# Planning to 'Hear the Farmer's Voice': an Agent-Based Modelling Approach to Agricultural Land Use Planning

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## Abstract

Agricultural land use is influenced not only by multiple aspects of biophysical and socio-economic processes, but also the cumulative impacts of individual farmer decisions. Farmers' activities and decisions at farm scale shape land use and water utilisation at regional scale, yet land use planning processes do not take into account farmers' knowledge and decision-making processes as they respond to, and in turn shape, change. Farmers' voices are missing in the planning system. In this paper, we address the complexity of agricultural land use planning and examine the possibility of agricultural land use planning from the bottom-up via simulation to integrate environmental, economic and human factors that influence land use change. We present an innovative approach to model the interactions between government policy, market signals, and farmers' land use decisions, and how the accumulated effects of these individual decisions change agricultural land use patterns at regional scale, using spatial and temporal agent-based modeling. A multi-stage mixed method spatial agent-based modeling (ABM) approach, aligned with the Geodesign framework, can incorporate local knowledge and decision-making into models of regional land use change. To illustrate the new approach, we examine the impact of milk market price on changes in land use in Tasmania, Australia. This approach brings together local knowledge with scientific, planning, and policy knowledge to generate dynamic scenarios for informed agricultural land-use planning decisions.

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**Highlights**

● Agricultural land-use planning is complex and needs to account for the impact of farm-scale decision making on regional-scale land-use.

● A multi-stage mixed method spatial ABM approach aligned with the Geodesign framework enables the incorporation of bottom-up farmer knowledge and decision-making into models of regional land use change.

● Modeling regional land-use change using spatial ABM brings local knowledge at micro-scale into dialogue with scientific, planning, and policy knowledge at macro scale to generate dynamic scenarios to inform agricultural land-use planning decisions.

**Keywords** Land-use planning · Geodesign · Knowledge partnering · Agent-based model

## Introduction

The agricultural landscape in Australia is experiencing considerable pressures from both development and conservation demands. As the population grows in Australia, urban encroachment into peri-urban agricultural land (Sinclair & Bunker, 2012) and land use conflicts surrounding the rural-urban interface (Schirmer, 2018) increase across Australia. Planning for agricultural land occurs within an environmental framework and remains disconnected from economic planning at the regional scale, despite the recognised importance of agriculture in regional economies. In spite of significant advances in environmental resource mapping, serious gaps exist, and it is difficult to find examples of where agricultural land use planning per se has been well developed.

Agricultural land use planning is complex. While farmers decide on land use at the farm scale, their decisions ultimately influence broader land use change (Gutzler et al., 2015). Planning for agricultural land use necessitates a mixture of considerations and assumptions drawn from statutory planning (legislation and regulation for controlling land use), strategic planning (policy and strategies for the present and future of regional and agricultural land use) and landscape planning (landscape and natural resource management), implemented at different geographical scales. An ongoing issue across different land use planning approaches is the lack of integration of socio-economic and socio-cultural information with biophysical information (Low Choy, 2018). This gap is particularly significant when planning for agriculture, where farmers manage resources over many hectares and their behaviours and decisions shape the use of land and water resources. The cumulative effects of farmers' actions and behaviours can have far-reaching implications but are not well integrated into current land use planning tools. Therefore, there is a need for the integration of an understanding of on-farm decision-making processes into land use planning tools to help decision-makers at other scales to make more informed decisions and strategies to shape the future of agricultural land.

Given the above, this study aims to investigate how we can integrate multiple forms of knowledge into agricultural land use planning, with particular attention to farmers' knowledge, and understand how the dynamics of farmer behaviours and decisions at micro-scale influence changes in land use patterns at a regional scale. This paper demonstrates an innovative spatial and temporal agent-based modelling (ABM) approach which integrates environmental, economic and social factors at multiple scales in the simulation modelling.

## Conceptual Framework for Rural Land-Use Planning

Finding a theoretical framework for rural land-use planning that preserves sufficient and suitable land and water resources for agricultural purposes is a continuing challenge. The separation of regional and local planning systems intensifies a range of conflicts of interest, from local land use development, such as new industrial dairy farms, to regional-scale issues like water allocation in a river basin. The complexity of agricultural land use planning requires the integrated contribution of different types of knowledge: including geographic and spatial knowledge, environmental and agricultural science, policy knowledge, social and economic knowledge, as well as the knowledge of the farmers who work the agricultural land.

Further, the connection between land use science and land use policy is also complex; policy does not necessarily align with the scientific evidence. Policy-making on land and water use is a social and political process. Strategic planning for natural resource management on the one hand, and economic development on the other hand, are frequently conducted in policy silos. Yet agricultural land use planning requires attention to both. Further, the challenges of planning for agricultural lands in Australia are exacerbated by demands for other uses of agricultural land and water resources. Agricultural landscapes are typically viewed through a neoliberal, productivist policy lens (Gray & Lawrence, 2001), and so framed narrowly as sources of economic value. Goverments and companies make decisions about agricultural land use at macro scale, while farmers make independent decisions about their lands, type of the crops, etc. at micro scale. Both macro-scale and micro-scale decisions influence the land use profile of a region (Fig. 1).

Previous studies demonstrate that advances in spatial technology and scientific modelling have been able to improve monitoring and reporting of land use change (Hicks et al., 2015). These types of tools also hold considerable promise for informing decision-making at both micro (farm) and macro (policy) scales. Hitherto, most of the techniques and models used for regional and strategic land use planning have taken a top-down approach to planning for land use change (Pissourios, 2014). While agricultural producers are the primary "implementers" of agricultural land use policy and planning, the decision-making is likely to be concentrated in the hands of policy makers and planners working at local, regional, state or national scales.

Bottom-up planning approaches that involve different rural land use stakeholders in the planning process, especially farmers, are one way of bringing relevant data across sectors and scales to inform planning approaches. This type of bottom-up
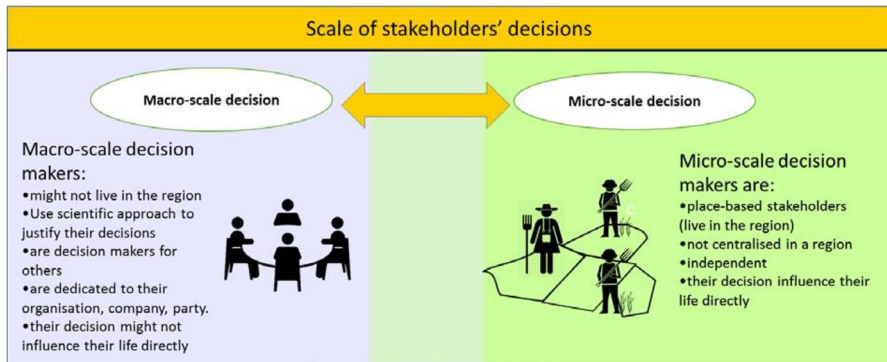
**Fig. 1** General characteristics of stakeholders and scale of their decisions

approach increases the probability of a prosperous agricultural land use plan (Cinà & Di Iacovo, 2015; Koontz & Newig, 2014; Roy & Ganguly, 2009). Various researchers have highlighted the value of stakeholder participation in bottom-up planning (Barreteau et al., 2010; Bots & van Daalen, 2008); yet this work has not explicitly acknowledged the role of farmers' knowledge, or explored the processes by which farmers' on-the-ground knowledge and decisions about their farming conditions and systems can be integrated into planning processes.

The importance of "farmer knowledge" or "rural people's knowledge" has, however, long been acknowledged in rural development work (Bicker et al., 2003; Chambers, 1983; Richards, 1985; Scoones & Thompson, 1994; Warren, 1995). This literature, grounded in development studies with influences from anthropology, emphasises that farmers have knowledge of local conditions and constraints, both physical and socio-economic, that non-farm-based policymakers do not have. In rural development theory and practice, efforts have been made to bring farmer knowledge and researcher knowledge into dialogue to inform better agricultural policy, though with considerable challenges (e.g. Chambers et al., 1989; Scoones et al., 2009). While the value of local land use knowledge is recognised in theory, it remains the case that the voices of the people who live in rural regions are often neglected in planning (e.g. statutory land use planning and regulation) and policy-making (Albrechts et al., 2003). The "farmer's voice" remains largely absent in agricultural land use planning.

Thus, we face a situation where farmers, policymakers, and land use scientists all have relevant data, information and knowledge to inform land use planning, but this knowledge remains largely disconnected. In this paper, we use the concept of Knowledge Partnering (Eversole, 2014) to describe an approach through which different types of relevant knowledge are recognised and brought into dialogue around a development issue. Knowledge Partnering is a bottom-up approach that recognizes the value of local knowledge and aims to create policy and practice dialogues that include localised forms of knowledge. In the case of land use planning for agriculture, a Knowledge Partnering approach can bring less-visible farmer knowledge into dialogue with policy knowledge and scientific knowledge to inform optimal land

use decision-making. We recognise that the knowledge relevant to land use plan-ning is not only dispersed across stakeholders but manifests at different scales; thus farmer knowledge is primarily local knowledge (Bicker et al., 2003), manifesting at the farm level or micro scale, while policy knowledge is a bird's eye view (Scott, 1998), often at regional, state or national scale. Thus, one approach to tackling the complexity of agricultural land use planning is through developing tools to enable knowledge partnering among stakeholders at multiple scales.

Micro scale decision-making by human agents within the macro-scale context of land use systems has been explored through Agent-based modelling (ABM) as a computer simulation in recent decades (Berger, 2001; Parker et al., 2002; Schreinemachers & Berger, 2011). ABM represents complex systems by modelling individual decision-makers' behaviour and interactions within the simulation (Heckbert, 2009). An agent-based model is suitable for the simulation of complex socio-economic systems (Harik et al., 2023). However, planners and modellers encounter challenges in adopting them widely for agricultural land use change assessments (Helbing & Balietti, 2011; Kremmydas et al., 2018). When applied to agricultural land use planning, an ABM can link different knowledge-sets at macro and micro scales, including the integration of the knowledge of farmers into the simulation model. It also can afford an opportunity to explore the impacts of government or industry strategies and policies on farmer's decision-making at the farm scale, and flow-on impacts to regional land use change, through the ABM simulations and scenario testing.

Top-down planning approaches have shaped planning practice in Australia (Murray et al., 2009) and are appropriate to set an overarching visions and policies (Pissourios, 2014) for agricultural land use planning. Yet as various researchers have argued, bottom-up approaches are particularly valuable in planning for agricultural land use (Cinà & Di Iacovo, 2015; Koontz & Newig, 2014; Roy & Ganguly, 2009). Farmers have distinct knowledge sets about farm dynamics at micro scale which are often invisible to policy makers at more macro scales (Chambers, 1983; Warren et al., 1995; Scott, 1998; Bicker et al., 2004).

This study demonstrates a bottom-up simulation model – Spatial Agent-Based Model (ABM) – that was constructed based on the knowledge of multiple stakeholders working at different scales. The ABM brought these insights into dialogue to generate a series of future scenarios for planning purposes. The study demonstrates how the integration of farmer, policy, and scientific knowledge with geospatial data could generate insights to inform land use decision-making that are not easily achieved in traditional land use planning approaches and systems.

## Materials and Methods

### Aim of the Study

This study demonstrates a new approach to agricultural land use planning from the bottom-up, using the ABM approach to conceptualise farmer decision-making and a simulation model to explore the interaction between government policy and farmers'

land use decisions. The model is able to integrate multiple forms of knowledge at different scales and simulate the interaction between macro-scale policy decisions and micro-scale farmer decision making, then model the accumulated effects of these individual decisions at the regional scale, in order to inform optimal land use decision-making.

## Case Study Area

We selected the Dorset region in the North East of Tasmania, Australia, as a case study for data collection. Dorset is a region experiencing change, transitioning from traditional crops to higher value-added production as access to guaranteed water expands. There are agricultural policy and strategies in Tasmania to double the irrigation volume available through Tasmanian Irrigation Schemes by 2025 (Department of Primary Industries Parks Water and Environment, 2019), to secure water for agricuture and encourage the production of alternative crops. Moreover, there are also significant opportunities for the region to consider new alternative crops and value-added processing (Davey et al., 2013). Therefore, it is a suitable case study to simulate different scenarios considering irrigation availability and milk price.

## Methods

The overall approach of this research was pragmatic, and mixed-method research methodology was employed for data collection and data analysis. Multistage mixed-method design, as described by Creswell (2015), aligned with Geodesign methodology (Steinitz, 2012), was adopted to design a structured process for integration of the methods and techniques.

Geodesign framework has been developed by Steinitz (2012) as an iterative design method for integration of land use planning and environmental science by using geospatial data and simulation models and collaboration among stakeholders. Our methodology was informed by the geodesign framework and its six main questions: how should the study area be described?; how does the study area operate?; is the current study area working well?; how might the study area be altered?; what differences might be the changes cause?; and how should the study area be changed? (Steinitz, 2012). The three distinct stages of this study include conceptualising the farmers' decision model, programming a spatial ABM based on farmers' decision model, and simulation of different agricultural scenarios. Figure 2 shows multistage mixed-method design of this study against the Steinitz framework, illustrating the value and application of iterative design thinking for complex planning such as that required for agriculture.

In the first stage, qualitative data was collected from farmers and other industry actors in the Dorset region with deep knowledge of farming in the region. Nineteen semi-structured interviews and surveys were conducted: 11 of the participants were practising farmers in the region, with more than 20 years of experience in farming. The other participants were sector experts from Tasmanian Irrigation, Dorset Council staff, local food processors, Natural Resource Management (NRM) staff,
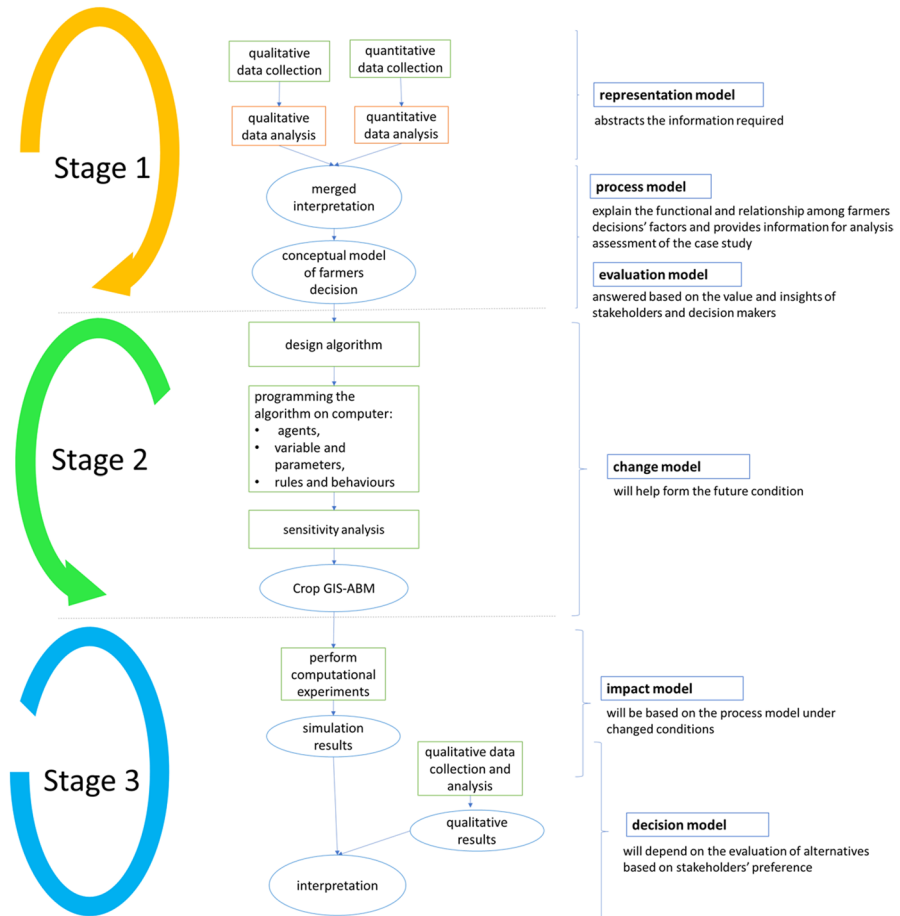
**Fig. 2** Multistage mixed-method design aligned with Geodesign methodology

and the state Department of Primary Industries, Parks, Water and Environment (DPIPWE). These experts all occupied high level professional roles with direct relevance to agriculture, and some also had influential roles as community members. Thematic analysis was employed to analyse the qualitative data, while the questionnaire data, mainly about crop types and influential decision factors, were analysed statistically. The results of both analyses were then merged and interpreted to develop a conceptualisation of a farmers' decision model.

In the second stage, spatial ABM algorithms were developed based on the conceptual model and computer codes were written based on the abstraction of the farmers' decision model, called Crop GIS-ABM. Farmers are conceptualised as agents; the model represents goal-directed human action by farmers and interventions that affect those actions. A farmer agent interacts with other agents (farmers) and their surrounding environment (farmland), as well as indirect interaction with

planning, policy and markets (e.g. market price of crops, irrigation expansion). As a result of these decisions and interactions, patterns of land use change emerge at the regional scale.

In the third stage, Crop GIS-ABM integrated social-economic and spatial data, and a scenario analysis was used to model the complex effects of the fluctuation of milk price on agricultural land use patterns. The results of simulation were compared with the overlayed sketched maps by multiple stakeholders to facilitate scenario analysis for planning purposes.

## Results

**Stage 1** The analysis of both interview and survey questionnaire data revealed some key differences between farmers and other land-use decision-makers. Farmers operate at micro scale; they live in the region, mostly make their decisions independently, and their decisions have direct impact on their income and livelihoods. The other group of stakeholders in agricultural decision-making are large companies (e.g. processing plants), state government-owned bodies, and local government; these stakeholders make decisions about agricultural land and irrigation expansion at the macro scale (regional scale). Their decisions are often based on a scientific or business approach and do not affect their lives directly; nevertheless, this macro-scale decision-making influences many people who live in the Dorset Region. Findings of the interviews revealed that these two groups sometimes had different insights. For example, while most of the macro-scale stakeholders mentioned the importance of land size in influencing adoption of agriculture practices, most of the farmers did not consider the size of the farm as a critical factor. This signals the importance of facilitating dialogue between the knowledge-sets of micro-level and macro-level decision-makers to gain a holistic understanding of issues. To do so, the spatial ABM was designed to capture insights about farmer decision-making and bring these into dialogue with decisions and dynamics at regional scale.

The analysis of the interview data allowed for the identification of key factors that influence farmers' choices regarding irrigation and alternative crops/livestock, from which themes were extracted. On the other hand, the analysis of survey data led to the ranking of factors according to their level of importance in farmers' decision-making process. Upon comparing the findings of the interview and survey analyses, it is apparent that there is a degree of similarity between the factors extracted from the interview data and those that were ranked in the survey analysis. Table 1 shows interview and survey findings identified the critical factors that influence farmers' decisions about land use.

Grouping the themes into three broad categories (biophysical, economic and social) suggests, not suprisingly, that there is a connectedness across some of the factors identified from the interview analysis and survey questionaire findings. The influential factors include crop suitability to their land, gross margin of the crop, the availability of irrigation, the rotation of crops and neighbours' proximity effect

**Table 1** Grouping and merging interview themes and survey questionnaire findings

| Major categories | Factors from the interviews (themes) | Factors from surveys |
| --- | --- | --- |
| Biophysical environment factors | Characteristics of the farmland | Local climatic conditions<br>Farm and land capacity<br>The perceived environmental benefit |
| Economic factors | Profitability and market price of alternative crops/livestock | Profitability<br>Transport costs to market<br>Labour availability<br>A forecast that the demands for processing products are going to increase |
|  | Irrigation availability | Irrigation costs |
|  | Availability of three-phase power | Government support/subsidy |
|  | Accessibility of value-add processing plant | Transport costs to the nearest processing plant |
| Social factors | Neighbour's decision for investing in irrigation, alternative crops/livestock | Neighbour's decision about growing alternative crops/livestock<br>The popularity of alternative crops/livestock among farmers<br>Experience of growing alternative crops |

factors (following the same agricultural practices as one's neighbour) (Fig. 3). As Fig. 3 shows the influential factors are the biophysical characteristics of the farmers' land parcel (adopted from Crop Suitability Map developed by Department of Primary Industries Parks Water & Environment -Tasmania (DPIPWE), economic factors (adopted from crop gross margins developed by DPIPWE), irrigation availability (adopted from irrigation districts developed by Tasmanian Irrigation), Neighbours proximity effects and considering the crop rotation factors into Crop GIS-ABM.

As a part of triangulation, the interview and survey results were compared with the existing literature. There is a similarity between influential factors that affect farmers' decision in this study and those identified by Macquarie Franklin (2013); for instance, higher price was a major factor influencing farmer's decisions to grow poppies and invest in irrigation infrastructure. Other literature (Sutherland et al., 2012; Tsusaka et al., 2015; Vroege, 2017) has documented the neighbourhood effect as an influential factor that affects farmers' decisions. Therefore, triangulation of research findings with other evidence, in this case, literature, verify the robustness of the conceptual model of farmer's decisions.

**Stage 2** The essential factors that were identified as being influential, based on stakeholders' insights, were incorporated into algorithms that were designed to align with the conceptual model of farmers' decision-making. These algorithms were integrated with spatial data to create a simulation model (Fig. 3), which is called Crop GIS-ABM. Finally, sensitivity analysis was performed to evaluate the impact of the parameters used in the model. The ODD+D protocol (Overview, Design
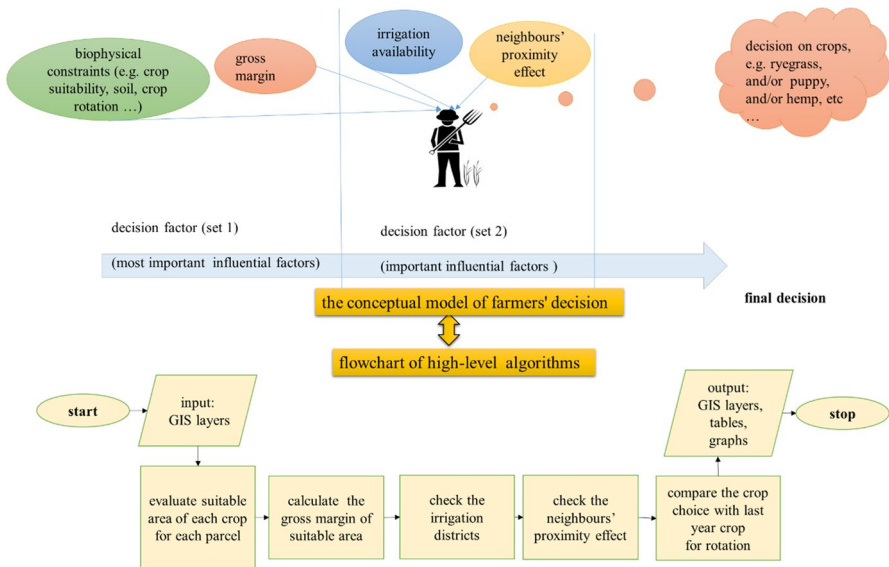


**Fig. 3** Conceptual model of a farmer's decision

Concepts and Details, as well as human Decision) of the model can be found in the Supplementary Information.

**Stage 3** A simulation model was further developed by integrating the important factors influencing farmer's decisions. Scenario analysis then explored the consequences of agricultural policy and milk commodity prices on farm-scale decisions and their effects at a regional scale. Based on the interviews and survey findings, most of the participants in this study indicated that the market price plays an important role in their decisions on crops selected for production. Crop GIS-ABM simulated this scenario to explore how the market price of milk (because dairy on ryegrass pasture is an important enterprise) might change agricultural land use patterns and influence the adoption of hemp (new alternative crop) production in the Dorset region. Macroeconomic variables such as trade policy play a critical role in determining the price of agricultural products (Tomek & Kaiser, 2014). For example, milk price is not governed by farmers; instead, macro-scale decision-makers (trading committees, policymakers, processing plants and retail companies) determine milk price based on market demands and agricultural policy. The market fluctuation for milk price influences dairy gross margin, and shifts in the milk price change farmers' expectations about the future prices of certain types of crops, which in turn affects farmers' decisions on which crops they might produce.

We examined this scenario by asking: if the price of milk increases, how many farmers might adopt a high-value new alternative crop, such as hemp, in comparison to producing ryegrass for dairy/livestock? In this scenario, the cumulative number of hemp adopters to total farmers can be used to demonstrate the effect of the milk price on their decisions. Table 2 illustrates the simulation results of hemp crop adoption under four experimental conditions in the Dorset region over ten years.

In the first experiment (E1), it was assumed that irrigation was not available in the Dorset Region and the price of the milk was relatively low during the ten years of simulation. The total number of farmers producing hemp under this scenario was around 310. In the second experiment (E2), the assumption was that no irrigation was available, but the milk price was relatively high over ten years. The result of simulation under the second experimental conditions showed around 212 farmers

**Table 2** Adoption of hemp under experimental conditions

| Experimental condition | E1 | E2 | E3 | E4 |
|---|---|---|---|---|
| | No irrigation | No irrigation | Irrigation available | Irrigation available |
| | Low milk price | High milk Price | Low milk price | High milk Price |
| Milk price ($ 5.2) | -10% $ 4.68 | + 10% $5.72 | -10% $ 4.68 | + 10% $5.72 |
| The accumulated number of Hemp adopters | 310 | 212 | 291 | 166 |

choosing to produce hemp. The number of hemp adopters under the third experimental (E3) conditions (irrigation available and a low milk price) was around 291. In the fourth (E4) experimental conditions, irrigation was available, and the milk price was high; in this scenario, around 166 farmers produced hemp. Looking across the results of the simulations for the experimental conditions, indicates (not surprisingly) that if irrigation is available and the milk price is high, more farmers will opt for dairy farming and fewer for a hemp crop.

The comparison of the simulation outcomes with and without Irrigation expansion under different milk prices is illustrated in Fig. 4. As the graph shows, there is a nonlinear relationship between the market and the adoption of the new alternative crop with/without irrigation. Specifically, the simulation suggests that the farmers' decision is more sensitive to the milk price when they invest in an irrigation scheme, but only when the price of milk is low. This would suggest that when farmers have invested in an irrigation scheme and the price of the milk decreases, they are more likely to produce high-value alternative crops such as poppies instead of ryegrass to cover the costs of irrigation. For example, the number of land parcels that produced ryegrass (to feed the dairy cattle) decreased by around 11% under the irrigation expansion scenario when the price of the milk declined from the base milk price of $5.20 kg/MS.

In the above scenario, while hemp is more profitable than ryegrass when the milk price dropped in the scenario, we do not see a spike in the adoption of hemp. While we mostly consider farmers as rational and profit-driven decision-makers, these results suggest that other factors are at play. Specifically, the impact of neighbours' decisions is significant; ryegrass (for producing livestock and dairy) is a very popular product among farmers in the Dorset region; farmers are comfortable producing it and many farmers' neighbours produce it. So in comparison with hemp, which is a new crop that has been recently introduced, farmers prefer to remain with ryegrass, and produce hemp at a lower ratio than milk. If a neighbour produces hemp, there is a high chance a farmer will produce the hemp in the next following years. Moreover, if irrigation is available, then the hemp adoption increases from
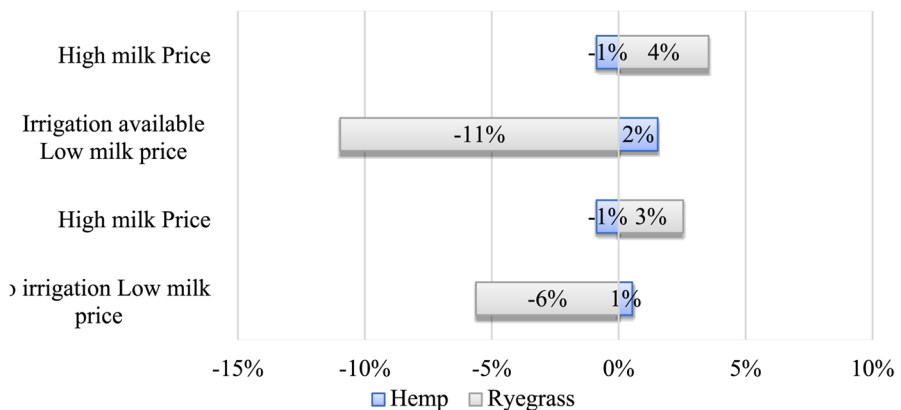


Fig. 4 Comparison of hemp adoption under four experimental conditions

1 to 2% in the region (Fig. 4). It can be concluded that farmers' crop decisions are based partly on the market price of milk, which is a common and well-established enterprise in the Dorset region, but alongside the milk market price, the expected profitability of hemp will play a key role in hemp adoption. Again, the simulation data and comparison of the simulation results demonstrate that farmers' decisions about crop type are complex. The simulation outcomes provided examples of the possible effects of changes in agricultural commodity prices and irrigation availability on land use patterns over the next ten years, taking into account farmers' own decision-making practices.

## Spatial Analysis of the Scenario

The spatial diffusion of hemp in the Dorset region under high/low milk price and with/without irrigation expansion was analysed through the simulated maps (Fig. 5). A summary of the spatial patterns shows:

- The land parcels that grew hemp under E1 (low milk price without irrigation) were clustered in three areas in the region during the ten years of simulation (North Scottsdale, Scottsdale, Bridport);
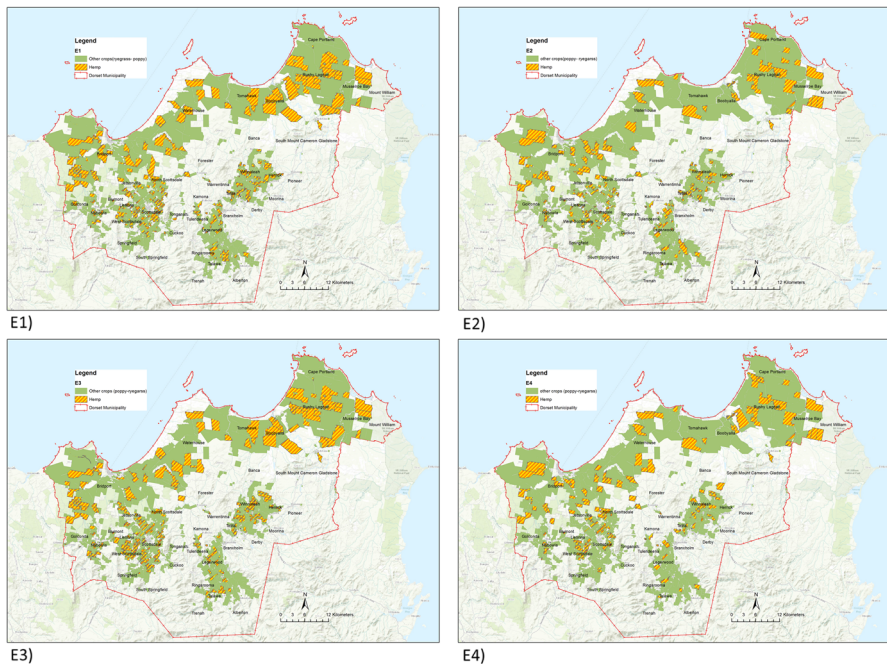


**Fig. 5** Spatial diffusions of hemp under four experimental conditions, E1) low milk price without irrigation, E2) high milk price without irrigation, E3) low milk price with irrigation, E4) high milk price with irrigation

- The land parcels that grew hemp under E2 (high milk price with irrigation) are the districts (e.g. North Scottsdale, Winnaleah, Derby & Rushy Lagoon) that grew the most hemp when milk prices were high but where there was no expansion of irrigation (E2);
- The land parcels that grew hemp under E3 (low milk price with irrigation) are concentrated mainly in three districts (Scottsdale, Winnaleah and Bridport) more than other areas; and.
- The land parcels that grew hemp under E4 (high milk price with irrigation) decreased, but the land parcels in three districts (North Scottsdale, Winnaleah, Rushy Lagoon) produced hemp more than other districts.

Spatial analysis of the diffusion of hemp adoption under different experimental conditions indicates that some areas within the region are more sensitive to milk prices and some areas are more sensitive to irrigation expansion.

Figure 6 illustrates, for example, that there are spatial areas that are more sensitive to milk price (i.e. North Scottsdale, Winnaleah, Waterhouse and Bridport); in these areas, the price of milk influences farmers' decisions to adopt hemp more than irrigation availability. The interview findings indicated that the market price of an agricultural commodity plays an important role in farmers' adoption decisions. The simulation outcomes supported the interview findings as the farmer agent made decisions independently based on their chosen agricultural practice, which was influenced by several interrelated factors: land capability, the price of the chosen crop, the neighbours' decisions, availability of irrigation and crop rotation. Factors such as
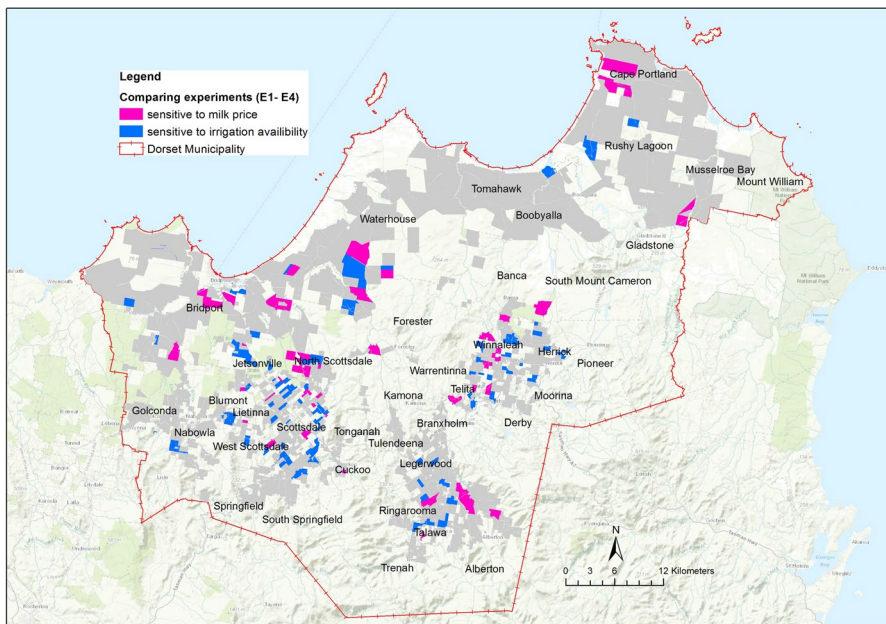


**Fig. 6** Spatial sensitivity of hemp adoption in four experimental conditions (E1-E4)

land capability, neighbours' practices, and irrigation availability varied spatially within the region, leading to different responses to a milk price change. Scenario analysis revealed that the milk price influences the farmers' adoption decisions on crop types, and some areas are more sensitive to milk price fluctuations (i.e. North Scottsdale, and Bridport). By contrast, other districts (i.e. Ringarooma and West Scottsdale) are more sensitive to the availability of irrigation in comparison to the changes in the price of milk.

**Qualitative Analysis of Simulation Outcomes**  In Stage 1, along with the questionnaire and interview the participant stakeholders were asked to draw on a map of the Dorset region, their perspectives on potential areas for alternative crops and irrigation expansion, based on their local knowledge and experience. The comparison between the result of the hemp adoption Fig. 5 and the Participant Sketched map Fig. 7 shows that there is a similarity between the areas that participants sketched as having the potential for hemp, and the outcome of the scenario simulation. As the Crop GIS-ABM outcomes showed a good match with the participants' insights, this suggests that the framework and model accurately incorporated farmers' knowledge expressed by participants into spatial ABM.

Using the Crop GIS-ABM for scenario analysis affords an opportunity to test different scenarios about changing milk price and irrigation availability and simulate and visualise the cumulative impacts of farmers' (micro-scale) decisions at regional
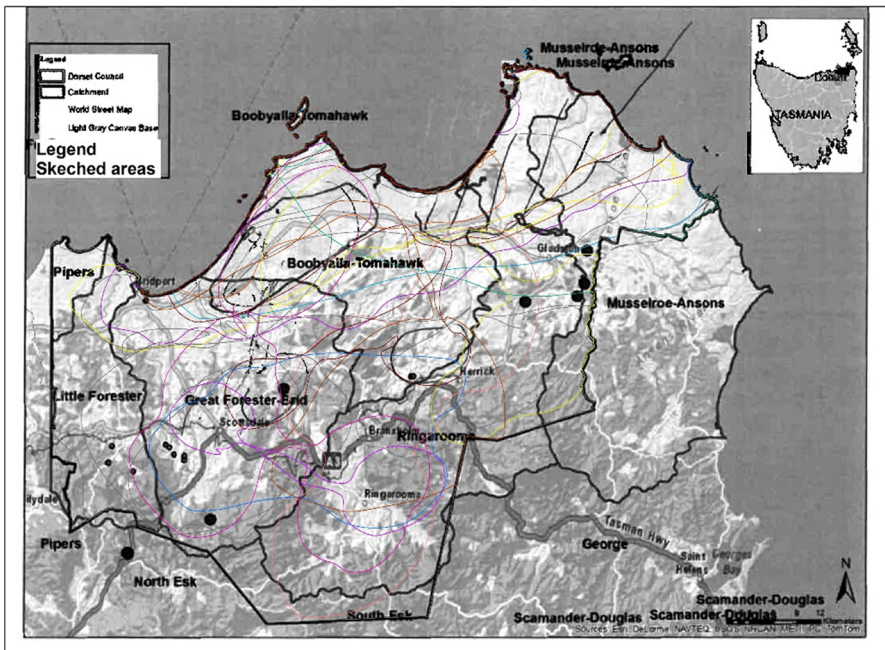


**Fig. 7** Digitised and overlayed sketched maps by participants

scale. This model has the flexibility to integrate farmer's knowledge with socio-economic and spatial data, and display the outcomes of simulation as maps, where a similar real-world experiment would be time-consuming, expensive and entirely impractical.

## Discussion

Agricultural land use planning in Australia can benefit from using a decision support simulation model (Shahpari, 2019). Simulation models for land-use planning in Australia are mostly built using top-down approaches (Thackway, 2018); these approaches do not recognise the role of farmers as agents and decision-makers whose knowledge and decisions influence land use changes. By contrast, the spatial ABM simulation described in this paper is a bottom-up approach that recognises farmers as autonomous agents with specific knowledge-sets (Chambers, 1983; Scoones & Thompson, 1994), and explores the cumulative impacts of their micro-scale decisions on regional scale land use changes. The relationship between human-environment interactions in ecological-social systems sometimes may be forgotten or ignored by modellers (Boone & Galvin, 2014). Spatial ABM enables integration of social-economic and ecological systems into a simulation model with the ability to take some human dynamics – in this case farmers' knowledge and decision-making – into account. While the Crop GIS-ABM does not provide all the data for policymaking and planning, it provides an opportunity to build and represent a shared understanding of the decision-making processes that influence land use change by considering stakeholders' insights about the changes. Using a bottom-up simulation model alongside top-down land use planning can facilitate a better-informed policy formulation process by simulating the possible impacts of the policy in the future, for example the effects of milk price change as examined in this study.

In land-use decision-making, different agents in different sectors, at different scales, have different knowledge-sets. This raises the challenge of how to integrate these very different types of knowledge to inform development decision-making, a process that has been theorised as Knowledge Partnering (Eversole, 2014). While Knowledge Partnering typically involves direct dialogue among stakeholders, or between stakeholders and a knowledge broker, the spatial ABM developed in this study provides an indirect mechanism for policy makers and land-use scientists to recognise and engage with farmer knowledge. This approach has "captured" key insights from farmer knowledge, as communicated in interviews and surveys, and then integrated these into a simulation model, the Crop GIS-ABM, which communicates these insights in a way that policy makers and land-use scientists can understand and use to inform agricultural land-use planning. This bottom-up process of developing the simulation model decreased the risks of ignoring social dynamics and interactions of agents at farm scale, by explicitly integrating farmer knowledge about crop decision-making into the design of the model.

Agricultural land use is dynamic and changes over time. Crop GIS-ABM enabled scenario analysis methods to be used to explore agricultural land use changes. In this project, the scenarios were designed to explore the impacts of an agricultural policy (irrigation expansion) on farmers' decision to choose a high-value crop such as hemp. Farmers' decisions about the adoption of new alternative crops, versus expanding their dairy production, were simulated over time to explore "what if" questions and the dynamics of how agricultural policy influences macro-scale land use patterns in regions. As the simulation outcomes illustrated, different patterns emerged under different irrigation expansion policy and milk price scenarios. Spatial analysis revealed that some areas are more sensitive to changes in milk prices than irrigation expansion and vice versa. It also showed how dynamic individual farmer decisions in a complex agricultural system influence the emergence of regional land use patterns.

The result of simulations also illustrated that that farmers, as agents, could potentially choose to access and adopt irrigation to intensify ryegrass production rather than grow a new alternative crop in their land parcels. Scenarios also afforded the opportunity to see what unfolded when there was a change in a key/core commodity price. The benefits of simulating a range of scenarios are that several possible changes in agricultural land use can be considered; this provides an opportunity for planners to consider not only possible impacts of existing policies, but also to proactively inform policy agendas. The kinds of patterns exhibited by the simulations demonstrate that fluctuations in the milk prices can change land use patterns in different areas of the region. These insights from the simulations provides a way for planners to integrate 'bottom-up' knowledge from key local stakeholders with other kinds of knowledge to inform land-use planning decisions.

Simulation outcomes also enabled us to explore the emergent land use patterns based on farmers' decisions on topics when there is little research literature available (e.g. the relationship between the size of the farm and crop type choices). Although studies have found that the size of the farm is an important factor that affects farmer's adoption investment (Feder et al., 1985; Liu et al., 2018; Ullah et al., 2018), there is a little guidance in the literature to understand the relationship between the size of the farm and adoption of a new type of crop (Caswell et al., 2001). The simulation of farmer behaviour under the milk price policy scenario showed that the size of the farm might not be a significant factor for decision-making about alternative crops, as long as the overall profit of adoption of the new alternative crop (e.g. hemp) can be achieved.

Sustainable agricultural land use cannot be accomplished without understanding the linkage among the economic, ecological, and social systems and the dynamic relations between farmers and the environment that they inhabit (Shahpari et al., 2021). The spatial ABM approach is a concrete way to bring farmers' knowledge, scientific knowledge (via spatial science), and policy knowledge into dialogue. Understanding the relationship between social, economic and ecological systems and the integration of the different relevant bodies of knowledge is critical for supporting evidence-informed agricultural land-use policy (Low Choy, 2018). The simulation model allows for consideration of several scenarios and the impacts of different kinds of change, such as fluctuations in commodity prices, changes in policy (e.g.

irrigation expansion in certain areas of the region) and the introduction of new crops (e.g. hemp). However, the Crop GIS-ABM has some intrinsic limitations, for example model calibration and validation, that are common to all spatial ABMs. The spatial ABM enables combining different types of knowledge at different scales to considering the consequences of a change in land use – such as the intensification of a traditional crop (as opposed to a new crop) like ryegrass when the milk price is high, because the costs of irrigation will be more than covered by the return on dairy investment and ryegrass.

This study demonstrates that knowledge partnering is possible in agricultural land use planning: it is possible to combine the local knowledge of farmers with other forms of knowledge in a structured way to inform decision-making. We can include farmers' voices in the planning system. As other authors have suggested (Batty et al., 2012; Boone & Galvin, 2014), spatial ABM can provide an opportunity for a bottom-up approach to land-use planning. This study tested this proposition in practice and demonstrated that spatial ABM is an appropriate approach for agricultural land use planning. The model developed in the project allows 'bottom up' farmer knowledge at the micro scale about land use to inform planners who make decisions at regional and state scales. It also allows visualisation of how the accumulated effects of individual farmers' decisions can change agricultural land use patterns at regional scale, and understand better the impacts of policies on land use change. The examples of scenario simulations demonstrate the capacity of the spatial ABM as an innovative method to facilitate knowledge partnering among different stakeholders to incorporate local knowledge in a way that is not easily achieved in traditional statutory and strategic planning systems.

## Conclusions

Agricultural land use planning is complex and dynamic processes, but it can be facilitated through modelling techniques that are able to capture and dialogue land-use knowledge at both micro (farm) and macro (regional) scales. This paper has argued that simulation models employing spatial ABM can facilitate the incorporation of bottom-up stakeholder knowledge into planning processes and bring local knowledge into dialogue with policy knowledge to inform better decisions: a process theorised as Knowledge Partnering (Eversole, 2014). The agent-based model acknowledges that farmers are active agents in land-use change, and that their knowledge and decisions at micro scale inform land use at macro scale. This paper has demonstrated how spatial ABM can be used in land-use decision-making to integrate "bottom up" and "top down" understandings of land-use change to inform agricultural land use planning.

This study demonstrated that spatial ABM is able to represent the complexity of the agricultural landscape in Australia, by capturing the complex interaction between (1) farmer's behaviour and decisions, (2) natural resource and spatial conditions, and (3) policy-making and planning at multiple scales. The model developed in this study is aligned with Geodesign methodology and able to incorporate the socio-economic and policy considerations that are central to agriculture in rural regions, alongside biophysical and spatial dynamics. In a context such as Australia, where land use is

contested and economic and environmental planning are disconnected, there is a need for integrative approaches to sustainable land use planning. The ability to develop models that incorporate social, economic and environmental considerations, and are informed by on-the-ground knowledge of farmers and other land-use actors, provide a new way for land-use planners to conceptualise the dynamics and implications of planning decisions across multiple domains and multiple scales.

Spatial ABM can be employed in practice to explore these dynamics through the development and testing of scenarios. In this study, the Crop GIS-ABM was developed to simulate the possible cumulative impacts of individual farmer decisions on agricultural land use changes in Tasmania, Australia. The Crop ABM-GIS model could be extended to investigate the direct and indirect impacts of climate change policy, or crop disease on farmers' behaviour and crop choices. Further models could be developed to explore how farmers in other parts of Australia and the world make decisions, and what are the impacts of their decsions on land use patterns.

This study highlighted that spatial ABM is an approach that can facilitate a better-informed agricultural land use planning by developing bottom-up simulations which not only incorporate farmers as autonomous decision-maker but also enable testing the dynamics of their decisions under different scenarios. Spatial ABM also facilitates knowledge partnering by incorporating farmers' knowledge with scientific, planning, and policy knowledge; these multiple forms of knowledge are incorporated into simulation models to inform land use planning. These models also illustrate how agricultural policy or changes in the market price of a commodity can change land use in the region. The spatial ABM provides a decision-support tool for recognising and understanding the cumulative effects of farmers' decisions for sustainable management of land and water resources.

# Appendix

## Initialisation

The market fluctuation for milk price influences dairy gross margin and shifts in the milk price change farmers' expectations about the future prices of certain types of crops, which in turn affects farmers' decisions on which crops they might produce. DPIPWE calculated that the gross margin for a dairy farm is around $3295/ha based on a price of $5.20/kg milk solids. If the milk price decreased to $4.68/kg milk solids, the gross margin dropped to $2768/ha, and conversely, if the milk price increased to $5.72/kg milk solids, the gross margin increased to about $3803/ha (Department of Primary Industries Parks Water and Environment Tasmania, n.d.). This ± 10% variation in gross margins was used to explore the sensitivity of milk price on spatial land use outcomes.

Ryegrass pastures are the mainstay of pasture-based dairy farming (Dairy Australia, n.d.) and the interview data analysed confirmed that ryegrass pasture for dairy farms and livestock is the most significant crop produced in the Dorset region. This being the case, the assumption for this scenario proposed that if dairy farmers

irrigate their land parcels, they could intensify ryegrass production and increase the dairy gross margin and productivity.

For the purposes of scenario, the Crop GIS-ABM simulated the effects of the milk price on farmers' decisions under four experimental conditions and, as is outlined in Table 3, each experimental condition represents the milk price (high and low) with and without irrigation expansion.

The Crop ABM-GIS model was initialised with hemp, ryegrass and poppy randomly allocated to land parcels. Each Farmer agent decided which option was the best choice of crop for his/her land under the four experimental conditions summarised.

Input data for the Crop ABM-GIS model consists of the State irrigation company's (TI) map along with DPIPWE GIS layers and census data. The gross margins of the crops (hemp, ryegrass and poppy) were extracted from DPIPWE department documents (Macquarie Franklin, 2012, 2018a, b) and Table 4 lists the parameters used in the model for the third scenario.

**Table 3** Experimental conditions (E) for the third scenario

| Experimental conditions | E1 | E2 | E3 | E4 |
|---|---|---|---|---|
| Irrigation | No irrigation | No irrigation | Irrigation available | Irrigation available |
| Milk price ($ 5.2) | -10%<br>$ 4.68 | +10%<br>$5.72 | -10%<br>$ 4.68 | +10%<br>$5.72 |

MS = milk solids

**Table 4** Parameter initialisation – Adoption of alternative crop under irrigation expansion

| Parameter in Crop GIS-ABM | Unit | Initialisation | Experimental conditions | Description |
|---|---|---|---|---|
| InnovationAdoptersRatio | % | 2.5 | E1, E2, E3 E4 | Adoption rate |
| PoppyGrossMargin | $ | 3030 | E1, E2, E3 E4 | Poppy gross margin |
| HempGrossMargin | $ | 1290 | E1, E2, E3 E4 | Hemp gross margin |
| RyegrassGrossMargin | $ | 2,786 | E1 | Ryegrass gross margin |
| | $ | 3,803 | E2 | |
| | $ | 2,786 | E3 | |
| | $ | 3,803 | E4 | |
| NeighboursEffectThreshold | [0–1] | 0.3 | E1, E2, E3 E4 | The effect of neighbour's choice |
| MaxTimestep | Year | 10 | E1, E2, E3 E4 | Maximum time step for simulation |
| Quantity | True/False | True | Crop dissimilarity within the neighbourhood | Quantity |
| Irrigation | True/False | True | The availability of the irrigation | Irrigation |

In the first and second experiments (E1 and E2), the Crop GIS-ABM did not consider the irrigation expansion districts, but it did include input from the irrigation districts for simulations in the third and fourth experiments' (E3 and E4). For each experiment, the simulation continued for ten years. The model stopped at the end of the time step, and the regional pattern of crops in the Dorset region under each experimental condition was visualised in the ArcGIS display.

**Author Contributions** Dr Sahar Shahpari conducted the conceptualisation, methodology, analysis, visualization, software, writing—original draft preparation; Prof. Robyn Eversole, contributed to the writing, review and editing, conceptualization.

**Declarations**

The research abides by the international and Australian codes on human and animal experimentation, the guidelines by the Australian Government's Office of the Gene Technology Regulator and the rulings of the Safety, Ethics and Institutional Biosafety Committees of the University. Human Research Ethics Committee (Tasmania) Network granted 'Minimal Risk Ethics Application Approval' (Ethics Ref: H0015467) to this research project on 25 February 2016.

**Informed Consent** The participants (or parent/guardian if the participant is a minor or incapable or legal representative) gave written informed consent for publication.

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