Participatory modelling for analysing interactions between high-priority Sustainable Development Goals to promote local sustainability

Reihaneh Bandari[1], Enayat A. Moallemi[2], Katrina Szetey[3], Claire Flanagan-Smith[4], Michalis Hadjikakou[1], Raymundo Marcos Martinez[3], Ali Kharrazi[5], Robert Šakić Trogrlić[5], and Brett Anthony Bryan[6]

[1]Deakin University
[2]Commonwealth Scientific and Industrial Research Organisation
[3]CSIRO
[4]RMCG
[5]IIASA
[6]Commonwealth Scientific and Industrial Research Organisation (CSIRO)

July 11, 2023

Abstract

The 2030 Agenda offers a list of global environmental, social, and economic objectives to attain sustainable development. However, achieving the Sustainable Development Goals (SDGs) is challenging given the complex interactions between different SDGs and their spillover effects. System dynamics models have the capacity to integrate multisectoral dynamics of SDG interactions. We developed a system dynamics model-the Local Environmental and Socio-Economic Model (LESEM)-to analyse and quantify context-based SDG interactions at the local scale using a participatory model co-design process with local stakeholders. The LESEM was developed for a case study in the Goulburn-Murray Irrigation District in northern Victoria, Australia. We present an illustrative application of the model that quantifies SDG interactions across four high-priority SDGs, namely clean water and sanitation (SDG 6), agricultural activities (SDG 2), economic growth (SDG 8), and life on land (SDG 15). Our results suggest that agricultural land area may shrink by 62,522 ha due to the decline in water resource availability (SDG 6) under a business-as-usual (BAU) scenario from 2022 to 2050. However, the results also highlight that agri-food production (SDG 2) is likely to increase due to intensification to meet future agri-food demand, and higher values of farm output may improve local prosperity. The projections also suggest that environmental pressures may increase due to increasing agricultural intensification and reduced water availability. The LESEM facilitates integrated and strategic decision-making and helps local policymakers identify and quantify potential trade-offs and synergies that benefit multiple SDGs, which eventually leads local communities toward sustainability.

Hosted file

`967938_0_art_file_11163477_rxds64.docx` available at https://authorea.com/users/558928/articles/653964-participatory-modelling-for-analysing-interactions-between-high-priority-sustainable-development-goals-to-promote-local-sustainability

Hosted file

`967938_0_supp_11163478_rxds95.docx` available at https://authorea.com/users/558928/articles/653964-participatory-modelling-for-analysing-interactions-between-high-priority-sustainable-development-goals-to-promote-local-sustainability

Participatory modelling for analysing interactions between high-priority Sustainable Development Goals to promote local sustainability

Reihaneh Bandari[1 6], Enayat A. Moallemi[2], Katrina Szetey[3], Claire Flanagan-Smith[4], Michalis Hadjikakou[1], Raymundo Marcos-Martinez[5], Ali Kharrazi[6 7], Robert Šakić Trogrlić[6], Brett A. Bryan[1]

[1]School of Life and Environmental Sciences, Deakin University, Melbourne, Australia

[2]CSIRO Agriculture and Food, Victoria, Australia

[3]CSIRO Black Mountain, Canberra, ACT, Australia

[4]Principal and Director, RMCG, Bendigo, VIC, Australia

[5]CSIRO Environment, Canberra, ACT, Australia

[6]International Institute for Applied Systems Analysis, Schlossplatz 1, Laxenburg A-2361, Austria

[7]Network for Education and Research on Peace and Sustainability (NERPS), Hiroshima University, Hiroshima, Japan

Corresponding author: Reihaneh Bandari (rbandari@ deakin.edu.au)

Abstract

The 2030 Agenda offers a list of global environmental, social, and economic objectives to attain sustainable development. However, achieving the Sustainable Development Goals (SDGs) is challenging given the complex interactions between different SDGs and their spillover effects. System dynamics models have the capacity to integrate multisectoral dynamics of SDG interactions. We developed a system dynamics model—the Local Environmental and Socio-Economic Model (LESEM)—to analyse and quantify context-based SDG interactions at the local scale using a participatory model co-design process with local stakeholders. The LESEM was developed for a case study in the Goulburn-Murray Irrigation District in northern Victoria, Australia. We present an illustrative application of the model that quantifies SDG interactions across four high-priority SDGs, namely clean water and sanitation (SDG 6), agricultural activities (SDG 2), economic growth (SDG 8), and life on land (SDG 15). Our results suggest that agricultural land area may shrink by 62,522 ha due to the decline in water resource availability (SDG 6) under a business-as-usual (BAU) scenario from 2022 to 2050. However, the results also highlight that agri-food production (SDG 2) is likely to increase due to intensification to meet future agri-food demand, and higher values of farm output may improve local prosperity. The projections also suggest that environmental pressures may increase due to increasing agricultural intensification and reduced water availability. The LESEM facilitates integrated and strategic decision-making and helps local policymakers identify and quantify potential trade-offs and synergies that benefit multiple SDGs, which eventually leads local communities toward sustainability.

Keywords

Sustainability, system dynamics, SDG interactions, multisectoral modelling, stakeholder engagement

1 Introduction

The Sustainable Development Goals (SDGs), established as part of the UN 2030 Agenda, include 17 goals and 169 targets which are "*integrated and indivisible*" (UN 2015). They represent a vision of a sustainable world and span economic, social, and environmental aspects of sustainable development. The 2030 Agenda recognises that these goals and targets are integrated and intertwined. The integration and complexity of the 2030 Agenda mean there may be conflicts when the goals interact (Moallemi et al. 2022b; Pradhan et al. 2017). If the decision-makers responsible for guiding action on the SDGs neglect these conflicting interactions, divergent results may occur upon the fulfilment of individual SDGs (Bandari et al. 2022; Nilsson et al. 2016). Understanding how these interactions occur and what the outcomes will be is a key factor in the successful implementation of SDGs (Nilsson et al. 2018).

Modelling is often used to develop an understanding of system interactions and their resulting synergies and trade-offs. System dynamics is a modelling method of particular benefit in this context because of its ability to incorporate feedback and capture complex systems processes (Neumann et al. 2018; Pedercini et al. 2020). System dynamics modelling makes causal interactions across complex systems' sectors explicit (Davis & Eisenhardt 2007; Moallemi et al. 2021; Pedercini et al. 2020). System dynamics can also quantify interactions between model components and thus guide decision-making regarding achieving the SDGs. For this reason, Di Lucia et al. (2021) argue that system dynamics is well suited to understanding SDG interactions from both the perspective of a developer and a decision maker.

Using participatory methods and engaging stakeholders is also essential for uncovering nuanced interactions within local social-ecological systems, ensuring that a diversity of views and understandings of the context is incorporated (Norström et al. 2020). System dynamics modelling has the capacity to support participatory for knowledge co-production in the modelling process (Vennix 1996). Participatory system dynamics modelling is a collaboration between scientists with domain knowledge, and stakeholders with local expert knowledge (Eker et al. 2018). Local knowledge can be of great utility in identifying the interactions that may be opaque to outsiders (Szetey et al. 2021). For instance, Kimmich et al. (2019) used participatory system dynamics in their research and found that co-producing a model with local experts resulted in a change in the research team's understanding of the problem. Additionally, they found that the participatory process was as important to the participants' future behaviour change as the outputs of the model.

A review by Moallemi et al. (2021) identified over 100 studies that used system dynamics for SDG interaction analysis and concluded that many of these did not focus on synergies and trade-offs. Both Moallemi et al. (2021) and Zhang et al. (2016) additionally identify that system archetypes (feedback loop structures that occur commonly in models of social-ecological systems) can be a useful tool in qualitatively characterising SDG interactions (Moallemi et al. 2022b). Van Soest et al. (2019) examined how the Integrated Assessment Modelling (IAM) community had been approaching SDG interactions and identified some key gaps in how IAMs are able to represent interactions, particularly with respect to the social SDGs. Collste et al. (2017) used a system dynamics model to quantify the interactions between selected SDGs at national-scale and conclude that they are best suited for examining SDG interactions.

In this paper, we develop a system dynamics model called Local Environmental and Socio-Economic Model (LESEM) to simulate the environmental and socio-economic dimensions of sustainability with a particular focus on their interactions. The model was co-produced in collaboration with local expert stakeholders in a case study in the Goulburn-Murray Irrigation District (GMID), in northern

Victoria, Australia, in the context of the locally relevant SDGs. The GMID region is a highly productive agricultural region with a complex socio-environmental system of interconnected components, including, for example, people, agriculture, water, economy, and environment. The LESEM simulates progress towards four high-priority SDGs as identified by Bandari et al. (2022) in the GMID region, including agricultural activities (SDG 2), water availability (SDG 6), economic growth (SDG 8), and life on land (SDG 15), and quantifies their interactions under a BAU scenario. We used the model to investigate the effects of driving forces of future change such as climate change, food demand change, and agricultural commodity prices upon local concerns regarding water availability, water quality, salinity, blue-green algal blooms, environmental protection, local economy, labour force, skilled workforce, population ageing, agricultural productivity, and land-use change. As a decision support tool, LESEM can assist policymakers and planners in analysing local issues with a more integrated and holistic approach, ultimately supporting sustainable development at the local scale.

2 Methods

2.1 Overview

As illustrated in Figure 1, the modelling process has four steps. In Step 1 we identified the socio-economic and environmental issues of high priority to local stakeholders in terms of the SDGs using a comprehensive contextual analysis involving interviews with local stakeholders, scientific papers and reports, and policy documents which has been fully described in Bandari et al. (2022). Additionally, as part of Step 1 we conducted a participatory process to further articulate the local challenges and construct theories of how the problems arose (i.e., dynamic hypotheses) via a workshop with a subcommittee of the Goulburn-Murray Resilience Taskforce. After delineating the system boundaries through problem identification and constructing dynamic hypotheses, we developed a system dynamics model of the GMID (Step 2). A second workshop was also conducted in Step 2, whereby a participatory model development process was conducted to confirm the model structure and identify and quantify additional important interactions with local stakeholders that were not captured in Step 1. In Step 3, we implemented the model, identified parameters that most strongly influenced model behaviour and validated its performance. Finally, in Step 4 we parameterised and conducted the model based on a Business-As-Usual (BAU) scenario.

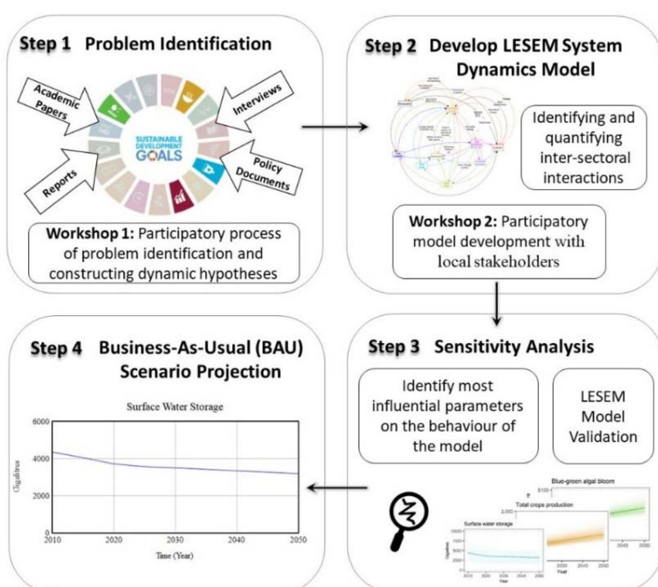


Figure 1. Conceptual schema of the LESEM participatory systems dynamics model-building process.

2.2 Study area

The Goulburn Murray Irrigation District (GMID) is a region in northern Victoria with 170,000 people and 27,000 square kilometres stretching from Cohuna in the west to Cobram in the east (Figure 2). It includes six local government areas of Moira, Greater Shepparton, Loddon, Campaspe, Gannawarra, and Swan Hill (GMIDWL 2018). The GMID is a strategic agricultural area comprising 15,000 agricultural properties (RMCG 2019), with extensive areas of horticulture, dairy, mixed cropping and grazing, and agricultural activities are an essential part of the economy (Pearson et al. 2013). The GMID faces major drivers of change such as climate change, water availability, global markets, technological change, water policy reforms, and market access (RPG 2020). Over the last twenty years, due to the effects of climate change, water recovery plans, and competition for water from outside the GMID, water availability for irrigation in this region has declined by almost 50% (RPG 2020).

Agriculture and the economy of the region are at risk due to decreasing water resource availability (Bandari et al. 2022). Additionally, factors such as ageing and declining demographics have impacted agricultural activities in the GMID and could potentially affect future food production and the wellbeing of the region (GBCMA 2013; RPG 2020). Furthermore, this region already has experienced environmental pressures like reduced water quality and salinity due to a combination of climate change and agricultural activities (Aither 2019). The GMID is a complex dynamic system with many interacting elements, including climate, global markets, water availability, technology, agriculture, environmental issues, and livelihoods (RPG 2020). Given the fast-changing nature of the GMID, utilising a system dynamic modelling approach can be beneficial in understanding the interplay between many uncertain parameters and in assisting policymakers to plan for the future.

Figure 2. A map of the case study area. The Goulburn Murray Irrigation District (GMID) is specified with a black boundary. The inset map indicates the case study location in the context of the state of Victoria, Australia.

2.3 Participatory model development

The model development process starts by delineating the system boundary. The primary sources of information for defining system boundaries (i.e., problem articulations and dynamic hypotheses) included policy documents, academic papers, local sector reports, and interviews with local stakeholders which has been fully described in Bandari et al. (2022). Developing the model in consultation with local expert stakeholders has been demonstrated as a beneficial way of elucidating complex processes in social-ecological systems (Pedercini et al. 2020). Hence, we conducted two face-to-face workshops with local expert stakeholders as participatory model development steps to complement the initial contextual framing.

During the initial workshop held in March 2022, we utilised in-person and online participatory techniques to facilitate the creation of a model with the Goulburn Murray Resilience Taskforce subcommittee. The Taskforce consists of community and regional leaders who have a deep understanding of the region, its sustainability challenges, and prospects; and are committed to promoting regional resilience. The subcommittee included 18 local stakeholders from organisations such as Goulburn Broken Catchment Management Authority (GBCMA), the Department of Energy, Environment and Climate Action (DEECA), Agriculture Victoria, Goulburn Murray Water, Goulburn Valley Water, Regional Development Victoria, and Murray Dairy (Figure 3). We presented and shared the identified priority SDGs and local challenges to the Goulburn Murray Resilience Taskforce subcommittee for verification and enrichment, and they provided valuable feedback and recommendations on how to improve the GMID model and make it more effective in addressing the local challenges.

To facilitate the participatory process, we displayed large posters demonstrating the relevant SDGs and their interactions. The participants were then asked to edit the interactions between the identified priority SDGs by adding or deleting interlinkages and writing a short explanation of how they believed SDGs were connected (Figure 3). During the first workshop, the system boundaries of the GMID were established by identifying the key sectors of local concern. Additionally, the interactions between different sectors were mapped out and the main local issues were defined, along with the contributing factors. On the basis of the first workshop, we identified the causal relationships between the different sectors and developed related variables to represent how those sectors align with the related local issues. We sketched out the causal relationships between the variables of different sectors in the form of causal loop diagrams and positive and negative feedbacks.

We hosted the second workshop in July 2022 with ten attendees from the Goulburn-Murray Resilience Taskforce. During this workshop, we first presented the causal loop diagrams, explained how they work, and how components and key variables are connected. We then asked the participants to draw upon their collective knowledge and confirm or improve the causal relationships (Figure 3). To facilitate this process, we printed each of the seven sector sectors as a separate poster and created identical online Mural Boards. In-person workshop participants gave feedback directly on the hardcopy posters and online participants posters gave feedback on the Mural Boards. The participants were asked to write on the causal relationship linkages an explanation of how they felt those components were connected. Following that, a group discussion (Figure 3) helped further improve some parts of the causal loop diagrams to better reflect local issues We iterated this process to improve each sector and their interactions aligned with the system understandings offered by local expert stakeholders.

System dynamics models are composed of three types of parameters: *stocks*, which are state variables represented mathematically; *flows*, which are the equations that describe the rate of change; and *auxiliary variables*, which are additional parameters that may include constants. Following the second workshop, CLDs were integrated and converted into quantitative stock-and-flow systems dynamics structures and parameterised to perform simulations. We implemented and formalised these causal feedback loops in Vensim DSS version 8.2.1 (Ventana Systems 2021) in seven sub-models: Demographics, Agriculture, Water Availability, Land-use, Economy, Fertiliser Use, and Water Quality sub-models, (See Section 3 for details). The stock-and-flow structures quantitively capture accumulations and depletions of stocks over time in response to flows throughout the system based on differential equations (Gohari et al. 2017; Naderi et al. 2021).

The Agriculture, Economy, Land use, and Water Quality sub-models were constructed according to the local issues identified with stakeholders and through the concepts and formulations extracted from different studies (Dean Delahunty et al. 2002; Navarro & Marcos Martinez 2021). In accordance with the dynamic hypotheses of the water sector and inspiration from the FeliX Model (Rydzak et al. 2010), the Water Availability sub-model was designed and adapted to the GMID and Goulburn-Murray Water (Baker et al. 2018; Cummins 2016; GMW 2018a, 2018b, 2018c; Gupta & Hughes 2018; Naderi et al. 2021; Rydzak et al. 2013; Wang et al. 2021). The Fertiliser Use sub-model was inspired by the FeliX3 Model and modified according to the local issues and source of nutrients in the GMID (GBWQWG 1995b; Rydzak et al. 2013). The Demographics sub-model was adapted from the RUSEM model (Navarro and Tapiador 2019), and other components like labour force and education were added to this sub-model according to stakeholder input (see Supplementary Information for detail).

Figure 3: Five images from the first workshop 1 (image credit: Jamie Rooney) and the second workshop (image credit: Reihaneh Bandari). The two images located at the bottom pertain to Workshop 1, while the three images situated at the top correspond to Workshop 2. Permission has been obtained from all stakeholders for including the images above.

2.4 Model validation

Direct structural tests and structurally-oriented behaviour tests were used to assess the validity of the model structure (Moallemi et al. 2017; Naderi et al. 2021). This involved evaluating mathematical equations, dimensional consistency of equations, sub-model variables, and all logical relationships in the model by comparing them with actual data and real-world knowledge and understanding of the GMID social-ecological system. Direct structural tests can be classified as theoretical or empirical (Barlas 1996). We undertook theoretical structure tests by comparing the model structure with locally available literature including reports, academic papers, policy documents, and interviews with local stakeholders (Bandari et al. 2022). We conducted empirical direct structural tests comparing the model structure with qualitative and quantitative information describing the real-world system. The participatory modelling process of this research formed the main part of direct empirical structural tests applied in two workshops with local expert stakeholders.

Structurally-oriented model behaviour tests were also used to indirectly evaluate the model structure's validity through simulation to detect potential model structural flaws. Because of the long-term nature of the system dynamics model, the emphasis of this test was more on pattern forecasting rather than point forecasting (Barlas 1996). Once the validity of the model structure was verified, the system behaviour patterns under the Business-As-Usual (BAU) scenario were compared with historical data from 2010 to 2022 to assess model applicability, reliability, and accuracy. We selected 12 output variables from the perspective of local sustainability. The selection of these 12 output variables for local sustainability was based on a combination of factors, such as their importance in achieving sustainability outcomes, consultation with local expert stakeholders, and the availability and quality of data. As the historical data records (2010 to 2022) were incomplete for these output variables, we used different historical data for each variable depending on availability.

We calculated the maximum relative error (M) to quantitatively evaluate model performance as the degree of divergence between the historical and simulated data for the 12 output variables (Eq.1) (Liu et al. 2015; Naderi et al. 2021).

$$M = \frac{\Sigma\,(Y_{sim} - \mathrm{Y_{obs}})}{\Sigma\,\mathrm{Y_{obs}}} \qquad (1)$$

Here, Y_{sim} and Y_{obs} represent the simulated and observed data points for the tested parameter, respectively. The threshold for an acceptable M value may vary depending on the application and context. However, in some contexts, the M value under 10% shows that the model satisfactorily fits the available data (Kotir et al. 2016).

2.5 Sensitivity analysis of dynamic model

The LESEM comprises an extensive array of socio-economic and environmental parameters. We initially compiled a list of 48 input parameters from various model components for conducting sensitivity analysis to analyse the behaviour of nine sustainability output variables. After evaluating them, we identified 36 parameters influential on model behaviour, while others had a more benign impact. The focus was placed on the parameters that were considered to be more uncertain in terms of their values and their capacity to considerably impact 9 model outputs (Samsó et al. 2020) using Morris elementary effects (Campolongo et al. 2007; Moallemi et al. 2022a; Morris 1991). The Morris method (Morris 1991) is a global sensitivity analysis technique that offers several benefits, including broad applicability and ease of use, making it particularly suitable for cases where there are a large number of input parameters. One key advantage of the Morris method is its ability to effectively identify input parameters that are not critical, without relying on strong prior assumptions about the underlying model (Pujol, 2009). Moreover, studies have shown that the Morris method strikes a good balance between accuracy and efficiency (Gao & Bryan 2016; Wang et al. 2020).

The names, units, and minimum and maximum values of each input parameter are listed in Table 1. As there is no information about the prior probability distributions for each model parameter, we assumed a random uniform distribution for each parameter with a symmetrical ±30% variation around the reference value of selected parameters as the uncertainty bounds following previous studies (Gao et al. 2016; Oijen et al. 2005; Song et al. 2012). The code and model file utilised for the sensitivity analysis can be found in Chapter 8 of the Supplementary Information. During sensitivity analysis, we identified flaws in the model that necessitated modifications, followed by re-testing.

This iterative process of model building is crucial for ensuring model accuracy and reliability. To assess the uncertainty of the influential variables (Table 1), we conducted Morris elementary effects sampling with 2000 simulations. The sensitivity was then expressed using the normalised values of the Morris index (μ*), which provides an indication of the overall impact of inputs on an output variable and ranks the inputs by the strength of their effect.

Table 1: Model parameter value ranges used for sensitivity analysis.

	Variable	Units	Reference value	Lower Bound	Upper Bound
	Demographic				
1	Avg migration rate	1/Year	0.00352	0.002	0.005
2	Fertility rate	1/Year	0.043	0.030	0.056
3	Mortality rate (Age group 0-14)	1/Year	0.00031	0.00022	0.00040
4	Mortality rate (Age group 15-64)	1/Year	0.00156	0.0011	0.0020
5	Mortality rate (Age group +65)	1/Year	0.03694	0.026	0.048
	Water availability				
6	Fraction of agricultural water allocation	(-)	0.27	0.189	0.351
7	Average used surface water recovery rate	1/Year	0.12	0.084	0.156
8	Fraction of outflow from catchment	1/Year	0.55	0.385	0.715
9	Infiltration coefficient	(-)	0.17	0.119	0.221
10	Reference Yarrawonga water yield	Gigalitres/Year	4726	3308	6144
11	Conveyance water fraction	1/Year	0.1	0.070	0.130
	Fertiliser use				
12	N and P runoff fraction in irrigated area	(-)	0.2	0.140	0.260
13	N and P runoff fraction in dryland area	(-)	0.075	0.053	0.098
14	Phosphorus fertiliser application for winter cereals irrigated land	Kg/head	15	10.5	19.5
15	Total nitrogen production per cow	Kg/head	70	49	91
16	Total nitrogen production per sheep	Kg/head	10	7	13
17	Nitrogen fertiliser application for winter cereals dryland	Kg/head	48	33.6	62.4
18	Nitrogen fertiliser application for hay dryland	Kg/head	70	49	91
19	Phosphorus fertiliser application for hay irrigated land	Kg/head	15	10.5	19.5
	Water quality				
20	Reference water storage height	Meter/year	185	130	241
21	Reference salt loads at Yarrawonga	tonnes/year	173423	121396	225450
22	Reference salt loads at Swan Hill	tonnes/year	233754	163628	303880
	Local economy				
23	Water requirement of dairy	Million litres/ha	2.68	1.88	3.49
24	Water requirement of beef	Million litres/ha	1.26	0.88	1.64
25	Price elasticity of demand for dairy	(-)	0.95	0.665	1.235
26	Price elasticity of demand for crops	(-)	0.38	0.266	0.494
	Agricultural activities and Land use				
27	Productivity of beef	tonnes/head	0.2	0.142	0.264
28	Productivity of dairy	litres/head	5854	4098	7611
29	Dryland winter cereals yield	tonnes/ha	2.03	1.42	2.64
30	Dryland hay yield	tonnes/ha	3.66	2.56	4.75
31	Dryland beef yield	heads/ha	0.71	0.50	0.92
32	Dryland dairy yield	heads/ha	0.76	0.53	0.99
33	Irrigated winter cereals yield	tonnes/ha	4.01	2.80	5.21
34	Irrigated hay yield	tonnes/ha	7.07	4.95	9.19
35	Irrigated beef yield	heads/ha	3.01	2.11	3.91
36	Irrigated dairy yield	heads/ha	1.79	1.25	2.33

2.6 Business-as-usual (BAU) scenario

To illustrate the application of the LESEM, we specified a BAU scenario to examine the consequences of continuing recent historical and expected future trends in key system components (Guo et al. 2018; Rydzak et al. 2013). We specified ten parameters under the BAU scenario, and the key assumptions in each sub-model are presented in Table . Certain parameters had a direct impact on individual sub-models, for example, migration rate, surface water recovery rate, and urban land use change, whereas other parameters such as livestock productivity, water yield, and agricultural commodity yield had a more widespread impact across multiple sub-models. To obtain a medium- to long-term projection of the results, the timeframe for the model simulation was set from 2010 to

2050. There are other parameters throughout the LESEM (Table), which were set to historical values and some of the parameters were changed to better fit the real-world data and simulation output. By calibrating these parameters, the model was able to reproduce behaviour that more closely resembled observed data. The Shared Socio-economic Pathway 2 combined with Representative Concentration Pathway 4.5 (SSP2) is commonly used as a BAU scenario because it presents a moderate trajectory for economic and population growth without significant policy interventions or technological advancements to address climate change. In this study, we utilised SSP2 to represent population and food demand, while RCP 4.5 was used as the BAU climate scenario which influenced both agricultural commodity yield and water yield.

Table 2: The list of parameters under the BAU scenario setting in each sub-model.

Sub-model (s)	Parameter	Description
Demographics	Migration rate	The average migration rate from 2010 to 2020 is 0.00352 of the total population in each age cohort based on primary data obtained from Australian Bureau of Statistics census data (ABS 2022).
	Agricultural education rate	The agricultural education rate is 0.0316 of the total population in the age cohort 15-64. It was calculated according to historical data obtained from the Australian Bureau of Statistics census data for 2011 (ABS 2022).
	Agriculture sector employment rate	The employment rate in the agriculture sector is 0.0825 of the total population in the age cohort 15-64. It was calculated according to historical data obtained from the Australian Bureau of Statistics census data for 2011 (ABS 2022).
Agriculture, Fertiliser use, Land use, and Economy	Demand for agricultural commodities	Demand for all agricultural commodities follows historical trends in per capita domestic production and consumption as per the Food and Agriculture Organisation Food Balance Sheets (FAO 2017) with food loss and waste assumed to remain at current levels (FAO 2011) and population following the SSP 2 scenario (Riahi et al. 2017) (Table S3).
	Livestock productivity	Livestock productivity time series (Table S1), including beef, sheep meat, wool (unit: tonnes/head), and dairy (unit: litres/head) under the BAU scenario was taken from (Navarro & Marcos Martinez 2021). The beef productivity trend shows a 0.984 % linear increase per annum, the sheep productivity trend shows a 0.671 % linear increase per annum, the dairy productivity trend shows a 1.238 % linear increase per annum, and the wool productivity trend shows a 0.769 % exponential decrease per annum.
	Agricultural commodity yield	Agricultural yield time series (unit: head/ha [livestock] or tonnes/ha [crops]) under the RCP 4.5 scenario (Table S2) was generated using the GAEZ 4 model for a number of crops and pastures from 2010 to 2050 (Fischer et al. 2021).
	Urban land use change	Average urban land-use change was set at 0.014 % per year from 2010 to 2050. This scenario was generated using historical land-cover maps at 30 m resolution from 1985 - 2015 (Calderón-Loor et al. 2021).
Water availability & Water quality	Water yield	The average water yield time series under the RCP 4.5 scenario from 2010 to 2050 was generated using InVEST model. This model was incorporated a number of different data sources, such as the Australian Soil and Land Grid, solar radiation data, WorldClim climate data, Priestley-Taylor evapotranspiration calculation (Sharp et al. 2018), and a reference plant evapotranspiration coefficient (Sharp et al. 2018). The BAU average water yield scenario (i.e., RCP 4.5) was predicted to decrease by 0.19 % per annum.
	Environmental water allocation	The current trend of environmental water allocation was derived from DELWP (2019) and DELWP (2021) from 2010 to 2019. We assume this trend continues to rise and reach 1100 Gigalitres/year of environmental water allocation.
	Surface water recovery rate	The average surface water recovery rate of 0.12 of total surface water use by all users was used, calculated based on historic data from 2015 to 2019 (VSG 2019).

3 Results

3.1 Model structure

The LESEM (Figure 4) is based on the four highest priority SDGs as Agriculture (SDG 2), water availability (SDG 6), economic growth (SDG 8), and life on land (SDG 15) which focus on socio-economic development outcomes and environmental impacts throughout the GMID. We assigned these four priority SDGs across seven main sub-models: (1) Demographics, (2) Agriculture, (3) Water Availability, (4) Land Use, (5) Economy, (6) Fertiliser Use, and (7) Water Quality (see Supplementary Information for more details). The LESEM captures the main characteristics and issues of the study area as identified through the participatory process. The seven sub-models of the system are affected by BAU scenario of migration rate, employment rate, education, surface water recovery rate, urban land use change rate, and environmental water allocation. The model captures the impact of SSP2 on agricultural productivity, and food demand, while the effects of RCP 4.5 are observed on water yield and agricultural yield (Figure 4).

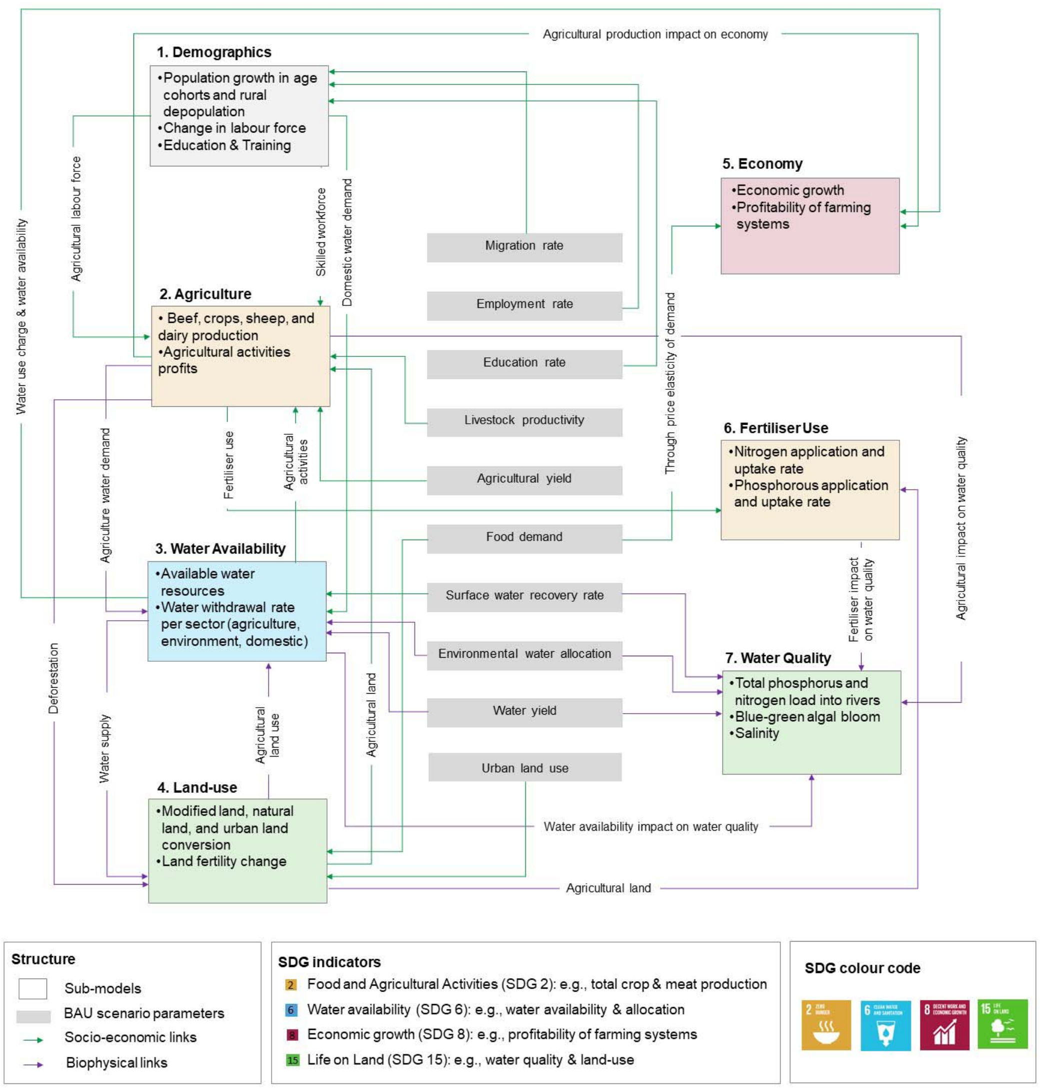


Figure 4. Structure and main sub-models of the LESEM. This model is composed of seven sub-models: Demographics, economy, Agriculture, food demand change, land use, fertiliser use, water availability, water quality, and ten BAU parameters (see Supplementary Information for detail).

3.2 Cause-and-effect interactions

In Figure 5, the integrated nature of the priority SDGs is illustrated with selected trade-offs and synergies and the impacts of various scenarios throughout the whole system. The availability of water (SDG 6) in the GMID has been impacted by climate change, increasing competition for water in the Murray-Darling Basin, and the Australian federal government's water policy reforms that involve redirecting water from agriculture to the environment (SDG 15) (Alston et al. 2018). Although allocating more water to the environment may have positive effects on water-dependent ecosystems (SDG 15), it may also lead to trade-offs with agriculture production (SDG 2), potentially resulting in reduced agricultural water availability, the contraction of agricultural land use, and diminished economic activity in the region (SDG 6), which can have negative impacts on the livelihoods of people and communities that rely on agriculture in the GMID. Furthermore, the increasing use of nitrogen and phosphorus-based fertilisers to boost agricultural productivity (SDG 2) can have negative impacts on water quality (SDG 15) and thus exacerbate the trade-offs between these SDGs.

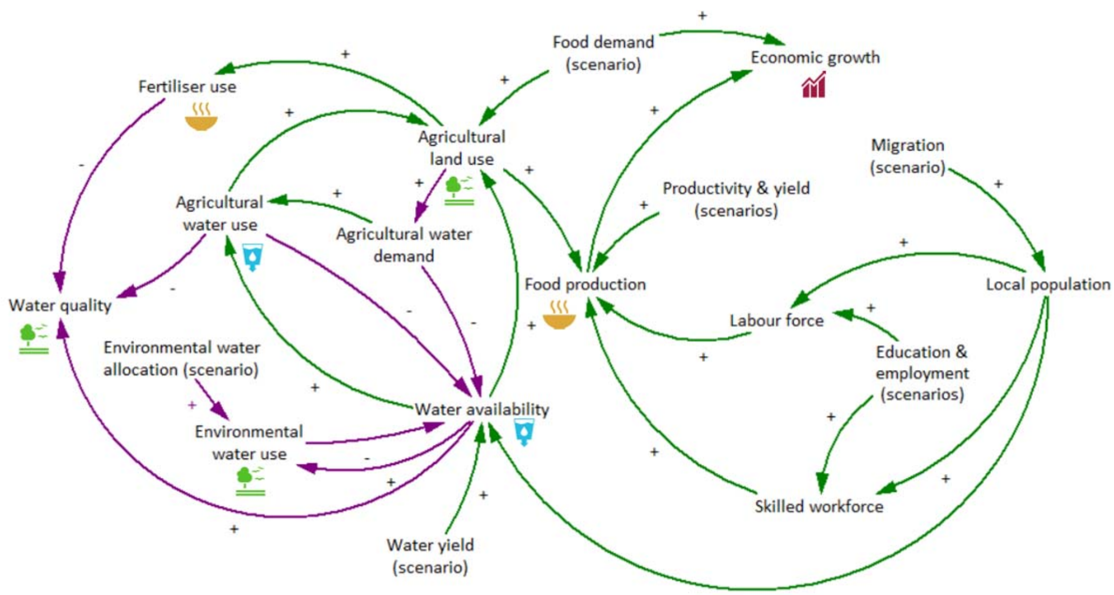


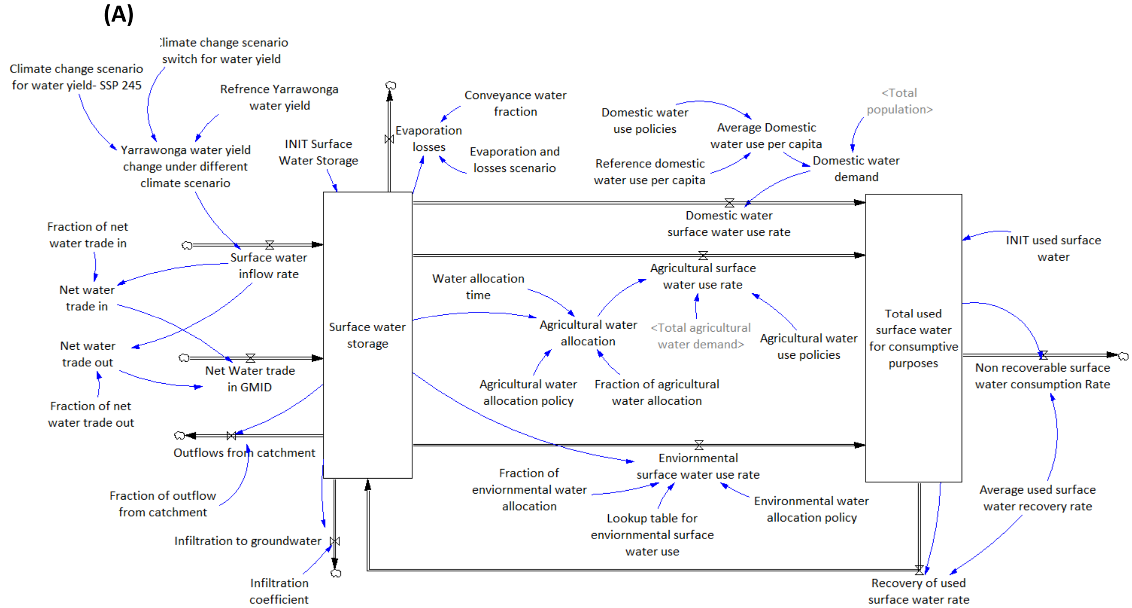
Figure 5: Selected causal loop diagrams including trade-offs or synergies interactions between agriculture (SDG 2), water availability (SDG 6), economic growth (SDG 8), and life on land (SDG 15). Positive feedback linkages are shown as a positive sign (+), whereas negative feedback linkages are shown with a negative sign (-). The purple arrows indicate the enviro-biophysical linkages. The green arrows indicate the socio-economic linkages. The SDGs icons are the courtesy of the UN SDGs communications material.

With increasing food demand, one potential response is the expansion of agricultural land to increase production. However, this expansion can be constrained by limitations to both water availability (SDG 6) and agricultural land. As a result, these limitations can lead to a switch from irrigated to dryland agriculture or a contraction in agricultural land. Yield and productivity also play important roles in determining food production (SDG 2) as they can directly impact the quantity of food produced and higher yields can lead to reduced agricultural land requirement to meet demand. Higher yields and productivity can result in an increase in food production (SDG 2). Increasing food production also directly influences economic growth (SDG 8). As another example, increasing the local population has positive effects on the increasing size of the labour force, particularly the skilled labour force, which can lead to synergistic effects on food production and economic growth in the GMID. However, it is also important to consider potential negative impacts that may arise from population growth, such as increased pressure on natural resources such as water use and increasing urban land use. Thus, addressing the challenges faced by the GMID requires a holistic approach that considers the interactions between different SDGs and strives to find win-win solutions that benefit both people and the environment.

3.3. Sub-model structure

Due to space limitations, we use an example of the Water availability sub-model (Figure 6) to illustrate how the sub-models work, while detailed descriptions of all sub-models are provided in the Supporting Information. In the form of *stocks* and *flows* diagrams, this sub-model shows interactions between surface water storage; water allocation for different consumptive uses; water use by different users; surface water recovery; net surface water trade in GMID; infiltration to groundwater; evaporation losses through the system; agricultural water demand; and domestic water demand. The Water Availability sub-model in LESEM is interconnected with other sub-models such as Demographics (using total population), Agriculture (based on the yield of beef, sheep, dairy, and crops), Economy (using water requirements for producing irrigated beef, sheep, and dairy pasture as well as crops), and Land Use (using projected beef, sheep, dairy, and cropping area). The detailed model documentation, including all seven sub-models, problem definition, equations, and data used is available in the Supplementary Information.

(A)



(B)

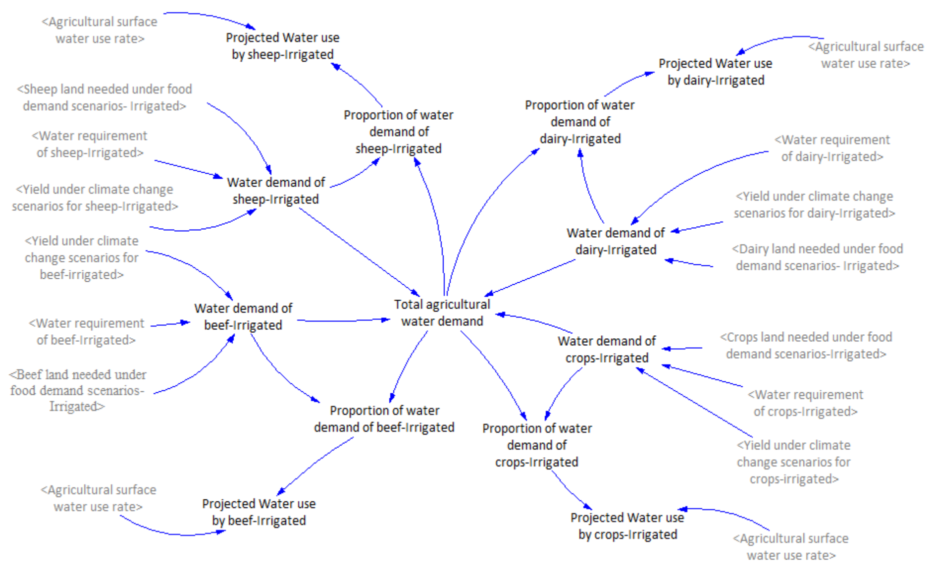


Figure 6. Schematic of system dynamics for the Water Availability sub-model. The Water availability sub-model separated into structures for water availability (A) and agricultural water demand (B). The Water availability sub-model includes causal loop diagrams, stock variables, flow variables, and other auxiliary variables. The shadow variables indicate the interlinkage between the Water sub-model and other sub-models. All these variables contain an equation described in Supporting Information.

3.4. Model validation

The LESEM BAU simulation results from 2010 to 2050 are shown in Figure 7, plotted alongside historical data obtained from local reports (Dairy Australia 2021; DAMD 2017; DELWP 2019; GBCMA 2017; HMC 2010; RMCG 2016a, 2016b, 2019), related websites of the Murray–Darling Basin Authority (MDBA) and Australian Bureau of Statistics census data (ABS 2022; MDBA 2022). The validation results for the 12 output variables demonstrated that the behaviour of the LESEM approximated their historical trends. It is evident from the simulation results that the projected trends of agricultural land, dairy land use, surface water storage, agricultural surface water use, and agricultural water allocation have been decreasing over time. In contrast, based on the simulation results, the output variables of cropping land use, dairy land use, environmental water allocation, river water salinity, annual agricultural revenue, population, and labour force exhibit an increasing trend in their projections.

The maximum relative error (M) values range from -0.05 for the area of surface water storage to 0.2 for annual agricultural revenue (Figure 7). The validation results indicate that the labour force, total population, agricultural water allocation, surface water use, surface water storage, and dairy production have shown better performance with the lowest M values equal to or below 5% compared to other output variables. Similarly, agricultural land, dairy land use, environmental water allocation, river water salinity, and cropping land use have M values equal to or below 10%. However, annual agricultural revenue has a relatively high M value of up to 20%, which could be due to uncertainties related to model structure, parameter, or input uncertainty (Kotir et al. 2016). Nevertheless, the purpose of the model is not to make precise numerical predictions of levels and volumes for key system variables, but rather to understand the dynamic behaviour patterns of these variables (Kelly et al. 2013; Kotir et al. 2016; Sterman 2002).

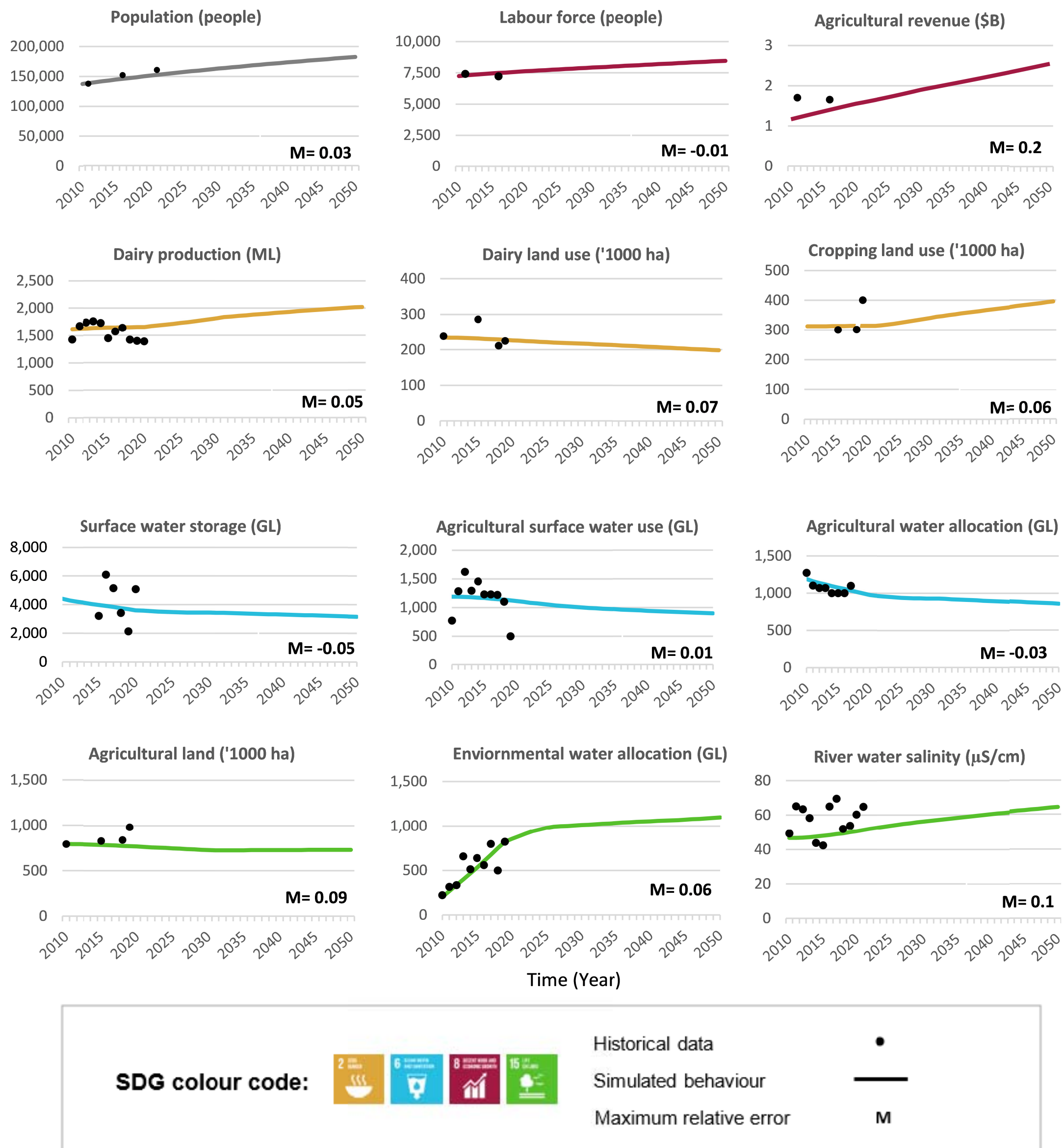


Figure 7. The comparison of the LESEM simulations with historical data. The graphs depict the BAU scenario projections for 12 output variables from 2010 to 2022, along with future projections to 2050.

3.5. Sensitivity and uncertainty analysis

Figure 8 displays the 36 influential model parameters selected and ranked by sensitivity analysis across all seven sub-models of the LESEM, including Demographics, Agriculture, Water availability, Land use, Economy, Fertiliser use, and Water quality sub-models by 2050. The results obtained from the Morris sensitivity analysis method revealed that the most influential input parameters were related to the Water Availability sub-model (SDG 6), followed by the Agriculture sub-model (SDG 2), and then the Demographics sub-model. As shown in Figure 8, the input parameter with the greatest influence on the output variables across most of the SDGs is water availability (SDG 6) in the region (specifically, the Reference Yarrawonga water yield). This parameter has an impact on multiple output variables, including surface water storage (SDG 6), agricultural revenue (SDG 8), blue-green algal bloom (SDG 15), crop production (SDG 2), and dairy production (SDG 2). Additionally, the parameter with the next highest influence is the fraction of agricultural water allocation (SDG 6), which affects output variables such as surface water storage (SDG 6), agricultural revenue (SDG 8), river water salinity (SDG 15), crop production (SDG 2), beef production (SDG 2), and dairy production (SDG 2). The diverse set of model input parameters enabled the demonstration of the interactions between different SDGs across all sub-models by showing the influence level of each input variable on output variables.

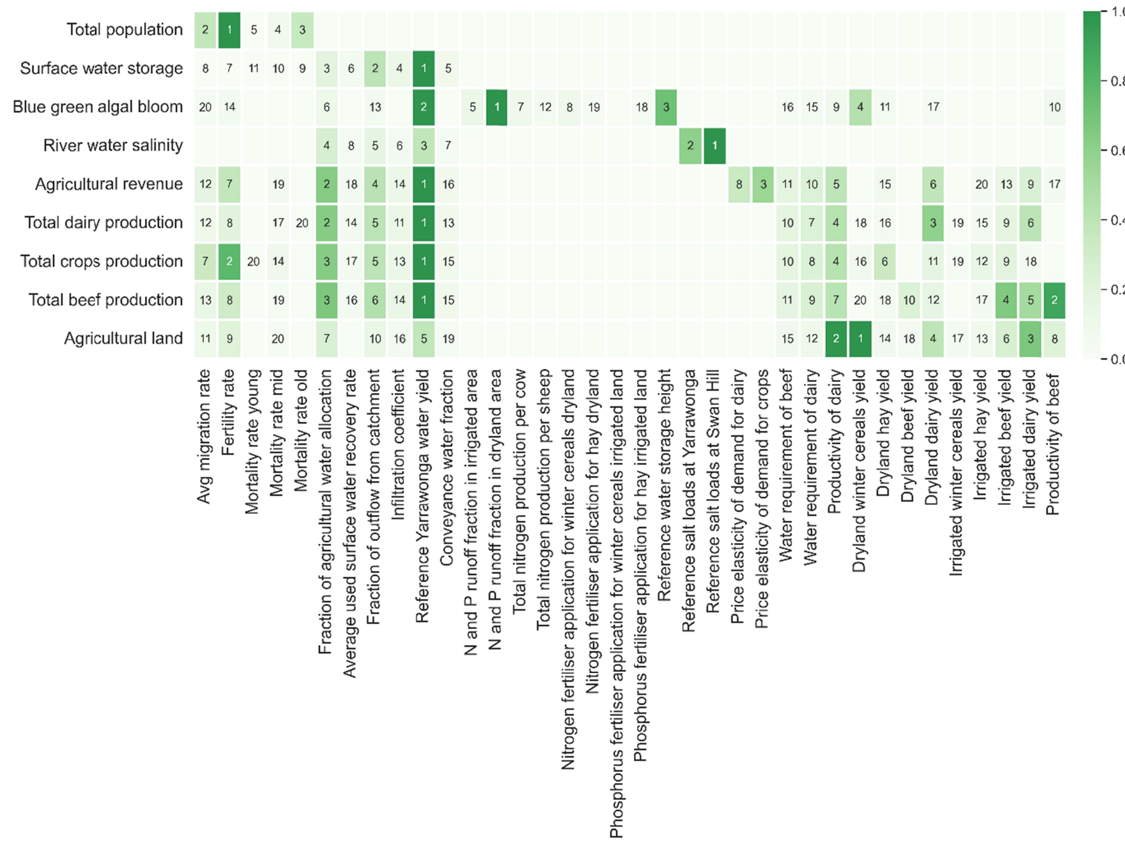


Figure 8. Ranking of model parameters based on their level of influence. Sensitivity is determined by calculating the normalised Morris index values (μ*) between 0 and 1. The sensitivity analysis investigated the effect of 36 input parameters (columns) on nine output variables (rows). A maximum of 20 of the most influential input parameters for each output variable are numbered. The colours in the grid cells represent the total sensitivity effects, while the numbers describe the rankings of parameter influence.

Figure 9 displays the uncertainty analysis outcomes for the nine chosen output variables. The results are presented as a density cloud representing the 2000 model simulations. The uncertainty ranges for certain variables, such as surface water storage, crop production, river water salinity, and dairy production, were much broader than other variables like total beef production and agricultural land, which had narrower ranges which tracked the median more closely. Furthermore, agricultural revenue, total population, and blue-green algal bloom exhibited relatively broader uncertainty ranges. Inspecting Figures 8 and 9 reveals that the blue-green algal bloom and agricultural revenue are influenced by a diverse range of input variables across all sub-models. This observation highlights the interactions of the SDGs and how changes in one aspect of the system can have cascading effects on other SDGs.

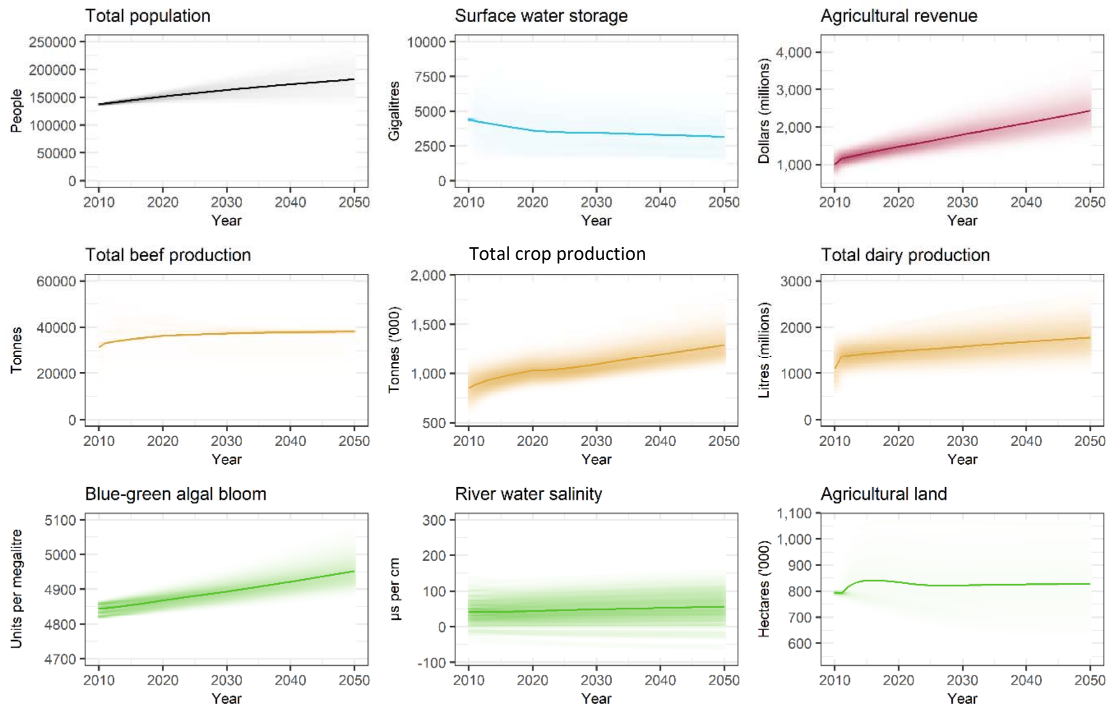


Figure 9. **The uncertainty analysis results of nine sustainability output variables.** The density cloud represents the variation in results obtained from 2000 simulations, considering the influence of 36 parameters on the model's behaviour.

3.6. BAU projection

The business-as-usual (BAU) scenario outcomes were projected for the period 2023-2050, with the assumptions listed in Table . Examples of the output variable projections under the BAU scenario are shown in Figure 7. The total population of GMID trajectories has shown an increase of 17%, primarily in areas such as Shepparton and Moira, which are less reliant on agriculture and not as affected by drought and water scarcity as other centres such as Gannawarra and Loddon. In contrast, rural areas with water scarcity have witnessed a shift towards larger farms and applying modern mechanisation of agriculture to stay competitive (RMCG 2016b). Nevertheless, a detailed analysis of age Demographics has revealed a trend of population aging and a decline in younger generation farmers (as shown in Figure S21 and Figure S22). The availability of irrigation water is a crucial factor in determining the area of irrigated land. The BAU scenario analysis projected the agricultural water allocation and agricultural water use in this region will gradually decrease until 2050 due to factors such as climate change, water trade, buybacks, and water reform policies (Figure 7). The projections indicate that from 2023 to 2050, there will be a 3% decrease in total agricultural land use, an 11% decrease in dairy land use, a 10% decrease in surface water storage and agricultural water allocation, and a 16% decrease in agricultural surface water use. Conversely, environmental surface water allocation is projected to increase by 17%.

The total cropping land use in the GMID is projected to increase by 24% by 2050. This is primarily due to the extensive cultivation of dryland crops, which require less irrigation water allocation, and the expected increase in agricultural productivity in the region. Consequently, agricultural revenue is expected to rise by 54% by 2050. The blue-green algal bloom in rivers and waterways is projected to increase by 2% due to nutrient pollution from agricultural runoff, exacerbated by climate change and decreasing available water in the GMID. Additionally, river water salinity in the GMID is projected to increase by 22% due to a combination of factors, including reduced water availability and increased evaporation, as well as agricultural practices such as irrigation, which can contribute to the build-up of salts in the soil and subsequent infiltration into groundwater and runoff into waterways.

4 Discussion

We have developed the LESEM system dynamics model through a participatory model building process with a group of local expert stakeholders. The LESEM enables a holistic view of environmental and socio-economic aspects of sustainable development by analysing interactions among selected, high-priority SDGs. By understanding SDG interactions in this local context, policymakers and planners can identify the unique sustainability challenges and opportunities facing their community and develop tailored strategies to address them. The participatory methods we employed helped to determine the system boundaries, priority SDGs, main local challenges and opportunities, and SDG interactions. We developed this model by incorporating multiple environmental and socio-economic aspects of sustainability via genuine stakeholder engagement during the model building process, paying particular attention to intersectoral connections using a participatory modelling approach (Moallemi et al. 2021). We illustrated the use of the model in projecting the trends of key sustainability outcomes by the year 2050 under a BAU scenario.

4.1. Synthesising SDG interactions in the study area

We provided several examples throughout all sub-models in the following section to demonstrate how LESEM can aid in analysing interactions between SDGs. The annual average water yield (SDG 6) under the BAU scenario (i.e., RCP 4.5) was projected to gradually decline (i.e., ~6% decrease from 2022 to 2050). This decline in stream flow as illustrated in Figure 7 exacerbates the depletion of surface water storage from 4400 Gigalitres (GL) to approximately 3166 GL over four decades. Multiple factors contribute to the reduced water availability in the GMID, including climate change, increased competition for water within the Murray-Darling Basin, and changes to water policy by the Australian federal government to reduce water available for irrigated agriculture and allocate water to the environment (SDG 15) (Alston et al. 2018; Hart 2016). However, the role of water markets in the GMID also plays a significant part in addressing water scarcity. The water market facilitates the allocation and trading of water entitlements, allowing for efficient water use and potential transfers between users. Under the BAU policy scenario and according to the Murray–Darling Basin water reforms (Hart 2016), environmental water allocation in the GMID increased from 224 GL in 2010 to approximately 823 GL in 2019 (Figure 7). A continuation of environmental water recovery, albeit at a greatly reduced rate, is expected to result in a further decline in average agricultural water use from 1188GL in 2010 to 897 GL in 2050.

The interactions of SDG 2 and SDG 6 have a significant impact on the development trajectories of agricultural land. The land use sub-model is influenced by the projected food demand under the BAU scenario, while also taking into account the constraints posed by the availability of agricultural land (i.e., maximum potential agricultural land, see Supplementary Information for more information) and water availability in the GMID. So, the reduction in available water (SDG 6) for agriculture and limited agricultural land is projected to cause a decrease in total agricultural land area (SDG 2) from 794,479 ha to 731,957 ha over the simulation period. However, the reduction in irrigated agricultural land is offset by an expansion in crop dryland production, which resulted in the overall expansion of cropping land-use from 312,827 ha in 2010 to 395,673 ha in 2050, driven by an increased demand for crop production.

The dairy industry (SDG 2) in the GMID is heavily reliant on irrigation water (SDG 6), which poses a significant challenge to farmers in responding to variable water supply and market prices. This challenge is especially acute during drought years when water is often traded to horticulture, reducing the availability of water for other uses (RMCG 2016a). Hence, the reduction in available water (SDG 6) is projected lead to a decline in dairy land use from 233,934 ha to 198,341 ha in 2050. In recent years, some dairy farms have become more flexible by transitioning away from the traditional reliance on grazing of perennial pastures, which have high water dependence. Instead, these farms use a mix of feed sources such as cut and carry, annual/perennial pastures, feed crops, silage, and holding feed stocks. This trend is likely to continue as long as it is profitable. However, in some parts of the GMID, there are still many dairy farms that heavily rely on perennial pastures. To address the challenge of irrigation water dependence, some mixed farms have shifted towards more dryland production, which requires lower inputs and involves opportunistic irrigation when water is more affordable and available. However, this transition can be challenging for farmers with small paddocks that are the legacy of ex-irrigation land, as they face substantial costs in adapting their farms to the new system (RMCG 2016a).

In this research, the agricultural productivity and yield for different commodities (SDG 2) under the BAU scenario (i.e., RCP 4.5 for agricultural yield) were projected to increase in the GMID, thus leading to an increase in agricultural production (SDG 2) in most agricultural commodities except wool. The generation and adoption of new knowledge and technologies, such as advanced farm machinery, better use of available technologies and management practices by farmers, improved chemicals and genetic modification, are key drivers of productivity growth in agriculture (Productivity Commission 2005). Productivity growth is crucial to the international competitiveness of Australia's agriculture sector which largely depends on world markets (Productivity Commission 2005). It can result in lower costs, increased output, higher farm incomes, and lower food prices for consumers. Furthermore, productivity growth in agriculture (SDG 2) can have positive environmental impacts by reducing agricultural land use (SDG 15) and water use by the farming sector (SDG 6) from 1188 GL in 2010 to 855 GL in 2050. Despite an overall reduction in agricultural land, increased agricultural productivity and yield are expected to lead to an eventual increase in agricultural production (SDG 2) and improve economic growth (SDG 8) in the GMID. For instance, crops production is estimated to grow from 889,579 tonnes in 2010 to 1,338,160 tonnes in 2050.

The development trajectories of agricultural revenue are significantly influenced by the interactions between SDG 2, SDG 6, and SDG 8. Agricultural productivity in the Agricultural sub-model, agricultural land in the Land use sub-model, and agricultural profit in the Economy sub-model are critical leverage points, which are essential for the ongoing viability of the economy across the GMID. Agricultural revenue was directly affected by food demand under the BAU scenario through the price elasticity of demand for different agricultural commodities and also by the input assumptions of the Land use and Agriculture sub-models. Agricultural revenue (SDG 8) was estimated to increase from 1.2 $B to 2.5 $B, respectively, from 2010 to 2050 (Figure 7 and Figure 8). Although we projected that agricultural land (SDG 2) shrinks due to water availability (SDG 6) restrictions, the model simulation results demonstrated growing revenue due to agricultural intensification, increasing agricultural yields (SDG 2), and increasing prices due to higher food demand for agricultural commodities including beef, sheep, dairy, and various crops under the BAU scenario. Agricultural intensification is supported by various measures like high input of fertilisers and pesticides, technological innovation including crop and livestock genotypes, enhanced management knowledge, and increased skilled labour availability (Hinz et al. 2020).

The interactions between SDG 2, SDG 6, and SDG 15 are critical to promoting sustainable agriculture, improving water quality, and preserving terrestrial ecosystems. The Water availability sub-model and Fertiliser use sub-model and their related assumptions and scenarios affected the Water quality sub-model. The blue-green algal bloom projection (SDG 15) showed an increasing trend under the BAU scenario from 4841 units per megalitre (ML) in 2010 to 4951 in 2050 units ML^{-1} (Figure 8) because of decreasing water yield (SDG 6) in the Murray River (Figure 7) and the increasing level of nutrient loss from agriculture practices (SDG 2). Without concomitant advances in nutrient-use efficiency, agricultural intensification and applying more fertilisers (SDG 2) in farming may result in higher nutrient loads (i.e., nitrogen and phosphorous) in runoff (SDG 15) which can adversely impact waterways (NCCMA 2016). Also, nitrogen and phosphorus combined with other conditions like high temperature and low flow lead to the growth of blue-green algae (GBWQWG 1995a; Lukasiewicz et al. 2012) and adverse outcomes such as fish kills (Vertessy et al. 2019). The growth of algal blooms imposes a cost on local communities due to side effects on the water quality of the Murray river (GBWQWG 1995a).

Another issue relating to agriculture in the GMID is an ageing population and rural depopulation (Bandari et al. 2022; RPG 2020). Although the total population projection demonstrates an increase from 137,322 people to 182,719 people from 2010 to 2050 (Figure 7), the rate of population changes in the 0-14 age cohort dropped from 2011 to 2021 (Figure S21). Furthermore, the rate of population changes in the 15-64 age cohort increased less compared with the sharp increase in the 65+ age cohort (Figure S21). This high rate of the ageing population shows an unsustainable Demographics structure, particularly in terms of the labour force which could affect the agriculture sector in the GMID. The change in labour force and skilled workforce affect the Agriculture sub-model by changing the agricultural productivity (SDG 2). This is because the 15-64 age cohort typically forms the bulk of the labour force, and as this cohort ages and moves into retirement, there may be a shortage of workers to replace them.

As the proportion of elderly individuals in the GMID population increases, there may also be increased pressure on social welfare systems and healthcare services. This can place a strain on government budgets and may require adjustments to social policies to accommodate the changing Demographics structure. To address these challenges, it is important to implement policies that support healthy ageing and promote the participation of older individuals in the labour force. In addition, there may be opportunities to encourage immigration and increase the birth rate to help balance the Demographics structure and ensure a steady supply of workers to support the economy. However, it is important to consider the social, cultural, and economic impacts of these policies, and to ensure that they are implemented in a way that is fair and equitable for all members of society. Overall, addressing the challenges associated with an ageing population requires a coordinated and collaborative effort from government, businesses, and civil society. By implementing policies and programs that support healthy ageing and promote the participation of older individuals in the labour force, it may be possible to ensure a more sustainable Demographics structure for the future.

4.2. Innovation and contribution

This paper contributes to the participatory modelling of SDG interactions through its innovative approach and collaborative efforts with local expert stakeholders. The study focused on the GMID, where the model was co-produced in collaboration with stakeholders with valuable local knowledge and expertise. This co-production process ensured that the model was contextually relevant to the GMID's specific challenges and aligned with the locally relevant SDGs. By involving local stakeholders in the modelling process, the paper enhances the inclusivity and effectiveness of the model by incorporating diverse perspectives and insights. This approach not only improves the accuracy and applicability of the model but also fosters a sense of ownership and engagement among the stakeholders, facilitating their active participation in shaping sustainable development strategies. Overall, the paper's innovation lies in its participatory approach to modelling SDG interactions, which empowers local stakeholders and enables more comprehensive and impactful decision-making processes.

4.3. Policy implications

The LESEM model results aid policymakers in identifying policy options and their outcomes for achieving SDGs and planning in the study area. For example, the model projections suggest that agricultural land area may decrease due to declining water resources availability, while agri-food production is likely to increase due to intensification to meet future demand (Productivity Commission 2005; RMCG 2016a). Policymakers should consider crop diversification with higher-value products or drought-resilient crops and improving water-saving technologies to mitigate the negative impacts of intensification on water availability and environmental sustainability, while also improving the future regional economy. In addition, the model can be used to evaluate the effectiveness of such policies and identify potential trade-offs and synergies with other SDGs. They can also test different scenarios of water yield and assess potential trade-offs between reducing the available water and water allocation for consumptive uses, agricultural production, water quality, and the economy. Furthermore, local policymakers can analyse a set of water recovery scenarios and study their impacts within and outside the Water Availability sub-model to estimate water saving or test environmental water allocation scenarios to assess the probable consequences on water quality, like salinity and algal bloom growth or agricultural water allocation.

LESEM can simulate the environmental impacts of applying more fertiliser for agriculture, including the impacts on nitrogen and phosphorus levels in soil and water, and the potential for harmful algal blooms. By simulating the impacts of different fertiliser application rates, policymakers can evaluate the potential environmental consequences of increased fertiliser use and design policies that promote sustainable agricultural practices. For instance, LESEM can simulate the effects of increased fertiliser use on soil quality and nutrient runoff and assess the potential for increased nitrogen and phosphorus levels in nearby water bodies. The model can also evaluate the potential for harmful algal blooms resulting from increased nutrient levels in water bodies, which can have significant impacts on aquatic ecosystems and human health. Using this information, policymakers can design policies that promote sustainable agricultural practices, such as adopting precision agriculture techniques that reduce fertiliser application rates while maintaining crop yields. These are a few examples of the policy implications of LESEM and how it can help policymakers to assess the effectiveness of policies.

4.4. Limitations and future work

LESEM like every other model is a simplified representation of the real-world (GMID in our case) social-ecological system. However, despite their simplicity, models can be valuable tools in policy-making as long as their limitations are not ignored (Gohari et al. 2017; Sterman 2002). We applied some simplifying assumptions in some of the sub-models, especially those with social parameters or those parameters which lacked available data. For example, we initially modelled the interaction between groundwater and surface water in the study area, but an insufficiency of reliable data posed a barrier to conducting this analysis. Therefore, we simplified this part of the model to only consider surface water because the most important challenge is declining the available surface water by almost 50% over the last 20 years (RPG 2020), and also surface water is the primary source of water supply in this area. In another example of simplification, in the Economy sub-system, we assumed that agricultural commodity prices changed through the price elasticity of food demand and other influential factors like farming costs (e.g., labour costs, quantity-dependent variable costs, operating costs, depreciation costs, and area-dependent variable costs) were held constant, except for water costs. Future work should examine a large number of scenarios covering a wide uncertainty space to cover future contingencies about socio-economic and environmental scenarios. Future model applications can examine the expected outcomes of the potential interventions to attain local sustainability goals and stress test important interventions to understand under what conditions the interventions may fail to achieve the sustainability goals.

5 Conclusion

This research highlights the potential contribution of system dynamics models in analysing the SDGs, their interactions, and the challenges associated with achieving sustainable development at the local level. Here we developed LESEM, a system dynamics model of local priority SDGs, through a participatory process with stakeholders to achieve local sustainability in the Goulburn-Murray Irrigation District in northern Victoria, Australia. LESEM considers and quantifies interactions among priority SDGs: Agriculture (SDG 2), water availability (SDG 6), economic growth (SDG 8), and life on land (SDG 15), under the BAU scenario and enables a systemic view of the environmental and socio-economic aspects of sustainability in the GMID from 2010 to 2050. Participatory modelling enabled a shared understanding of the important local dynamics between demographics, agriculture, economy, and environmental factors amongst researchers and stakeholders. The LESEM projections indicated that under the BAU scenario, agricultural land area may decrease due to declining water availability, with agricultural intensification helping to meet future food demand and via increased agri-food production, which could benefit the economy. But at the same time, intensification could lead to increased environmental pressures, such as nutrient runoff, blue-green algal bloom, and water pollution. These results indicate the need for sustainable management practices that balance economic development with environmental protection in the GMID to ensure sustainable development. This model gives us a tool to assess the system's leverage points for supporting policy-making and evaluation of potential interventions that generate stability and sustainability within this local area. This can inform the development of more integrated and effective policies and planning strategies that simultaneously address multiple sustainability issues. While the LESEM model was developed for a specific case, its ability to simulate progress towards multiple SDGs and measure their interactions can be adapted to other regions facing complex sustainability challenges.

6 Supplementary information

The manuscript contains additional information that supports the findings of this research.

7 Code and data availability

The model file, codes, and datasets generated during this study are available at the URL/DOI: 10.5281/zenodo.8110625. For additional information and resource requests, please direct your inquiries to Reihaneh Bandari (email: rbandari@deakin.edu.au).

8 Acknowledgements

The authors are grateful to the RM Consulting Group and the Goulburn Murray Resilience Taskforce for their valuable feedback through the model development phase. We thank Dr. Marco Calderon-Loor for the urban land use change data. This project was funded by The Ian Potter Foundation (grant number 20190016), North Central Catchment Management Authority, and Deakin University, Australia.

9 References

RMCG 2016, Basin Plan - GMID socio-economic impact assessment, Final Report for the GMID Water Leadership Forum, RM Consulting Group, October 2016.

ABS 2022, *Search Census data*, Australian Bureau of Statistics, <https://www.abs.gov.au/census/find-census-data>.

Aither 2019, *Goulburn Regional Profile: An analysis of regional strengths and challenges*, Infrastructure Victoria, A Report prepared for Infrastructure Victoria, www.infrastructurevictoria.com.au/wp-content/uploads/2019/04/Aither-Goulburn-Regional-Profile-March-2019.pdf.

Alston, M., Clarke, J. & Whittenbury, K. 2018, 'Limits to adaptation: Reducing irrigation water in the Murray-Darling Basin dairy communities', *Journal of Rural Studies*, vol. 58, pp. 93-102, DOI https://doi.org/10.1016/j.jrurstud.2017.12.026.

Baker, D., Dunn, A. & Olszak, C. 2018, *Water markets report*, Aither,Melbourne, VIC, https://www.aither.com.au/wp-content/uploads/2019/03/Aither-Water-markets-report-2017-18-3.pdf.

Bandari, R., Enayat, A.M., Rebecca, E.L., David, D. & Brett, A.B. 2022, 'Prioritising Sustainable Development Goals, characterising interactions, and identifying solutions for local sustainability', *Environmental Science & Policy*, vol. 127, pp. 325-36, DOI https://doi.org/10.1016/j.envsci.2021.09.016.

Barlas, Y. 1996, 'Formal aspects of model validity and validation in system dynamics', *System Dynamics Review 12, 183–210*, https://www.researchgate.net/profile/Mahdi_Bastan/post/How_to_validate_a_System_Dynamics_Model/attachment/59d6257c79197b8077983cc6/AS:317830619172868@1452788133199/download/1996+Barlas+Yaman+Formal+aspects+of+model+validity+and+validation+in+system+dynamics+1.pdf

Calderón-Loor, M., Hadjikakou, M. & Bryan, B.A. 2021, 'High-resolution wall-to-wall land-cover mapping and land change assessment for Australia from 1985 to 2015', *Remote Sensing of Environment*, vol. 252, DOI 10.1016/j.rse.2020.112148.

Campolongo, F., Cariboni, J. & Saltelli, A. 2007, 'An effective screening design for sensitivity analysis of large models', *Environmental Modelling & Software*, vol. 22, no. 10, pp. 1509-18, DOI 10.1016/j.envsoft.2006.10.004.

Collste, D., Pedercini, M. & Cornell, S.E. 2017, 'Policy coherence to achieve the SDGs: using integrated simulation models to assess effective policies', *Sustainability Science*, no. 6, p. 921, DOI 10.1007/s11625-017-0457-x.

Cummins, T. 2016, *Water Market Trends, Trends in Northern Victorian Water Trade 2001-2015*, The State of Victoria Department of Environment, Land, Water and Planning 2015, www.waterregister.vic.gov.au.

Dairy Australia 2021, *Murray Dairy trends report*, Dairy Australia, https://cdn-prod.dairyaustralia.com.au/murray-dairy/-/media/project/murraydairy/national-home/resources/2021/10/26/murraydairy2021reports/final-3662-murray-dairy-trends-report_2021_d6_web_1020.pdf?rev=d8a1ff43452a409dbc383352fa77498b.

DAMD 2017, *Regional irrigated land and water use mapping in the Goulburn Murray Irrigation District - Dairy evaluation*, Dairy Australia and Murray Dairy, https://www.gbcma.vic.gov.au/downloads/CatchmentEconomy/RILWUM_DairyEvaluationFinal2017_LowRes.pdf.

Davis, J.P. & Eisenhardt, K.M. 2007, 'Developing theory through simulation methods', *Academy of Management Review*, no. 32(2): 480–499., DOI https://doi.org/10.5465/amr.2007.24351453.

Dean Delahunty, Sinclair Knight Merz & Trust, N.H. 2002, *North-east salinity strategy surface water salinity monitoring: Ovens catchments - 2001*, Goulburn Murray Water, Tatura : Sinclair Knight Merz.

DELWP 2019, *Water Market Trends*, The State of Victoria Department of Environment, Land, Water and Planning, https://nla.gov.au/nla.obj-1641380916/view.

DELWP 2021, *Victorian Water Accounts-2019-2020, a statement of Victorian water resources*, the Department of Environment, Land, Water and Planning (DELWP), https://waterregister.vic.gov.au/water-availability-and-use/victorian-water-accounts.

Di Lucia, L., Slade, R. & Khan, J. 2021, 'Decision-making fitness of methods to understand Sustainable Development Goal interactions', *Nature Sustainability*, vol. 5, no. 2, pp. 131-8, DOI 10.1038/s41893-021-00819-y.

Eker, S., Zimmermann, N., Carnohan, S. & Davies, M. 2018, 'Participatory system dynamics modelling for housing, energy and wellbeing interactions', *Building Research & Information*, vol. 46, no. 7, pp. 738-54, DOI 10.1080/09613218.2017.1362919.

FAO 2011, *Global food losses and food waste – Extent*, causes and prevention. Rome, https://www.fao.org/3/i2697e/i2697e.pdf.

FAO 2017, *FAO balance sheets* Food and Agriculture Organization of the United Nations <http://www.fao.org/faostat/en/#data/FBSH>.

Fischer, G., Nachtergaele, F., Velthuizen, H.v., Chiozza, F., Franceschini, G., Henry, M., Muchoney, D. & Tramberend, S. 2021, 'Global Agro-Ecological Zones (GAEZ v4) Model documentation', *Rome, FAO*, DOI https://doi.org/10.4060/cb4744en.

Gao, L. & Bryan, B.A. 2016, 'Incorporating deep uncertainty into the elementary effects method for robust global sensitivity analysis', *Ecological Modelling*, vol. 321, pp. 1-9, DOI https://doi.org/10.1016/j.ecolmodel.2015.10.016.

Gao, L., Bryan, B.A., Nolan, M., Connor, J.D., Song, X. & Zhao, G. 2016, 'Robust global sensitivity analysis under deep uncertainty via scenario analysis', *Environmental Modelling & Software*, vol. 76, pp. 154-66, DOI 10.1016/j.envsoft.2015.11.001.

GBCMA 2013, *Goulburn Broken Regional Catchment Strategy 2013-2019*, Goulburn Broken Catchment Management Authority, https://www.gbcma.vic.gov.au/downloads/RegionalCatchmentStrategy/GBCMA_RCS_2013-19.pdf.

GBCMA 2017, *Regional Irrigated Land and Water Use Mapping In The Goulburn Murray Irrigation District: Technical Report*, https://www.gbcma.vic.gov.au/downloads/GMID_studies/RILWUM_TechnicalReportFinal2017_LowRes_30_3_2017.pdf.

GBWQWG 1995a, *Dryland Diffuse source nutrients for Goulburn Broken Catchment*, Goulburn Broken Water Quality Working Group https://www.gbcma.vic.gov.au/downloads/WaterQuality/GB_Water_Quality_WG-Dryland_Diffuse_Source_Nutrients_for_GBC-Issues_Paper_2.pdf.

GBWQWG 1995b, *Nutrients in irrigation drainage water from the Goulburn and Broken catchments : summary*, Goulburn Broken Water Quality Working Group, https://www.gbcma.vic.gov.au/downloads/WaterQuality/GB_Water_Quality_WG-Irrigation_Drainage-Issues_Paper_5.pdf.

GMIDWL 2018, *An Inquiry into the effectiveness of the implementation of the Basin Plan and water resource plan*, Goulburn Murray Irrigation District (GMID) Water Leadership, Productivity Commission Murray-Darling Basin Plan: Five-year Assessment, https://www.pc.gov.au/__data/assets/pdf_file/0020/227540/sub062-basin-plan.pdf.

GMW 2018a, *2017/18 Annual Report*, Goulburn-Murray Water, https://www.g-mwater.com.au/about/reports-and-publications/annualreports.

GMW 2018b, *Corporate Plan 2018/19 to 2022/23*, Goulburn-Murray Water, https://www.g-mwater.com.au/downloads/gmw/Corporate_Plans/2018-19_CorporatePlan.pdf.

GMW 2018c, *Goulburn-Murray Water*, Goulburn-Murray Water, retrieved retrieved 8 May 2019, <https://www.g-mwater.com.au/>.

Gohari, A., Mirchi, A. & Madani, K. 2017, 'System Dynamics Evaluation of Climate Change Adaptation Strategies for Water Resources Management in Central Iran', *Water Resources Management*, vol. 31, no. 5, pp. 1413-34, DOI 10.1007/s11269-017-1575-z.

Guo, L.-l., Qu, Y., Wu, C.-y. & Wang, X.-l. 2018, 'Identifying a pathway towards green growth of Chinese industrial regions based on a system dynamics approach', *Resources, Conservation and Recycling*, vol. 128, pp. 143-54, DOI 10.1016/j.resconrec.2016.09.035.

Gupta, M. & Hughes, N. 2018, *Future scenarios for the southern Murray–Darling Basin water market*, Australian Bureau of Agricultural and Resource Economics and Sciences, https://www.agriculture.gov.au/sites/default/files/documents/abares-future-scenarios-for-southern-mdb.pdf.

Hart, B.T. 2016, 'The Australian Murray–Darling Basin Plan: challenges in its implementation (part 1)', *International Journal of Water Resources Development*, vol. 32, no. 6, pp. 819-34, DOI https://doi.org/10.1080/07900627.2015.1083847.

Hinz, R., Sulser, T.B., Huefner, R., Mason-D'Croz, D., Dunston, S., Nautiyal, S., Ringler, C., Schuengel, J., Tikhile, P., Wimmer, F. & Schaldach, R. 2020, 'Agricultural Development and Land Use Change in India: A Scenario Analysis of Trade-Offs Between UN Sustainable Development Goals (SDGs)', *Earth's Future*, vol. 8, no. 2, DOI 10.1029/2019ef001287.

HMC 2010, *Changing land use in the GMID 2006 – 2010*, HMC Property Group, https://www.gbcma.vic.gov.au/downloads/CatchmentEconomy/Changing%20land%20use%20in%20the%20GMID%202016-2010%20FINAL.pdf.

Kelly, R.A., Jakeman, A.J., Barreteau, O., Borsuk, M.E., ElSawah, S., Hamilton, S.H., Henriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E., van Delden, H. & Voinov, A.A. 2013, 'Position paper: Selecting among five common modelling approaches for integrated environmental assessment and management', *Environmental Modelling and Software*, vol. 47, pp. 159-81, DOI 10.1016/j.envsoft.2013.05.005.

Kimmich, C., Gallagher, L., Kopainsky, B., Dubois, M., Sovann, C., Buth, C. & Bréthaut, C. 2019, 'Participatory Modeling Updates Expectations forIndividuals and Groups, Catalyzing BehaviorChange and Collective Action inWater-Energy-Food NexusGovernance', *Earth's Future*, vol. 7, no. 12, pp. 1337-52, DOI 10.1029/2019ef001311.

Kotir, J.H., Smith, C., Brown, G., Marshall, N. & Johnstone, R. 2016, 'A system dynamics simulation model for sustainable water resources management and agricultural development in the Volta River Basin, Ghana', *Sci Total Environ*, vol. 573, pp. 444-57, DOI 10.1016/j.scitotenv.2016.08.081.

Liu, H., Benoit, G., Liu, T., Liu, Y. & Guo, H. 2015, 'An integrated system dynamics model developed for managing lake water quality at the watershed scale', *J Environ Manage*, vol. 155, pp. 11-23, DOI 10.1016/j.jenvman.2015.02.046.

Lukasiewicz, A., Finlayson, C.M. & Pittock, J. 2012, *Identifying low risk climate change adaptation: A case study of the Goulburn Broken Catchment Management Authority*, Charles Sturt University, https://cdn.csu.edu.au/__data/assets/pdf_file/0012/884298/72_Gouburn-Broken-Case-Study.pdf.

MDBA 2022, *Live River Murray Data*, Murray–Darling Basin Authority (MDBA), <https://riverdata.mdba.gov.au/system-view>.

Moallemi, E.A., Aye, L., de Haan, F.J. & Webb, J.M. 2017, 'A dual narrative-modelling approach for evaluating socio-technical transitions in electricity sectors', *Journal of Cleaner Production*, vol. 162, pp. 1210-24, DOI 10.1016/j.jclepro.2017.06.118.

Moallemi, E.A., Bertone, E., Eker, S., Gao, L., Szetey, K., Taylor, N. & Bryan, B.A. 2021, 'A review of systems modelling for local sustainability', *Environmental Research Letters*, vol. 16, no. 11, DOI 10.1088/1748-9326/ac2f62.

Moallemi, E.A., Gao, L., Eker, S. & Bryan, B.A. 2022a, 'Diversifying models for analysing global change scenarios and sustainability pathways', *Global Sustainability*, vol. 5, DOI 10.1017/sus.2022.7.

Moallemi, E.A., Hosseini, S.H., Eker, S., Gao, L., Bertone, E., Szetey, K. & Bryan, B.A. 2022b, 'Eight Archetypes of Sustainable Development Goal (SDG) Synergies and Trade-Offs', *Earth's Future*, vol. 10, no. 9, DOI 10.1029/2022ef002873.

Morris, M.D. 1991, 'Factorial Sampling Plans for Preliminary Computational Experiments', *Technometrics*, vol. 33, no. 2, pp. 161-74, DOI 10.1080/00401706.1991.10484804.

Naderi, M.M., Mirchi, A., Bavani, A.R.M., Goharian, E. & Madani, K. 2021, 'System dynamics simulation of regional water supply and demand using a food-energy-water nexus approach: Application to Qazvin Plain, Iran', *J Environ Manage*, vol. 280, p. 111843, DOI 10.1016/j.jenvman.2020.111843.

Navarro, J. & Marcos Martinez, R. 2021, *Estimating long-term profits, fertiliser and pesticide use baselines in Australian agricultural regions*, User Guide. CSIRO, Australia.

NCCMA 2016, *North Central Victoria Regional Sustainable Agriculture Strategy*, North Central Catchment Management Authority, http://www.nccma.vic.gov.au/sites/default/files/publications/nccma_sustainable_agriculture_strategy_2016_final_web.pdf.

Neumann, K., Anderson, C. & Denich, M. 2018, 'Participatory, explorative, qualitative modeling: application of the iMODELER software to assess trade-offs among the SDGs', *Economics-the Open Access Open-Assessment E-Journal*, vol. 12, no. 1, DOI 10.5018/economics-ejournal.ja.2018-25.

Nilsson, M., Chisholm, E., Griggs, D., Howden-Chapman, P., McCollum, D., Messerli, P., Neumann, B., Stevance, A.S., Visbeck, M. & Stafford-Smith, M. 2018, 'Mapping interactions between the sustainable development goals: lessons learned and ways forward', *Sustain Sci*, vol. 13, no. 6, pp. 1489-503, DOI 10.1007/s11625-018-0604-z.

Nilsson, M., Griggs, D. & Visbeck, M. 2016, 'Map the interactions between Sustainable Development Goals', *Comment in Nature*, vol. 53, no. 7607, DOI https://doi.org/10.1787/agr_outlook-2015-en.

Norström, A.V., Cvitanovic, C., Löf, M.F., West, S., Wyborn, C., Balvanera, P., Bednarek, A.T., Bennett, E.M., Biggs, R., de Bremond, A., Campbell, B.M., Canadell, J.G., Carpenter, S.R., Folke, C., Fulton, E.A., Gaffney, O., Gelcich, S., Jouffray, J.-B., Leach, M., Le Tissier, M., Martín-López, B., Louder, E., Loutre, M.-F., Meadow, A.M., Nagendra, H., Payne, D., Peterson, G.D., Reyers, B., Scholes, R., Speranza, C.I., Spierenburg, M., Stafford-Smith, M., Tengö, M., van der Hel, S., van Putten, I. & Österblom, H. 2020, 'Principles for knowledge co-production in sustainability research', *Nature Sustainability*, vol. 3, no. 3, pp. 182-90, DOI 10.1038/s41893-019-0448-2.

Oijen, M.V., Rougier, J. & Smith, R. 2005, 'Bayesian calibration of process-based forest models: bridging the gap between models and data', *Tree Physiology 25, 915–927*, DOI https://doi.org/10.1093/treephys/25.7.915.

Pearson, L.J., Biggs, R., Harris, M. & Walker, B. 2013, 'Measuring sustainable development: The promise and difficulties of implementing inclusive wealth in the Goulburn-Broken catchment, Australia', *Sustainability: Science, Practice, and Policy*, vol. 9, no. 1, pp. 16-27, DOI https://doi.org/10.1080/15487733.2013.11908104.

Pedercini, M., Arquitt, S. & Chan, D. 2020, 'Integrated simulation for the 2030 agenda', *System Dynamics Review*, vol. 36, no. 3, pp. 333-57, DOI 10.1002/sdr.1665.

Pradhan, P., Costa, L., Rybski, D., Lucht, W. & Kropp, J.P. 2017, 'A Systematic Study of Sustainable Development Goal (SDG) Interactions', *Earths Future*, vol. 5, no. 11, pp. 1169-79, DOI https://doi.org/10.1002/2017ef000632.

Productivity Commission 2005, *Trends in Australian Agriculture*, https://www.pc.gov.au/research/completed/agriculture.

Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., HumpenAaAaAeA der, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A. & Tavoni, M. 2017, 'The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview', *Global Environmental Change*, DOI 10.1016/j.gloenvcha.2016.05.009.

RMCG 2016a, *Basin Plan- GMID socio-conomic impact assessment*, RM Consulting Group, GMID Water Leadership Forum., http://rmcg.com.au/app/uploads/2017/01/Basin-Plan-Impact-GMID_Final_14-October-2016.pdf.

RMCG 2016b, *Understanding Water Availability Farm/Food Processor Viability in the GMID– Phase 1 understanding the issues*, RM Consulting Group, https://www.gbcma.vic.gov.au/downloads/GMID_studies/20161205final_Understanding_Water_availability_post_consultation.pdf.

RMCG 2019, *GMID Strategic Plan: Regional Insights*, RM Consulting Group., https://www.rmcg.com.au/app/uploads/2019/07/InsightsPaper_Finalv2_r.pdf.

RPG 2020, *Goulburn Murray Resilience Strategy*, Regional Partnership Goulburn. , http://www.rmcg.com.au/app/uploads/2020/08/GMID-Resilience-Strategy_04_Sep_20.pdf.

Rydzak, F., Obersteiner, M. & Kraxner, F. 2010, 'Impact of Global Earth Observation - Systemic view across GEOSS societal benefit area', *International Journal of Spatial Data Infrastructures Research*, pp. 216–43, DOI 10.2902/1725-0463.2010.05.art9.

Rydzak, F., Obersteiner, M., Kraxner, F., Fritz, S. & McCallum, I. 2013, *FeliX3 – Impact Assessment Model Systemic view across Societal Benefit Areas beyond Global Earth Observation*, Austria: IIASA. Model Report and Technical Documentation, https://github.com/iiasa/Felix-Model/blob/master/Felix3_ModelReport.pdf.

Samsó, R., de Blas, I., Perissi, I., Martelloni, G. & Solé, J. 2020, 'Scenario analysis and sensitivity exploration of the MEDEAS Europe energy-economy-environment model', *Energy Strategy Reviews*, vol. 32, DOI 10.1016/j.esr.2020.100582.

Sharp, R., Douglass, J., Wolny, S., Arkema, K., Bernhardt, J., Bierbower, W., Chaumont, N., Denu, D., Fisher, D., Glowinski, K., Griffin, R., Guannel, G., Guerry, A., Johnson, J., Hamel, P., Kennedy, C., Kim, C.K., Lacayo, M., Lonsdorf, E., Mandle, L., Rogers, L., Silver, J., Toft, J., Verutes, G., Vogl, A.L., Wood, S. & Wyatt, K. 2018, *InVEST User's Guide, Integrated Valuation of Ecosystem Services and Tradeoffs*, The Natural Capital Project, Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund, https://naturalcapitalproject.stanford.edu/software/invest.

Song, X., Bryan, B.A., Paul, K.I. & Zhao, G. 2012, 'Variance-based sensitivity analysis of a forest growth model', *Ecological Modelling*, vol. 247, pp. 135-43, DOI 10.1016/j.ecolmodel.2012.08.005.

Sterman, J. 2002, 'Business Dynamics, System Thinking and Modeling for a Complex World', in Massachusetts Institute of Technology.

Szetey, K., Moallemi, E.A., Ashton, E., Butcher, M.C., Sprunt, B. & Bryan, B.A. 2021, 'Participatory planning for local sustainability guided by the Sustainable Development Goals', *Ecol. Soc*, vol. 26,

UN 2015, *Transforming our world: the 2030 Agenda for Sustainable Development*, A/RES/70/1. UN General Assembly, New York, https://sustainabledevelopment.un.org/content/documents/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf.

Van Soest, H.L., Van Vuuren, D.P., Hilaire, J., Minx, J.C., Harmsen, M.J.H.M., Krey, V., Popp, A., Riahi, K. & Luderer, G. 2019, 'Analysing interactions among Sustainable Development Goals with Integrated Assessment Models', *Global Transitions*, vol. 1, pp. 210-25, DOI https://doi.org/10.1016/j.glt.2019.10.004.

Vennix, J. 1996, *Group Model Building : Facilitating Team Learning Using System Dynamics*, Wiley.

Ventana Systems, I. 2021, *Vensim DSS. Ventana Systems Inc*, Ventana Systems Inc <https://vensim.com/>.

Vertessy, R., Barma, D., Baumgartner, L., Mitrovic, S., Sheldon, F. & Bond, N. 2019, *Independent assessment of the 2018-19 fish deaths in the lower Darling*, https://www.mdba.gov.au/sites/default/files/pubs/Final-Report-Independent-Panel-fish-deaths-lower%20Darling_4.pdf.

VSG 2019, *Victorian Water Accounts*, Victoria State Government, <https://accounts.water.vic.gov.au/>.

Wang, C., Peng, M. & Xia, G. 2020, 'Sensitivity analysis based on Morris method of passive system performance under ocean conditions', *Annals of Nuclear Energy*, vol. 137, DOI 10.1016/j.anucene.2019.107067.

Wang, G., Xiao, C., Qi, Z., Meng, F. & Liang, X. 2021, 'Development tendency analysis for the water resource carrying capacity based on system dynamics model and the improved fuzzy comprehensive evaluation method in the Changchun city, China', *Ecological Indicators*, vol. 122, DOI 10.1016/j.ecolind.2020.107232.

Zhang, Q., Prouty, C., Zimmerman, J.B. & Mihelcic, J.R. 2016, 'More than Target 6.3: A Systems Approach to Rethinking Sustainable Development Goals in a Resource-Scarce World', *Engineering*, vol. 2, no. 4, pp. 481-9, DOI 10.1016/j.Eng.2016.04.010.