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Business As Usual Versus Climate-responsive, Optimised Crop Plans – A Predictive Model for Irrigated Agriculture in Australia in 2060

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Abstract

Climate change is impacting people's lives, with management of water resources and food security being major concerns for the future of many countries. In this paper, future water availability, crop water needs, yields, market costs and returns of current crops in a case study area in Australia are evaluated under future climatic conditions. The predictive methods on which the work is based have the advantage of being robust—they are able to simultaneously consider many climate change models—giving greater confidence in determining what the future will hold in this regard. The results indicate business as usual, in terms of the quantity and types of crops that can be grown presently, will not be sustainable in the medium and long term future. Instead, modelling indicates that changes in production and land use to maximise revenue per megalitre of water will be needed to adapt to future conditions and deliver climate-smart agriculture.

Keywords Crop planning · Water resource management · Food security · Climate change · Robust optimisation · Predictive model

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1 Introduction

The changing climate will impact on quality of life into the medium and long term future (Albert et al. 2021). In the Australian context, many climate models are predicting a hotter and drier climate that will affect the nation's ability to grow food crops to feed the population to a level that is enjoyed currently (Grose et al. 2020). Using the authors' newly developed robust framework (Randall et al. 2022), that is able to consider the effects of multiple climate change models simultaneously, this paper describes an approach to adaptive water management by tailoring cropping intensity to optimise risk and return suitable for the local environment (Whish et al. 2019), providing suggested changes in agriculture production that are likely to maintain ecosystem function (Khan et al. 2006), minimise farm risk and maximise agricultural resilience through efficient use of limited water resources (Hochman et al. 2013).

The Australian Government Department of Agriculture, Water and the Environment has estimated that cropping farms have already experienced an average fall in profits of 35% in the past 20 years, largely attributable to effects of drought and climate variability (ABARES 2019). This means that farmers have higher debt loads, while consumers bear higher prices and item shortages. Science has techniques and tools that can help to reduce these declines. There is an emerging view that there is a crucial need to plan water resource management in the context of competing economic, societal and environmental values and demands (Tidwell and Van Den Brink 2008; Gorelick and Zheng 2015). The discipline of decision science, particularly optimisation and operations research, offers essential tools for such planning. These give decision and policy makers the opportunity to reduce uncertainty and help to make better decisions that ideally create the best possible outcome on defined criteria. Farmers, regional planners (such as local councils), state and federal government need these optimisation-aided approaches for crop planning under climate change to ensure appropriate cropping over the coming decades and to understand how climate change can affect the types of crops that can be sustainably grown into the far future.

The most vital resource in all of this is water, a fundamental necessity for all other endeavours. Australia is a semi-arid/arid continent in which water is an extremely precious and limited resource (Peel et al. 2007), and its availability patterns are being affected by climate change (Freund et al. 2017). It must be shared for uses including, but not limited to, direct human needs (e.g., drinking water), industrial use, agricultural purposes, and environmental management (Prosser 2011). In recent years, water for the latter has been decreasing which has disrupted normal river function, particularly in the Murray-Darling system (Speer et al. 2021). The appropriate balance of water usage across human water consumption and the environment is necessary. This is difficult as climate modelling predicts temperature rises and decreased rainfall. Sensible adaptive management of existing water resources will be required to ensure long-term cropping sustainability.

Xevi and Khan (2005) presented both a model of water management for a selection of crops for a semi-arid agricultural area, and a goal programming approach to solving this system under different climatic conditions. Their model sought to maximise or minimise expressed objectives by modifying the cropping selection and area for the selected crops, subject to scarce, average and abundant water availability scenarios. These did not account for, or predict, variable conditions. Their three stated objectives were to maximise net revenue, minimise the variable costs associated with growing the crops and minimise groundwater pumping. One of the limitations of the model is that the relationship between water requirements and the groundwater pumping needed is not defined and a limitation of the goal programming approach is that the three objectives are aggregated into a weighted sum. Thus, it is difficult using this approach to adequately examine trade-off solutions which offer a variety of choices for a human decision maker.

Lewis and Randall (2017) addressed these concerns and focussed on the water management issues faced by farmers and regional planners in the Murrumbidgee Irrigation Area (MIA). They redefined the problem as a multi-objective one and applied a well-known optimisation framework to generate Pareto-efficient solutions. This work optimised two key output variables: maximising the net revenue generated by the chosen combination of crops while minimising the corresponding environmental flow deficit for a particular year. Subsequent work has progressively added to the agricultural and environmental realism of the body of work. As examples, sensible river extraction limits varying across seasons, adding important commercial crops, and giving human decision makers a range of appropriate trade-offs from which to select.

Most land use research uses simulations for trade-off decisions; an example is Connor et al.'s Land Use Trade-Off (LUTO) (Connor et al. 2015). Using Linear Programming (LP) the land-use trade-offs prioritised maximisation of economic returns from land over the secondary objective of maximisation of biodiversity services, despite Australia having a rudimentary ecoservice industry (Connor et al. 2015; Settre et al. 2019).

The Land-Use Sequence Optimiser (LUSO) (Renton and Lawes 2009) schedules crops with consideration to accumulative biotic stresses, capturing effect of current land use on future use. The inclusion of weed and disease algorithms adds realism to the modelling. However, LUSO assumes all years are 'average' production years, potentially underestimating pest loads, and omitting the role stochastic weather has on populations. A further limitation is that only a single land unit can be analysed, inhibiting its contribution to whole-farm management decisions, unless the model is run over all paddocks, a resource-consuming exercise.

While Renton and Lawes (2009) state combinatorial problems of temporal land use options are complex and that heuristic search algorithms are resource parsimonious, they discount the near-optimal solutions generated, preferring an exact value as required in sensitivity analysis. This may be appropriate for individual farm analysis but at larger scale, regional production shifts are required, so "near-optimal" solutions are fit for purpose, identifying coarse-grain shifts in enterprises. The deficiency with LUSO lies in its time scale and robustness.

Randall et al. (2020) further developed a temporal model from the previous work of Lewis and Randall (2017). A temporal problem is defined as: "an optimisation problem in which all relevant temporal data is considered, as well as the interactions and cumulative effects of these data" (p. 2). In effect, these problems are a set of joined problems in which each member of the set represents one time unit (such as a year).

While the temporal model allows for planning over extended time horizons, it can only use one climate prediction model at any one time. Given that there are many such models available with no absolute certainty about which will prevail, it was necessary to enhance the temporal modelling so that it could simultaneously accept multiple climate models and derive robust crop allocations over time. This has been presented in Randall et al. (2022) and named Robust Temporal Optimisation (RTO). In this context, the term "robust" means that solutions (crop mixes over time) will produce objective values, such as net revenue and environmental flow deficit, that will vary minimally despite which model it is evaluated against. (This contrasts with a risk management approach adopted by some others, such as Elnashar and Elyamany (2022)). Thus, such solutions give greater certainty for future planning and understanding how cropping patterns will change in the medium to far future. The results indicated that stable crop mixes into the far future could be found, despite which climate prediction may eventuate.

The solutions considered are generated algorithmically from predictions of future climatic conditions. Validation of the accuracy of predicted outcomes is challenging. Optimisation models are inherently complex to validate. Although some researchers have considered the idea of formal optimisation validation (Aspinall et al. 2007), it depends on the ability to objectively measure changes in resource measures of differing instances. For validation to occur, instances would need to have eventuated and outcomes measured. Given the solutions require changes in agricultural practices under changing environments, this is difficult to achieve. This prevents validation of model outputs against measurable agricultural data. Rather, confidence in model outputs depends on validation of model inputs and the internal logic of the model.

The rest of this paper is organised as follows. Section 2 shows how we can use the latest models and the robust temporal optimisation framework to help determine the feasibility of current practices into the future. Specifically, both a scaling and an optimisation approach are used, which include a number of experimental results. These deserve close consideration and are discussed in Sect. 3. Finally, in Sect. 4, the implications of the work are given as well as new research directions that are currently being explored.

2 Methods and Results

As described in Randall et al. (2022), an RTO algorithm has been applied to conditions predicted by four global climate models, downscaled to regional landscapes (Evans et al. 2014) using the Weather Research and Forecasting (WRF) model with three regional climate models (Ji et al. 2016). This yields an ensemble of 12 climate predictions, each with varying changes in ambient temperatures and levels of precipitation in the regions that influence local conditions and water available for irrigation in the MIA. Data from the ensemble of climate predictions is available for an historical, baseline period (1990–2009), the immediate future (2020–2039) and more distant future (2060–2079) (NSW Department of Planning and Environment 2022a). Climate data from the 2020–29 and 2060–69 periods, combined with data on crop requirements, has been structured for use by the optimisation process and is available online (Lewis et al. 2022).

Agriculture in the MIA is dependent on local rainfall, irrigation from the Murrumbidgee River that rises in the Snowy Mountains, and groundwater sources. Rainfall was directly predicted from the climate modelling data. Access to groundwater is subject to legislative control and has been progressively limited to Long-Term Average Annual Extraction Limits (Kumar 2013). This is explicitly accounted for in constraints applied in the optimisation process. At present, license to access surface water for irrigation from the river is provided annually at different levels of security. Regional water strategies and water sharing plans are under active development, including setting Sustainable Diversion Limits (SDLs) for water that can be consumed within catchments (NSW Department of Planning and Environment 2022b; Wang et al. 2018). In addition to agricultural irrigation, this water use also includes for urban and industrial needs, as well as that intended to maintain river and environmental health.

In order to allow realistic modelling for future time periods, some reasonable estimate was needed for SDLs. Consulting consolidated data for water used in agriculture in the

Murrumbidgee catchment from 2005 to 2018 (Aither 2019) and using historical water course discharge data from the Australian Bureau of Meteorology (BoM) for the Murrumbidgee River at Wagga Wagga (BoM station 410001), and the main canal at Berembed (BoM station 410013) (Australian Government Bureau of Meteorology 2022) for the same period, a median estimate for annual diversion to the MIA was 26% of the main stream flow in the Murrumbidgee River. This corresponded at the time to an annual diversion of some 600 gigalitres (GL), though across drought years median flow was limited to about 380 GL, a median proportion of 35%. For the purposes of this study, an SDL of 26% was used. This was calculated as a proportion of the estimated stream flow based on predicted precipitation in the Snowy Mountain catchments. The computational framework is illustrated in Fig. 1.

Two periods were chosen for study from data available from the NARCliM project: the current to immediate future (2020–2029) and the more distant future (2060–2069). The optimised crop selections in the 2020's will be considered the "baseline" for this study. All values of net revenue are expressed in 2020 dollars to allow direct comparison of results between different time periods. The regional climate in the distant future is predicted to be generally hotter and drier, with a significant drop in precipitation in the Snowy Mountains. These projections imply a drop in the water available in the river for irrigation. How this reduction is addressed is open to a number of approaches.

2.1 Scaling "Business As Usual"

Agricultural enterprises in the MIA could continue to cultivate baseline crop mixes – a "business as usual" approach. However, with less water available for irrigation, the areas planted of irrigated crops may need to be reduced. Taking the cropping mix solutions generated by the RTO for the 2020s, and reducing all crop areas proportionally until they consume no more than the water available monthly under all climate model projections for the 2060s produces a set of "scaled" solutions that are feasible. The extent of the reduction in area cultivated is shown in Fig. 2. To generate the results shown in the figure, solutions

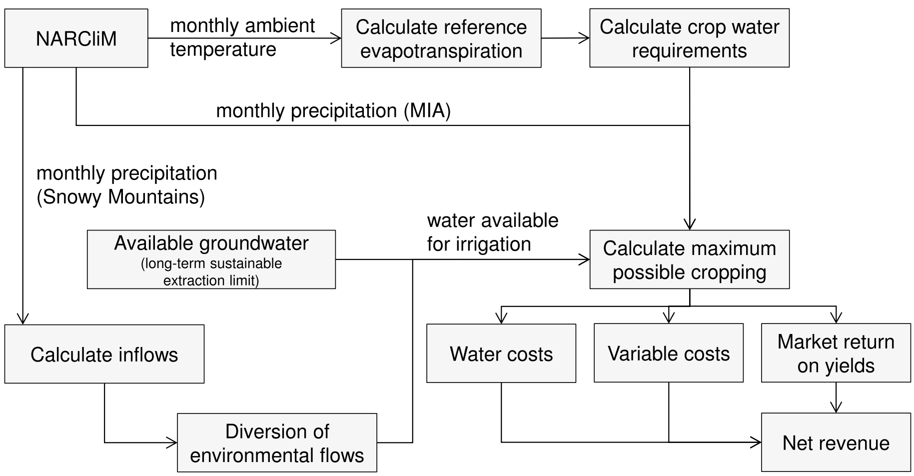

Fig. 1 Computational framework for processing data from a single climate model. The same framework is used with each of the 12 climate scenarios

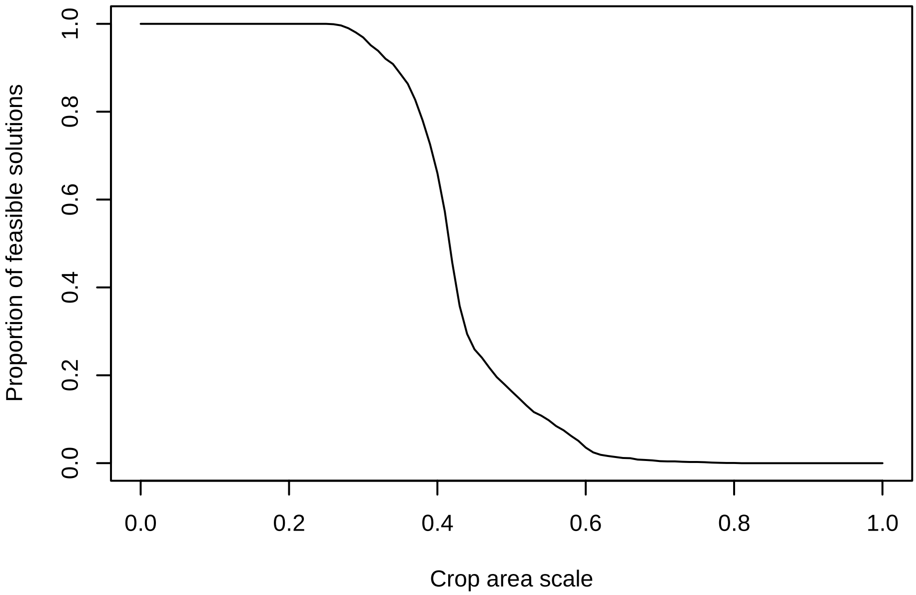

Fig. 2 Scaling solutions from 2020s to be feasible in 2060s

were scaled to meet flow restrictions in each year. It is not until the area cultivated is reduced to less than 30% of the 2020s crop area that all solutions are feasible under 2060s conditions. This implies a considerable reduction in achievable net revenue from irrigated crops, as shown in Fig. 3, which plots 2020 solutions scaled to be feasible in the 2060s that are in the 99th percentile by net revenue, i.e., highest achievable net revenue.

Figure 3 is a parallel coordinates plot (Inselberg and Dimsdale 1990) – each solution in the set in the 99th percentile of net revenue achieved is represented by a line on the plot joining the values of each of the parameters (areas of crops planted, net revenue over 10 years in dollars, and deficit in flows released for other, downstream uses in megalitres over 10 years) on the corresponding, parallel vertical axes. By inspecting the intersection of the line representing a particular solution with a vertical axis representing a particular cropping area (in hectares) or outcomes, the solutions can be characterised and compared.

For example, by following a line on the plot representing a solution from the 2020s, a general trend can be seen for larger areas planted with canola and cotton, in contrast to solutions scaled to be feasible in the 2060s that can only plant smaller areas of these broadacre crops. Both groups of solutions also emphasise planting vegetable crops, particularly in winter. The 2060s-scaled solutions yield lower net revenues, which are achieved with higher environmental flow deficits than for solutions from the 2020s. This is reflective of the reduction in water available for irrigation in the predicted climates of the 2060s.

In the work described in Lewis and Randall (2017) it was discovered that the optimisation algorithm would greedily allocate the majority of the cultivable land to lucrative but perishable crops, producing unrealistic solutions that were unlikely to realise predicted profits in practice. Constraints were applied to production of perishable commodities to generate more realistic solutions, limiting them to 10% of the national annual production, and these constraints have been maintained in subsequent modelling. In the face of the drastic reduction in net revenue predicted due to climate change, consideration could be

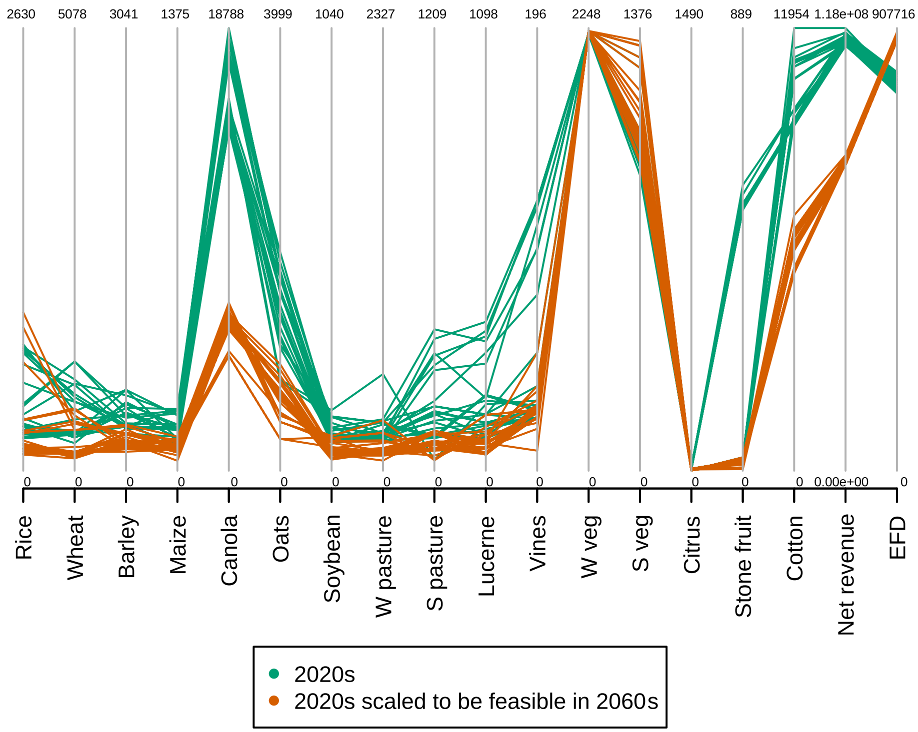

Fig. 3 Solutions from 2020s scaled to be feasible in 2060s and filtered by net revenue achieved

given to easing these constraints. By allowing unconstrained cultivation of these horticultural crops, subject to availability of water, the impact on revenues can be ameliorated, as shown in Fig. 4.

This figure contrasts the unconstrained results with the data shown in Fig. 3. It should be noted that vertical axes have been scaled to maximum values which may have changed from those in the earlier figure, for example for vegetable crops. Maximum values may be set by solutions that do not reach the 99th percentile in terms of net revenue and hence have been filtered out of the results presented. With unconstrained horticulture, the highest net revenue for scaled solutions was achieved. However, inspection of the figure shows that virtually nothing else has been planted. Once again, the optimisation algorithm has chosen to put "all its eggs in one basket" – it is hardly "business as usual".

2.2 Computationally Optimising Crop Selection

An alternative approach to attempting to continue "business as usual" is to allow the RTO algorithm to try to find optimal cropping responses to the changes in climatic conditions predicted for the 2060s. The solutions generated in such an experiment, taken from the 99th percentile by net revenue achieved, are shown in Fig. 5. As may be seen in the figure, the solutions generated for the 2060s remain quite similar in the most part to those from the 2020s, but with reduced net revenues, and increased deficits in environmental flows released. One point of difference is a significant increase in summer vegetable crops.

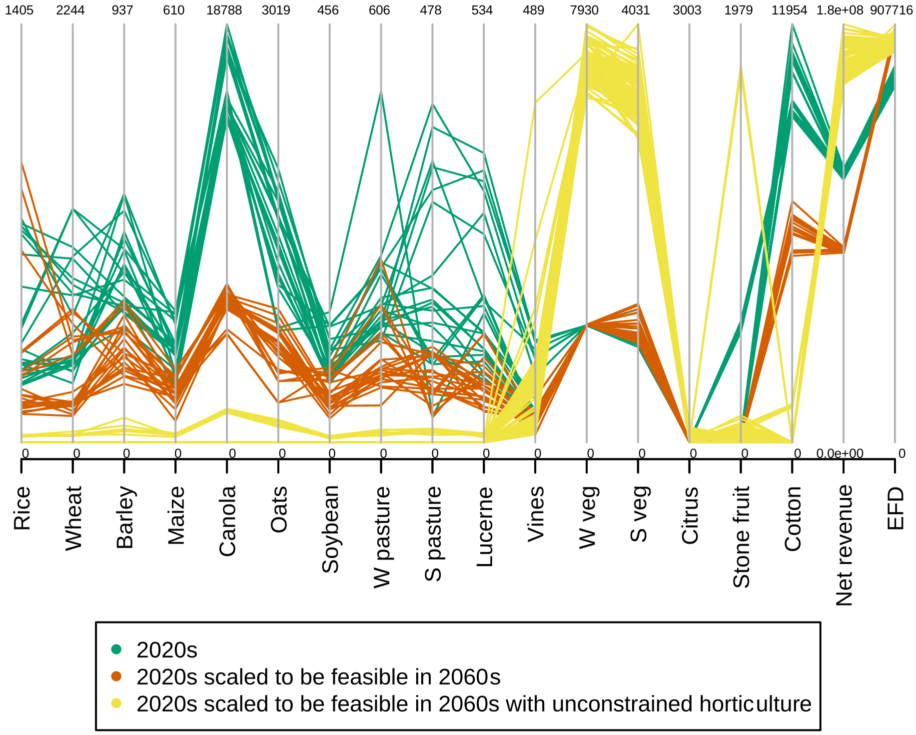

Fig. 4 High net revenue solutions from 2020s scaled (with unconstrained horticulture) to be feasible in 2060s

As a point of reference, Fig. 5 also includes the 2020s solutions scaled to be feasible in the 2060s. The net revenues for the "business as usual" solutions are the lowest of all three sets of outcomes, and their environmental flow deficits are higher. Use of the optimisation algorithm has delivered marked benefit.

As for the scaled solutions, the "optimised" solutions could benefit from allowing increased horticultural cropping. This has already become evident in the increased cultivation of summer vegetables suggested by the RTO algorithm for the 2060s time period, when compared to its solutions for the 2020s. To avoid "runaway" production of these perishable commodities, as occurred in earlier experiments, the 2060s optimisation was limited to doubling the horticulture crop areas. For comparison, a similar doubling of horticulture was allowed for in the scaled 2020s solutions, in addition to the scaled, baseline solutions. The outcomes are shown in Fig. 6.

Comparing Figs. 5 and 6 a number of distinct features may be seen. Obviously, the area given to vegetables (the most lucrative horticultural crops) has been doubled. The land to achieve this has come largely from de-emphasising the broadacre crops of cotton and canola.

In terms of the net revenue generated from irrigated agriculture, doubling the area given to horticulture significantly improves the profitability of agriculture in the MIA. The 2060 solutions deliver the highest net revenues, the 2020s scaled to be feasible in the 2060s the second highest (both greater than horticulture-constrained, optimal results in the 2020s). The 2060 outcomes deliver slightly better results in terms of environmental flow release,

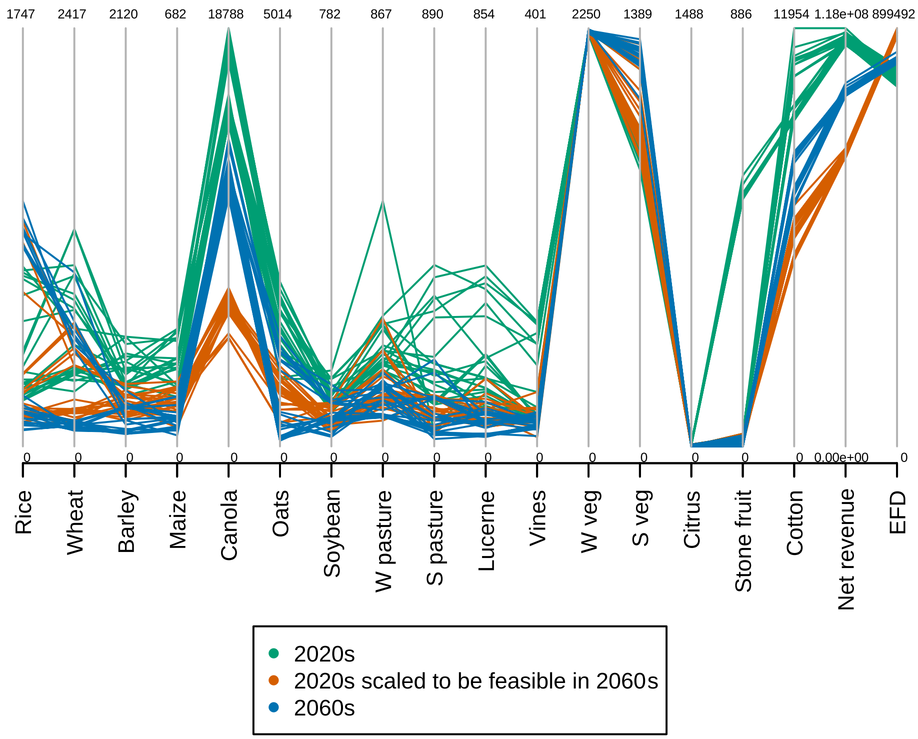

Fig. 5 Comparison of high net revenue solutions across different eras

though not achieving targets as well under the constrained water availability of the 2060s as in the 2020s.

The focus of the results presented so far has been on net revenues achieved. The optimisation algorithm has a second objective, which is to deliver downstream flows for other stakeholders in the regional water sharing plans. Under normal conditions, highest priority is given to the environment (NSW Department of Planning and Environment 2022b). For example, in the MIA there are the Ramsar wetlands of the Fivebough and Tuckerbil Swamps (Ramsar Sites Information Services 2002). For this reason the amount by which a targeted downstream release each month is not met is referred to in this modelling as an *Environmental Flow Deficit* (EFD), though downstream flows also may be subject to urban, industrial or indigenous cultural needs and uses. Based on historical data (Xevi and Khan 2005), the monthly target was set at 100 ML.

Consideration should be given to the extent to which solutions generated by the optimisation process also meet this EFD objective. Figure 7 presents the 99th percentile by net revenue of solutions for the 2060s with doubled limits on horticulture, compared with solutions for the same period and conditions that are in the 1st percentile by EFD, i.e., the most water-efficient solutions. In the figure it may be seen that the cultivation of vegetables is almost identical between the two cohorts of solutions. However, the water-efficient solutions also favour increased planting of other horticultural crops such as citrus, vines and stone fruit. Another contrast is the drastic reduction in cultivation of cotton and canola, both broadacre crops with large water requirements. Care must be taken in interpreting

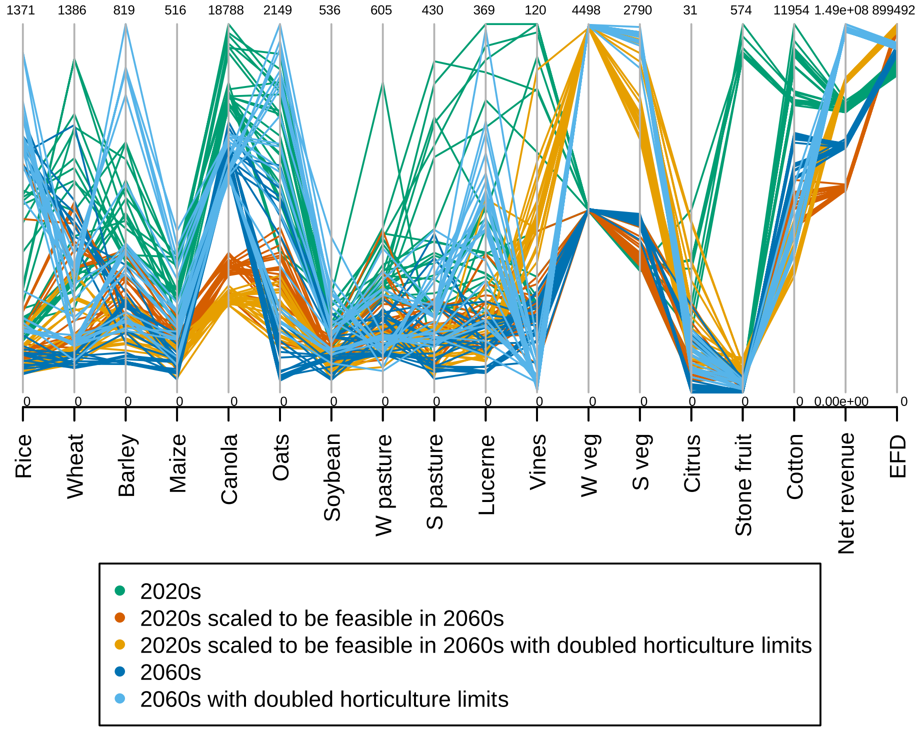

Fig. 6 Comparison of high net revenue solutions across different eras (with doubled horticulture limits)

these plots – barley and oats appear to have significant differences between cohorts but these differences are less significant given the total areas of cultivation of these crops are an order of magnitude smaller than that devoted to cotton and canola.

Another feature that may be noted through inspection of Fig. 7 is that in the 2060s *no* solutions are able to consistently meet environmental flow targets; even the most water-efficient solutions have EFDs that are substantially above zero. Inspection of the input data to the optimisation process reveals that available inflows exceeded targets in only 37% of all months (averaged over different climate models.) Some previous work explored seasonal variation of targets (Lewis et al. 2017) and application of constraints to ensure minimum downstream flows were maintained, with some degree of success. However, attempting to prescribe absolute volumes of water in the uncertain future conditions under climate change is prone to failure; a different approach is advisable.

As the optimisation algorithm employed is a multi-objective evolutionary algorithm, it produces Pareto-optimal sets of solutions. The analyses presented using parallel coordinate plots have focussed on distinct subsets of the solutions generated – those with greatest net revenue or with minimal water usage. This particular, visual analytic approach has been used to try to investigate specific differences in the crop mixes that achieve these outcomes. It can be informative to view *all* the solutions against both objectives. The sets of solutions for the 2020s, the 2060s, and the 2060s with doubled horticultural limits are shown in Fig. 8. Only the solutions in the upper extremes of

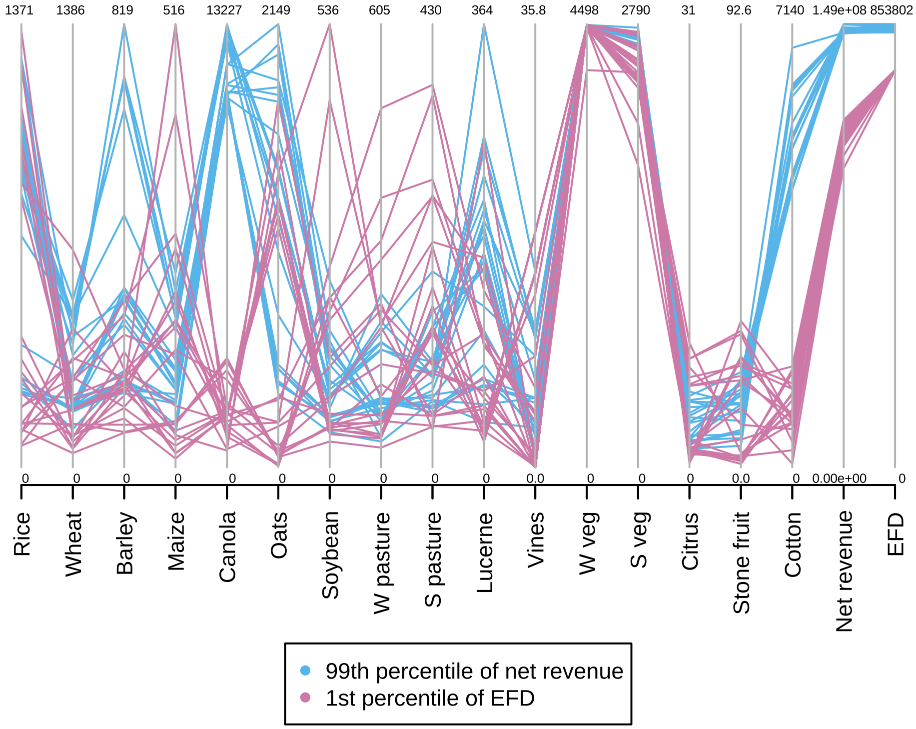

Fig. 7 Comparison of water efficient solutions with high net revenue solutions for 2060s with doubled horticulture limits

each of the curves have been examined in preceding figures, with solutions from the lower extreme of the curve representing the 2060s with doubled horticultural limits also shown in Fig. 7.

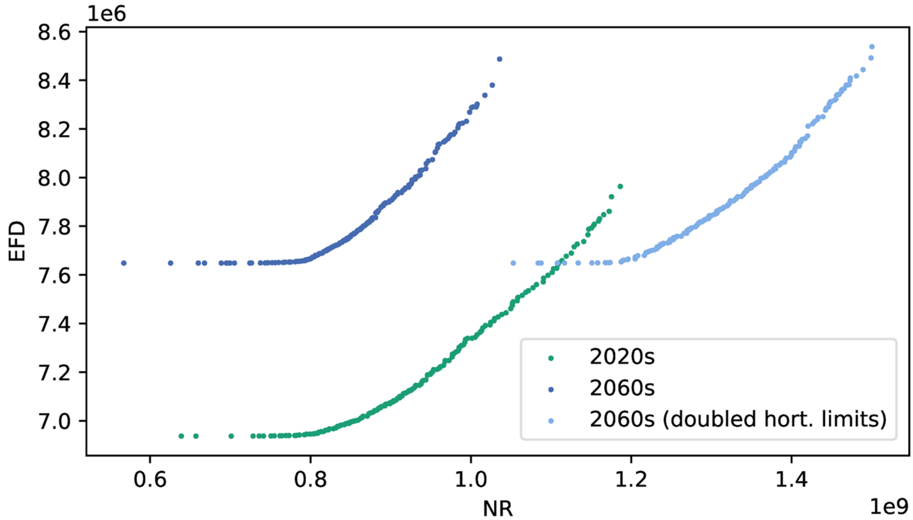

Fig. 8 Pareto optimal sets of solutions in different eras

As may be clearly seen, each set experiences a "floor" in the EFD that can be achieved. The floor for the solutions of the 2020s is at a deficit of significant size. Even for that era, the environmental flow targets formulated for an earlier period in previous work (Lewis and Randall 2017) are unachievable, and the problem grows farther into the future. At low levels of water consumption, solutions can increase net revenues by a variety of means differing very little in the amounts of water used. Beyond this level there appears to be an approximately linear relationship between net revenue gained and water used. Water efficiency in irrigated agriculture is an increasingly important factor. Furthermore, for any given level of water consumption, changes in land use can significantly impact profitability. As the figure also demonstrates, the optimisation tools provide a spectrum of outcomes from which decision makers can choose, depending on economic and environmental priorities.

3 Discussion

Figure 6 shows that there is a general decline in predicted net revenues achievable from irrigated agriculture in the MIA in the 2060s. This is largely due to the reduced availability of water, as was inferred from Fig. 7 and confirmed by inspection of the associated inflow data. If, in response to this reduction in available water, an approach is adopted of simply scaling down the area cultivated while continuing the cropping mixes of the 2020s – "business as usual" – there is a predicted reduction in net revenue achievable from irrigation of 28%. If, however, climate-aware optimisation of cropping is undertaken, this reduction in revenue can be roughly halved.

Testing the proposition that increasing production of lucrative horticultural crops may be beneficial showed reductions in net revenue can be reversed. Doubling the area dedicated to horticulture can lead to a 28% *increase* in net revenue achievable within the same water budget. Implementing a change like this would require capital investment in necessary infrastructure – detailed cost/benefit analyses would be needed. The benefits of maintaining profitability of agricultural enterprises, domestic value-add to commodities, and developing potential regional employment opportunities in food processing need to be weighed against competing priorities in sharing scarce water resources.

There are further responses to declining availability of water for irrigated agriculture that have not been considered in this study. For example, broadacre farming may be able to increase dryland cropping, and water itself may be considered as a commodity in an active trading market. In investigating other responses, the ability of computational tools to deliver insights has been demonstrated to be practical and useful.

For this study, NARCliM has provided information about future ambient conditions and precipitation in the MIA case study region. Detailed information about the water requirements, costs and revenues was also obtained to synthesise problem instances (Randall et al. 2020; Randall et al. 2022). From these, it has been possible to derive optimised cropping plans for the MIA case study area over the period 2060–69. Given climate and detailed crop data for a different area, it would be possible to generate future predictions for any other region.

4 Conclusions

The outcomes of different approaches to adapt to climate change for irrigated agriculture in the medium and long-term future have been investigated using simulation and optimisation methods. These have shown that a simple approach of scaling down existing cropping practices as available water resources decrease leads to unacceptable reductions in net revenue. However, using climate-aware optimisation of cropping plans can reduce these losses, and implementing changes in land use can even reverse them. The importance of using sophisticated, data-driven tools to help plan and predict agricultural production beyond the immediate future cannot be underestimated. With a rapidly changing climate and population increases, governments and farmers alike, in any region, can use these tools to make sensible policy and operational decisions now that may mitigate the worst of the effects in the future. This adaptive use of precious water resources will allow for achieving the goal of global food security.

A number of important areas are currently being pursued in future work:

- To date the model has been restricted to a single crop per annum on a particular parcel of land. Moving the modelling basis to temporal modelling over one or more decades allows the cropping perspective to change from single crops to considering whole-of-farm climate-smart agriculture, reflecting the realities of crop rotations and more detailed consideration of land use capabilities.
- The lack of a sophisticated treatment of market forces and price setting in modelling to date has necessitated the use of elementary constraints on horticultural crops. A more realistic consideration of supply-chain and market dynamics is needed to implicitly constrain the algorithmic tendencies towards monocultures.
- The second objective targeting environmental (and other) water needs is to be reformulated to avoid using environmental flow targets, instead aiming for minimal water use. It is accepted that there will be a “floor” on the outcomes given the need for some agricultural water use, and a “ceiling” imposed by competing needs for water, but these can be dealt with by filtering outputs. This will simplify the computational modelling and allow external factors governing water allocations to be applied easily, and varied to explore “what if” scenarios.

Author Contributions Andrew Lewis: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing, Supervision. James Montgomery: Conceptualization, Software, Investigation, Data Curation, Writing - Review & Editing, Visualization, Supervision. Max Lewis: Investigation, Visualization. Marcus Randall: Conceptualization, Software, Writing - Original Draft, Writing - Review & Editing, Funding acquisition, Supervision, Project administration. Karin Schiller: Methodology, Validation, Writing - Review & Editing.

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Data availability The datasets generated and analysed during the current study are not publicly available, but are available from the corresponding author on reasonable request.

Declarations

Conflicts of interest The authors have no relevant financial or non-financial interests to disclose.

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