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Interactive land use strategic assessment: An assessment tool for irrigation profitability under climate uncertainty

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ABSTRACT

The Interactive Land use Strategic Assessment (ILSA) tool allows irrigators to examine and compare the likely effects of a range uncertain future climates on their individual enterprise along multiple time frames. The scientific basis of the tool is predicated on the influence of the prevailing climate conditions on expected levels of water allocations for irrigation activities under multiple climate scenarios.

The model reports both annual returns and ten year average annual expected returns, given probability weighted allocations for a selected decade and climate scenario. Irrigators are able to adjust default farm operational parameters to suit their particular circumstances and examine the expected returns across multiple possible future water availability and market price years.

A case study in the Loxton irrigation district of Southern Australia demonstrates the models capability examining the effects climate change, climatic variability, and water trade have on irrigation operations in a manner that is understandable to irrigators.

1. Introduction

While much of the scientific community possess a detailed understanding of the uncertainties around climatic and hydrologic futures, this information is rarely translated into forms that are suitable for planning by irrigators. Irrigators have demonstrated their adaptability to changing commodity markets and water availability (Meyer, 2014; Iglesias and Garrote, 2015) however, tools to consider future scenarios of market and climate-influenced factors are not in place. Here we address this need and demonstrate a case study in the Loxton irrigation district of Southern Australia.

Historical improvements in agricultural production through fertilizer applications, genetic improvements and the development of irrigation has allowed the rate of global food production to outstrip population growth (Ruttan, 2002; Alston and Pardey, 2014). More recently, global growth in population, changing market demands, diminished productivity gains, future climate uncertainty and reductions in fresh water supplies (Tilman et al., 2011, Mueller 2012; Elliott et al., 2014) are combining to change the operating environment of the agricultural sector. While productivity gains in rain fed agriculture and closing the actual to potential yield gap are important fields of research, irrigated agriculture currently supplies 40% of global food needs (WWAP, 2012). The importance of irrigated production in meeting future food demand continues to increase (Elliott et al., 2014).

Global demands for fresh water have increased throughout most of the previous century and are expected to continue to grow into the future (Gleick, 2003). Of all human activities, irrigated agriculture is the largest demand on global freshwater supplies (Elliott et al., 2014) representing an estimated 70% of all extractions. This increasing demand for water resources has coincided with infrastructure development and institutional regulation to ensure reliable supplies of water. As such, irrigators plan their agricultural businesses decisions around these supplies and seek to maximise financial returns. For many irrigators, the process of planning for future climate conditions relies on previous experience. Decisions about crop types, irrigation systems, water prices and allocations of water have previously been made using farm economics and experience within a relatively stable long term climate and water supply. However, towards the end of the 20th century and throughout the first decade of the 21st, conditions have changed with less certainty of expected water supply and greater competition for available water. Hence many irrigators are now operating with greater variability in available water allocations.

The global scientific community has been striving to model and understand the likely effects of climate change on the certainty of

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supply and has produced a large body of research across the major irrigation basins of the world. Farmers operating under future water scarcity conditions is a theme that is prevalent in the USA's Colorado River Basin (Bark et al., 2014; Fathelrahman 2014), across Europe and particularly Italy, France and Spain (Dono et al., 2013; Rubino 2013; Graveline and Merel, 2014), China (Tao et al., 2008; Thomas, 2008; Wang et al., 2014; Chen 2019)and Australia (Connor et al., 2009; Jiang and Grafton, 2012; Connor et al., 2014; Kirby 2014).

In Australia, recent experiences with drought and low commodity prices has increased irrigator understanding of how their production environment now involves considerably greater financial risks than it had previously (Schwabe and Connor, 2012; Connor et al., 2009). Planning future farm management activities in the face of uncertain and potentially scarce water supplies, coupled with low commodity prices, presents a considerable challenge for irrigators. While inter-annual variations in water allocations increase uncertainty and exert an influence on irrigated farm management decisions, many irrigator's economic planning decisions are now robust enough to survive short term fluctuations in water supply (Gorantiwar and Smout, 2003; Droogers and Aerts, 2005; Dono et al., 2013). Management approaches such as deficit irrigation or mothballing (Fereres and Auxiliadora Soriano, 2007; Connor et al., 2008), improved irrigation water use efficiency (Morison et al., 2008) and drought tolerant cultivars (Guoth et al., 2009; Verulkar 2010) can enable irrigators to wait out short term deficits in water supply. With the introduction of water property rights and water trading in southern Australia, some of the savvier farm managers have benefited from trading in the water markets (Wheeler et al., 2014a) to mitigate losses from allocation shortfalls (Weinberg et al., 1993; Wheeler et al., 2014b). Longer term or decadal sequences of allocation deficits have larger effects on long term planning decisions including capital asset investment, crop choice, debt consolidation and or opting out of irrigation altogether.

Here we describe an interactive web based software framework designed to allow irrigators to engage their own experience with a series of predefined plausible future climate scenarios. The Interactive Land use Strategic Assessment (ILSA) tool aims to allow each irrigator to examine and compare the likely effects of a range of uncertain future climates on their individual enterprise along multiple time frames. The model produces reporting on expected returns to future irrigated production weighted across possible future water availability and market price years considering the downside economic risks of possible future droughts. Developed within the context of a local irrigation community in Loxton, South Australia the model can be adapted to other regions, crops, irrigation systems climate change models and, water markets.

2. Materials and methods

2.1. Interactive land use strategic assessment tool

The scientific basis of the ILSA tool is predicated on the influence of the prevailing climate conditions on expected levels of water allocation for irrigation activities under multiple climate scenarios. The tool is not designed as a climate state transition model but rather a comparative static approach whereby the effects of each climate change scenario are only considered at the full run adjustment. The tool itself is developed using the JavaScripting language and delivered to end users via a user interface available in any web browser. It is comprised of multiple input sub-modules and databases whose interdependencies are managed through a central economic production and decision module (Fig. 1). The tool is preloaded with default parameter settings to align with current predictions of possible future climate and generic farm data. Users first choose which specified climate scenarios they wish to test and then choose whether to accept the default farm values or change them to suit their own circumstances. The model allows users to test and compare multiple scenarios of climate change, allocation volume and frequency, commodity types, irrigation systems, commodity prices, input costs and crop production. User decisions are tested and results displayed in graphical and tabular formats instantaneously.

In the following sections we describe each of the component modules that feed into the model and the main economic decision module in detail. Every component module, with the exception of the climate module, has dependencies on other component parts that requires careful sequencing of operations within the internal model structure. User inputs however, can be entered in any sequence as the model is fault tolerant to input order. The model itself operates in two distinct stages. The first stage runs the precursor modelling through two separate but interdependent modules (climate module, Allocations module). These modules are built and run outside of the ILSA decision tool itself to populate a database of expected allocations under a range of historic and future climate change scenarios. Stage two runs the ISLA tool itself and is comprised of two modules (Crop Production, Economic Production). This second stage collects input data from the allocations database, along with crop production parameters to produce estimates of production, profitability and water use under various current and future scenarios.

2.2. Climate change module

Following the approach of (Connor et al., 2009) this study applied three future climate change scenarios (Table 1), each representing increasingly drier and hotter possible future climates consistent with those used by the IPCC (Van Vuuren et al., 2011). While we recognise the potential for additional variability and complexity of the General Circulation Models in climate scenarios (Phogat et al., 2018, Chen 2019), this simplified approach was taken to avoid excessive levels of complexity, limiting uptake and engagement.

Climate change deltas from RCPs 2.5, 4.5, 8.5 are interpolated to 5° rasters and applied as block shifts to daily climate data for rainfall and temperature. The resulting climate files represent a future where hotter and drier condition might prevail. In order to provide an indication of the likely effects of these feasible future changes in climatic conditions, historical measures of rainfall, temperature and potential evapotranspiration are modified according to specified scenario proportions (Table 1) to reflect new climate records by scenario. We note that historical variation in climatic conditions will remain consistent throughout all scenarios as a result of this process and this may not represent the full scope of future climate uncertainty. Climate scenario altered climate files provide the input data used to define rainfall changes, in each of the catchments in the basin and can be updated to reflect new information.

Hydrological modelling takes in existing georeferenced climate data from the historical record. We apply the expected change in future climate uniformly across space and time.

2.3. Water allocation module

Water allocation estimation requires detailed understanding of the complete hydrological system of the study area catchment as well as the institutional arrangements that govern the use of water within these catchments and the spatial distribution of existing irrigation land uses and water retention infrastructure. Modelling these complex systems requires considerable expert knowledge and computational power. For ease of application the ISLA tool adopted a hybrid approach that utilises existing river modelling and cross references it with a less complex water use accounting model as described in the following sections.

The allocation module collects climate data from the climate module and inputs it into the (Kirby et al., 2006) water use account model. The water use account model estimates the likely future runoff and inflows under current sharing rules, levels of development and, various climate change conditions. Inflows to upstream reaches of the Murray-Darling Basin become the source of supply to downstream irrigators subject to allocation rules. As prevailing conditions become

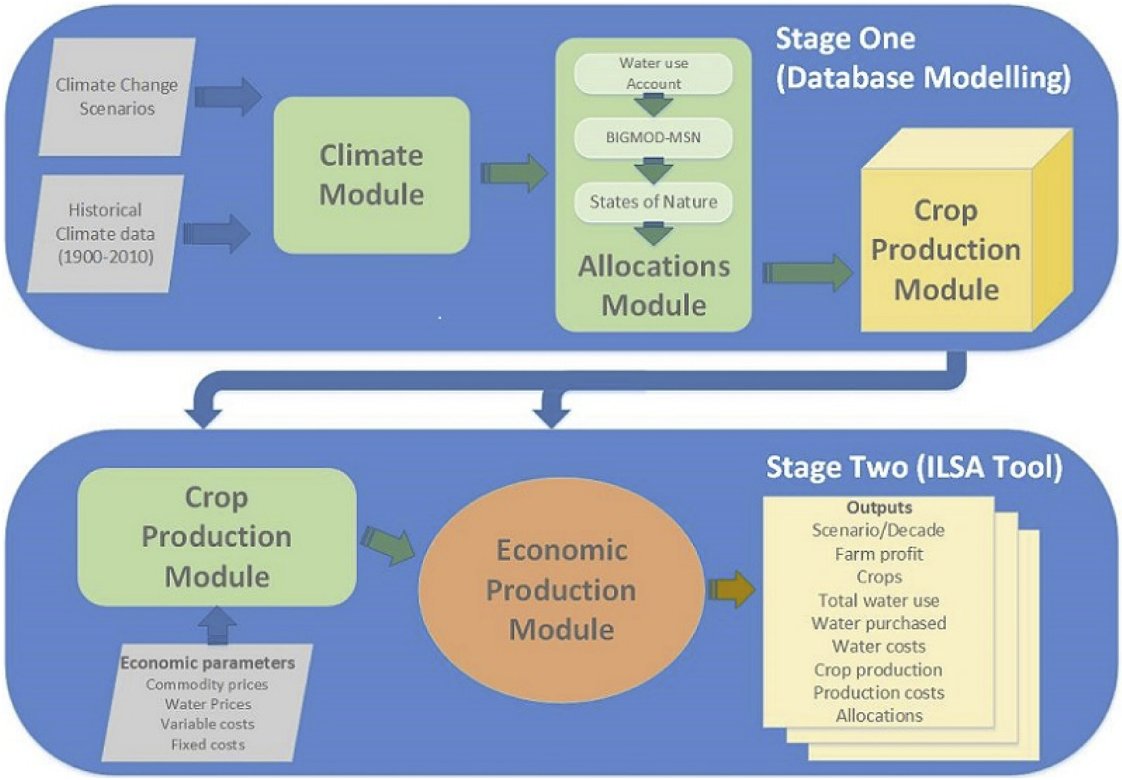

Fig. 1. Schematic flow of the ILSA tool and component parts.

Table 1
Climate change scenarios - variations from historical baselines.

	Temperature change (°C)	PET change (%)	Rainfall change (%)	Runoff ; change (%)
Mild	+1	+4	−5	−13
Moderate	+2	+8	−15	−38
Severe	+4	+15	−25	−63

hotter and drier and the water storage levels decrease, the level of annual irrigation water allocation will also decrease.

The estimated reductions in runoff for each future climate change scenario are then loaded into the Murray-Darling Basin Commission's river operations model MSM-BIGMOD (MDBA, 2012). MSM-BIGMOD is a monthly simulation model (MSM) and daily flow (BIGMOD) that estimates flows, salinity, and likely allocations under the current water sharing and accounting arrangements across Australian states and territories. This approach provides an estimate of the allocations we might expect to observe in both the historical climate record and alternative climate change scenarios. Empirical data around historical allocations is influenced by changes in the system (dams, land use, management rules) over time. In keeping with the comparative static nature of the model it was important to determine the expected historical allocations given current infrastructure and allocation rules. The model calculates expected annual allocations from 1900 through to 2010.

Roundtable discussions were held with a group of 8 prominent local irrigators to test the validity and believability of the modelling approach. Irrigators were engaged in an interactive dialogue and asked to describe their understanding of climate change, how it impacts their decision making and how they currently make forward looking decisions. During these roundtable discussions, irrigators expressed concerns that understanding the probability of any given level of allocation at any given point in time is too complex to make effective long term planning decision. While it is quite common to refer to future climate change on decadal time steps (Nam et al., 2015, Phogat 2018; Rowshon et al., 2019), ILSA decisions at farm level are made along ten year horizons. Consideration is given to the number of years in ten where allocation will be large enough to make a profit, number of low allocation years likely to result in a loss and what the average is expected to be over the whole ten years. In response, the approach in this study has been to stratify these probabilities into five clear states of nature (Table 2) where each state of nature represents the probability of a certain range of allocations occurring throughout the 110 year time series. These states of nature do not define exact levels of allocations in volumetric measures but rather define specific proportions of allocation that are a probabilistic average for that state. While annual allocations are categorised into a specific state, individual annual allocation volumes are maintained throughout the model.

Users are able to select any ten year period to examine and within the selected decade the annual allocations are classified by the model into states of nature. This gives the user a general idea of what type of decade they can expect. As the actual allocation data used in the model varies between decades, the same composition of years in ten for each state of nature across two or more decades will not return exactly the same outcomes. The states of nature provide a general indication of expected outcomes only.

Table 2
Annual allocations as percentage of historical entitlement for each state of nature.

State of Nature	Normal Wet	Normal Dry	Dry	Very Dry	Extremely Dry
Annual Allocations	≥ 95%	80–95%	60–80%	25–60%	≤ 25%

2.4. Crop water production module

The functional relationship between applied water (rain dependant and irrigated) net of evapotranspiration and productive yield provides the basis for the estimation of expected crop yields and the marginal rates of water application where irrigators could expect to maximise profit. General standardized functions that have been widely used and validated (Doorenbos and Kassam, 1979) are applied and calibrated with local empirical data. Future climate change scenarios are expected to bring hotter and drier conditions across a majority of Australian irrigation districts. This will invariably lead to greater stress on irrigated commodity crops and subsequent changes in the crop plants response to expected rates of evapotranspiration. This stress response subsequently leads to a variation in the functional form of the crop water response function. Mapping those responses to variations in climate represents a clearer picture of the effects of climate change on irrigated agriculture but additionally comes with considerable increases in complexity. As the purpose of this model is to identify the effects of climate change on allocations.

Crop production is measured as a functional response to water and a number of other limiting factors such as nutrients, light (Letey et al., 1985, Kan 2002; Keating et al., 2003). The approach used in this study makes a number of assumptions around the plants access to non-water related needs and focuses on the water response functions as the primary driver of production. In Eq. (1), the functional relationship between applied water and water available for use by the crops is determined following a process adapted from (Connor et al., 2012) and (Kan et al., 2002). This function estimates crop available water based on the FAO (Richard et al., 1998) crop water requirement for specific crops, a salinity constant and rates of applied water.

$$et\,(w,\,C)_j = \frac{et_{\max j}}{1 + \beta_0 (C + \beta_1 w_j^{\beta_2})^{\beta_3}} \leq et_{\max j} \tag{1}$$

Where et_{maxj} is the maximum evaporation rate required for full yield for each crop (Richard et al., 1998) and *et* is the volume of water available to crops as a function of a salinity constant (*C*), the volume of applied water (*w*) for each crop (*j*). The parameters β_0, β_1, β_2 and, β_3 are drawn from (Connor et al., 2012) which are estimated from local data models.

Crops require a minimum level of available water to promote growth and any subsequent yield. Productivity responds aggressively to additional water at first then marginally diminishes leading to the S-shaped curve of crop yield water response. This nonlinearity of typical crop water production relationships is reflected by the volume of evapotranspiration available to the crop as described in the functional form of Eq. (1). At very high water application rates yields begin to decline as soil aeration is compromised until complete yield loss occurs quite abruptly. Although this is typically well beyond any economically feasible water application rate and is subsequently not represented in this function. Yield is therefore estimated based on the water available to the crop as defined in Eq. (1) and follows the functional relationship described in (Connor et al., 2012) and earlier in (Kan et al., 2002).

Crop yield is determined through either a linear or quadratic functional response to actual evapotranspiration following the approach of (Letey et al., 1985) and later used in (Connor et al., 2012). While typically linear for most crops, scalar terms ψ engage as binary triggers for linear and quadratic functional responses for individual crop types.

$$Y_j = \psi_1 [et_j (w_j, C) - et_{min}] + \psi_2 [et_j (w_j, C) - et_{min}]^2 \tag{2}$$

Resulting crop water production curves were coupled with local Primary Industries and Resources South Australia (PIRSA) values (Fig. 2) and presented to local irrigators at an end user workshop. The workshop was a key engagement process aimed at facilitating user "buy in" to the tool and ensure that the functions applied were well understood. We found general agreement with the functional relationships

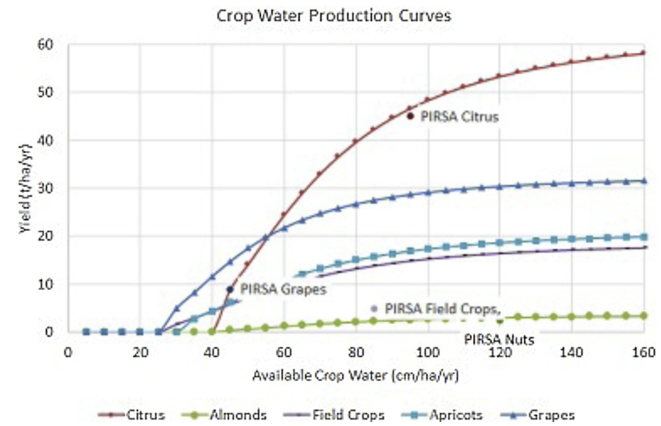

Fig. 2. Crop water production functions as derived through Eqs. (1) and (2), Primary Industries and Resources South Australia (PIRSA) estimates are included for cross reference.

despite some concern at less optimal crop water decision points, particularly in the absence of water.

Crop water production functions are generic representations of expected outcomes only. It is possible that, due to heterogeneity in individual farmers capabilities, biophysical landscape characteristics, and or nuanced climatic variability that the functional form of the crop water production functions could vary considerably. The potential for user adjusted functions was discussed with irrigators and although it would more accurately represent individual circumstances, the added complexity would create unnecessary difficulty in unpacking the effects of climate change scenarios. Given the generic functions were considered to be suitably representative of long term average outcomes no alterations in the crop water production functions are included.

2.5. Economic module

The economic decision module is a two-stage comparative static long run decision planning model. In the first stage, long run fixed asset decisions around commodity types (for perennial crops) and irrigation infrastructure are made. These decisions have large costs associated with them that are amortised over a fixed depreciation period. Once long run decisions are fixed, short run (annual) decisions are made. Short run decisions include items like volume of water to apply, water to sell or buy and are constrained by the prior long run decisions.

The underlying economic decision model estimates expected profits under various future climate scenarios given consideration to long and short run effects. The user is presented with a baseline set of estimates, derived from empirical studies, for each of the input parameters. They then choose to accept or alter these parameters to suit their own particular circumstances. Profit is calculated over two separate planning horizons, annually and decennially, at crop and farm level allowing users to consider both the short term and long run effects of each decision. Any water bought or sold on the water market is captured in the function as an additional cost or revenue to the operation. The general specification of profit is described in Eq. (3) below:

$$\pi = ((\mathrm{Pj} * \mathrm{Ys,\,j}\,(\mathrm{Ws,\,j})) - (\mathrm{pws} * (\mathrm{was,\,j} - \mathrm{Ws,\,j} - \mathrm{ET}_s)) - \mathrm{vc}_{s,j} - \mathrm{fc}_{s,j}) * \mathrm{As{,}j} \tag{3}$$

Where;

π = profit in dollars

j = index of commodity type (wine grapes, citrus, nuts, pasture, stone fruit)

h = index of irrigation technology (flood, overhead, under canopy, drip, pivot)

s = index of state of nature (normal wet, normal dry, dry, very dry, *extremely dry)*

S = index of Climate change scenario (baseline, s1, s2, s3)

P = price of each commodity ($/tonne)

Y = Yield of each commodity (expected)

W = Water (planned application in ML/ha)

wa = water allocation in ML/ha

ET = volume of potential Evapotranspiration above or below the long term average

Pw = the market equilibrium price per unit water traded on the market ($/ML)

vc = variable costs of production not related to water

fc = fixed costs (crop and irrigation establishment costs treated as an annual cost)

A = Area (ha)

Annual outcomes are expected to vary by individual states of nature and climate scenario and while helpful in making informed operational decisions are considered less useful for longer term planning. To consider longer term effects of variability profits from each individual state of nature are averaged over the decade by calculating the state of nature probability (*pr*) weighted average of all states in the decade (*d*). The long run profit function is described in Eq. (4).

$$\pi_d = \sum\nolimits_{s,pr} *((\sum\nolimits_j ((\mathrm{Pj} * \mathrm{Ys, j}\,(\mathrm{Ws, j})) - (\mathrm{pws} * (\mathrm{was, j} - \mathrm{Ws, j} - \mathrm{ET}_s)) - \mathrm{vc}_{s,j} - \mathrm{fc}_{s,j}) * \mathrm{As, j}) \tag{4}$$

2.6. Water price

To characterise the relationship between water scarcity and the price that growers are likely to experience in the water market we apply the approach developed in Brennan (2006), and more recently documented in Connor et al. (2011). This approach estimated the relationship between water allocation and water prices using actual allocations and water prices experienced from 1998 to 2004 and described it in functional form (see Eq. 5). Using the (Brennan, 2006) functional relationship we predicted water prices (Table 3) using average rainfall and allocations for each state of nature. Future climate change scenarios are considered as changes in the frequency distribution of the allocation levels we consider those prices to hold for each state of nature across all climate change scenarios.

$$\ln(P_w = 7.84 - 1.308A - 0.00718R) \tag{5}$$

where:

Pw = the price of water ($/ML)

A = allocation as a percentage of entitlement.

R = the average rainfall under each state of nature

ln = natural log

2.7. Interface

The ILSA tool is written in the JAVA scripting language and delivered through an online interface. Users first set up and define any variations of their farm they intend to test and compare. The tool then presents a series of default values that broadly represent those expected in the selected region. Users can choose to accept the default values or edit inputs to more accurately represent their individual circumstances. Results of every decision are presented in live graphical outputs allowing the user to visually compare options as well as actual data (Fig. 3).

3. Results

The case study described here aims to examine the model under both default parameter conditions and real farm data. We tested the model on a single hectare basis for two crops (grapes and stone fruits) under the default parameters and just stone fruits with real farm data. Although the model allows farmers to assign any volume of irrigation water they choose to apply to each crop within their total entitlements, our case study fixed those levels to 5.5 ML/ha for grapes and 6.5 ML/ha for stone fruits. This enabled effective financial comparisons between years, decades, climate and water trading scenarios.

While the model allows the user to specify any 10 year period of time we chose three representative decades in this case study. Ten year time periods were selected to examine a normal wet period (1910–1919), a normal dry period (1950–1959), and a predominantly normal with extreme drought (2000–2009) in the historic record Fig. 4. Throughout the historic record there were no predominantly drought periods to examine. Each decade is also tested under three climate change scenarios (historical, mild, moderate) and the results examined both with and without water trade. Importantly, the model assumes decision makers are imperceptive to evapotranspiration (ET). As such, ET is considered as always equal to an average year within the decision set and the effects of any variations in ET are simply borne out in the outcomes.

The geographic focus of the case study is the irrigation region around Loxton and Bookpurnong in the south eastern Australian Riverland (Fig. 5) but with local data and recalibration it could be applied to other irrigation districts around the globe. The region is dominated by irrigated agriculture, primarily wine grapes and tree fruits such as citrus and stone fruits with a large proportion of the population employed in this sector. The area of irrigated agriculture has been expanding although recent drought and variability in irrigation allocations and commodity prices has introduced additional uncertainty to irrigators.

3.1. Real farm data results

In addition to the default model testing we exercised the model with some real world data provided by a local stone fruit grower. While this data remains commercial in confidence we were provided with suitable parameters including on-farm fruit price, cost of production, fruit yield and total water applied to test the model. Data from the grower included a number of varieties across a three year period allowing the model to examine the likely effects on the farm's operation under range of circumstances. We first examined the spread in average annual profitability across crop varieties and selected three representative varieties. A low profitability variety (Diamond Bright), a moderate profitability variety (Dapple Dandy), and a high profit variety (August Red) and compared them with the default stone fruit in the model (Fig. 6).

Using the data provided we regressed crop water production functions for each of the selected varieties. Using the same three decades and climate change scenarios used in the default model case study we

Table 3
Estimated water price by state of nature for purchases in the water market.

State of	Normal Wet	Normal Dry	Dry	Very Dry	Extremely Dry
Nature	> 95%	80 - 95%	60 - 80%	25 - 60%	< 25%
Allocation (A)	95	87.5	80	60	20
Rainfall (R)	331.86	204.35	170.7	123.26	109.57
Water Price ($)	17.29	60.00	100.06	245.74	501.24

State Of Nature	Years/10	Alloc (%)	Applied (ML/ha)	Yield (t/ha)	Crop ($/t)	Irrig ($/ha)	Op Costs ($/ha)	Fixed ($/ha)	Price ($/ML)	Used (ML)	Bought (ML)	Profit ($Total)
Wet	7	100.00	9.5	40.0	$ 300	$ 3620	$ 5284	$ 586	$ 17.30	95	27	$ 24627
Normal	0	0.00	0.0	0.0	$ 0	$ 0	$ 0	$ 0	$ 60.00	0	0	$ 0
Dry	1	70.00	9.5	40.0	$ 300	$ 3620	$ 5284	$ 586	$ 100.06	95	48	$ 20344
Very Dry	1	40.00	9.5	40.0	$ 300	$ 3620	$ 5284	$ 586	$ 245.74	95	68	$ 8422
Extremely Dry	1	20.00	9.5	40.0	$ 300	$ 3620	$ 5284	$ 586	$ 501.24	95	81	$ -15718
Ten year average	10	83.00	9.5	40.0	$ 300	$ 3620	$ 5284	$ 586	$ 96.81	95	0	$ 18544

Fig. 3. Example of results screen from the ILSA tool (see Supporting information for more screen grabs).

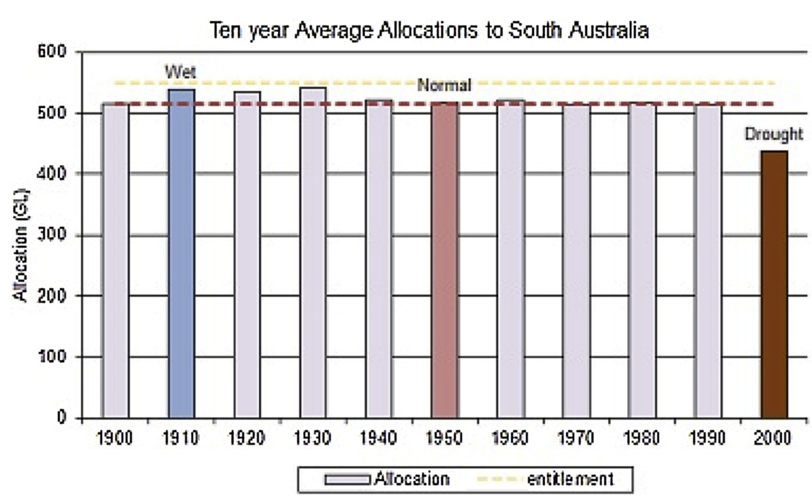

Fig. 4. Historical allocations to South Australia for selected decades with example “wet”, “Normal” and “Drought” periods.

examined the likely effects using the real farm data set.

Average annual returns over the decade indicate that the default values for stone fruits represents a more conservative estimation of production and profitability in the region when compared to other varieties. Under historic climate conditions, the default model returns an average of $7,103.33 across the decades while the three

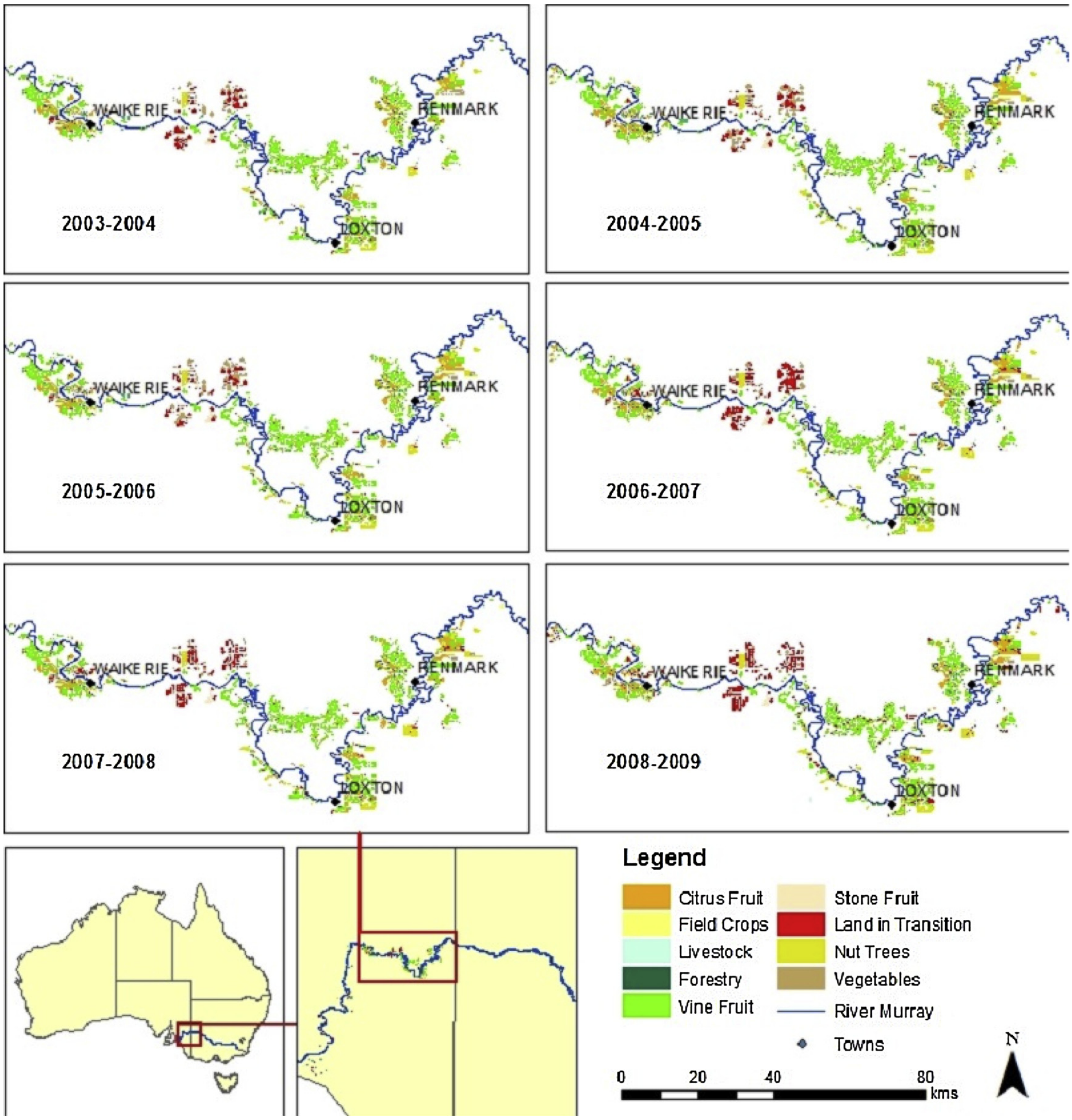

Fig. 5. Five year time series of land use in the Loxton and Bookpurnong irrigation region.

representative varieties from the real farm data returned from $50,287.01 for the best performing variety (August Red), and for the other varieties $23,881.17 (Dapple Dandy), and $2,256.40 (Diamond Bright). During the normal decade, given the shape of the crop water production functions, profitability relative to the wet decade falls slightly for some varieties and rises for others as the water applied moves around the more marginally optimal region of the production function relationship. Profitability of the default and August Red varieties declined to $7,030.76 (1.02% less) and $48,279.63 (3.99% less) while the Dapple Dandy and Diamond Bright varieties improved profitability to $24,818.85 (3.93 more) and $3,078.66 (36.44% more). Under the drought decade all varieties suffer reductions in profits relative to both the wet and normal decades. Profits in this decade were $3,410.66 (51.98% < wet and 51.49% < normal) for the default variety, $33,515.78 (33.35% < wet and 30.58% < normal) for the August Red variety, $16,255.25 (31.93% < wet and 34.54% < normal) for the Dapple Dandy variety, $-2,177.17 (196.49% < wet and 170.72% < normal) for the Diamond Bright variety.

Introducing the assumed effects of climate change reduced profitability across all varieties. Under the mild climate change scenario profitability falls to $2264.46 (−68.6%) for the Default variety, $23,897.06 (−52.5%) for August Red, $13,901.21 (−41.7%) for Dapple Dandy, $-3,710.05 (−264.4%) for Diamond Bright), in the wet decade. Profitability continues to fall to $5,200.30 (−26%) for the Default variety, $40,208.52 (−16.7%) for August Red, $21,770.40 (−12.3%) for Dapple Dandy, $766.76 (−75%) for Diamond Bright), in the normal decade. During the drought decade profits were $1,954.23 (−42.7%) for the Default variety, $26,885.87 (−19.8%) for August Red, $14,049.56 (−13.6%) for Dapple Dandy, $-1,082.02 (−50.3%) for Diamond Bright).

Under the moderate climate change scenario profitability falls even more to $-4,405.71 (−162%) for the Default variety, $2,682.39 (−94.5%) for August Red, $230.59 (−99%) for Dapple Dandy, $-7,994.14 (−454%) for Diamond Bright), in the wet decade. Profitability continues to fall to $5,176.19 (−26.3%) for the Default variety, $39,809.24 (−17.5%) for August Red, $21,750.71 (−12.4%) for Dapple Dandy, $-7,994.14 (−259%) for Diamond Bright), in the normal decade. During the drought decade profits were $-9,265.72 (−371%) for the Default variety, $-17,150.70 (−151.2%) for August Red, $-10,161.90 (−162.5%) for Dapple Dandy, $-10,892.80 (−400%) for Diamond Bright).

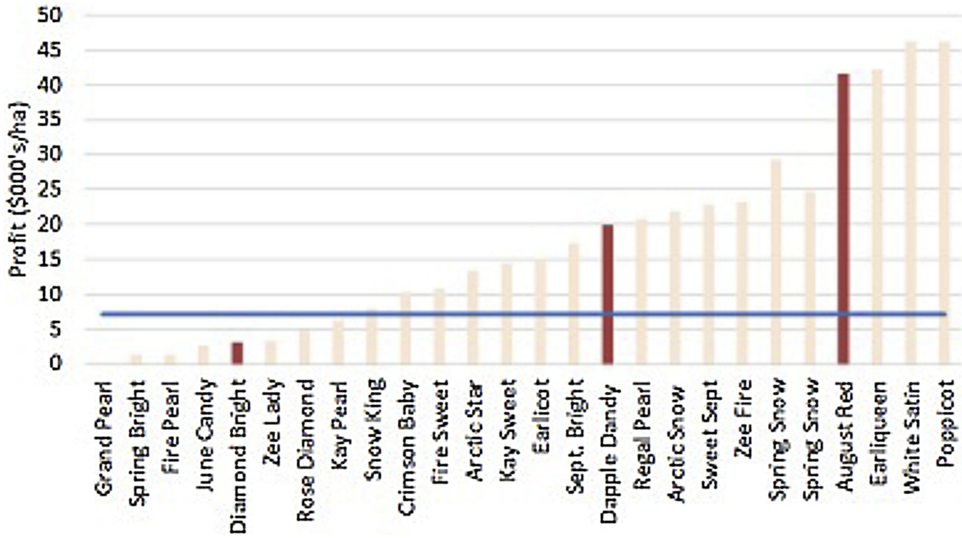

Fig. 6. Profitability of various stone fruit varieties (case study selected varieties highlighted) with the long term average returns to the default (water unlimited) model (blue line).

3.2. Modelled results

Under the historic climate scenario, grapes returned average annual profits per hectare of $6,357.20 (stdev 105) in the wet decade, $2,913.02 (stdev 127) in the normal decade and, $2,179.44 (stdev 5,386) in the drought decade (this decade included the “millennium drought”, 2002–2010). Stone fruits returned average annual profits of $7,078.92 (stdev 42) in the wet decade, $498.99 (stdev 93) in the normal and, $1,295.53 (stdev 4,942) in the drought decade. The drought decade without trade is the only decade where irrigators face considerable economic loss years. In these years, the magnitude of the loss is greater than the profits of the best years in the decade. With more profitable years in the decade than loss making years, the average annual returns for the decade are still positive but considerably smaller and the degree of variability of returns is much greater than the mean return (Fig. 7).

When water trade was specified in the default model, grapes returned $6,360.36 (stdev 114) or $3.15 more profit in the wet decade, $6,333.91 (stdev 37) a $3,420.89 improvement in the normal decade and, $4,653.68 (stdev 1557) in the drought decade, a $2474.24 improvement in average annual profits. Under trading conditions stone fruits average annual profits for a wet decade were $7,134.22 (stdev 25) or a $55.30 improvement in profits, $7,037.91 (stdev 81) in a normal decade, a $6625.89 profit increase and $4,808.93 (stdev 2,056) with a $3,513.39 improvement in average annual profits during the drought decade.

The ILSA tool also allows irrigators to consider the effects of climate change on profitability. Under a mild climate change scenario grape returns were $4,516.41 and stone fruits $8,101.80 less than historic climate without trade and $511.16 (grapes), $735.54 (stone fruits) less with water trade in the wet decade. The reductions in profit decrease to $92.01 (grapes), $241.87 (stone fruits) without trade and $401.26 (grapes), $585.46 (stone fruits) with trade in the normal decade. During the drought decade, mild climate change reduced profits by $3,721.67 (grapes), $8,274.20 (stone fruits) without trade and $2,851.25 (grapes), $4,093.72 (stone fruits) with trade (Fig. 8).

Moderate climate change further reduced the profitability of irrigated agriculture when compared to the historic climate. During the wet decade, profits were $11,839.45 (grapes) and, $14,613.14 (stone fruits) less without trade and $2,571.79 (grapes), $3,353.88 (stone fruits) less with trade. During the normal decade profits were $450.15 (grapes) and $810.79 (stone fruits) less without trade and $401.26 (grapes), $585.45 (stone fruits) less when irrigators are allowed to trade. In the drought decade profits were $12,099.61 (grapes), $13,446.57 (stone fruits) less profit without trade and $7,995.76 (grapes), $11,434.70 (stone fruits) with trade (Fig. 9).

4. Discussion

While large scale irrigation infrastructure development has been intended to smooth the boom bust cycle of typical agricultural enterprises, farmers still operate with the expectation of good years and

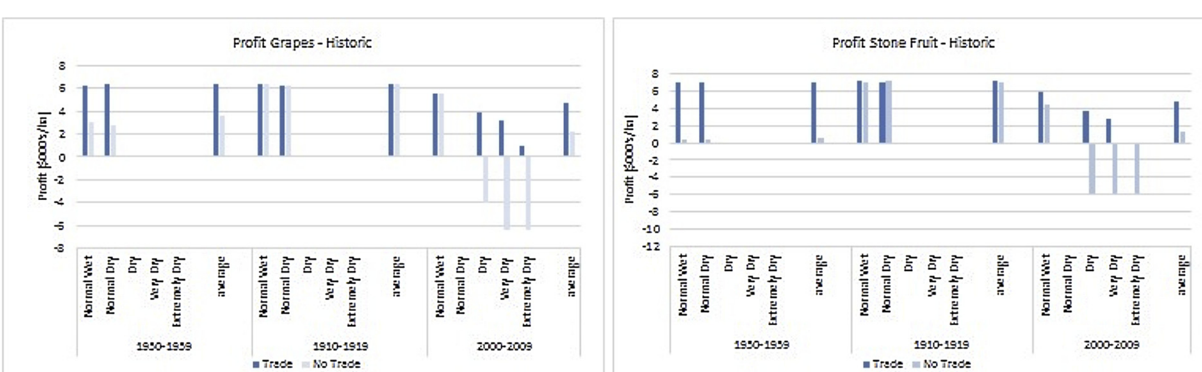

Fig. 7. Projected profits for Grapes and Stone fruits under historical climate for the three selected decades by state of nature both with and without water trade.

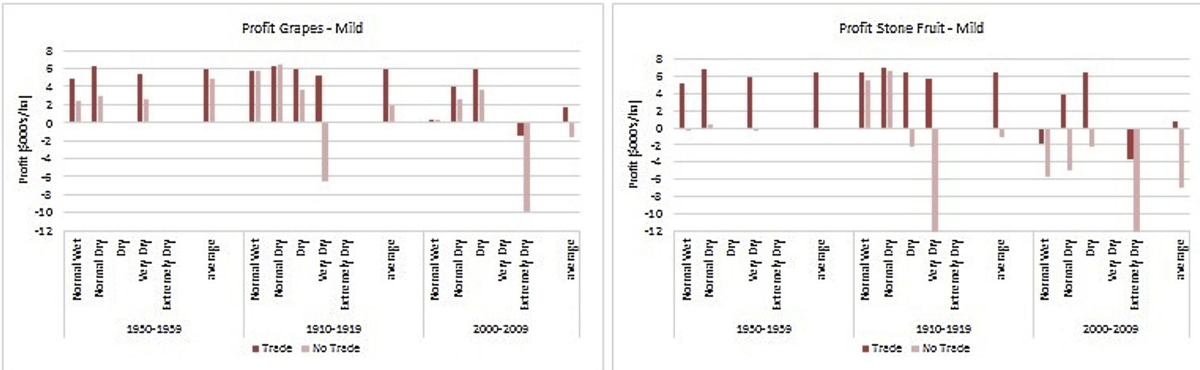

Fig. 8. Projected profits for Grapes and Stone fruits under Mild climate change for the three selected decades by state of nature both with and without water trade.

bad years and generally plan optimistically in the long run while operating in a "best-you-can" mode in the short term. Decadal average returns used in this model provide irrigators with an understanding of the likely long term viability of their operations within a planning horizon and probability framework they can understand. In applying the ILSA tool we found that our case study demonstrated individual decades within the same climate scenario can produce very different outcomes for irrigators. While decades with larger numbers of drought years presents a potential 25% reduction in average annual profits the greater risk to irrigation enterprises may in fact come from the large increase in variability of returns and large loss making years. Multiple loss making years have the potential to impact cash flows and can put enterprises at risk of insolvency.

Decadal average returns applied and compared across climate change scenarios, consider long run viability under a changing climate. The comparative static nature of the ILSA tool approach allows users to consider what their enterprise might look like if climate conditions aligned more closely to alternative scenarios. For example users can question what would happen if they made the same decisions under a mild climate change scenario for the normal decade. We provide an example of those events under the case study and demonstrate that average annual profits would be likely to fall and variability of returns increase.

With the granting of water property rights in south eastern Australia in 1994 (Young and McColl, 2005) the annual assigning of water allocations presents a resource asset that can enable an irrigator to manage their operations whether for production or water trading. An overall analysis of the sample data indicates that where an effective water market is operational and that market has water to trade, crops and varieties that are productive and well managed are resilient to reductions in allocations. This resilience is produced when the cost of additional water is a small part of the total cost structure and is not limiting. Additionally the sample data indicates that having surplus entitlement provides insurance against low allocation years at a fairly modest rate. With the price of water in high allocation years so low the benefits of selling surplus in those years is considerably less than the cost of purchase in low allocation years which is also much less than the cost of lost production. For farms with entitlements in excess of demand in normal years the irrigator carries a stranded asset in over allocation years. This excess water could be considered as an insurance product against low allocation years. The cost of that insurance would be the market value of the excess entitlement and the return would be the additional production of the water available in low allocation years. The insurance value of excess water has not been examined in this study and may provide the basis of further research.

Although the ILSA tool flexibility allows users to limit the error by modifying inputs that more accurately represent their particular operations, it does not serve to provide a single comprehensive overview of all possible outcomes. Limitations in the quality and quantity of data inputs prevent the model from producing a clear estimation of outcomes under all circumstances. Nuances in the management mix, water application rates and in particular the timings of allocation announcement and water applications are not able to be represented in the model.

Detailed future irrigation prediction models require a complex set of interacting decision variables. The ILSA tool does not aim to provide predictive scenarios of future irrigation profitability tool but rather it is a planning tool that aims to isolate the effects of climate change from other important factors such as commodity prices, irrigation timings, rates and applications. While the ILSA tool has its outcomes based in economic terms it does not consider the potential variability of these other variables and their effects on future irrigation profitability. Irrigators can input variation in the commodity prices to suit their circumstances but the ILSA tools makes no predictions of probable

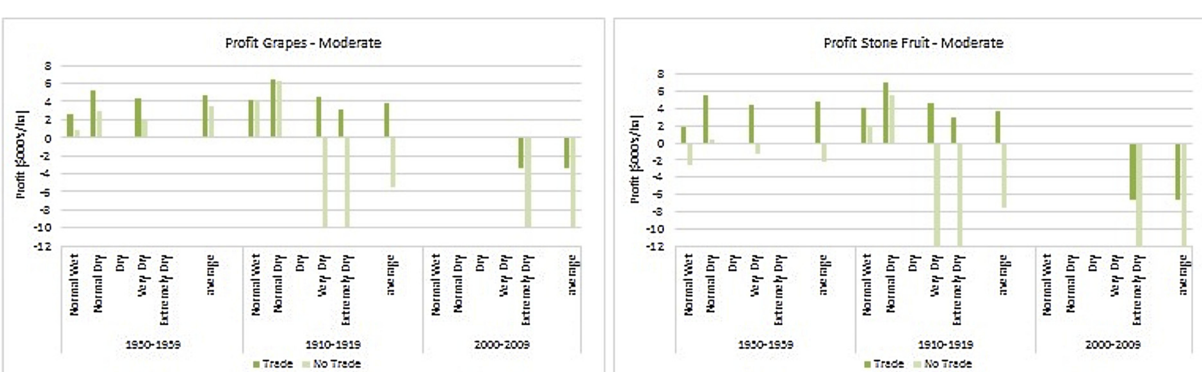

Fig. 9. Projected profits for Grapes and Stone fruits under Moderate climate change for the three selected decades by state of nature both with and without water trade.

future commodity prices Detailed future irrigation prediction models require a complex set of interacting decision variables. The ILSA tool does not aim to provide predictive scenarios of future irrigation profitability tool but rather it is a planning tool that aims to isolate the effects of climate change from other important factors such as commodity prices, irrigation timings, rates and applications. While the ILSA tool has its outcomes based in economic terms it does not consider the potential variability of these other variables and their effects on future irrigation profitability. Irrigators can input variation in the commodity prices to suit their circumstances but the ILSA tools makes no predictions of probable future commodity prices. Individual irrigation management decisions around timing, rates and application are typically made subject to individual irrigator preferences, knowledge and more micro-scale factors such as weather and market conditions. They are likely to allow irrigators to make small adjustments that could offset some of the effects of climate change. Consideration was given to allowing irrigation management decisions to be explored through user adjustment of the crop water production functions. However, translating management decision variations with uncertainty into the production functions was expected to be too difficult for the average user as it would require predictions of short time scale (daily, weekly) weather information out over a 50-year prediction horizon.

The use of different varieties of crops in specific conditions may alter the suitability to local physical and climatic conditions, or particular user behaviour. Crop water production functions that allow the user to adjust the response to more accurately reflect their own circumstances would represent a useful improvement in the model. Within the model design ensuring the functional form of the crop water production functions is correct is critical. Non intuitive results can occur when users operate at the marginal part of the curve and the crops responses to water changes. Slight errors in water application rates such as incorrectly accounting for rainfall events or lower than average evaporation rates can lead to over watering and a shift to a declining crop water response. When this occurs operation that would appear to be optimised may result in returns lower than expected. The functional form of the crop water production curves used in this tool were developed from existing literature. Although tested in expert user workshops, the functional form of these curves may not accurately reflect all crop varieties in all locations.

The crop water production functions used in this study may present a very different scenario to the empirical data provided by local agencies (PIRSA, Fig. 2). Either through misreporting, large area consolidation errors or unrepresentative sampling the local agency data generally presents a more conservative view of production potential.

While there is evidence to indicate an increased demand for irrigation water under a future hotter and drier climate, the crop water production functions used in this model account for the expected change in demand. What is not considered is the potential for the functional form of those crop water production functions to change due to other factors such as altered CO_2 conditions, heat stress, and heat waves beyond the existing evapotranspiration calculations.

While globally uniform climate change adjustments neglect the local nuance in climate change effects, water flows are derived from a system that encompass a catchment over 1,059,000 $km^{2.}$ Spatial heterogeneity in climate change effects would present an opportunity for improvement in the modelling approach.

The ILSA tool allows users to adjust input parameters that more effectively fit their individual circumstances, as such the tool acts as process model rather than a prediction tool. Calibrating the tool to specific outcomes risks significant misalignments when users make individual changes. Each input module draws from well tested and validated processes, but the overall tool is not calibrated to specific outcomes.

5. Conclusion

Historically, irrigators have made farm operation decisions with uncertainty around future climate conditions. Knowledge of the impacts of possible future climate change and climatic variability allows irrigators to more effectively manage risk and reward in decisions made across both the short and long terms. The ILSA tool provides a user friendly adaptable platform for local irrigators that considers the importance of inter-annual variability for long run planning and financial viability. The ILSA tool's simplified approach to climate change and climate variability allows users to understand the possible impacts on their operations in a manner they can relate to. Users can test multiple scenarios of allocations, climate, crops, management decisions and market forces and compare the most effective solutions. The "years in ten" approach to probability distribution creates a simplified connection between complex scientific understandings of climate change and agricultural production decision cycles.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agwat.2019.105751.

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