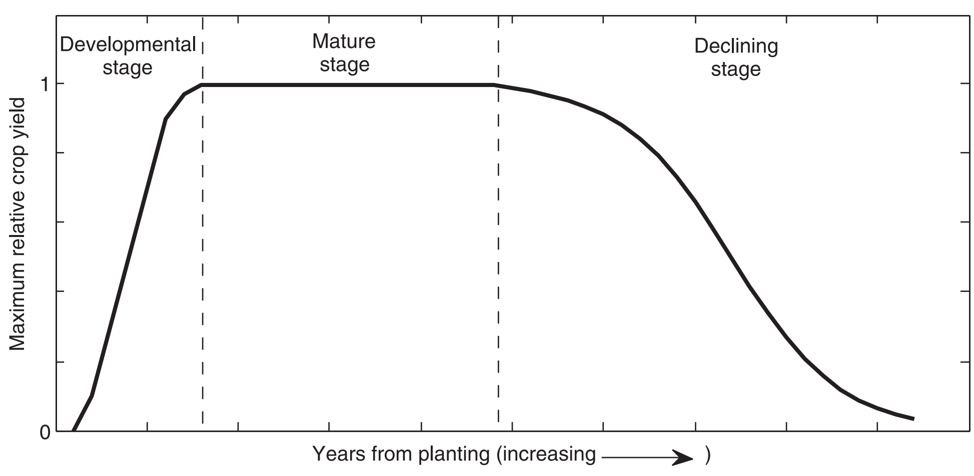

Figure 2. Productivity stages of a perennial crop over its lifespan.

technology and perennial crop plantings. Together, these objectives still represent the farmer as a profit-maximizing agent; however, this disaggregation allows for each decision process to be represented by the most appropriate metric. The model represents the short-run decision as maximization of annual profit within the constraints of current environmental state and previous long-run investment decisions and the long-run decision as a maximization of expected equivalent annual worth of capital stock investment options available to the farmer, including delaying investment to subsequent years.

[25] The short- and long-run decisions are evaluated sequentially at each simulated time step. To ensure that the outcome of both long- and short-run decisions are taken into account in subsequent decisions, the farmer is modeled as having a stock of financial capital that varies in time. The value of this stock in any given year is represented by an attribute analogous to a bank account. Flows into and out of this bank account result from revenue generated and both fixed and variable costs incurred at each time step, respectively. Both short- and long-run decision models are described further.

[26] The objective of the short-run farmer decision model is to maximize profit in the current year on the basis of the known current climatic state with irrigation water volume as the decision variable. The objective function is

$$\text{Maximize} \ \ \pi_t = Y(v_t; E_t, i_t)p_c - v_t c \tag{1}$$

subject to

$$v_t \leq a_t V, \tag{2}$$

where π_t is the gross profit in year t; $Y(\,)$ is the crop yield function describing gross yield (from crop production model); v_t is the volume of irrigation water applied in year t (decision variable); E_t is a vector describing environmental state in year t composed of terms representing pan evaporation and rainfall; i_t is the age of current farm capital (irrigation infrastructure and crop plantings); p_c is the market price for crop c; c is the volumetric cost of irrigation water application for technology r; V is the irrigation water entitlement of the farmer in a year of full allocation; a_t is the fractional allocation level in year t.

[27] The optimization is constrained only by irrigation water availability ($a_t V$), which is determined as part of the water allocation process within the regulator component model and is therefore exogenous to farmer decision processes. The water availability constraint ensures that in years with zero allocation, water cannot be applied as irrigation. Coupled with the irrigation water availability constraint is a soft constraint describing the smallest volume of irrigation water that must be applied in each year. Unless contradicted by the water availability constraint, farmers must apply at least enough irrigation water to ensure half the maximum evapotranspiration requirements for the crop are met or the maximum volume of water available, whichever is less. This soft constraint takes into account seasonal rainfall and is included in an effort to further represent the imperfect reversibility of investments in perennial crop plantings.

[28] The short-run objective function explicitly incorporates the trade-off between irrigation water application and crop yield, allowing farmers to carry out deficit irrigation i.e., where yield is sacrificed by deliberately underwatering the crop in an attempt to maximize profit rather than yield.

[29] The objective of the long-run decision model is to maximize the expected benefits from long-run investments in farm infrastructure, composed of planting perennial crops and irrigation equipment. The age-productivity relationship described earlier is the driver of investment in new farm infrastructure. The decision variable is a binary variable representing the "invest–not invest" nature of the long-run decision. The model does not use any heuristic constraints on the long-run decision to prevent retiring new or force replacement of old farm infrastructure. Instead, it relies upon the concave nature of the solution space defined by feasible investment strategies and the outcome of past decisions in the context of previously experienced climate.

[30] The outcome of past short- and long-run decisions made in the context of experienced variability of climatic state are accounted for by the state of the farmer's stock of financial capital at any point in time. This attribute is described by a variable analogous to a bank account that operates as a line of credit. The value of this variable (i.e., the "account balance") changes in time and is updated by adding (or subtracting) annual profit (or loss) from farming activity in the current time step to the value of the attribute at the previous time step along with interest on debt or savings and other costs borne by the farm in that time period. The flow of the farmer's financial capital is described by

$$\mathrm{AB}_t = \mathrm{AB}_{t-1} + \mathrm{AB}_{t-1}\mathrm{IR} + \pi_t - \mathrm{FC} - \mathrm{VC} - H - x_t(\mathrm{IC} - \mathrm{SV}_t), \tag{3}$$

where AB_t is the account balance in year t; IR is the annual interest rate paid or received on the account balance; FC is the fixed cost of access to water (e.g., license or connection fees); VC is the variable cost of farm operations (i.e., annual operating costs not including costs directly associated with water use decisions); H is the annual farm income requirement for non-farm-related expenditure; $x_t = 1$ for years when the farmer invests in infrastructure and 0 for all other t; IC is the capital cost of new farm infrastructure; SV_t is the salvage value of farm infrastructure in year t.

[31] It is assumed that variable costs are incurred regardless of the irrigation application decision because of the perennial nature of the crop and ongoing maintenance requirements of the farm. Other variables are as previously defined.

[32] As a result of the binary nature of x, the fact that IC represents the full capital cost of farm infrastructure, and the representation of AB as a line of credit, the model requires no assumptions on either the time period over which fixed costs are amortized or the age of farm infrastructure at which investment in new infrastructure is either prohibited or compulsory.

[33] To include the temporal dimension of the long-run decision process, the evaluation of investment options uses a variable planning horizon. The length of this horizon is based on the expected productive life of the investment (a fixed period) and the expected performance of the existing farm infrastructure between the current time step and that

at which the investment would be made (a variable period). Investment in new infrastructure only occurs when the expected value of investing in the current time step is greater than that estimated by delaying the investment decision by a year or more. In order to compare investment options with various planning horizons, the evaluation process uses the equivalent annual worth of each option as the grounds on which they are compared.

[34] When estimating the expected value of investment options, the current account balance is used as the basis from which expected financial benefits of investment are estimated. This approach ensures the financial realization of past farmer decisions is taken into account. To estimate the value of renewing infrastructure, a time series of future cash flow from the current year to the end of the planning horizon is estimated on the basis of expected future climate conditions. This time series of expected cash flow is used to calculate the expected value of the farmer's account balance at the end of the planning horizon.

[35] As an example of the variable planning horizon approach, if the expected productive life of farm capital (irrigation infrastructure and crop plantings) is 25 years, when the farmer evaluates the option of investing in the current year, the projected account balance at the end of the planning horizon is 25 years into the future and therefore takes into account the salvage value of the current investment, the fixed cost of the new investment, and the discounted expected annual costs and revenue over the 25 years. When, however, the farmer evaluates the option of delaying the decision to invest by one year, the projected account balance at the end of the planning horizon is 26 years into the future. This account balance takes into account the discounted salvage value of the current investment and fixed costs associated with the new investment, which occurs one year into the future, the expected costs and revenue the current investment will generate in the next year, and the expected costs and revenue of the new investment for the 25 years beyond the point of investment. This approach allows for consideration of costs and benefits associated with both current and new farm infrastructure and crops regardless of the point in time the investment occurs and therefore captures the value to the farmer of delaying investment. However, the mismatch in the temporal dimension of the estimation of future farm performance that comes from the option to delay is accounted for by using the equivalent annual worth of the investment as the basis of comparison. Using the projected future account balance for each option also allows for the financial realization of past investment decisions to be treated as a lump sum payment at the end of the planning horizon and the equivalent annual worth to be calculated as an annuity over that same time period.

$$EW_y = \frac{\widehat{AB}_y}{(1+IR)^{(y+l)}}\left(\frac{IR}{[1-(1+IR)^{-(y+l)}]}\right), \tag{4}$$

where EW_y is the estimated equivalent annual worth of investing in new farm infrastructure y years into the future, l is the expected productive life of the investment, and $\widehat{AB}_y$ is the projected account balance l years beyond year y, the point of investment. On the basis of assessment of investment options available to the farmer in the current year t, the projected account balance l years after delaying investment by y years beyond year t is determined using

$$\widehat{AB}_y = \sum_{u=1}^{y+1}\Big[\widehat{AB}_{u-1} + ir(\widehat{AB}_{u-1}) + \hat{\pi}_u - FC - VC - H - x_u(IC - SV_u)\Big] \tag{5}$$

subject to

$$\widehat{AB}_0 = AB_t,$$

where $\hat{\pi}_u$ is the estimated annual profit in the uth year beyond year t, x_u is a dummy variable equal to 1 when $u = y$ and 0 for all other u, and SV_u is the salvage value of existing farm infrastructure U years into the future. Other variables are as previously defined. Investment in renewed farm infrastructure only occurs when EW_0 is greater than EW_y for all other y.

2.2.4. Model Dynamics

[36] The sequence of component model execution follows the order described in Table 1. Data extracted from the model display strong temporal variability as a result of the complex dynamics of both stochastic environmental state and short- and long-run farmer decision processes and should be further analyzed to derive a set of secondary indicators that describe system performance over the whole simulation run. Application of Monte Carlo simulation methods allows for probabilistic representation of these secondary indicators. The Monte Carlo simulation is executed using multiple time series of randomly generated synthetic data for climate inputs.

[37] As this model is intended to provide an indication of climate change impacts for a generalized case, model runs must be long (i.e., greater than 100 years) to provide sufficient data for analysis and to ensure that the influence of any individual shock is not overrepresented within the results. Long model runs are also important to minimize sampling errors resulting from the use of randomly generated synthetic data in a Monte Carlo simulation. It is necessary to stress that time series of model outputs over individual model runs should not be considered as accurate predictions of farm conditions over the specific climate future represented by that run, but rather as data to be used for comparative analysis of a generalized case that takes into account both long- and short-run decision processes.

3. Case Study

3.1. Background

[38] The Murray Darling Basin (MDB) is located in southeastern Australia. It covers over 1×10^6 km^2, and agriculture within the system makes a significant contribution to Australia's agricultural production, particularly within the irrigated sector [*Bryan and Marvanek*, 2004]. The Sunraysia district of the MDB is located in northwestern Victoria, and like many other semiarid regions of the basin, the district's predominant industry is irrigated agriculture, a legacy of early to mid-twentieth century policies designed to promote economic development and expansion

Table 1. Sequence of Component Model Execution Within the Simulation Time Step

Process	Component	Description
1. Update exogenous processes	Climate river regulator	Generation of stochastic variables describing climate-based inputs to farm processes
2. Update perception	Farmer	Propagation of data from environment sector that allows the farmer to form a view of the current system state
3. Short-run decision	Farmer	Selection of appropriate level of irrigation water use given current system state
4. Short-run response	Field farmer market	Realization of the farmer's short-run decision (crop growth, harvest, update bank balance)
5. Long-run decision	Farmer	Analysis of long-run options based on current and expected future climatic states; selection of investment strategy
6. Decision execution	Farmer field	Realization of the farmer's long-run decision (investment in new infrastructure, update bank balance)

in the basin's sparsely populated regions [*Quiggin*, 2001]. In recent years the region has been faced with the most severe drought on record, and current conditions within the basin suggest that water has been substantially overallocated.

[39] Most future climate scenarios for this region suggest that as a result of climate change, average annual rainfall will decrease while annual potential evaporation will increase, impacting the demand for, and availability of, irrigation water. These changes are likely to occur amid more pronounced variability of climatic conditions between cropping seasons and increased probability of prolonged drought [*Stokes and Howden*, 2008].

[40] The objective of the case study was to evaluate the impact of climate change on the financial viability of a stylized typical farm in the Sunraysia district. The study is a comparative analysis based on the expected range of climate futures for a baseline case and three climate change scenarios. The impacts considered in this study were limited to those influenced by interannual climate variability rather than the costs associated with climate change adaptation. The stylized farm was considered to have perfect knowledge of the long-run average climate conditions for each climate scenario and therefore held sufficient water entitlements to optimize crop production for the average climate state. However, the farmer was represented as unable to anticipate the future climate sequence for any scenario. The results of the study were used to investigate the role of variability and sequencing effects in determining model output.

3.2. Model Development

[41] In order for the proposed model framework to represent the case study location, component models were specified to represent conditions experienced by farmers in the Sunraysia district under four climate change scenarios. This case study adopts the four climate change scenarios used by *Connor et al.* [2009] and described by the parameters shown in Table 2.

[42] The modeled farm produces wine grapes using drip irrigation. This is a common crop and irrigation technology combination in Sunraysia and is also considered to be an efficient and high-value use of irrigation water. This specification is described in terms of each model sector.

3.2.1. Environment Sector

[43] Values for annual rainfall and pan evaporation were generated using simple lag 1 Markov models. The application of the Markov approach followed the methodology described by *Grayson et al.* [1996]. Parameters used to specify the model were derived from daily rainfall and pan evaporation data recorded by the Australian Bureau of Meteorology at Mildura Airport from 1946 (rainfall) and 1965 (pan evaporation) to 2008. These daily data were used to produce time series of annual values based on a July to June water year, corresponding to local cropping seasons. Time series of rainfall and pan evaporation for each climate change scenario were created using synthetically generated data for baseline conditions and scaling them using the parameters shown in Table 2.

[44] The river and regulator components of the environmental sector were combined into a single component model, and this was used to generate multiple time series of water allocation levels on the basis of each climate scenario. The model uses a state transition probability matrix based on a set of discrete allocation levels between 0 and 100% using 10% intervals. The transition probabilities were calculated on the basis of predicted allocations using the MSM-BIGMOD model [*Murray Darling Basin Commission*, 2002] (the flow and salinity routing model used by the Murray Darling Basin Authority) as used by *Connor et al.* [2009].

3.2.2. Market Sector

[45] While the proposed framework presented here is capable of using a crop market component model that includes dynamic price effects, for the purposes of this case study it was assumed that crop prices are exogenous to the modeled system and are constant. While uncertainty in future crop price is a determinant in farmer long-run decisions (particularly with reference to technology adoption), the explicit aim of this study is to investigate the role of the dynamic nature of variability in climatic processes in assessing the viability of established farming approaches. As noted by *Carey and Zilberman* [2002], including a dynamic representation of crop price adds additional complexity that may increase model realism at the cost of masking the processes of interest.

3.2.3. Farm Sector

3.2.3.1. Field Model

[46] Crop production was represented as a function of the volume and quality of water available to plants for growth and potential evapotranspiration. Water volume includes both effective rainfall and applied irrigation water, and water quality is the volume-weighted average salinity of rainfall and irrigation water. Maximum potential evapotranspiration was derived from annual pan evaporation using monthly crop growth factors taken from *Lipman*

Table 2. Climate Change Scenarios and Consequences on Rainfall and Runoff[a]

Scenario	Average Temperature Change (°C)	Average Potential Evapotranspiration Change (%)	Average Rainfall Change (%)	Average Runoff Change[b] (%)
Baseline	0	0	0	0
Mild	+1	+4	−5	−13
Moderate	+2	+8	−15	−38
Severe	+4	+15	−25	−63

[a]Estimates based on results from *Pittock* [2003] unless otherwise indicated.
[b]Estimates based on the work of *Kirby* et al. [2006].

et al. [1998]. The crop yield response relationship was taken from *Kan et al.* [2002] and adapted to allow for interannual variation in maximum potential evapotranspiration. The function takes the form

$$\mathrm{RY} = \frac{\alpha_0 + \alpha_1 \mathrm{ET}_{\mathrm{adj}} + \alpha_2 {\mathrm{ET}_{\mathrm{adj}}}^2}{Ym_r}, \tag{6}$$

where RY is the relative yield, α_0, α_1, and α_2 are empirically derived constants, m_r is the maximum potential gross yield of the crop for the reference site used to derive the empirical constants, and $\mathrm{ET}_{\mathrm{adj}}$ is the actual evapotranspiration adjusted to allow transposition of modeled conditions to those of the site for which empirical constants were derived. This process is described by

$$\mathrm{ET}_{\mathrm{adj}} = \frac{\mathrm{ET}m_r}{1 + \beta_0 \left[\mathrm{EC}_W + \beta_1 \left(\frac{\mathrm{AW}}{\mathrm{ET_m}} \mathrm{ET}_{m_r} \right)^{\beta_2} \right]^{\beta_3}}, \tag{7}$$

where ET_{m_r} is the maximum potential annual evapotranspiration for the crop at the reference site used to derive empirical constants; $\mathrm{EC_w}$ is the weighted average salinity of the rainfall and applied irrigation water; AW is the total water available to the plant by irrigation and rainfall in the current year; $\mathrm{ET_m}$ is the maximum evapotranspiration for the crop at the site of model application for that year; β_0, β_1, β_2, and β_3 are empirically derived constants.

[47] The empirically derived constants α_j and β_k are unique to a specific combination of crop and irrigation technology and implicitly account for the effects of nonuniform irrigation water application. The benefit of this approach is that it provides a crop yield–water function that is smooth and monotonically increasing, with RY' (the derivative of RY with respect to AW) approaching zero with increasing AW. This allows the model to represent the diminishing net marginal benefit of applying additional irrigation water and, by extension, to represent deficit irrigation behavior more realistically than a discontinuous von Liebig function, which although popular in the literature, favors corner solutions.

[48] The age-productivity relationship described in section 2.2.3.1 is represented using a set of estimated maximum attainable yield values for each year. The yearly values were estimated from farm extension literature and are based on a 5 year developmental stage and the field entering the declining stage 25 years after investment [*Dakis et al.*, 2001; *Weber et al.*, 2003]. During the declining stage, the maximum attainable yield is assumed to decrease to zero in a linear fashion over 15 years.

[49] This case study does not consider the potential impacts of elevated atmospheric CO_2 on crop productivity as limited empirical information from Australian studies are currently available. Studies on similar perennial crops in California, United States (which shares many characteristics with the southern MDB), conclude that the negative yield impacts of increasing temperature are greater than the yield benefits that would be expected from CO_2 fertilization [*Lobell et al.*, 2006].

[50] The salvage value of farm irrigation infrastructure was assumed to initially equal the purchase cost of infrastructure and to decrease with time using an exponential decay function with an assumed depreciation factor of 25% of remaining value per year.

3.2.3.2. Farmer Model

[51] The expected productive life of farm infrastructure was assumed to be 25 years on the basis of procedures found in typical extension literature [*Dakis et al.*, 2001; *Weber et al.*, 2003]. The interest rate was assumed to be 8% per year on debt and 5% per year on savings. The capital cost of farm infrastructure and variable costs not related to water use were derived from *Connor et al.* [2009]. Fixed and variable costs associated with water use were acquired from the historical supplier of irrigation water to farms in the case study location.

3.3. Model Application

[52] The dynamic nature of the model means that annual farm profit varies considerably between simulated cropping seasons and is therefore not a suitable metric for describing the underlying financial viability of the farm. Instead, this case study used an alternative version of the farm income requirement (H in equation (3)) as a metric describing financial viability. The farm income requirement in the farmer economic model accounts for household expenditure that does not involve investing in farm capital or operations but must still be met to maintain the viability of the household (see *Iglesias et al.* [2003] for a typical application of this approach). This value is likely to vary significantly between individual farms and is therefore impossible to accurately determine for a generalized case. Given this difficulty, the model specification used in this study does not assume a minimum farm income requirement. Instead, for each run the model was solved to find the maximum farm income requirement ($\widehat{H}$) that does not deplete the farmer's stock of financial capital over that model run. The change in this stock over any model run is represented by the slope of the linear regression of the farmer's bank balance variable against time. This method of analysis removes annual variation of the financial state caused by the dynamic nature

of the model, with a regressed slope of zero indicting the farmer neither accumulates nor diminishes his stock of financial capital over the course of the model run. In this context, $\widehat{H}$ represents the maximum annual dividend that could be taken from the farm without jeopardizing the ongoing profitability of the farm. This study employed $\widehat{H}$ as an estimator of long-run farm profitability and therefore an indicator of the underlying viability of the farm.

[53] Initial conditions within the model were set in keeping with the application of the model to a well-established, informed, and technologically advanced stylized farm. The farmer bank account was initialized at zero.

[54] The model was run over 100 replicates of randomly generated 200 year synthetic time series of climate data for each climate scenario. This resulted in a set of 100 estimated farm profitability values (one for each run) and 20,000 values for variables determined on an annual basis (e.g., seasonal volume of applied irrigation water and crop yield). This 200 year run length was considered to be sufficiently long to meet the requirements described in section 2.2.4.

[55] For each climate scenario, the model was also run over a single 200 year simulation using steady state expected value models for annual rainfall, pan evaporation, and water allocation level to determine estimated farm profitability values in the absence of climatic variability and resultant sequencing effects. The results from the model using steady state climate representation were used as a basis upon which the benefits of using the proposed dynamic stochastic simulation over traditional approaches were evaluated.

4. Results and Discussion

4.1. Impact of Climate Change on Farm Profitability

[56] Estimates of farm profitability using both stochastic and steady state climate models are shown in Table 3. Results generated using the steady state climate model provide an estimation of farm profitability under average climate conditions and exhibit an inverse relationship between farm profitability and climate change severity (Table 3). The negative value of this estimate under severe climate change conditions indicates that the farmer would expect the farm to have a loss and would therefore employ his capital elsewhere or invest in long-run adaptation measures. These aspects are outside the scope of this paper, and for that reason, results for the severe climate change scenario are not considered further in this paper.

[57] Figure 3 is a box plot of farm profitability estimates obtained for the baseline, mild, and moderate climate change scenario under drip irrigation using the stochastic climate model. The upper and lower bounds of the box indicate upper and lower quartile values, respectively, with the vertical line within the box indicating the median. Ranges of data are shown using whiskers that are at most a factor of 1.5 greater than the interquartile range. Outliers beyond this range are shown individually.

[58] Results generated using the stochastic climate model also indicate that average estimates of farm profitability decrease with increasing severity of climate change. Figure 3 clearly illustrates that under baseline and mild climate change conditions the difference in average values between the baseline and mild scenarios is significant ($p = 0.05$); however there is only a 10% reduction in this parameter. Results from the moderate climate change scenario show a more marked reduction in farm profitability, reducing the average estimate compared with baseline conditions by 64%.

[59] These results are consistent with the steady state model estimates and the intuitive expectation that farm profitability would suffer under worsening climate change as an outcome of increased crop water requirements, decreased natural rainfall, and decreased availability of irrigation water. While this relationship is present in results generated by both the steady state and stochastic models, the steady state model results do not suggest that climate change will reduce farm profitability to the same degree as those from the stochastic model.

[60] Comparison of steady state model estimates with average values generated using the stochastic model shows that under baseline climate conditions, there is no significant difference in estimated farm profitability using the two modeling approaches. Under increasingly severe climate change scenarios, estimates of farm profitability obtained using the steady state expected climate model are significantly higher than average values from the stochastic climate simulations (for $p = 0.05$). For the mild climate change scenario, the steady state model estimates a fall in farm profitability of 8%, which is close to the 10% average reduction estimated by the stochastic model. Under moderate climate change the farm profitability estimated by the steady state model is reduced by 31% in comparison with the baseline case, whereas the stochastic model estimates a 64% reduction in the same parameter, a discrepancy of 33 percentage points.

4.2. Role of Climate Variability and Sequencing in Estimating Farm Profitability

[61] As the steady state and stochastic models are identical in all aspects other than the structure of the climate component model, the discrepancies in estimated farm profitability can only result from two distinct, but related, sources: climate variability and climatic sequencing. Incorporating climatic variability requires that a model incorporates the various possible states of nature and the relative frequency with which they occur, whereas climatic sequencing is a result of how this variability manifests itself in the temporal dimension. Introducing climatic variability to a dynamic model invariably produces sequencing effects. For this reason, analyzing the influence of these effects independently poses a challenge. Regardless, the combined impact of climate variability and sequencing can be clearly seen in the difference between results obtained using the stochastic

Table 3. Estimated Farm Profitability

Climate Scenario	Estimated Farm Profitability ($/yr): Steady State Climate Model	Estimated Farm Profitability ($/yr): Stochastic Climate Model	Probability That Estimate by Dynamic Model Will Exceed Steady State Estimate[a]
Baseline	33,234	33,146	0.45
Mild	30,695	29,715	0.32
Moderate	22,861	11,913	0.01
Severe	−16,121	-	-

[a]Based on Kaplan-Meier estimates of the estimated farm profitability cumulative distribution function using stochastic rainfall, pan evaporation, and allocation submodels; $n = 100$.

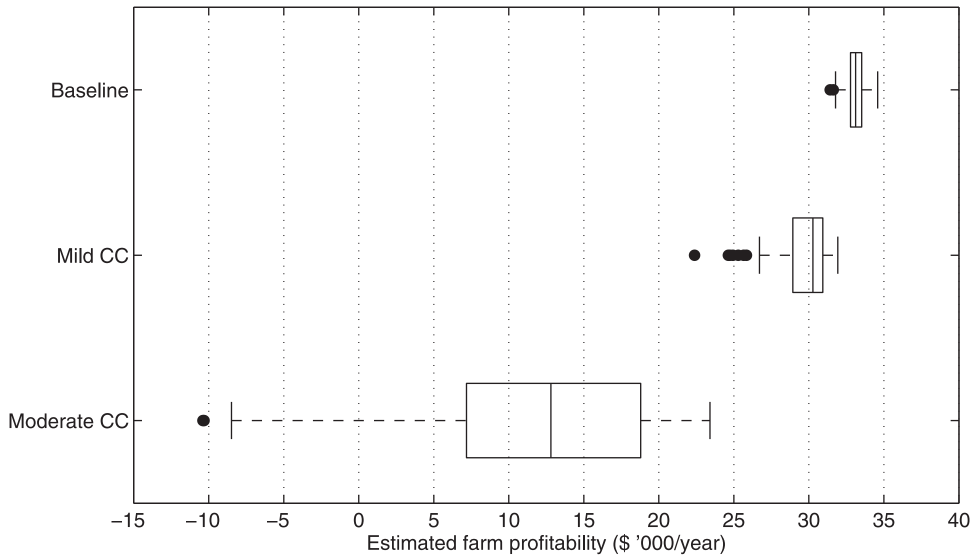

Figure 3. Estimated farm profitability under climate change using drip irrigation. Whiskers indicate $\leq$1.5 interquartile range; $n = 100$.

climate model (which has both variability and sequencing) and those generated using the steady state climate model (which has neither).

[62] Looking at the spread and location of farm profitability estimates generated by Monte Carlo simulation of the stochastic model relative to those generated using the steady state model supports the assertion that ignoring both climatic variability and sequencing effects underestimates the impact of climate change. Given that the farm profitability estimate determined by the steady state model for the baseline case is not significantly different from average farm profitability estimated by the stochastic model and that the spread of these values from the stochastic model is relatively small, it seems reasonable to suggest that climate variability and sequencing effects have limited influence on farm profitability under baseline conditions. This observation does not hold for other climate change scenarios, with significant differences between farm profitability estimates generated using the steady state and stochastic models.

[63] The importance of sequencing effects (as distinct from climate variability), which can only be represented using a dynamic model, can be seen in the variability present in estimates of farm profitability within each climate scenario using the stochastic climate model. Under baseline conditions, the coefficient of variation of farm profitability estimates is 0.02. The value of the coefficient of variation increases to 0.06 and 0.66 under mild and moderate climate change, respectively.

[64] Results from the model were analyzed using mutual information as a nonlinear measure of dependence [see *May et al.,* 2008] to test if any significant relationships existed between the relative frequencies of climatic states in each run (which will vary in randomly generated series of synthetic data of finite length) and that run's estimate of farm profitability. The analysis found no such relationships.

[65] While the analysis above has demonstrated the impact of sequencing effects in isolation to climate variability, the dynamic nature of this model makes it impossible to perfectly isolate the effect of variability from sequencing. However, the finding that sequencing effects are responsible for the spread in estimates of farm profitability makes it possible to infer a qualitative relationship between climate variability and model output.

[66] If the degree of temporal variability of climatic state did not impact upon the model output, it would be expected that the distribution of profitability estimates would be located close to each relevant steady state estimate. The results presented in Table 3 show that this is not the case (using the average value as the central location of farm profitability estimates generated using the stochastic model). Comparison of average profitability values with estimates generated using the steady state model indicates that the increased climate variability associated with worsening climate change leads to the consistently lower estimates of farm profitability described in section 4.1.

[67] Even after taking into account the increasing uncertainty in model output with worsening climate change that results from sequencing effects, the severity with which the steady state model underestimates reduced farm profitability is clear. Under baseline conditions, 45% of stochastic model runs generated farm profitability values higher than the steady state model output (based on the Kaplan-Meier estimate of the cumulative distribution function [*Kaplan and Meier*, 1958]). Under mild climate change, only 32% of farm profitability estimates from model runs using the stochastic model are higher than the steady state estimate, and this measure decreases to only 1% under moderate climate change.

[68] This discrepancy stems from the fact that the steady state model cannot take into account the impact of climate variability on water availability and the resulting impact this has on annual profits. The concave nature of the crop water production function combined with the fixed price model results in a concave farmer profit function. Following from this, the farmer's marginal profit function is continually decreasing with respect to water application levels and asymptotically approaches the marginal cost of water

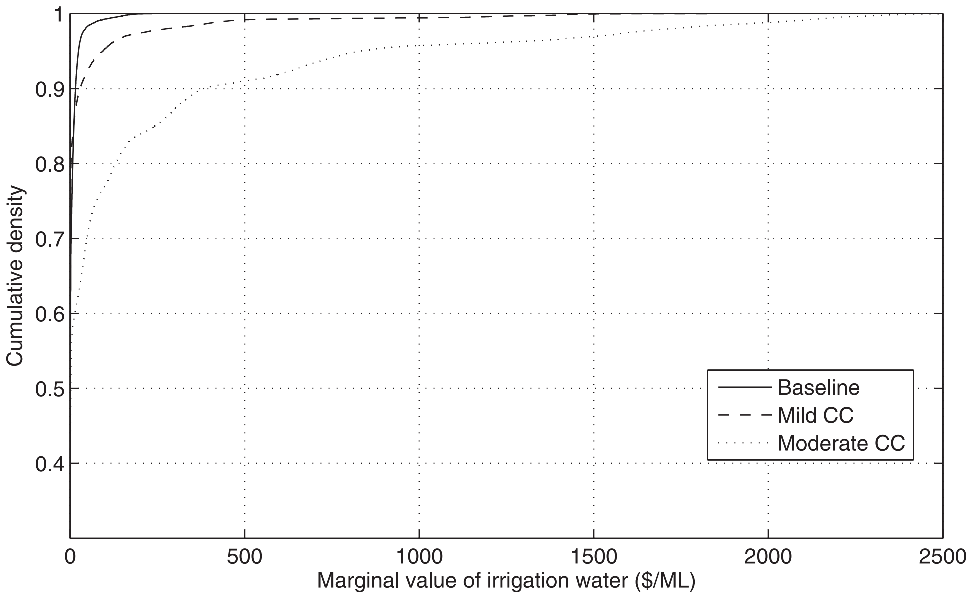

Figure 4. Marginal value of irrigation water conditional on nontrivial yield.

application. This indicates that shortfalls in irrigation water application (caused by availability constraints) have a much higher cost in terms of lost production than excess volumes do in terms of benefits. With greater variability of climate inputs, the expected irrigation water shortfall is higher, meaning that the farmer's selected level of irrigation water application is further from the optimal point where the marginal profit is zero. This phenomenon is reflected in the marginal value of irrigation water (MVIW) to the farmer under the different climate change scenarios.

[69] For each cropping season simulated by the model, the MVIW was estimated by calculating the change in annual farm profit that resulted from the application of a single megaliter of irrigation water in addition to the irrigation water volume determined by the farmer short-run decision model, which considers irrigation water use constrained by water availability rules. The MVIW calculations neglected years with immature crops as crop production is influenced more by crop age than irrigation water application in those years. Average values of MVIW for each climate change scenario were calculated as $5/ML under baseline conditions, $22/ML under mild climate change, and $147/ML under moderate climate change. The increase in average value that occurs from the baseline through mild and moderate climate change scenarios is consistent with what would be expected as irrigation water becomes increasingly scarce and production is more severely constrained by water availability. The trend of increasing average MVIW values is clearly visible in the empirical cumulative density functions of MVIW data shown in Figure 4.

[70] Figure 4 clearly shows the increased frequency of years with nonzero MVIW values that occurs with greater variability in climatic inputs associated with more severe climate change.

[71] As with all modeling exercises, the results presented in this paper should be considered within the context in which they were generated. While they are not intended to predict the impacts of climate change on irrigated agriculture in absolute terms, they do, however, provide a clearer understanding of the dynamic relationships that are likely to play a key role in determining the viability of irrigated agriculture under climate change. As mentioned in section 3.2, the model has been applied to a well established, informed, and technologically advanced theoretical farm. Assessing the impact of the assumptions necessary to specify the model, particularly the initial model conditions, is beyond the scope of this paper but should be the subject of further research.

5. Summary and Conclusions

[72] This paper presents a dynamic simulation model framework for assessing some of the impacts of climate change upon irrigated agricultural systems. The framework employs the farm as a meaningful indicator of these impacts as it is the level at which decisions on resource use are ultimately made. This scale of model framework is appropriate given that system response to climate change is the cumulative effect of decisions made by individual actors.

[73] By integrating multiple component models including explicit representation of decision-making behavior, the framework is able to represent complex relationships between climate variability, sequencing of climatic events, and long- and short-run farmer decisions. The framework was applied to a generic, stylized farm in the Sunraysia district of the Murray Darling Basin, Australia, for comparative analysis of three climate change scenarios against a baseline historical climate scenario. Application of the model framework using both steady state expected values and dynamic stochastic representations of climate showed that the steady state climate representation overestimated farm profitability compared to average estimates for the stochastic model. The degree of this overestimation increased with increasing severity of climate change. This is highlighted by the fact that even though the spread of farm profitability estimates increases with increasing climate change

severity, the vast majority, if not all, of these estimates are lower than the corresponding steady state estimate. This overestimation was most pronounced for moderate and severe climate change scenarios. The importance of climatic sequencing in determining farm profitability is highlighted in the spread of estimates of farm profitability generated using Monte Carlo simulation techniques on the stochastic model. The uncertainty in farm profitability estimates increases with increasing climate change and is a result of multiyear sequences of climatic state, rather than short-lived perturbations from expected conditions.

[74] The impact of climate variability on farm viability is most clearly explained by the changes in expected marginal value of irrigation water under varying degrees of climate change. Increasingly severe climate change leads to s higher expected marginal value of irrigation water as a result of an increased frequency of years in which crop production is limited by water availability.

[75] These results strengthen the argument for using dynamic integrated models for analyzing the impact of climate change on agricultural systems. In many cases component models can be drawn from existing literature. The modular architecture and explicit representation of the decision making of actors within the system make for a versatile tool for comparative analysis of alternative scenarios.

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