

Article

Optimising Long-Range Agricultural Land Use Under Climate Uncertainty

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Abstract

To address the difficult problem of maintaining profitable and resilient agriculture under a changed climate, long-term prediction and planning are needed. One approach capable of helping with this endeavour is mathematical modelling and optimisation. Using a temporal framework, this paper outlines a spatio-temporal agricultural land use sequencer (STALS) model, where feasible climate-aware annual crop land uses are determined for a real-world case study region, the Murrumbidgee Irrigation Area in Australia. The results of this approach identified desirable transitions in land use and changes in the production system. The analysis revealed two differing possibilities of land use: one with a concentrated crop mix, the other more diverse. However, both suggest higher-value crops, such as horticultural species, will maximise regional economic benefit with comparable minimal water usage under climate change. To maintain regional agricultural economic benefit under reduced water availability and increased temperature, a transformation of land use is needed.

Keywords: digital agriculture; land use; water resource management; climate change adaptation; multi-objective optimisation; decision support system



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1. Introduction

Increases in global temperatures are now inevitable, even if global concerted action is taken to reduce greenhouse gas emissions [1]. This reality has a multilayered impact on agriculture, from production impediments to economic losses at the farm through to national level. Agriculture is expected to become increasingly constrained by broad shifts in climate regimes. Under such conditions, many existing cropping patterns and land-use practices may lose viability, undermining both productivity and profitability [2]. The loss of agricultural productivity due to the changing climate has been supported by historical analyses that estimate climate change has already trimmed global agricultural total factor productivity by about 21% since the 1960s [3].

Australia, in particular, has a high risk potential due to slow soil formation [4,5], a large area of arid climate [6], and risk of extreme weather events [7]. For agriculture to

remain productive and sustainable, it will need to be climate-resilient. To this end, Australia's national science agency, CSIRO, has identified four future scenarios that suggest possible transformative pathways: not all facilitate the attainment of a prosperous agricultural sector [8]. Scenario 1—Regional Ag capitals—seeks adoption of transformative technologies to increase productivity whilst reducing emissions. Scenario 2—Landscape stewardship—using land for carbon sequestration and environmental restoration, aspires to actively improve ecosystem services and biodiversity. Scenario 3—Climate Survival—involving relocation of industries with some diversification of the farming system, will slow biodiversity deterioration, and it is expected to see a plateauing of productivity. Farm business viability is uncertain. Scenarios 4—System Decline—premised on delayed climate response, the farm business is exposed to the impact of extreme weather and biosecurity outbreaks, with eroded profitability due to declining yields.

This work provides a quantitative perspective on what the economic contribution of annual crop production to a region may look like over time, to the end of the century, under what could be described as a *Climate Survival* Scenario 4, as presented in Ag2050 [8]. The results quantify the regional economic impact for two climate models, in addition to identifying solutions which maximise farm net revenue with minimal water usage, while realising crop diversity. These insights not only contribute to policy development and strategies that mitigate the predicted climatic effect on food and fibre production but motivate the adoption of innovation as proposed in the scenario *Regional Ag capitals* [8].

To achieve sustainable agriculture within a predicted climate envelope, modelling to inform production planning can reveal opportunities to secure future economic regional community resilience. Work on previous temporal crop prediction models that has been foundational to the present study can be found in [9–12]:

- Lewis and Randall [12] used a nature-inspired algorithm to generate trade-off solutions for water scenarios of wet, average, and dry. In this work, historic water allocation scenarios and predicted abiotic agricultural input parameters are employed.
- Randall et al. [10] added a temporal dimension of resource allocation to their earlier works of [13,14]. Further adding realism, this research incorporates land assessment evaluation capturing crop yield potential of a soil.
- Bachinger and Zander [9] represented agronomic decisions in formulating alternative land use but with no consideration of a future changed climate.
- Lawes and Renton [11] focussed on maximising farm income through alternative land use; however, all years are viewed as 'average' production years. A further disadvantage was the discounting of near-optimal solutions generated, preferring an exact value, appropriate for farm analysis but not for regional-scale land-use shifts investigated in this work.

An overarching issue with the aforementioned works is that they largely treated land as a homogenous resource. This study will instead explicitly allocate valid sequences of crops to parcels of land to examine how land production capacity and temporal agronomic decisions combine to generate climate-conscious land uses into the future. The spatio-temporal agricultural land use sequencer (STALS) that is proposed in the present study is a novel multi-objective optimisation model, combining abiotic data to determine annual crop requirements and viability under future climatic conditions taking into account land capability, water availability, and economic data.

Forecasting future economic data is intrinsically difficult due to the volatility of geopolitical landscapes [15] and natural disaster events [16]. As such, this research has made economic assumptions of commodity prices are farm gate value in Australian dollar Au\$, with no inflation applied (to make results for different time periods comparable), and water costs are 2024 present value. Hence, the economic data must be viewed as indicative.

Future water volumes were discounted, informed by the water sharing plan for the case study area [17] and relevant CSIRO water availability report [18]. The detail of assumptions is available in the Supplementary Material.

To evaluate the system, the Murrumbidgee Irrigation Area (MIA) in Australia is used as a case study region. The MIA was chosen for its diverse crop mix, regional city (Griffith) and towns' (Leeton, Narrandera, and Yenda) economic reliance on irrigated agriculture, and its position within the Murray–Darling Basin.

There are approximately 2213 irrigated farms in the case study area [19] with an average farm size of 200 ha [20]. Irrigated production systems are predominately vines (wine and table grapes), orchards (citrus and nuts), and broad acre crops of grain (cereal and pulse), oil, and fibre. Dryland farming is an option for winter crops. Grain production supports local livestock enterprises of beef feedlot and poultry and dairy farms, which are not considered in this research.

Common rotation systems are pasture-based rotation, and/or a cereal-based rotation, with a very small number of farmers following a continuous cropping land use [20]. Examples for winter rotation are wheat–barley–faba bean–canola–fallow; and for summer rotation, rice–fallow–wheat or canola–maize or soy bean [21].

The case study area has a cold, semi-arid climate [6], characterised by long, hot, dry summers with historical average maximum temperatures of 30 °C, with extended periods above 35 °C [20] and short, cold winters with an average maximum of 15 °C [22]. The average rainfall is 400 mm, with some winter dominance [23]. Two agro-climatic zones have been identified within the MIA: West and East. The East historically experienced higher rainfall and lower daily average temperatures, lower Growing Degree Days, and lower annual evapotranspiration compared to the West [24].

The region shares characteristics with other food-producing regions of semi-arid and arid climates around the world, such as California Central Valley (USA) [25], Spanish Levante region [26], Iranian Southwest province [27], and the Horn of Africa interior and South Africa's Western Cape region, both in Sub-Saharan Africa [28].

Globally, water stress is rising due to population growth, auxiliary activities of manufacturing, and food and fibre production [29]. The latter consumes approximately 70% of fresh water [30] and is the most exposed to climate change, with socioeconomic consequences [31]. Changes in climate are modifying rainfall patterns [32] and increasing evaporation and evapotranspiration from historical norms [33] under which current agricultural activity evolved. How agriculture combats these challenges is the motivation for this research.

1.1. Background

Agricultural outputs depend on a number of interacting components, which include soil, climate, and species [34]. The use of computational optimisation tools and techniques has been beneficial for many agricultural applications, yet few multi-objective models concurrently consider crop planning, projected climatic conditions, and water management [35]. This background reviews work that is relevant to the present study, in the areas of land management units, water, and multi-objective optimisation.

1.1.1. Land Management Units and Rotation Sequences

To realistically model the allocation of crop sequences to large tracts of arable land, the agronomic features of that land must be considered. For the purposes of this study, a *Land Management Unit* (LMU) is defined as an area of land with discrete chemical and physical attributes, identifiable by soil classification [36,37]. These attributes guide how the economic benefit will be derived from land of a particular type [38,39].

The choice of annual cropping activity on a given LMU is directed by historic operational activities that consider allelopathic relationships between crops [40]. The purpose of this rotation of species is to ameliorate biotic stress loads in successive crops [41,42], improve soil structure and fertility [43], and mitigate herbicide resistance [44,45], activities that represent industry best practice. In addition, incorporating a diverse mix of cropping enterprises may reduce farm business financial risks [46].

Rule-based approaches to crop selection introduce flexibility into production systems, exploiting favourable seasonal conditions by increasing cropping intensity [43,47,48]. The economic benefit of rule-based crop selection to a given LMU is demonstrated using the Australian Agricultural Production Systems Simulator (APSIM) by [43], whose findings will be a useful comparison for this work.

From Rodriguez et al. [48], investigation of future farm performance has been conducted for two alternative agronomic decision paradigms: plastic, consideration of abiotic metrics in the land use decision; and rigid farming, based on calendar schedules. In addition, their use of a single climate model limits its future insights. The present work's use of two alternative climate models, one hotter and drier, the other warmer and wetter, provides a broader spectrum of possibilities.

As noted by [47], crop patterns emerge over time when a rule-based approach to land-use choices is adopted. This research employs a rule-based approach to crop selection and highlights the benefit of in silico experiments, where insights to future states are realised now, providing lead time for decision making.

A changed climate will only exacerbate the burdens of pests and disease on agricultural crops [49,50], potentially reducing farm net revenue from increased management requirements [51] and a discounted commodity price due to reduced quality [52]. Diversified land use across a region is one strategy to mitigate this biotic impact.

1.1.2. Water Availability

Globally, river system extraction rates are reducing river flows, affecting environmental diversity and groundwater recharge [53], while climate change affects river flows through the increased frequency of extreme events such as droughts of extended duration [7,54].

The evaluation of agricultural water resource carrying capacity [55] and linking national water and food security are priorities, particularly in arid-climate countries [56]. Other water needs for the environment, industry, food production, and hydroelectricity generation complicate water allocation. This is the situation in the case study area, where precipitation in the Murrumbidgee River catchment must meet all these needs [57], not only for the MIA but contributing to the southern Murray–Darling basin, Australia's largest and most important irrigation water source [58].

The volume of irrigation water delivered to the MIA is determined by complex hydrological modelling [17] and Snowy Hydro Limited reservoir management [59]. The Murrumbidgee River is a regulated system that requires an access entitlement to extract water [17,60]. The prioritisation of water is directed through legislation, namely the New South Wales Government *Water Act 2000* [60] and the *Water Sharing Plan for the Murrumbidgee Regulated River Water Source Amendment Order 2022*, which prioritise water allocation based on licence class [17]. The implications of this legislation are that the volume of irrigation water available not only changes in accordance with precipitation in the catchment but also depends on the licence category.

1.1.3. Multi-Objective Optimisation in Crop Selection

Although it has been argued that the application of optimisation to agricultural problems is beneficial [61], modelling the complex relationships between different agronomic

components is challenging. Determining future sustainable agricultural land use in an optimisation framework should consider agronomic decisions, available water (both irrigated and rainfed), and predicted climate possibilities. However, recent systematic reviews found that, despite increasing research focus, few studies in this area included all these elements when investigating this problem [35,62].

Nature-inspired optimisation tools that operate on a collection of alternative solutions simultaneously are well suited to such real-world multi-objective problems. The dominant optimisation objectives in computational agriculture are *maximising agricultural revenue* coupled with *minimising water use* [35]. Previous approaches to achieve this have either defined the problem decision variable as an area allocated to broadacre crops or considered water allocation to an area or a user. What farmers and regional planners require is timely information that provides long-range insights that simultaneously show what future land use may look like under predicted climates to maximise water end-user economic benefit.

While much work in the area of agricultural land-use optimisation performed snapshot planning for individual years, examples are [63] minimisation of nitrate pollutant strategies and [64] focus on crop–livestock optimisation; Randall, Montgomery, and Lewis [10,65] developed a temporal model in which a set of ten sequential planning problems, each spanning a year, is solved concurrently. The model aimed to maximise overall net revenue and minimise environmental river flow deficit (the amount by which environmental targets are not met). Similar to other works in the field, it treated land as a uniform resource, able to be arbitrarily divided and allocated to any crop, omitting the interplay of crop and soil type.

1.2. Aims of This Study

The present work incorporates increased agricultural realism by applying an LMU production capacity assessment and agronomic rotation rules, which direct next season's land use, based on currently understood best-practice decisions, to heuristically build climate-informed ten-year land-use plans, an implementable time horizon [66], which aligns with crop sequencing [67,68]. This is evaluated using two different climate models to the end of the century. There exists a tension between the water needs of perennial crops and annuals, which greatly complicates any concurrent optimisation of these disparate methods of land use. Consequently, this study explores annual broadacre crop species, seeking to answer the following questions:

1. How could regional production capacity change under different climate models through time, measured as net revenue attained against water consumed?
2. Will there be a temporal change in the mix of annual cropping enterprises on a given land unit and, if so, when does this change occur?

2. Materials and Methods

To resolve the research questions, an optimisation system will be required. This will consist of a multi-objective optimisation model of multi-year agricultural land use (Section 2.1) that is subject to crop rotation sequence rules (Section 2.2), informed by projected climatic conditions and regional characteristics (described for the case study region in Section 2.3). Details of the particular solver used in the present work and experimental design are given in Sections 2.4 and 2.5.

2.1. Optimisation Model and Solution Construction

The model assigns land uses (crop plantings and fallows) over time to areas that are referred to as 'land parcels', or simply parcels. A parcel is a fixed-sized unit of land that belongs to a particular class of land management unit. For the work in this study, this

has been set as 200 ha, the average farm size in the MIA [69]. However, it is simply a parameter of the process. While this is larger than the parcels of land an individual farm would deal with in the MIA, it is an appropriate size for regional land-use planning. In this work, the duration of a land-use plan is set as 10 years, drawn from 80 years of climate projections. Decade-long decision horizons are humanly manageable [70], enabling the identification of transition points, useful for supply chain planning, enhancing the model's use as a Decision Support System (DSS). Using the framework outlined below, the optimiser generates climate-informed land-use alternatives assigned to an LMU.

The problem is a form of the multiple knapsack problem (MKP) [71], as the optimiser must choose a selection of crops (forming the land-use solutions) for each land parcel over time. Thus, it may be considered as $\mathcal{NP}$ hard.

The system simultaneously optimises two objectives across a fixed horizon under the constraints of water availability and rules restraining valid crop sequencing. The first objective, shown in Equation (1), maximises overall net revenue through the combined crop plantings across land parcels and time. The second objective is selectable, with two alternatives currently supported. Option 1, shown in Equation (2), minimises overall irrigation water usage, similar to much of the past work in this domain (see, for example, Randall et al. [65]). Option 2, shown in Equation (3), aims to achieve a desired proportion of legumes in the planting mix (the target used here being an average of one-third of plantings within each parcel being a legume variety). This goal was selected given the important role legumes play in the farm system from ameliorating pest and disease loads to contributing to soil health, but it is also illustrative of various alternative planning goals that could be used. Below, optimising for revenue and irrigation water is denoted (NR, water), while optimising for revenue and increased legume planting is denoted (NR, legume).

The temporal unit used in this work is a month, based on crop growth cycles, given that many crops have defined growth and watering requirements that can be approximated by whole months. Optimisation is calculated over a calendar year, while a water year is June–July. (Data from two water years are used in a single calendar year calculation).

$$\text{Maximise } \sum_{p=1}^P \sum_{i=1}^{|x(p)|} \left(\text{rev}(x(p,i), \text{LMU}(p)) - c_w(s(p,i)) \cdot w(x(p,i), s(p,i)) \right) \quad (1)$$

$$\text{Minimise } \sum_{p=1}^P \sum_{i=1}^{|x(p)|} w(x(p,i), s(p,i)) \quad (2)$$

$$\text{Maximise arg min} \left\{ \text{target}_{\text{leg}}, \left(\sum_{p=1}^P \frac{\sum_{i=1}^{|x(p)|} [x(p,i) \text{ is legume}]}{\sum_{i=1}^{|x(p)|} [x(p,i) \text{ is non-fallow}]} \right) / P \right\} \quad (3)$$

where:

P is the number of land parcels,

$x(p,i)$ is the decision variable, the i th crop planted on parcel p ,

$\text{rev}(c,l)$ is the net revenue of crop c on a parcel in LMU l ,

$\text{LMU}(p)$ is a function that returns the LMU to which parcel p belongs,

$c_w(t)$ is the cost of water per megalitre in planning month t ,

$s(p,i)$ is the the start month of the i th crop planted on parcel p ,

$w(c,t)$ is the total water requirement of crop c starting in month t on a parcel, and

$[condition]$ is 1 if $condition$ is true, 0 otherwise.

Solutions are constrained by the duration of the planning horizon and application of rotation sequence rules, which are described next.

2.2. Rotation Sequencing Rules

A solution is constructed by determining the sequences of crops (including fallow periods) on each land parcel. This process could be performed in parallel (making one decision per land parcel at a time) or sequentially, planning the entire sequence for a parcel at a time (which is the approach used here). Constructing solutions sequentially leads to those rotation sequences for land parcels that are constructed earlier gaining priority access to available irrigation water. To ensure that parcels across diverse land management uses have equitable access to water, the solver randomises the order in which parcels are processed each time it constructs a new solution.

The following considers the construction of a single land parcel given biophysical properties, climatic conditions, and available water. The solver begins at the first month of the planning period and then moves forward through time as each land use is selected. At each step, the set of available annual crops is filtered by applying the following elimination rules, which are applied in sequence (the order was chosen to maximise early elimination and reduce computational effort):

1. **LMU Compatibility:** Only crops that *can* be grown on a particular LMU are considered.
2. **Available Time:** Only crops whose planting time does not exceed the planning horizon are considered. This is required due to the crisp end in the optimisation model.
3. **Rotation Rules:** Informed by industry best practice agronomic decisions [72], crops are precluded from being grown within a defined time period of previously planted crops. In the present work, this is modelled as a set of rules per crop. If any rule is matched, then a candidate crop is excluded. Each rule is a tuple (*Others*, *m*, *n*): if crops from the set *Others* have occupied the land parcel *n* or more times in the preceding *m* months, then the candidate crop is excluded.
4. **Sowing Temperature:** Crops are planted based on an approximation of soil temperature. If overnight minimum temperature is within a crop-specific range for fewer than five days within the 20 day period around the present day planting date, then it is excluded from consideration as planting conditions are unfavourable. The 20 day window captures the temperature trend that satisfies a crops planting preference.
5. **Available Water:** To enable comparison of crops with different growth phases, three development stages have been defined: (1) Initial, germination to developed plant; (2) Growth, developed plant mid season to flowering, and (3) flowering to harvest. A crop's water requirements across these three growth stages are calculated, taking into account the effect of projected temperatures on ETo. To determine if there is sufficient water for crops to reach economic potential, rainwater 14 days prior to planting through to harvesting is allocated to a crop. Including rainfall 14 days prior to planting acknowledges soil moisture, which would permit planting regardless if rain fell at the time of planting. Any rainfall within the first and second growing periods that is in excess of the crop's requirements carried over into the next growing period to emulate water held in the soil. The following rules are then applied to dryland and irrigated crops:
 - For a dryland crop, rainfall in each growth stage, including carried over amounts, must meet the requirements for that stage.
 - For an irrigated crop, the remaining water demand after rainfall must be met by available irrigation water. This is determined by monthly inflows and what water has been allocated to previously constructed land parcels.

If these conditions cannot be met, then the crop is excluded from current consideration.

study region, is NARcliM (New South Wales (NSW)/Australian Capital Territory Regional Climate Modelling) [77], which uses several global climate models, dynamically down-scaled to produce a range of predicted future climates. NARcliM1.5 was chosen for its coverage of the Murrumbidgee River catchment, and its local scale [77,78]. Greenhouse gas emissions Representative Concentration Pathways (RCP) 8.5 was deemed the most appropriate, as the CO₂ levels align with historical total emissions and the most likely state for the mid-century based on current global responses [79]. Two global circulation models were selected, one warmer and drier climate, ACCESS1.3, the other warmer and possibly wetter, CanESM2. These models have positive scores for historic climate representation, and in the case of CanESM2 a good predictor of extreme El Niño [80].

Both models give daily predictions of precipitation and minimum and maximum temperatures from 1 January 2020 through to 31 December 2099. NARcliM1.5 offers several evapotranspiration calculation approaches. The FAO56 Penman–Montieth evapotranspiration parameter [78,81] was selected based on its inclusion of wind speed, a variable predicted to depart from historic norms [82]. Projected annual rainfall and average daily ETo for both models is shown in Figure 2. The shaded decades are those for which problem instances are derived in the present work, the start and end decades of 2020–2029 and 2090–2099, with 2050–2059 selected as a dryer period located between the two.

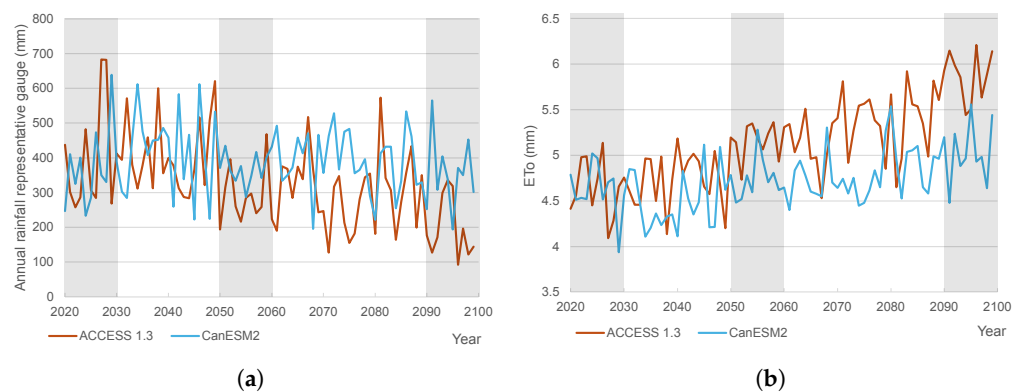


Figure 2. Key climatic indicators from ACCESS 1.3 and CanESM2 for a reference location within the case study region in NSW, Australia. (a) Projected annual rainfall. (b) Projected average daily ETo by year.

2.3.2. LMUs

This input was customised for the six main soil types of agricultural importance in the case study area. The area of each soil type was estimated from a soil map connected to IrrigATEway [83], using the Quantum Geographic Information System (QGIS) version 3.6.3. In this study, a total area of 141,000 ha (1410 km²) is considered, apportioned to the region's main soil types as shown in Table 1.

Table 1. Soil types, area in hectares, and number of planning parcels.

Soil Type	Area (ha)	Parcels
Self-mulching clay	49,292	246
Hard-setting clay	15,171	76
Transitional red-brown earths	20,851	104
Red-brown earths	31,520	158
Sand-over clay	20,764	104
Deep sandy soils	3402	17
Total	141,000	705

Land-use evaluation was assessed using Food and Agriculture Organisation [84] guidelines applied to the six soils to determine crop yield potentials [85]. All LMUs in the case study area are assessed as having a Land and Soil Capability (LSC) 1 and 2 [86], appropriate for agricultural cropping purposes.

2.3.3. Crops and Productions Systems

The core annual agricultural enterprises which drive the MIA regional economy and consume irrigated water are cotton, rice, and horticulture (summer and winter crops) [20]. (While current production in the MIA also includes wine and table grapes, stone fruits, citrus, and nuts, these perennial varieties are not modelled in the present work.). To correctly represent annual cropping systems, supporting rotation species must also be available for the model to choose as a feasible temporal land-use alternative. The identification of these rotation species was made by triangulating data from published work [42,87,88], industry reports [89], and interviews with local experts (Australian Human Research Ethics approval KS00798). This established the following complementary system crops:

- Winter bulk grain cereal crops of barley, oats, and wheat.
- Summer grain crops of rice and C4 carbon fixation plants maize, millet, and sorghum, capable of reducing photorespiration under the high temperatures experienced in the case study area [90]).
- Pulse crops of chickpea, faba bean, field pea, lentil, mung bean, and vetch; oil crops canola (winter) and sunflower (summer).
- Horticultural crops are beetroot, brassicas (cauliflower and broccoli), carrots, cucumber, eggplant, garlic, lettuce, muskmelon (i.e., rockmelon), onions, potatoes, pumpkins, tomato, and watermelon [20].

The full crop characteristics are given in the Supplementary Material (this is available upon request from the corresponding author). To represent regional agricultural production realities, dryland crops are included. These are grown only with precipitation, using no irrigation water. The dryland K_c coefficients were modelled as 80% of those for the same crop if grown under irrigation (paired with lower projected revenue).

2.3.4. Water Scenarios

To represent the breadth of seasonal fluctuations experienced in the MIA, within which agriculture production operates, five available irrigation water scenarios are defined. For this work, these are *drought*, *very low*, *low*, *mid-range*, and *high*. These water scenarios and corresponding available irrigation water volumes were derived from Murrumbidgee River water allocation statements [91], which occurred in representative years, shown in Table 2.

Table 2. Water scenarios represented by year.

Precipitation Ranking	Representative Year
Drought	2007
Very low	2019
Low	2009
Midrange	2015
High	2012

For the case study area, the sources of water for agricultural production are rain on farm land and irrigation water. The latter is derived from the Murrumbidgee River catchment. Future available irrigation water was calculated based on the precipitation in the Murrumbidgee River catchment area for the representative years. The volumes were discounted across the 80-year horizon used in this study to reflect catchment precipitation

degradation [18]. This general approach can be applied to any water source, while customisation, such as that required for this case study, ensures the global capabilities of the model. (The Murrumbidgee River is a government-regulated water source [17].) These customisation details are available in the Supplementary Material.

In this work, it is assumed that irrigation water is available to all LMU parcels and is delivered to crops through overland infrastructure. Only surface water is used, omitting other sources such as ground water.

2.3.5. Economic Based Variables

The key economic driver in irrigated agricultural production is the price of water. MIA irrigators access and purchase water through the Australian water market. Monthly water prices (\$/ML) for the representative years were extracted from the NSW Government Water Trading Dashboard [92]. The details of this element are provided in the Supplementary Material.

A crop's gross margin (GM) is determined from its projected revenue, less the cost of water. Gross margins (GM) enable comparison between enterprises, appropriate for this study. The projected income for each crop was informed by secondary source data (government and industry). These are adjusted based on the climate condition under which the crop is grown to reflect higher prices when water is more scarce and lower prices during the rarer high allocation years to reflect possible oversupply. This is given in Table 3.

Table 3. Crop income adjustments based on water allocation level.

Water Allocation Category	Crop Income Coefficient
Drought	160%
Very low	130%
Low	110%
Mid-range	100%
High	80%

To enable comparisons between different time periods, all dollar amounts are adjusted to 2023 values.

2.4. Solver Method

A plan for each parcel of land is a sequence of crops that should be selected to take into account previously planted crops as well as projected climatic and water conditions. This lends itself to the use of *constructive techniques* [93] that progressively build solutions one element at a time. By far the most well used, and effective, of these is Ant Colony Optimisation (ACO) [94].

A multi-objective variant of an ant colony optimisation approach [95], Ant Colony System (ACS), is used in the present work. At each iteration, the solver constructs multiple solutions. For each solution, a plan for each land parcel is constructed for the entire problem duration. Parcels are processed sequentially, but in randomised order to avoid bias toward numerically lower LMUs. For each parcel, the solver applies the elimination rules described in Section 2.2 above to identify a subset of feasible crops at that point in time. If no crops are available, a month-long fallow is inserted. If a sequence of fallows reaches 18 months, then a cheaper form of fallow is inserted in their place, reflecting the different management practices for longer fallow periods.

Given a non-empty set of candidate crops, the solver makes a stochastic decision that is biased to the learned utility of a crop being planted in that year of the planning problem and a crop's gross margin, which rewards short-term gain from the selection. The selection

rule, with high probability, will select the most attractive crop. With lower probability, it makes a biased random choice in proportion to each option's attractiveness. This ensures diversity in solutions. A land parcel is considered complete when it can add no more crops, as it would exceed the allotted time. Once all solution have been constructed, they are merged with the solution archive, and multi-objective Pareto calculations [96] determine which non-dominated solutions are kept. This archive, at the termination of the solver, contains a number of trade-off solutions that can be analysed.

2.5. Experimental Design

Six problem instances are defined based on planning decade (2020–2029, 2050–2059, 2090–2099) and climate model used (ACCESS1.3, CanESM2). The water allocation levels for these instances are shown in Figure 3.

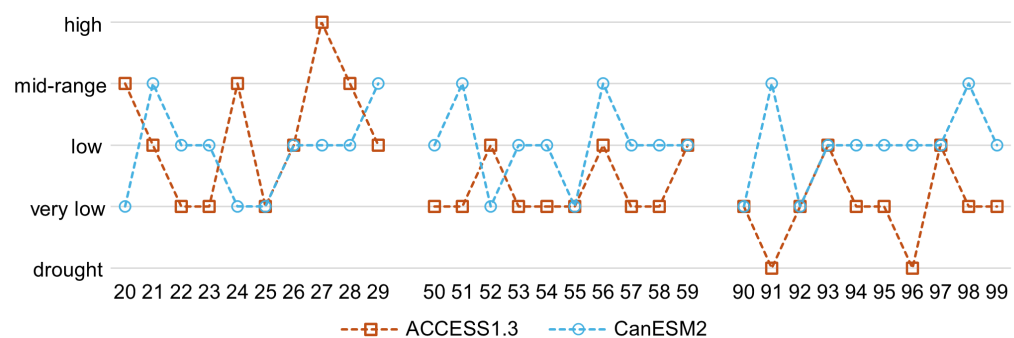


Figure 3. Water scenarios for the selected decades (within the 2000s) and climate model. Years 2020–2029 are based on the climate model, not observed reality.

The multi-objective ACS algorithm was applied to each instance with a working population of 20 solutions (generated each iteration) and 2000 iterations (so 40,000 solutions are evaluated), with an archive size of 20 (the number of solutions kept at the end). ACS control parameters were selected through an initial sensitivity analysis to produce good solutions for all instances. Solution sets produced across multiple randomised trials (within each decade–model problem) were filtered to derive a set of best trade-off solutions per problem instance.

2.6. Analysis

The model outputs to be considered useful should exhibit land-use combinations that satisfy best-practice agronomic decisions. This requires species from categories of cereal (wheat and rice), legume (mung bean and chickpea), brassicas (canola, cabbage, and broccoli), and alliums (onions and garlic) to be planted in a given LMU at a frequency over a decade to provide agronomic benefit.

The attainment curves were calculated using the 20 highest-performing solutions for the net revenue objective. The proportion of crop planting is calculated as the number of crop plantings for a species within a calendar year divided by the total number of crops planted (all species on all LMUs). This approach was applied so solutions were not biased towards crops that occupy the land for longer than others. Crops are presented by category for each decade investigated. These data were examined for the specific crop choices planted on a stated LMU to identify which crops in what soil contributed to the proportion of plantings, providing deeper insights into the dryland and irrigated production systems.

3. Results

The optimisation solver described in previous sections was used to quantify the case study area's future agricultural economic production capacity for two climate models. Further investigation identified which crops contribute to this revenue while simultaneously locating crop mix transition points.

The key crop groups highlighted demonstrate what a climate-smart landscape may look like for the case study area. The first set of solutions presented satisfy the two objectives of maximising net revenue with minimal water usage and net revenue maximisation with legumes comprising a threshold proportion of planting. A second dataset displays the interaction of net revenue and legumes when consideration is given to simultaneously maximising net revenue with minimal water consumption. This dataset includes the complementary investigation of maximising net revenue with minimal water usage when the proportion of legume planted is set as an objective. This information may assist in counteracting possible diminished agricultural economic value caused by the impact of climate on agricultural production capabilities.

As precipitation drives agricultural production, reduced predicted water availability diminishes gross margins for irrigated crops through increased water prices and constrains dryland crop choices. The economic attainment surfaces of Figure 4 illustrate this relationship. These are composed of individual solutions at different points along each surface. Each solution comprises 10-year crop sequences for the 705 parcels of land. Due to the density of this information, it was summarised to enable analysis and understanding of changes in production systems over time.

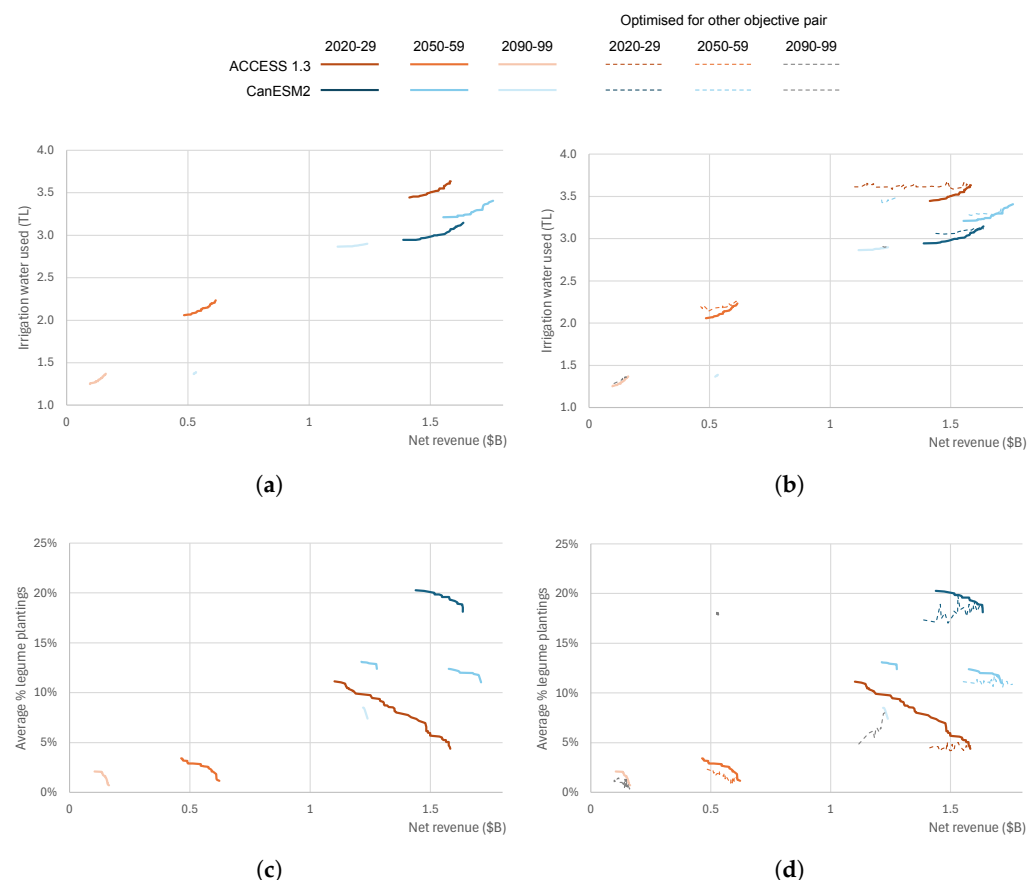


Figure 4. Trade-off solutions when optimising against the two alternative objective pairs shown in their original objective space (left column) and when re-evaluated in the other objective space (right,

dashed lines) for 2020–2029, 2050–2059, and 2090–2099 under ACCESS1.3 or CanESM2 climate projections. Note some solution sets form disjoint groups: CanESM2 in 2090–2099 when optimising (NR, water), with revenues around AU\$0.5B and AU\$1.2B; CanESM2 in 2050–2059 when optimising (NR, legume) with revenues around AU\$1.25B and AU\$1.65B. (a) (NR, water) optimised solutions. (b) With (NR, legume) solutions shown. (c) (NR, legume) optimised solutions. (d) With (NR, water) solutions shown.

3.1. Bi-Objective Climate Comparison

3.1.1. Two-Objective Optimisation

The trade-off attainment surfaces of both groups of bi-objective solution sets for each decade–climate model problem are shown in Figure 4a Net Revenue, Water, and (c) Net Revenue, Legume.

Examining Figure 4a, the 2020–2029 decade, farm net revenue is projected to be AU\$1.5B for both ACCESS1.3 (hotter and drier) and CanESM2 (warmer and wetter). However, to produce this economic benefit, there is a 0.5TL difference in irrigation water usage. This emphasises the importance of using different climate models to generate results that span the spectrum of future possibilities. The impact of a changed climate is observed in 2050–2059, where the hotter and drier predicted climate provides 2TL of available water, resulting in a regional economic contraction in net revenue of AU\$1B from the 2020s decade. In comparison, the regional production capability of the warmer and wetter climate shifts upward to AU\$1.6B, coinciding with a 0.2TL increase in available water from 20 years earlier.

The end of century decade 2090–2099 portrays a future of constrained land use, especially for the ACCESS1.3 climate model. Here, there are a large number of fallows, and only the highest commodity price \$/ML water are feasible options. The drier and hotter climate can only generate AU\$100M over the decade, based on 1.3TL of irrigation water availability. In comparison, the warmer and wetter climate enables regional production to remain relatively unchanged from the 2020–2029 decade. Of interest is that the solver discovered two distinct groups of solutions for the CanESM2 model at the end of the century, one with far lower water use (1.7TL) and correspondingly lower revenue (approximately Au\$600 million), seen in Figure 4a. Figure 5 shows the split of land uses for an exemplar solution from this lower region of the objective space.

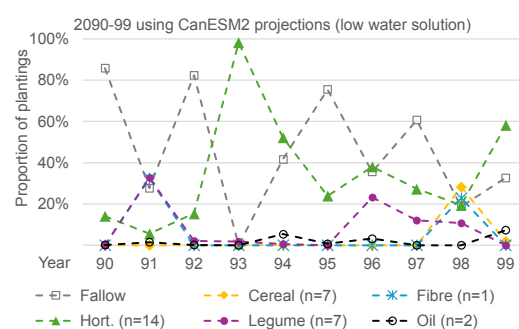


Figure 5. Illustrative land use (by crop category) from lower-revenue solution group produced for 2090–2099 with CanESM2 and NR–water objective. This solution is worth \$B0.533 and requires 1.39 TL of irrigation water (see Figure 4a).

In contrast, when legumes are set as the complementary objective to maximising net revenue Figure 4c, net revenue remains around Au\$1.5B across models in the 2020s for both climate models. However, the percentage of legume planted shifts downwards from a high of 20% in 2020–2029 for the warmer and wetter (CanESM2) to a low of 5% for the hotter and drier climate model (ACCESS1.3). The possibility of legume planting contracts in

2050–2059 onwards under the ACCESS1.3 hotter and drier climate to a range of 1–4%. The implications of this will be presented in the discussion. Although the CanESM2 provides more water to support legume planting, this comes at a cost, with regional agricultural net revenue shrinking by a range of up to Au\$1B.

3.1.2. Re-Evaluated Solutions

This dataset demonstrates that regional economic benefit is strongly determined by the climate model and how the parameter metrics shift over the decades to the end of the century. This is evidenced in Figure 4b where climate model attainment curve positions remain in a ranked order of ACCESS1.3 water usage of 3.5TL to deliver Au\$1.5B, followed by CanESM2 using 3.25TL in 2050–2059 and 3TL in 2020–2029. This lower water usage may be explained by increased precipitation. When crop diversity is added to the equation, the economic attainment curves are similar in rank by climate model to Figure 4c, although there is a contraction in the solution range (refer to Figure 4d).

3.2. Temporal Land-Use Comparison

A single solution was investigated to identify which crops are contributing to the economic attainment curves and locate possible shifts in land use over the three investigated decades. For brevity, the solutions of self-mulching clays, the predominant soil type of the MIA, are explored. Note that some staples such as potatoes, carrots, and onions are not discussed, as they are a suboptimal choice on self-mulching clay.

3.2.1. 2020–2029 Problem Instance

Both climate models generate solutions with a similar mix of crop species and planting proportions, albeit in different years. The warmer and wetter climate solutions generated by the CanESM2 model align with the reality of the case study area for the years 2020–2024. In contrast, the comparatively hotter and drier climate (ACCESS1.3) did not include cotton, a crop that was planted after the 2019 drought to take advantage of high water allocations and precipitation in 2021–2023 for these same years [97]. An explanation for this is the ACCESS1.3 lower rainfall prediction than observed for the period. Analysis of ACCESS1.3 precipitation data identified leptokurtic distribution (kurtosis 33.6115), compared to CanESM2's more normal distribution (kurtosis 3.3892). Although CanESM2 is a good predictor of El Niño events, the result of rice not being planted until 2080 illustrates the model's difficulty in predicting La Niña events.

The commonality in the solution components of this decade is expected, as the impact of a changed climate has not begun to fully express itself, unlike in the 2050s, where the proportion of cotton planting is reduced in the ACCESS1.3 solutions, compensated for by a higher proportion of fallow.

3.2.2. 2050–2059 Problem Instance

The 2050-decade crop mix reflects low-to-midrange water availability throughout the decade. Here, fallows are consistently selected as the most feasible option in the hotter and drier environment. Although not contributing economically, fallows satisfy the bi-objective of least water usage. In comparison, CanESM2 returns results of dryland cotton as an option in 2052 and 2058, while irrigated cotton is the preferred system in 2050, 2054, 2056, 2057, and 2058 (1%, 5%, 1%, 14%, 39% respectively). In contrast, only dryland cotton is feasible in an ACCESS1.3 environment in 2059 with a planting proportion of 59%. Legumes are selected by both climate models, albeit at low planting proportions: in 2051 irrigated mung beans (1% planting proportion) and 2056 irrigated lentils (3% planting area) for the ACCESS1.3 climate. The wetter climate of CanESM2 favours irrigated mung beans in 2059, with a planting proportion of 56% of the case study area.

Cereals are an essential component of the cropping system. CanESM2 selected cereals for 2051 and 2053 in a planting proportion of approximately 34% dryland sorghum and 2% irrigated sorghum, respectively. These planting proportions allude to Sorghum C4 advantage in hotter environments. In comparison, ACCESS1.3 suggests cereals in 2054 and 2057 to be Millet and dryland Sorghum, respectively (both are C4 plants). Differences in planting percentage arise from model metrics and current STALS selection rules. That is, STALS eschews crops unless they appear profitable. A complementary rule of promotion would be beneficial. The encouragement of STALS to plant crops informed by industry best-practice rotation sequences would better reflect the reality of agricultural production systems.

Although horticulture is a reliable contributor to solutions in this mid-century decade, there is considerable variability between the results under each climate model. In a drier ACCESS1.3 environment, irrigated pumpkin is the most selected option (44% of the plantings in 2056), followed by irrigated beetroot in 2052 (33% planting), irrigated eggplant in 2051 (22%) and irrigated cucumber in 2056 (21%).

3.2.3. 2090–2099 Problem Instance

In the hotter and drier climate (ACCESS1.3), land use is dominated by two alternatives: fallow, satisfying the minimal water usage objective, and horticultural crops, which deliver the highest economic return per ML of water input. The fallow planting proportion range of 66–96% throughout the decade highlights how the climate can potentially render a productive regional economy weak and unproductive. Although this land use is complemented by lower planting proportions of 4–34% of high-value horticultural crops, the model does not consider product quality, which can be degraded due to increased temperatures, resulting in depressed commodity value.

In contrast, the diversity of the crop mix in CanESM2 solutions reflects the higher available water demonstrated in the choice of dryland crops—sorghum (2093, 63% planting proportion) and cotton (2094 and 2096, 30% and 37%, respectively). These crops are complemented by a combination of horticulture (2091 30% planting proportion) and legumes (2091 lentils 23% and irrigated mung bean 2098 5%).

The corresponding land use for a solution from the lower revenue attainment curve depicted in Figure 5 is significantly different from that of Figure 6; namely, cotton is not a consistent contributor except in 2092 and 2098. Although horticultural crops are an important land use in both solutions, the timing and proportion of planting are different. The role of cereals is greatly reduced in the lower revenue solution, with 2098 experiencing 30% planting proportion compared to 62% in 2091 and 8% in 2094 for the higher revenue attainment curve.

Considering the 2020–2029 decade, both climate models suggest cotton (the single fibre crop in the mix) as a viable land use, along with horticulture, a dietary staple of short shelf life. However, cereals are also promoted as a feasible alternative to a lesser degree. 2050–2059 is a transition point for both climate models, where two categories (fallows and horticulture) dominate the planting proportions. By the end of the century, the solver can only locate two categories which satisfy the bi-objective for the ACCESS1.3 hotter and drier climate. In comparison, CanESM2's warmer and wetter climate frees the STALS to identify a broader mix of land use. This diversity in land use contributes to a healthy regional economy.

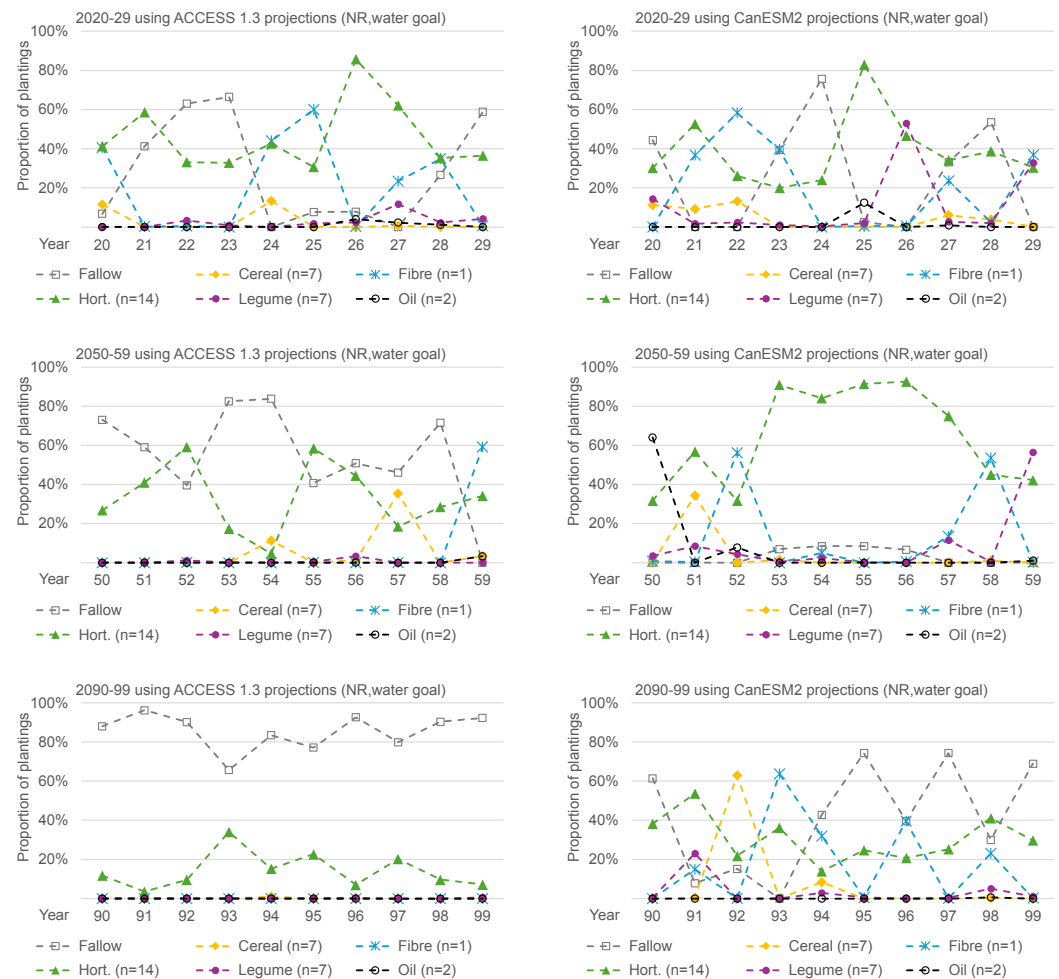


Figure 6. Illustrative land use (by crop category) for highest-revenue solution when optimising for NR–water in different time periods and under different climate projections.

3.3. Diversity

Having crop diversity in agricultural land use contributes to reducing economic risk in a region [98]. Figure 7 at first glance mirrors that of Figure 6. However, there are subtle differences. When adjusted for the legume objective, the contribution of cereals to regional economic benefit is reduced in 2020–2029 CanESM2 (warmer and wetter climate), stemming from lower planting proportions in 2027. The reason for the close alignment of land use will be examined in the discussion. A temporal examination of Figure 7 was completed for ACCESS1.3 2090–99. It focussed on the left side of each dashed attainment curve, which is the *minimum* net revenue attained when seeking a legume planting proportion threshold, while considering minimal water consumption. Self-mulching clays (LMU 1), the predominant soil type of the MIA, were analysed to illustrate temporal changes in land use within a decade and across the experiment horizon. Figure 8 shows the actual areas allocated by the solver to this LMU for the 2090–2099 ACCESS1.3 instance. The solver has favoured horticultural crops given limited projected rainfall, and these crops are typically high income, although this indicates that additional economic realism is required in the next iteration of the model to account for market forces (see Section 4.4).

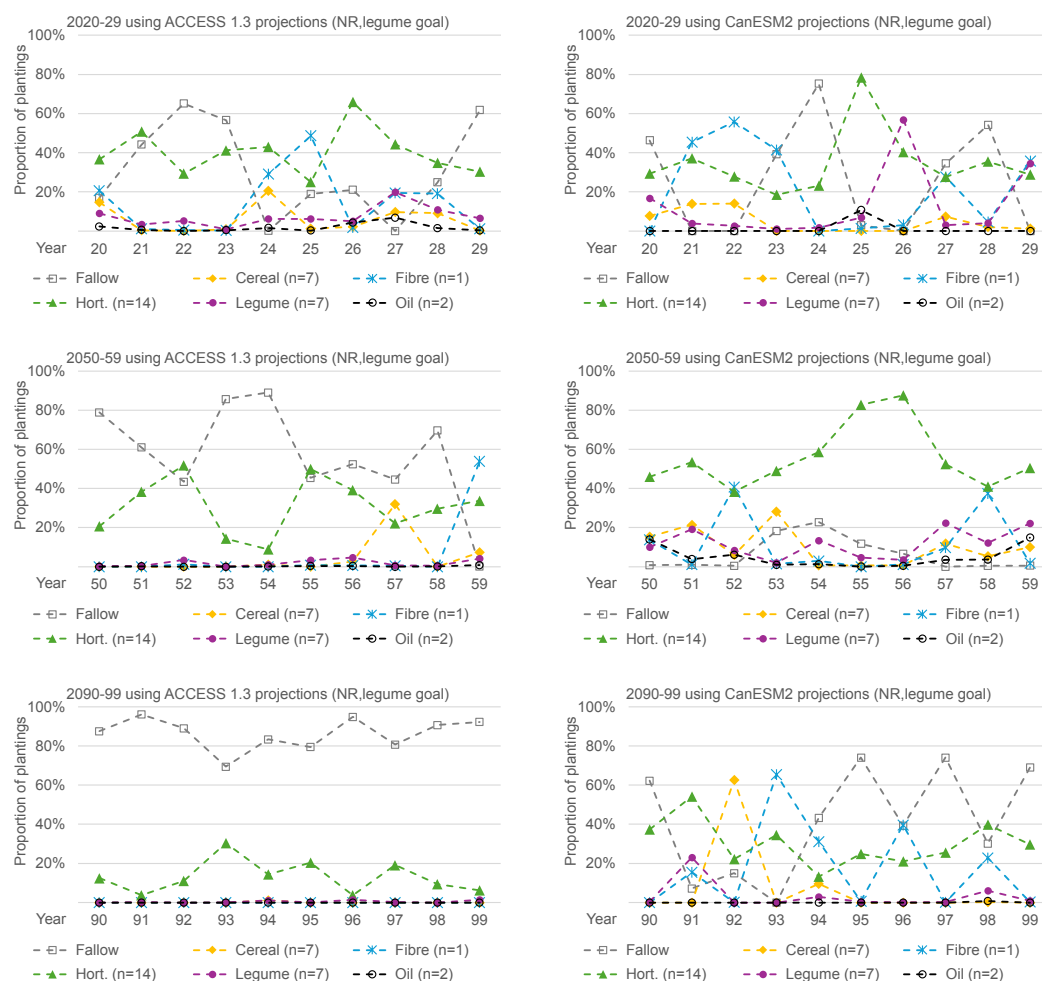


Figure 7. Illustrative land use (by crop category) for highest average legume planting solution when optimising for NR–legume in different time periods and under different climate projections.

Crop	Year									
	90	91	92	93	94	95	96	97	98	99
Eggplant	6400	4000	6200	8400	7800	16000	200	8600	800	4800
Cucumber	200	600	400	13400	4600	400	4000	10800	5800	
Garlic			600	9200	4800	3200		9400		
Broccoli	3400			600	3000	1000		400	1000	1200
Millet					800					
Cauliflower	200									
Pumpkin						200				

Figure 8. Actual area in hectares allocated to crops on the self-mulching clay LMU selected by the solver for 2090–2099 under ACCESS 1.3 when optimising (NR, water); summarised across all LMUs in Figure 6, bottom left.

3.3.1. 2020–2029 Problem Instance

Assessing legume land-use options in a hotter and drier climate (ACCESS1.3), a diverse mix of species spread consistently throughout the decade is proposed, which includes chickpeas, lentils, field pea, and soybean, all of which are irrigated; meanwhile, dryland vetch is a possibility in 2028 (1% planting proportion).

Alternative land use in the warmer and wetter climate (CanESM2) to maximise legume planting has a greatly reduced horticultural mix of only nine species. Both broccoli and eggplant (*Solanum melongena*) have a planting proportion range of 6–19% and 4% to 17%, respectively, for self-mulching clay. However, when red-brown earths are investigated, winter potatoes and pumpkin are viable alternatives. Of the grains available for STALS to

select from, it chose the legumes irrigated lentils in 2029 and mung bean in 2025 and 2026. Millet, a C4 cereal, was included in 2020 and 2028; however, other cereal staples, such as wheat, are omitted.

3.3.2. 2050–2059 Problem Instance

This decade illustrates the impact that a hotter and drier climate is beginning to have on agricultural land use. STALS' crop choices for the ACCESS1.3 model are dominated by fallow and horticultural crops. Of the grains, irrigated maize and dryland sorghum are the preferred options, although at a low planting proportion, 3% in 2057 for maize and 31% and 9% (2057 and 2059, respectively). In comparison, the warmer and wetter climate predicted by CanESM2 permits a broader land-use mix comprising cereals (irrigated barley, rice, millet, and sorghum); legumes (faba bean, field pea, lentils, mung bean and soybean); oil crops of canola and sunflower, and all horticultural species.

3.3.3. 2090–2099 Problem Instance

At the end of the century, the full impact of a hotter and drier climate (ACCESS1.3) on food and fibre production is emphatic. To maximise the objective of legume planting, the dominance of long fallow periods and only six species highlight tightly constrained land use choices, refer to Figure 7. Although a warmer and wetter climate broadens land-use options, even within this landscape, some previously included species such as Muskmelon are omitted.

4. Discussion

This project has demonstrated STALS' ability to identify sensible annual crop land-use choices to unveil what a climate-smart landscape may look like for the case study area over time. The usefulness of STALS as a DSS in evaluating a region's long-range agricultural production capabilities informed by two predicted climate models captures a wider range of potential climate possibilities, assisting in constructing stratagems to ameliorate the impact on the case region's socioeconomic condition. It answered the two research questions delivering insights into:

1. The region's temporal production capacity under the different climate models, and
2. Which crops are the 'best-best' options to maintain a resilient and sustainable regional economy dependent on agricultural enterprises.

The distinct contraction in regional economic value shown in Figure 4 illustrates the size of this shrinkage, which will have implications for the socio-economic health of the study area [99]. The increased area of fallow, although not directly contributing to farm revenue, has an implied benefit that arises in future crop health and yield on a given LMU [100], while plasticity in farming activity, working with the season rather than against it, has been evaluated as a viable strategy to maintain farm viability [48].

The land-use limitations identified for the hotter and drier (ACCESS1.3) climate, would transform agribusiness in the region, disrupting food and fibre supply chains and distribution channels. For horticulture to expand and meet the challenge of energising the MIA economy, capital investment will be required [101]. Although the long-range predicted climatesmart landscape of a warmer and wetter climate (CanESM2) resembles that of the 2020s with similar crop diversity, the low proportion of legume plantings is concerning. Legumes are an integral component of an agricultural production system and a staple protein food source for many people globally [102].

4.1. Climate Model Comparison

Water availability drives the solution curve, and for this reason alone, the alignment between each experiment's attainment curve is expected, as STALS seeks EIA by maximising return \$/ML. Due to ACCESS1.3's lower predicted precipitation coupled with increased temperature, it is not unexpected that fallows dominate the solutions in all investigated decades. The relatively lower input costs to maintain fallow compared to crop production make it a viable option for STALS. This contrasts with CanESM2's comparatively higher precipitation, which allows the solver to select a greater variety of crops within each solution.

Both climate models include high-value horticultural crops in the solution for all decades investigated. Although cotton is included in the ACCESS1.3 solution for 2020–2029, it does not appear again until 2058–2059. Rather, cereals contribute to solutions that satisfy the bi-objective in 2053–2059. However, even these predominantly winter crops are missing from the solution in 2090–2099, reflecting reduced water availability and elevated temperatures, driving increased evapotranspiration and constraining the production window.

CanESM2 solutions in comparison include a more diverse mix of crops for all examined decades. The 2050s and 2090s crop selection resembles those of the 2020 land-use reality, albeit with an increase in fallow. This increase in fallow, although potentially reducing production output and regional economic value, can be a strategy to maintain farm profitability and sustainability [48]. The inclusion of fallows in this research supports [43], who conducted whole-farm economic analysis in a case study area with rainfall comparable to this study region (300–350 mm annually). The inclusion of long fallows as a rotation option with wheat contributed to an increase in net cash flow compared to a continuous wheat cropping system.

As noted in the limitations Section Uncertainty and Limitations, this iteration of the model contains a constrained rotation rule that disallows certain crops given recent land use but does not *require* particular land uses to be actively included in rotation sequences, which is seen with ACCESS1.3, reducing the proportion of cereal and fibre crop plantings to near zero. This does not reflect reality, where cereals are an integral component of cropping systems and fibre is a lucrative crop for the case study area. This result highlights the limitations of STALS in its current format. However, this is already being addressed in the next iteration of STALS with the introduction of additional rules that enable crop selection from groups based on industry best-practice rotation sequencing.

Using two climate models, which represent the poles of predicted future climates, enables end users to decide which model they believe is the most likely scenario and, accordingly, select crops from the solutions which satisfy their needs. A further benefit of the solver is the ease with which the detail of solutions can be investigated using Excel, filtering by soil type or crop.

4.2. Land Use

As farmers, acting as rational agents, can change land use to maximise \$/ML [103], STALS may be a useful tool in this decision-making process. However, it is noted that a trade-off exists between optimising revenue and resilience of a farming system. A cropping system commonly includes cereals to assist in weed control, biofumigation crops such as brassicas to control pests and disease, and legumes, which contribute to soil nitrogen for the benefit of subsequent crops [104]. Nevertheless, alternative crops, land use such as carbon sequestration [105], and agroecosystems of intercropping [106] and orphan crops [107] may contribute to maximising \$/ha and \$/ML in a water-scarce and elevated-temperature climate.

The small planting proportion of winter cereals (barley, oats, wheat) is due to the lower commodity price compared to horticultural produce. Rice, a summer cereal, has been grown in the case study area since the opening of the development [108], and over the years it has improved its water efficiency [109,110]. However, the future does not look promising, with the solver only identifying one suitable year, 2029, in a warmer and wetter climate. Of course, this does not mean that rice cannot be grown in the future, but it does indicate an uncertain future for this crop in the long term. Information such as this stimulates conversations around alternative land use and industry restructuring.

Seven legume crops were included for this investigation based on climate and soil suitability. The small planting proportions of legumes may have accompanying negative effects on soil degradation and pest and disease loads [111]. This concern was addressed by establishing the third objective, a 'legume planting proportion threshold'.

4.2.1. Alternative Land Use

The similarity of the attainment curves between the experiments, Figures 6 and 7, indicates that the models' selection rules consistently produce similar land-use sequences regardless of objective. However, the implications of ACCESS1.3 constrained land use exposes the regional economy to increased risk, unlike CanEMS2's more diversified land uses.

The low planting proportion of wheat for all climate scenarios supports the findings of Wang et al. [112], who identified that the largest loss of wheat yield occurred at the driest sites, Griffith, which is in this research's footprint. Similarly, the land-use patterns presented in this study complement the findings of Hochman et al. [113] that diverse land use is more profitable. However, the southern limit of that work was Dubbo, which is north of the case study area in this investigation.

Cotton's long-range contribution to the regional economy (dryland and irrigated) represents its comparatively high commodity value and adaptability to climate change. Although gross margins are sensitive to water prices [114], the possibility of dryland cotton ensures that it remains a feasible land use [115]. Of particular interest is the selection of sorghum in 2057 for the hotter and drier climate. This reinforces the production advantage C4 crops have in high temperatures.

Like all DSS's, STALS outputs must be scrutinised by a human to assess the feasibility of land use; Figure 8 is evidence of this. Using eggplant as an example, the proposed area for a single LMU type is large. There are two factors contributing to this. Firstly, the solver currently lacks a market-based feedback mechanism to adjust projected crop income based on supply (compared to demand). Secondly, the model currently only considers annual crops, while in reality, the current area planted to perennials in the case study area approximates 23% of land (32,430 ha), which is thus unavailable for annual crops. This spotlights the importance of deep investigations into the feasibility of such land-use transitions, including the consideration of market demand, resource access, such as labour, along with storage infrastructure, and logistic needs. Both aspects will be investigated in future work.

4.2.2. Model Comparison

The findings of this work are compared to Lewis et al. [116], who tested their model in the same case study area and used NARcliM1.0 although with an unspecified representative concentration pathway (RCP) for greenhouse gas emissions. Their objectives were to maximise net revenue and minimise environmental water deficit; this can be reinterpreted and repurposed to represent the objective of minimising agricultural water consumption of this research. Whereas they identify the area allocated to a crop, this research plans sequences of plantings on parcels of land. This current work further improves on this

precursor research through the addition of agronomic decision rules and the inclusion of fallow as land use, adding realism to the modelling. The inclusion of fallows unveils a truer representation of land use to the end of the century.

Like Lewis et al. [116], this work identified horticultural crops and cotton as feasible choices in the 2020s through the 2090s. The difference between the two works is in the land use assigned to canola. In this research, for both climate models, the planting proportions are comparatively low compared to the earlier high planting area (2020s). Both works identify a temporal contraction of economic benefit originating from climate change.

The comparison of our findings of land use in semi-arid regions demonstrates globally identified similarities. Adeyemo and Otieno [117] investigated an irrigation area in South Africa, using only four species, and maize (a C4 crop) was identified as a feasible land use in all solutions, which aligns with our results. Abdelkader and Elshorbagy's [56] tri-objective of minimising water use to maximise food production and trade included a realistic mix of agricultural crops, including horticultural vegetables, pulses (legumes), oil crops and cereals, rice, and wheat. Again, their findings align with this work, with vegetables being selected as a good land use due to their high gross margins. Similarly, wheat is not identified as a feasible crop in constrained water environments. This last point justifies a deeper investigation, as wheat is a staple food for many people worldwide.

When considering the contribution of nutritional value to human diets arising from crop water consumption, not all horticultural species are alike. Fulton et al.'s [118] analysis of California, USA, which has a food crop mix comparable to the case study area, identified broccoli as a low-water consumer for its relatively high nutritional benefit, compared to potatoes and rice, both of which are staple foods. The findings of the current study also identified broccoli as a positive land-use choice, while winter potatoes were only offered as an option twice in the hotter and drier climate (ACCESS1.3, in 2057) and once for the warmer and wetter climate (CanESM2, in 2052). Cucurbitaceae species (pumpkin and cucumber) are positioned as mid-range water consumers and nutrition contributors. The added benefit of this work over Fulton et al. [118] is its evaluation of species land use informed by predicted climate. However, both are limited by their omission of long-range climate impact on product quality and nutritional value.

4.3. Solver

The speed with which the climate is changing has increased [119], reducing the lead time for action whilst increasing the need for long-range forecasts [120]. When provided with RCP8.5 climate projections, the solver offers an array of feasible solutions in time for adoption. Further, the solver's design easily accommodates sensitivity tests to changes in input metrics, which adds to the robustness of solutions.

The benefit of optimisation is its parsimonious approach in combining numerous, complex, and large datasets to distill valuable information, which can be transformed into advantageous strategies. Optimisation outputs only present a spectrum of possibilities, and it takes a human to investigate solutions and interpret in context for the end user's objectives and goals. To explain the need for human scrutiny, Figure 8 is used to explore the reality of production and the implications of the suggested land use of eggplant. This experiment focussed on high-priority objectives, biased toward net revenue and minimal water consumption. However, the solver, using similarly formatted datasets, can investigate other objectives of interest, such as maximising crop protein with minimal land area.

Although STALS delivers a large volume of solutions, these can be readily investigated using Excel. An end user can select which climate model they believe is the likely future scenario, then filter by crop or soil type, identifying the years in which it delivers a positive economic value. This tool can assist farmers with future business planning, water utility

entities with long-range demand projections, and policy makers in mapping a resilient and sustainable future for agriculture [8,121].

Uncertainty and Limitations

The use of different climate models, each representing plausible abiotic conditions, allows the uncertainty of agricultural production systems in the case study area to be qualified [122]. However, the large difference in metrics between the two climate models inhibits the identification of robust solutions. This limitation could be improved by identifying which climate model is the likely future reality through the analysis of the predicted climate model parameters to those observed. This comparison may reveal a trajectory that aligns with one of the climate models, reducing uncertainty and improving the usefulness of STALS outputs to end users. However, as extreme weather events are increasing, modelling and forecasting such events requires a new approach, one which is still being refined [123].

While the five water scenarios are based on actual water allocation percentage volumes [91], the mid- to end-of-century discounted volumes are only indicative, as future policy decisions and hydrology modelling consequences cannot be foreseen [17]. The implication of this is the model may be overestimating revenue and underestimating water usage.

The crop income adjustments due to water costs shown in Table 3 are pragmatic choices, reflecting a simplified impact of supply and demand driven by seasonal conditions. Future versions of the solver will require more sophisticated economic modelling.

Although this research considered the foundational elements that comprise a robust rotation sequence, the impact of these on soil health has not been modelled in detail. In addition, the different agricultural management systems of land use, for example, pivoting land use from broad-acre cropping to horticulture, is not considered. A further omission is the possibility of land-use stewardship services, which is promoted as a feasible complementary activity to food and fibre production [8].

The regional net revenue presented in Figure 4 under-represents the reality of agriculture's contribution to the region's economy, as only annual species are considered in this work. In reality, perennial crops and livestock production systems augment the region's contribution to the nation's terms of trade. For the region to initiate land-use change, regional planners should reflect on the implications of such change at the farm level, with consideration as how best to support primary producers facing increasing complex business operations due to a changed climate.

A further limitation is that the model does not have a feedback mechanism on the crop yield potential for a soil informed by abiotic data. Employing an application programme interface (API) to connect STALS, with a crop production simulator such as the Australian Agricultural Production Systems Simulator (APSIM), would augment its global application.

The solver's singular focus on the bi-objectives, specifically net revenue, explains the promotion of eggplant over tomatoes. Both species are Solanaceae and highly suited to self-mulching clay, yet STALS' NR focus selects eggplant over tomato. Although this solution aligns with the research objectives, supply chain and market considerations should also influence land-use decisions. In addition, the role of dryland crops in the investigated solution set is minimised, with only the most valuable crop of cotton and sorghum, a C4 crop, capable of producing in elevated air temperatures being feasible land use.

Although the approach taken is appropriate for this problem, the experimentation has identified limitations which should be addressed in the next iteration of the model. These are:

1. The agronomic rules are not exhaustive and, more importantly, they eliminate possibilities. Although guiding the optimiser towards healthy crop rotation sequences,

this iteration of the model does not elevate crops based on their integral role in the production system, namely legumes.

2. The simplistic approach to a crop yield potential on a given LMU.
3. The lack of river catchment hydrology modelling and the effect of reservoir operational management policy.

4.4. Future Work

As can be seen from this work, the benefit of STALS as a DSS has been demonstrated for regional planners, industry, water stakeholders, and other end users. It can certainly be added to by considering available irrigation water volumes through catchment hydrology modelling. The classification of crops based on plant taxonomy, thus limiting crop choice from within a group, would rationalise the system selection process. In addition, positive rules would promote crops based on their contribution to soil health and their ameliorating effect on crop pest and disease loads. An example of this could be that the system selects a crop from within the cereal group, and after three years of cereal planting on a stated LMU, STALS must select a crop from the legume group. These additions to the current work would capture the agronomic strategies used in agricultural production systems. Finally, attention will be paid to issues around modelling perennial crops.

5. Conclusions

This study developed a spatiotemporal agricultural land-use sequencer to identify annual crops which maximise revenue whilst concurrently minimising water usage for a case study area. The model STALS combined biotic and abiotic parameters to generate feasible land-use solutions to the end of the century, using two differing climate models, one hotter and drier, the other warmer and wetter. The combining of such large datasets was achieved through the employment of a nature-inspired ant colony optimisation algorithm.

Results include an objective trade-off curve, which quantifies economic production capacity and its corresponding water usage. A deeper analysis identified which crops in what soil contribute to these solutions.

Land usage by crops in the projected hotter and drier is reduced in the 2050 and 2090 decades, resulting in a regional agricultural economic contraction. In comparison, the projected warmer and wetter climate retains a diverse mix of species and farming system, with dryland cropping as a feasible land use, while maintaining revenue levels comparable to the 2020s. For both climate projections, high-value horticultural crops are prominent land-use options. When legume planting becomes an objective, the solver was constrained for crop choice.

These early insights to the impact a changed climate may have on the case region will be salient in stimulating conversations on alternative transformative pathways which contribute to a resilient and sustainable future for agriculture.

Supplementary Materials: The following supporting information can be downloaded at <https://osf.io/qv9nb/overview>: Model Assumptions; Crop Characteristics; Water Scenarios; Economic Based Variables.

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