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Special Section:
Multi-Sector Dynamics: Advancing Complex Adaptive Human-Earth Systems Science in a World of Interconnected Risks

Key Points:
- We used a participatory approach to co-design a systems model with stakeholders for analyzing local sustainability
- The model quantifies the interactions among SDG 2, SDG 6, SDG 8, and SDG 15 and we applied it under a Business-As-Usual (BAU) future
- Under the BAU, agri-food production increased despite less water due to intensification, but there were environmental spillover effects

Supporting Information:
Supporting Information may be found in the online version of this article.

Correspondence to:
R. Bandari,
rbandari@deakin.edu.au

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Participatory Modeling for Analyzing Interactions Between High-Priority Sustainable Development Goals to Promote Local Sustainability

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

[1]School of Life and Environmental Sciences, Deakin University, Melbourne, Australia, [2]International Institute for Applied Systems Analysis, Laxenburg, Austria, [3]CSIRO Agriculture and Food, VIC, Australia, [4]CSIRO Black Mountain, Canberra, ACT, Australia, [5]Principal and Director, RMCG, Bendigo, VIC, Australia, [6]CSIRO Environment, Canberra, ACT, Australia, [7]Network for Education and Research on Peace and Sustainability (NERPS), Hiroshima University, Hiroshima, Japan

Abstract Achieving the Sustainable Development Goals (SDGs) is challenging given the complex interactions between different SDGs and their spillover effects. We developed a system dynamics model—the Local Environmental and Socio-Economic Model (LESEM)—to analyze 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 the Goulburn-Murray Irrigation District in Victoria, Australia, to assist policymakers in analyzing local issues with a more integrated and holistic approach to sustainable development at the local scale. The process of participatory systems dynamics modeling facilitates integrated and strategic decision-making and can help local policymakers identify and quantify potential trade-offs and synergies that benefit multiple SDGs, which eventually leads local communities toward sustainability. We present an illustrative application of the model that quantifies SDG interactions across four high-priority SDGs, namely clean water and sanitation (SDG 6), zero hunger (SDG 2), economic growth (SDG 8), and life on land (SDG 15). We illustrate the use of the model in assessing key SDG indicator trajectories under a business-as-usual (BAU) scenario from 2010 to 2050. Under the BAU, agri-food production increased despite a decline in water resource availability, with gains driven by intensification and increased agricultural productivity. This boosted local prosperity and reduced the amount of agricultural land required to meet future agri-food demand, thereby reducing pressures on terrestrial ecosystems and creating the space for ecological restoration and carbon storage in soils and biomass. However, agricultural intensification impacted water quality through increases in algal blooms and river salinity.

Plain Language Summary The 17 Sustainable Development Goals represent a comprehensive and ambitious plan to improve society, boost the economy, and protect the environment. However, it's challenging to achieve these goals because they interact with and impact one another in complex ways. To better understand these interactions, we apply a system dynamics model to analyze how different goals influence each other at a local level by involving the input of stakeholders. In this study, we focused on four critical goals: zero hunger, clean water and sanitation, economic growth, and life on land. We explored projections from 2010 to 2050 under business-as-usual trends. The results revealed that, even if water becomes scarcer, food production can still go up if we farm smarter and more efficiently. This is good for the local economy and means that less land is needed for farming, which helps the environment. It also creates room for nature to bounce back and for the soil and plants to store more carbon. However, agricultural intensification can adversely affect water quality. Our model supports decision-makers in balancing multiple goals, identifying potential trade-offs, and synergies that benefit the sustainable development of local communities.

1. Introduction

The Sustainable Development Goals (SDGs), established as part of the UN 2030 Agenda, represent a vision of a sustainable world spanning economic, social, and environmental dimensions and include 17 goals and 169 targets which are "*integrated and indivisible*" (UN, 2015). The integration and complexity of the 2030 Agenda mean there may be conflicts when the goals interact (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

Author Contributions:

Conceptualization: Reihaneh Bandari, Enayat A. Moallemi, Brett A. Bryan
Data curation: Reihaneh Bandari, Claire Flanagan-Smith, Michalis Hadjikakou, Raymundo Marcos-Martinez, Brett A. Bryan
Formal analysis: Reihaneh Bandari, Katrina Szetey, Claire Flanagan-Smith
Funding acquisition: Brett A. Bryan
Investigation: Reihaneh Bandari, Enayat A. Moallemi
Methodology: Reihaneh Bandari, Enayat A. Moallemi, Claire Flanagan-Smith, Brett A. Bryan
Project Administration: Brett A. Bryan
Resources: Reihaneh Bandari, Michalis Hadjikakou, Raymundo Marcos-Martinez, Brett A. Bryan
Software: Reihaneh Bandari, Katrina Szetey
Supervision: Enayat A. Moallemi, Brett A. Bryan
Validation: Reihaneh Bandari, Enayat A. Moallemi, Ali Kharrazi, Robert Šakić Trogrlić, Brett A. Bryan
Visualization: Reihaneh Bandari, Katrina Szetey, Brett A. Bryan
Writing – original draft: Reihaneh Bandari
Writing – review & editing: Reihaneh Bandari, Enayat A. Moallemi, Katrina Szetey, Claire Flanagan-Smith, Michalis Hadjikakou, Raymundo Marcos-Martinez, Ali Kharrazi, Robert Šakić Trogrlić, Brett A. Bryan

fulfillment 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).

Modeling is often used to develop an understanding of system interactions and their resulting synergies and trade-offs. System dynamics modeling in particular is of 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 modeling makes causal interactions across complex systems' sectors explicit (Davis & Eisenhardt, 2007; Pedercini et al., 2020) and hence, can quantify interactions between model components and thus guide sustainability decision-making. 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 contextual understandings is incorporated (Moallemi, de Haan, et al., 2021; Norström et al., 2020). System dynamics modeling has the capacity to support participatory modeling process for knowledge co-production (Vennix, 1996). Participatory system dynamics modeling 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 behavior change as the outputs of the model.

A review by Moallemi, Bertone, et al. (2021) identified over 100 studies that used system dynamics for analyzing SDG interactions and concluded that many of these did not focus on synergies and trade-offs. Both Moallemi, Bertone, et al. (2021) and Zhang et al. (2016) additionally identify that system archetypes (feedback loop structures that commonly occur in models of social-ecological systems) can be a useful tool in qualitatively characterizing SDG interactions (Moallemi, Hosseini, et al., 2022). Van Soest et al. (2019) examined how the Integrated Assessment Modeling (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. Jagustović et al. (2021) developed a context-based system dynamics model to inform the sustainable transformation of food systems through investigating synergies and trade-offs in a climate-smart village. These studies illustrate the potential for systems modeling for analyzing SDG interactions including synergies and trade-offs.

In this study, we developed a system dynamics model called the Local Environmental and Socio-Economic Model (LESEM) to simulate the local 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 locally relevant SDGs. The GMID is a highly productive agricultural region with a complex social-ecological system of interconnected components with major components including, people, agriculture, water, economy, and environment. The LESEM simulates progress toward four high-priority SDGs in the GMID region as identified by Bandari et al. (2022), including zero hunger (SDG 2), clean water and sanitation (SDG 6), economic growth (SDG 8), and life on land (SDG 15), and quantifies their interactions. The model captures 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, labor force, skilled workforce, population aging, agricultural productivity, and land use change. We illustrate the use of the model under a BAU scenario from 2010 to 2050. LESEM, as a decision-support tool, enables policymakers and planners to adopt a comprehensive and integrated perspective when addressing local challenges, thereby facilitating sustainable development at the local level. This paper is structured as follows: we describe how we co-developed, validated, and ran the model under a business-as-usual scenario. We then synthesize and discuss the implications of the model results, and analyze the interactions identified. We conclude with examining policy implications and what future research may lead from this research.

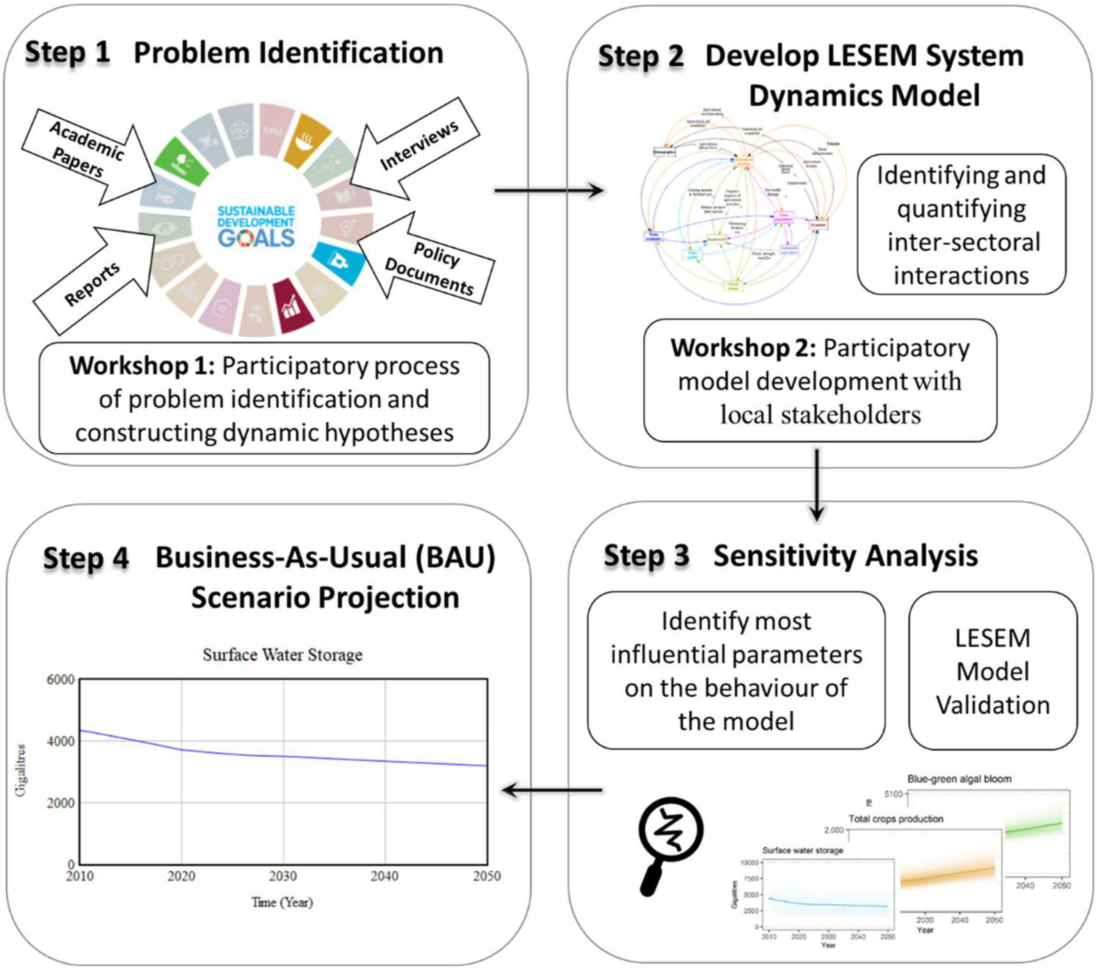

Figure 1. Conceptual schema of the LESEM participatory systems dynamics model-building process.

2. Methods

2.1. Overview

As illustrated in Figure 1, the modeling 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 other 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 behavior and validated its performance. Finally, in Step 4 we parameterized the model and conducted simulations based on a Business-As-Usual (BAU) scenario.

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

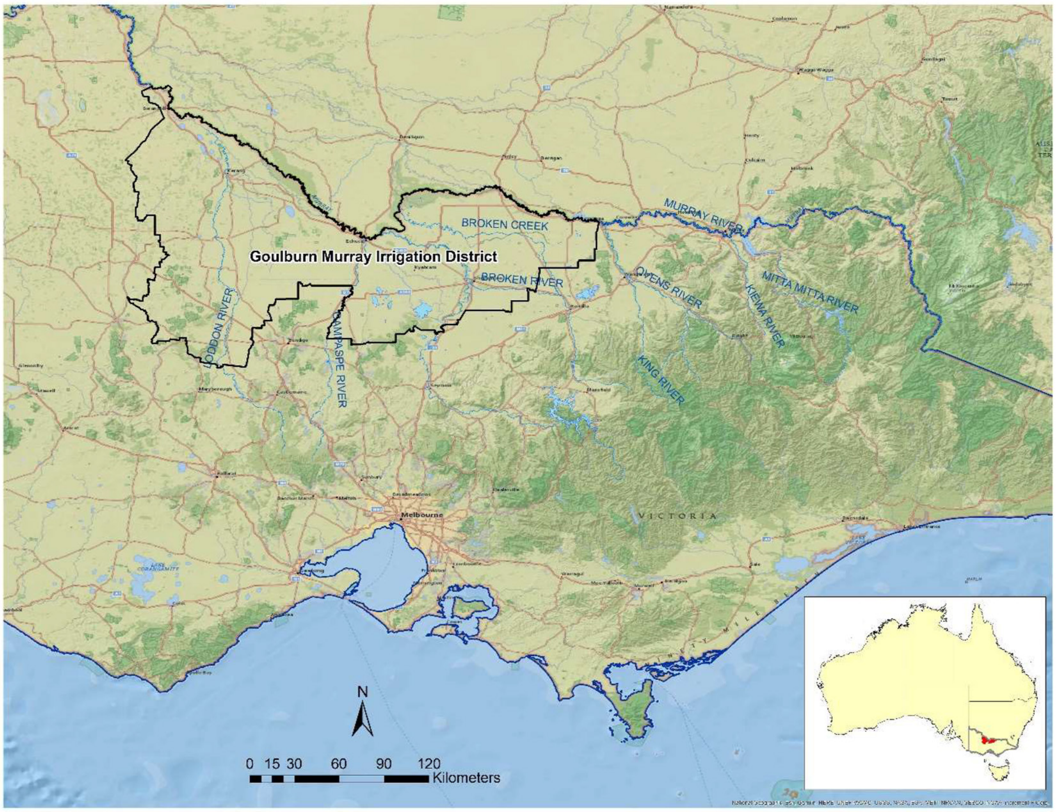

Figure 2. A map of the case study area. The Goulburn Murray Irrigation District (GMID) is specified with a black boundary. The inset map indicates the case study location in the context of the state of Victoria, Australia.

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 20 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 for agriculture (Bandari et al., 2022), the product of extensive water buybacks for the environment and climate change. Additionally, factors such as ageing and declining demographic trends have impacted agricultural activities in the GMID through reduced workforce (particularly skilled) availability and could potentially affect future food production and human wellbeing in the region (GBCMA, 2013; RPG, 2020). Furthermore, this region has already 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 social-ecological 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 complexly interacting processes and in assisting policymakers to plan for the future.

2.3. Participatory Model Development

The decision to employ system dynamics (SD) was made collaboratively by our research team, which consists of experts with diverse backgrounds and experience in employing a range of participatory methods and modeling

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techniques in addressing sustainability challenges at the local scale. The choice of SD was driven by its proven effectiveness in capturing complex feedback relationships, understanding sectoral linkages, and recognizing non-linear patterns in socio-economic and environmental systems, as substantiated by numerous studies (Babatunde et al., 2017; Greeven et al., 2016; Sterman et al., 2012; van Beek et al., 2020; Wiedmann, 2009). Furthermore, SD has a rich history of being employed in sustainability research, offering a deep understanding of the potential effects of actions, including unanticipated outcomes, and assisting in decision-making processes.

We began the model development process by delineating the system boundary. The primary sources of information for defining system boundaries (i.e., problem articulation and dynamic hypotheses) included policy documents, academic papers, local sectoral reports, and interviews with local stakeholders which has been fully described in Bandari et al. (2022). The simulation model was constructed using Vensim software (Ventana Systems Inc, 2021), and the simulation period spanned 2010 to 2050, utilizing annual time steps to provide a detailed and structured analysis over the selected time frame. 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, which was about *system understanding*, we utilized in-person and online participatory techniques to facilitate the co-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 organizations such as the Goulburn Broken Catchment Management Authority (GBCMA), the Australian Government Department of Energy, Environment and Climate Action (DEECA), Agriculture Victoria, Goulburn Murray Water, Goulburn Valley Water, Regional Development Victoria, and Murray Dairy. 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 develop the GMID model to more effectively address 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. 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 challenges were defined, along with the contributing factors. Using this information, 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 10 attendees from the Goulburn-Murray Resilience Taskforce. During the second workshop, which was about *model feedback and improvement*, we first presented the draft of GMID system dynamics model including 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. To facilitate this process, we printed each of the seven 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 helped further improve some parts of the causal loop diagrams to better reflect local challenges. We iterated this process to improve each sector and their interactions aligned with the system understandings offered by local expert stakeholders. Finally, to validate and refine the model results, we maintained ongoing communication with experts from the RM consultancy group and members of the Goulburn Murray Resilience Taskforce. Their insights were instrumental in confirming the accuracy and relevance of our findings.

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 and may include constants. Following the second workshop, causal loop diagrams were integrated and converted into quantitative stock-and-flow systems dynamics structures and parameterized to perform simulations. We implemented and formalized these causal feedback loops in Vensim DSS version 8.2.1 (Ventana Systems Inc, 2021) in seven sub-models: Demographics, Agriculture, Water Availability, Land use, Economy, Fertilizer 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 also inspired by the FeliX model and modified according to local biogeochemical processes and land management in the GMID (GBWQWG, 1995b; Rydzak et al., 2013). The Demographics sub-model was adapted from the RUSEM model (Navarro & Tapiador, 2019) and other components like labour force and education were added to this sub-model based on stakeholder input (see Supporting Information S1 for details).

2.4. Model Verification and Validation

Direct structural tests and structurally oriented behavior tests were used to assess the validity of the model (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 modeling process of this research formed the main part of direct empirical structural tests applied in two workshops with local expert stakeholders.

Structurally oriented model behavior tests were also used to indirectly evaluate the model structure's validity through simulation to detect potential 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 behavior 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 15 output variables from the perspective of local sustainability. The selection of these 15 output variables for local sustainability was based on a combination of factors, such as their importance in achieving sustainability outcomes, consultation with local stakeholders, and the availability and quality of data. As the historical data records (2010–2022) were incomplete for some of 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 output variables (Equation 1) (Liu et al., 2015; Naderi et al., 2021).

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

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, M values under 10% shows that the model satisfactorily fits the available data (Kotir et al., 2016).

2.5. Sensitivity Analysis

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 analyze the behavior of eight output variables. After evaluating them, we identified 36 parameters that were most influential on model behavior, 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 model outputs (Samsó et al., 2020) using Morris elementary effects (Campolongo et al., 2007; Moallemi, Gao, et al., 2022; 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 screen input parameters that are benign, 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). During sensitivity analysis, we identified flaws in the model that necessitated modifications. Following the identification of flaws and subsequent modifications to the model, we conducted other rounds of validation. This iterative process allowed us to refine the model to a more accurate representation of the system dynamics we are investigating for this region. The revised model demonstrated better alignment with the historical data, thereby providing a more solid foundation for our analysis and conclusions. 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 normalized 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.

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 10 parameters under the BAU scenario, and the key assumptions in each sub-model are presented in (Table 2). 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. The timeframe for the model simulation was set from 2010 to 2050. There are other parameters throughout the LESEM (Table 2) 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 behavior that more closely resembled observed data. The Shared Socio-economic Pathway (SSP) 2 (O'Neill et al., 2017; Riahi et al., 2017) combined with Representative Concentration Pathway (RCP) 4.5 (van Vuuren et al., 2011) 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 utilized 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.

3. Results

3.1. Model Structure

The LESEM (Figure 3) is based on the four highest priority local SDGs: zero hunger (SDG 2), clean water and sanitation (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: (a) Demographics, (b) Agriculture, (c) Water Availability, (d) Land Use, (e) Economy, (f) Fertilizer Use, and (g) Water Quality (see Supporting Information S1 for 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 SSP 2 on agricultural productivity, and food demand, while the effects of RCP 4.5 were observed on water yield and agricultural yield (Figure 3).

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	4,726	3,308	6,144
11	Conveyance water fraction	1/Year	0.1	0.070	0.130
	Fertilizer 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 fertilizer 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 fertilizer application for winter cereals dryland	Kg/head	48	33.6	62.4
18	Nitrogen fertilizer application for hay dryland	Kg/head	70	49	91
19	Phosphorus fertilizer 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	173,423	121,396	225,450
22	Reference salt loads at Swan Hill	tonnes/year	233,754	163,628	303,880
	Local economy				
23	Water requirement of dairy	Million liters/ha	2.68	1.88	3.49
24	Water requirement of beef	Million liters/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	liters/head	5,854	4,098	7,611
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

Table 2
Description of Key Parameter Settings Under the BAU Scenario 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, Fertilizer 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 2010 levels (FAO, 2011) and population following an SSP 2 trajectory (Riahi et al., 2017) (Table S3 in Supporting Information S1)
	Livestock productivity	Livestock productivity time series (Table S1 in Supporting Information S1), including beef, sheep meat, wool (unit: tonnes/head), and dairy (unit: liters/head) under the BAU scenario was taken from Navarro and 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 in Supporting Information S1) 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 to 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 the 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 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 (2019a) 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)

3.2. Cause-And-Effect Interactions

In Figure 4, the integrated nature of the priority SDGs is illustrated with selected trade-offs and synergies and the impacts of various parameters under the BAU scenario 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

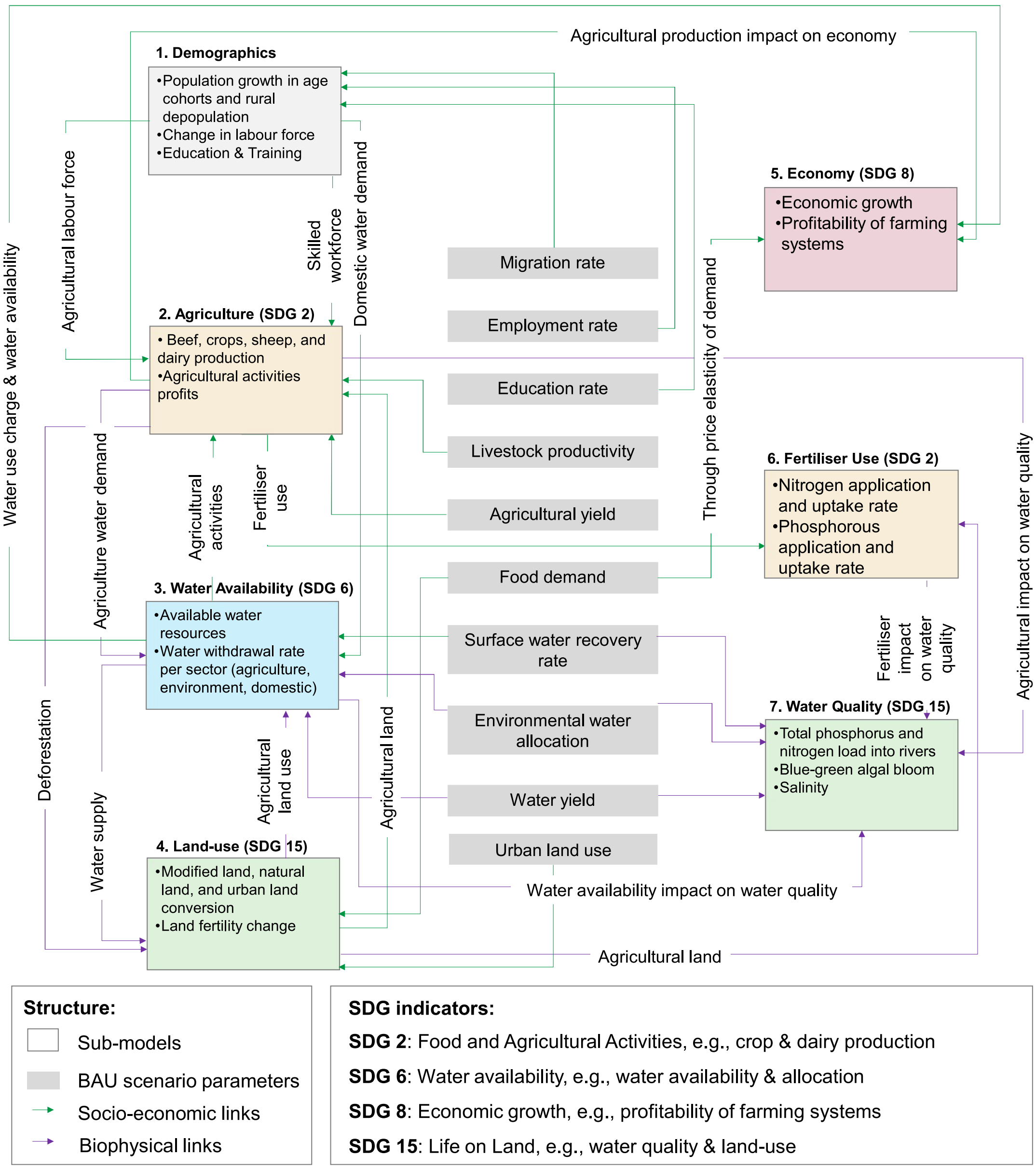

Figure 3. Structure and main sub-models of the LESEM. This model is composed of seven sub-models: Demographics, economy, Agriculture, food demand change, land use, fertilizer use, water availability, water quality, and 10 BAU parameters (see Supporting Information S1 for detail).

Murray-Darling Basin, and the Australian 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 agricultural 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.

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

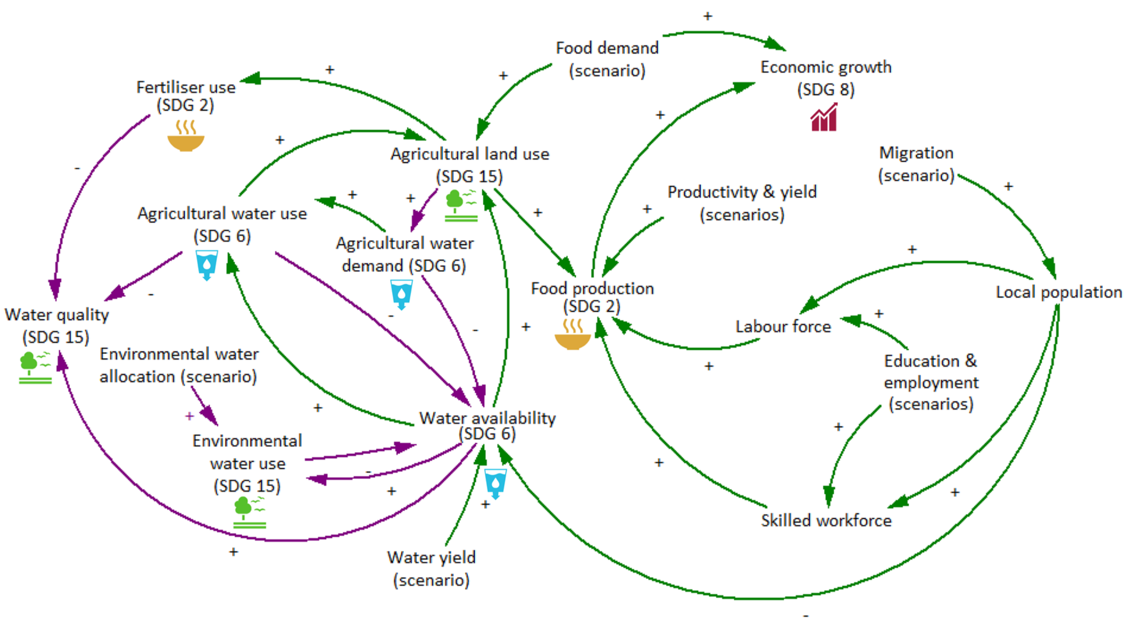

Figure 4. Causal loop diagram capturing the interactions, trade-offs, and synergies between agriculture (SDG 2), water availability (SDG 6), economic growth (SDG 8), and life on land (SDG 15). Positive feedback linkages are shown as a positive sign (+), whereas negative feedback linkages are shown with a negative sign (−). The purple arrows indicate the enviro-biophysical linkages. The green arrows indicate the socio-economic linkages. The SDG icons are courtesy of the UN SDG communications material.

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 5) to illustrate how the sub-models work, while detailed descriptions of all sub-models are provided in the Supporting Information S1. In the form of *stocks* and *flows* diagrams, this sub-model shows interactions between net water availability; water allocation for different consumptive uses; water use by different users; surface water recovery; net surface water trade in the GMID; infiltration to groundwater; evaporation losses through the system; agricultural water demand; and domestic water demand. The Water Availability sub-model in the LESEM is interconnected with other sub-models such as Demographics (via total population), Agriculture (via the yield of beef, sheep, dairy, and crops), Economy (via water requirements for producing irrigated beef, sheep, and dairy pasture, as well as crops), and Land Use (via 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 Supporting Information S1 (Figures S1–S24).

3.4. Sensitivity Analysis

Figure 6 displays the 36 influential model parameters selected and ranked by sensitivity across all seven sub-models of the LESEM 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 the Demographics sub-model. As shown in Figure 6 the input parameter

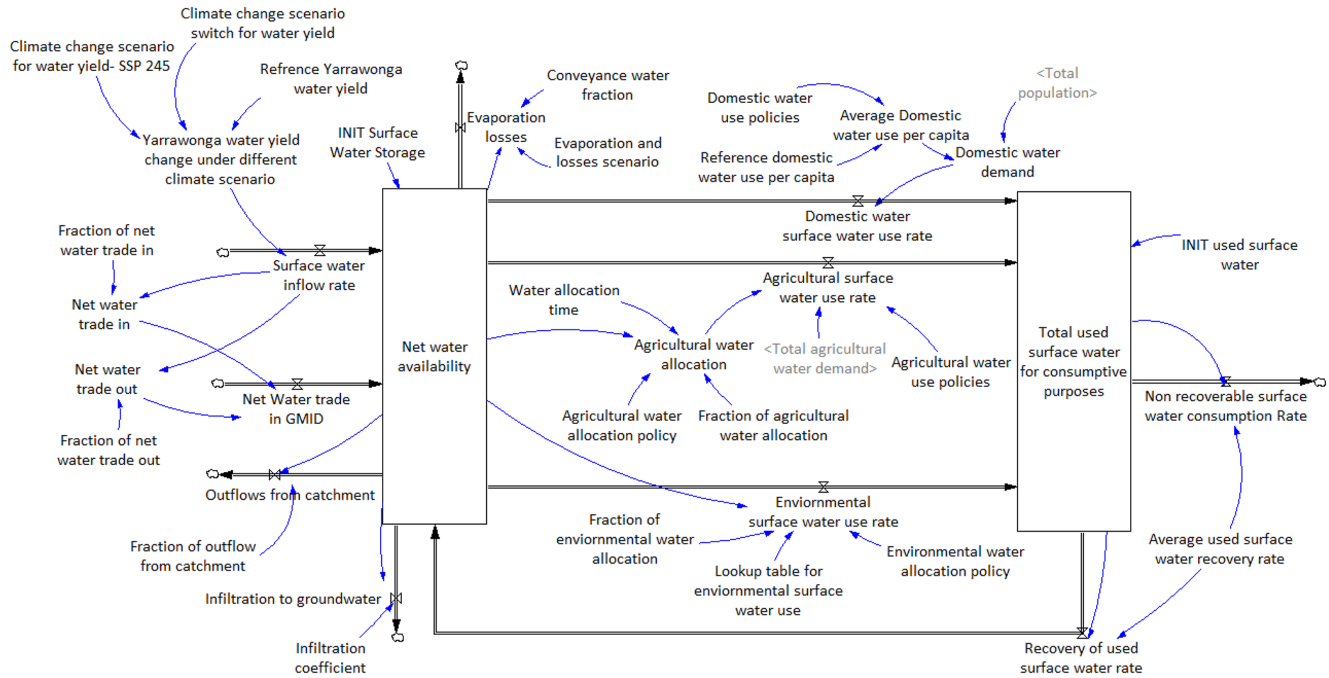

Figure 5. Stock and flow structure of Water Availability sub-model. The Water Availability sub-model includes stock variables, flow variables, and other auxiliary variables. The shadow variables indicate the linkage between the Water sub-model and other sub-models. All these variables contain an equation described in Supporting Information S1.

with the greatest influence on the output variables across most of the SDGs was water availability (SDG 6) in the region (specifically, the Reference Yarrawonga water yield). This parameter has an impact on multiple output variables, including net water availability (SDG 6), agricultural profit (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 was the fraction of agricultural water allocation (SDG 6), which affected output variables such as net water availability (SDG 6), agricultural profit (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.

3.5. BAU Projection and 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, 2019a; 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 output variables demonstrated that the behavior of the LESEM approximated their historical trends. Although historical data for crop production and blue-green algal bloom was unavailable, projections for these output variables remain essential. It is evident from the simulation results that the projected trends of agricultural land, dairy land use, net water availability, 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 profit, population, and labor force exhibit an increasing trend in their projections.

The maximum relative error (M) values ranged from −0.05 for the area of net water availability to 0.2 for annual agricultural profit (Figure 7). The validation results indicate that the labour force, total population, agricultural water allocation, surface water use, net water availability, 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

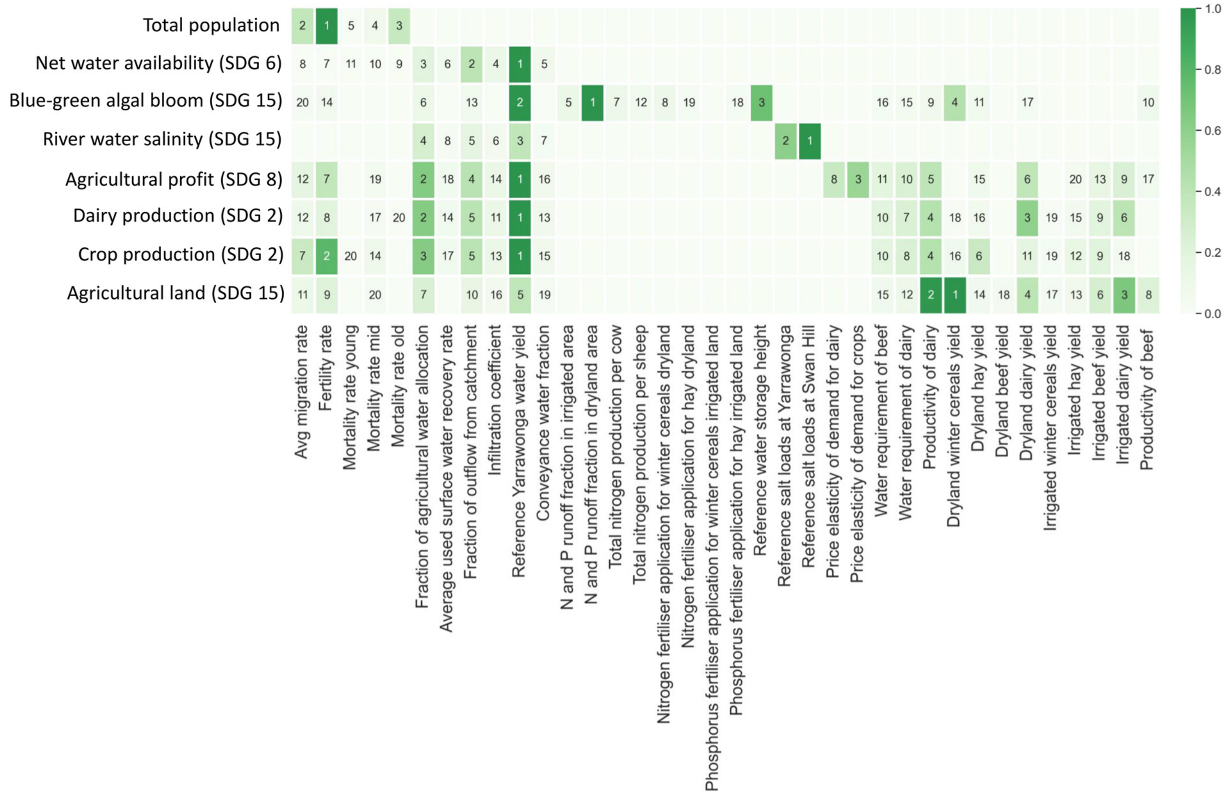

Figure 6. Ranking of model parameters based on their level of influence. Sensitivity is determined by calculating the normalized Morris index values (μ^*) between 0 and 1. The sensitivity analysis investigated the effect of 36 input parameters (columns) on eight output variables (rows). A maximum of 20 of the most influential input parameters for each output variable are numbered. The colors in the grid cells represent the total sensitivity effects, while the numbers describe the rankings of parameter influence.

or below 10%. However, annual agricultural profit 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 behavior patterns of these variables (Kelly et al., 2013; Kotir et al., 2016; Sterman, 2002).

The BAU scenario outcomes were projected for the period 2023–2050, with the assumptions listed in Table 2. 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 centers 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 Figures S21 and S22 in Supporting Information S1). 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 was a 3% decrease in total agricultural land use, an 11% decrease in dairy land use, a 10% decrease in net water availability and agricultural water allocation, and a 16% decrease in agricultural surface water use. Conversely, environmental surface water allocation was projected to increase by 17%.

The total cropping land use in the GMID was 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 profit was expected to rise by 54% by 2050. The blue-green algal bloom in rivers and waterways was projected to increase by 2% due to nutrient pollution

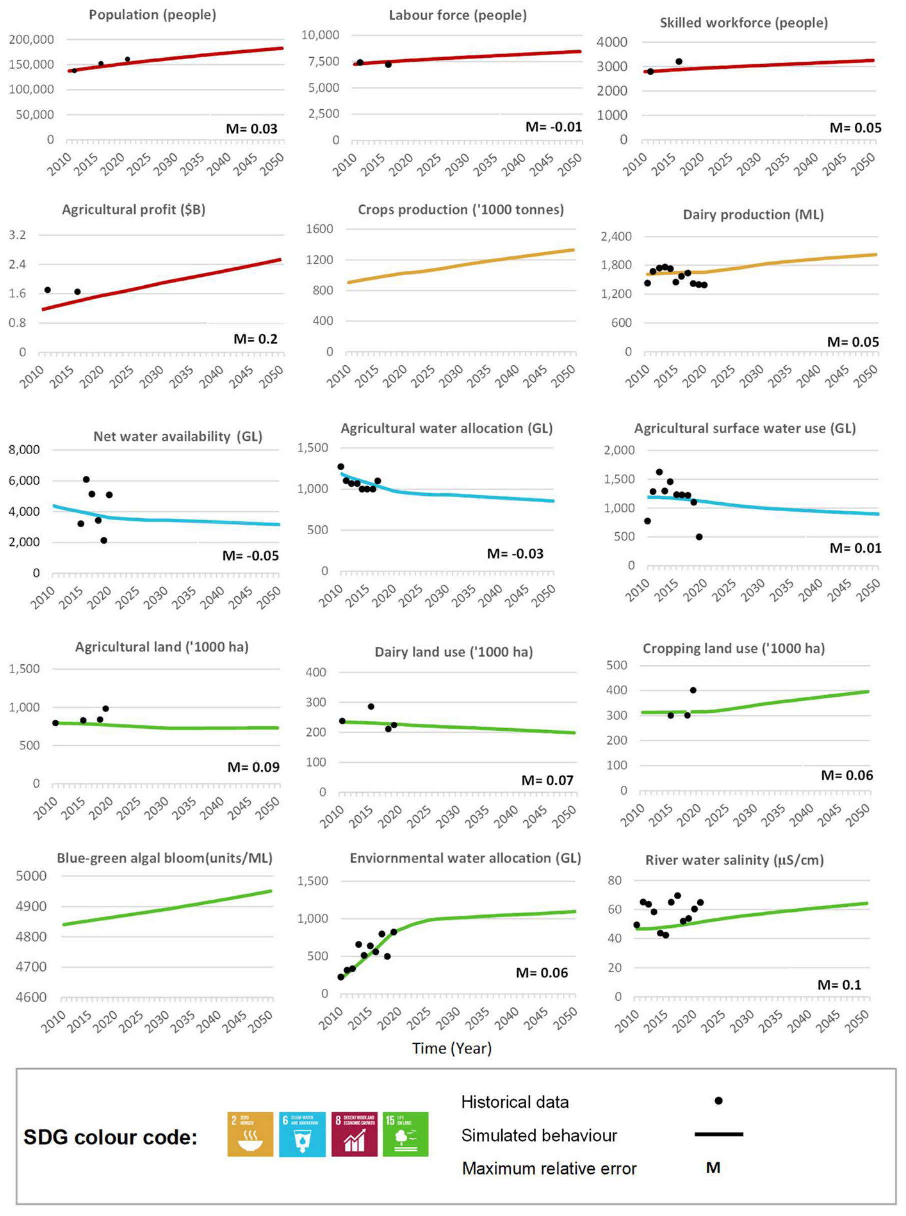

Figure 7. The outcomes of the BAU projections for key SDG indicators. The graphs depict the BAU scenario projections for 15 output variables from 2010 to 2022, along with future projections to 2050. Note that no historical data was available for crop production or blue-green algae.

from agricultural runoff, exacerbated by climate change and decreasing available water in the GMID. Additionally, river water salinity in the GMID was 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 stakeholders. The LESEM enables a holistic view of environmental and socio-economic aspects of sustainable development by analyzing 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 modeling approach (Moallemi, Bertone, 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. Synthesizing 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 analyzing 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 net water availability from 4400 Gigalitres (GL) to approximately 3166 GL over four decades. Multiple factors have contributed to 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 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 (SDG 15) 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 (SDG 6) from 1188 GL in 2010 to 897 GL in 2050.

The interactions of SDG 6 and SDG 15 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 Supporting Information S1 for more information) and water availability in the GMID. The reduction in available water (SDG 6) for agriculture is projected to contribute to a decrease in total agricultural land area (SDG 15) 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 (SDG 15) from 312,827 ha in 2010 to 395,673 ha in 2050, driven by an increased demand for crop production.

The dairy industry 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 (SDG 15) 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 irrigated 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 requirements by the farming sector (SDG 6) from 1188 GL in 2010 to 855 GL in 2050.

The reduced requirement for agricultural land to meet global agri-food demand by the GMID allows the spared land to be converted to natural land via ecological restoration thereby benefiting local biodiversity conservation. Former agricultural land can also be used to store carbon in soils and biomass, thereby contributing to climate change mitigation. The agricultural land use (SDG 15) indicator and the fact that when we require less agricultural land then we reduce pressure on terrestrial ecosystems, reduce the likelihood of further disturbance through deforestation and land clearance, and allow the space for the restoration of ecosystems. Freeing up agricultural land can also create space for increasing carbon sequestration in soils and vegetation, thereby contributing to climate change mitigation. 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 improved economic growth (SDG 8) in the GMID. For instance, crops production is estimated to grow from 906,510 tonnes in 2010 to 1,338,148 tonnes in 2050.

The development trajectories of agricultural profit 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 profit was directly affected by food demand under the BAU scenario through the price elasticity of demand for different agricultural commodities and by the input assumptions of the Land use and Agriculture sub-models. Agricultural profit (SDG 8) was estimated to increase from 1.2 $B to 2.5 $B, respectively, from 2010 to 2050 (Figure 7). Although we projected a reduction in land area actively used for agriculture (SDG 15), the model simulation results demonstrated growing agricultural profit due to agricultural intensification, increasing agricultural yields and productivity (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, ensuring water availability, and improving water quality. The Water Availability sub-model and Fertiliser Use sub-model and their related assumptions 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 2010–4951 in 2050 units ML^{-1} (Figure 7) 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 increased fertiliser application (SDG 2) 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 River Murray (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 in Supporting Information S1). 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 in Supporting Information S1). This high rate of population ageing shows an unsustainable demographic 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 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 older adults 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 demographic 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 demographic 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 demographic structure for the future.

Our study pinpointed critical interactions among the SDGs. A notable synergy was found in the rise of agricultural productivity and yield (SDG 2), which bolstered both the region's agricultural production and economic growth (SDG 8). The increase in productivity led to a reduction in agricultural land (SDG 15) in the region because less land area was required to meet food demand. Though there is an inherent synergistic relationship between net water availability (SDG 6) and its agricultural allocation and use, our data revealed that diminished net water availability adversely affected the region's agricultural production (SDG 2). We also identified a critical interaction between reduced net water availability (SDG 6) and increased river water salinity (SDG 15). In addition, an increase in fertiliser application (SDG 2) was found to compromise water quality, resulting in a surge of blue-green algal bloom (SDG 15). These results underscore the complex interactions between sustainability goals, highlighting the importance of comprehensive policy considerations.

4.2. Innovation and Contribution

This study contributes to the progress in uncovering SDG interactions and enhancing local stakeholder involvement in the implementation of the 2030 Agenda. Moallemi, Bertone, et al. (2021) emphasized existing gaps and opportunities for enhancing genuine stakeholder engagement and promoting a deeper analysis of SDG interactions using the rich feedback structure inherent in system dynamics models. In this study, we collaboratively devised a sophisticated system dynamics model designed to encapsulate all three facets of the SDGs - encompassing environmental, socio-economic, with a special emphasis on SDG interactions. Moreover, we implemented an extensive stakeholder engagement process, actively involving stakeholders from the initial phase of defining the system boundaries to the critical stage of validating the results, thereby ensuring a comprehensive and collaborative approach to sustainability analysis.

4.3. Policy Implications

Our study is grounded in the understanding that the successful realization of the United Nations 2030 Agenda for SDGs is fundamentally anchored in local initiatives (UN, 2015). Our research serves as a local socio-economic and environmental management tool, empowering local policymakers and planners to address local challenges with a comprehensive and integrated perspective, thereby fostering sustainable development at the grassroots level. For example, the model projections suggest that agricultural land area may decrease due to declining water resource 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 water yield scenarios 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 analyze 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.

More than just focusing on local improvements, we envision these local systems as the building blocks that, when united, can form a resilient and sustainable global network. This approach allows for the nurturing of sustainable development from the grassroots level, eventually scaling up to contribute significantly to global sustainability efforts. Although, we acknowledge the critical necessity of aligning local endeavours with broader spatial and temporal sustainability objectives. To this end, our future research will seek to develop local governance structures to champion policies that not only facilitate resilience at the local level but also resonate with global sustainability goals. This includes exploring potential contributions to climate change mitigation and biodiversity conservation, thus ensuring a harmonious integration of local actions within the larger framework of global sustainability efforts and adapting to evolving uncertainty scenarios.

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 modeled 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., labor 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 larger 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.

Advancing in one SDG can create "spillovers"—unforeseen consequences that affect the same or other SDGs at various levels (Engström et al., 2021; SDG Watch Europe, 2019). We acknowledge that in this study, some of the local priority SDG indicators such as dairy production are in conflict with global SDGs. We fully acknowledge the environmental ramifications of dairy production, particularly its potential contribution to climate change and SDG 13. Hence, it is imperative to initiate research that precisely identifies the "spillovers" resulting from local sustainability initiatives and crafts effective governance strategies to mitigate potential adverse effects across other scales. Such efforts would pave the way for a more synchronised approach to achieving sustainability at both local and global levels, promoting harmony and positive impacts across all scales.

5. Conclusion

This research highlights the potential contribution of system dynamics models in analyzing the SDGs, their interactions, and the challenges associated with achieving sustainable development at the local level. Here we developed the 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. The LESEM considers and quantifies interactions among priority SDGs: zero hunger (SDG 2), clean water and sanitation (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 modeling 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 other regions will require bespoke understandings of their unique local social, economic, and environmental processes, the process of participatory systems modeling, tailored to specific local needs, facilitates integrated and strategic decision-making. This, in turn, assists local policymakers in identifying and quantifying potential trade-offs and synergies that benefit multiple SDGs, ultimately guiding local communities toward sustainability.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All resources, including the model file, codes, and data sets generated and utilised in this study, are comprehensively documented and accessible in Bandari et al. (2023). The LESEM simulation model was crafted using Vensim DSS version 8.2.1 (Ventana Systems Inc, 2021) and is thoroughly detailed in the aforementioned source. Data sets integral to our research are derived and adapted from various reputable sources. The Demographic sub-model data, encompassing metrics like migration rate, agricultural education rate, and agriculture sector employment rate, is adapted from ABS (2022) and documented in Bandari et al. (2023). Our food demand data for all agricultural commodities aligns with the production and consumption parameters delineated in the Food and Agriculture Organisation Food Balance Sheets (FAO, 2017). We have also incorporated food loss and waste assumptions as per FAO (2011), with all relevant data available in Bandari et al. (2023). Livestock productivity data was sourced from Navarro and Marcos Martinez (2021). The Global Agro-Ecological Zones (GAEZ) 4 model was utilised to assess the effects of climate change on agricultural productivity, producing agricultural commodity yield multipliers under the RCP4.5 (BAU) scenario (Fischer et al., 2021). Average water yield time series under the RCP4.5 scenario was generated using the InVEST model (Sharp et al., 2018). The environmental water allocation was derived from DELWP (2019a) and DELWP (2021) and the average surface water recovery rate data adopted from VSG (2019). Comprehensive data sets and all related information are accessible in Bandari et al. (2023) for further insights and analysis.

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References

ABS. (2022). Search census data [Dataset]. Australian Bureau of Statistics. Retrieved from 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. Retrieved from 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*, *58*, 93–102. https://doi.org/10.1016/j.jrurstud.2017.12.026

Babatunde, K. A., Begum, R. A., & Said, F. F. (2017). Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review. *Renewable and Sustainable Energy Reviews*, *78*, 61–71. https://doi.org/10.1016/j.rser.2017.04.064

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

Bandari, R., Moallemi, E. A., Lester, R. E., Downie, D., & Bryan, B. A. (2022). Prioritising sustainable development goals, characterising interactions, and identifying solutions for local sustainability. *Environmental Science & Policy*, *127*, 325–336. https://doi.org/10.1016/j.envsci.2021.09.016

Bandari, R., Moallemi, E. A., Szetey, K., Flanagan-Smith, C., Hadjikakou, M., Marcos Martinez, R., et al. (2023). Data for participatory modelling for analysing interactions between high-priority sustainable development goals to promote local sustainability. *Zenodo*. https://doi.org/10.5281/zenodo.8110625

10.1029/2023EF003948

Barlas, Y. (1996). Formal aspects of model validity and validation in system dynamics. *System Dynamics Review*, *12*(3), 183–210. https://doi.org/10.1002/(sici)1099-1727(199623)12:3<183::aid-sdr103>3.0.co;2-4

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 [Dataset]. Remote Sensing of Environment, *252*, 112148. https://doi.org/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*, *22*(10), 1509–1518. https://doi.org/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*, *6*, 921–931. https://doi.org/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. Retrieved from www.waterregister.vic.gov.au

Dairy Australia. (2021). *Murray dairy trends report*. Dairy Australia. Retrieved from 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. Retrieved from https://www.gbcma.vic.gov.au/downloads/CatchmentEconomy/RILWUM_DairyEvaluationFinal2017_LowRes.pdf

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing theory through simulation methods. *Academy of Management Review*, *32*(2), 480–499. https://doi.org/10.5465/amr.2007.24351453

Dean, D., Merz, S. K., & Trust, N. H. (2002). *North-east salinity strategy surface water salinity monitoring: Ovens catchments—2001, Goulburn Murray Water*. Sinclair Knight Merz.

DELWP. (2019a). Water market trends [Dataset]. The State of Victoria Department of Environment, Land, Water and Planning. Retrieved from https://nla.gov.au/nla.obj-1641380916/view

DELWP. (2021). Victorian water accounts-2019–2020, a statement of Victorian water resources [Dataset]. The Department of Environment, Land, Water and Planning (DELWP). Retrieved from 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*, *5*(2), 131–138. https://doi.org/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*, *46*(7), 738–754. https://doi.org/10.1080/09613218.2017.1362919

Engström, R. E., Collste, D., Cornell, S. E., Johnson, F. X., Carlsen, H., Jaramillo, F., et al. (2021). Succeeding at home and abroad: Accounting for the international spillovers of cities' SDG actions. *npj Urban Sustainability*, *1*(1), 18. https://doi.org/10.1038/s42949-020-00002-w

FAO. (2011). Global food losses and food waste—Extent, causes and prevention [Dataset]. FAO. Retrieved from https://www.fao.org/3/i2697e/i2697e.pdf

FAO. (2017). FAO balance sheets [Dataset]. Food and Agriculture Organization of the United Nations. Retrieved from http://www.fao.org/faostat/en/#data/FBSH

Fischer, G., Nachtergaele, F., Velthuizen, H. V., Chiozza, F., Franceschini, G., Henry, M., et al. (2021). Global agro-ecological zones (GAEZ v4) model documentation (version 4) [Software]. FAO. 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*, *321*, 1–9. 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*, *76*, 154–166. https://doi.org/10.1016/j.envsoft.2015.11.001

GBCMA. (2013). Goulburn broken regional catchment strategy 2013–2019, Goulburn broken catchment management authority. Retrieved from 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. Retrieved from 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. Retrieved from 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. Retrieved from 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. Retrieved from https://www.pc.gov.au/__data/assets/pdf_file/0020/227540/sub062-basin-plan.pdf

GMW. (2018a). 2017/18 annual report, Goulburn-Murray Water. Retrieved from https://www.g-mwater.com.au/about/reports-and-publications/annualreports

GMW. (2018b). Corporate plan 2018/19 to 2022/23, Goulburn-Murray water. Retrieved from 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 Retrieved from 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*, *31*(5), 1413–1434. https://doi.org/10.1007/s11269-017-1575-z

Greeven, S., Kraan, O., Chappin, É. J. L., & Kwakkel, J. H. (2016). The emergence of climate change mitigation action by society: An agent-based scenario discovery study. *The Journal of Artificial Societies and Social Simulation*, *19*(3). https://doi.org/10.18564/jasss.3134

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*, *128*, 143–154. https://doi.org/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. Retrieved from 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*, *32*(6), 819–834. https://doi.org/10.1080/07900627.2015.1083847

Hinz, R., Sulser, T. B., Huefner, R., Mason-D'Croz, D., Dunston, S., Nautiyal, S., et al. (2020). Agricultural development and land use change in India: A scenario analysis of trade-offs between UN sustainable development goals (SDGs). *Earth's Future*, *8*. https://doi.org/10.1029/2019ef001287

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

Jagustović, R., Papachristos, G., Zougmoré, R. B., Kotir, J. H., Kessler, A., Ouédraogo, M., et al. (2021). Better before worse trajectories in food systems? An investigation of synergies and trade-offs through climate-smart agriculture and system dynamics. *Agricultural Systems*, *190*, 103131. https://doi.org/10.1016/j.agsy.2021.103131

Kelly, R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., et al. (2013). Position paper: Selecting among five common modelling approaches for integrated environmental assessment and management. *Environmental Modelling & Software*, *47*, 159–181. https://doi.org/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 for individuals and groups, catalyzing behavior change and collective action in water-energy-food nexus governance. *Earth's Future*, *7*(12), 1337–1352. https://doi.org/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. *Science of the Total Environment*, *573*, 444–457. https://doi.org/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. *Journal of Environmental Management*, *155*, 11–23. https://doi.org/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. Retrieved from 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). Retrieved from 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*, *162*, 1210–1224. https://doi.org/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*, *16*(11), 113004. https://doi.org/10.1088/1748-9326/ac2f62

Moallemi, E. A., de Haan, F. J., Hadjikakou, M., Khatami, S., Malekpour, S., Smajgl, A., et al. (2021). Evaluating participatory modeling methods for co-creating pathways to sustainability. *Earth's Future*, *9*. https://doi.org/10.1029/2020ef001843

Moallemi, E. A., Gao, L., Eker, S., & Bryan, B. A. (2022). Diversifying models for analyzing global change scenarios and sustainability pathways. *Global Sustainability*, *5*, e7. https://doi.org/10.1017/sus.2022.7

Moallemi, E. A., Hosseini, S. H., Eker, S., Gao, L., Bertone, E., Szetey, K., & Bryan, B. A. (2022). Eight archetypes of sustainable development goal (SDG) synergies and trade-offs. *Earth's Future*, *10*. https://doi.org/10.1029/2022ef002873

Morris, M. D. (1991). Factorial sampling plans for preliminary computational experiments. *Technometrics*, *33*(2), 161–174. https://doi.org/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. *Journal of Environmental Management*, *280*, 111843. https://doi.org/10.1016/j.jenvman.2020.111843

Navarro, A., & Tapiador, F. J. (2019). RUSEM: A numerical model for policymaking and climate applications. *Ecological Economics*, *165*, 106403. https://doi.org/10.1016/j.ecolecon.2019.106403

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

NCCMA. (2016). *North central Victoria regional sustainable agriculture strategy*. North Central Catchment Management Authority. Retrieved from 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*, *12*. https://doi.org/10.5018/economics-ejournal.ja.2018-25

Nilsson, M., Chisholm, E., Griggs, D., Howden-Chapman, P., McCollum, D., Messerli, P., et al. (2018). Mapping interactions between the sustainable development goals: Lessons learned and ways forward. *Sustainability Science*, *13*(6), 1489–1503. https://doi.org/10.1007/s11625-018-0604-z

Nilsson, M., Griggs, D., & Visbeck, M. (2016). Map the interactions between sustainable development goals. *Comment in Nature*, *53*(7607). https://doi.org/10.1787/agr_outlook-2015-en

Norström, A. V., Cvitanovic, C., Löf, M. F., West, S., Wyborn, C., Balvanera, P., et al. (2020). Principles for knowledge co-production in sustainability research. *Nature Sustainability*, *3*(3), 182–190. https://doi.org/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*(7), 915–927. https://doi.org/10.1093/treephys/25.7.915

O'Neill, B. C., Kriegel, E., Ebi, K., Kemp-Benedict, E., Riahi, K., Rothman, D. S., et al. (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, *42*, 169–180. https://doi.org/10.1016/j.gloenvcha.2015.01.004

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*, *9*(1), 16–27. https://doi.org/10.1080/15487733.2013.11908104

Pedercini, M., Arquitt, S., & Chan, D. (2020). Integrated simulation for the 2030 agenda. *System Dynamics Review*, *36*(3), 333–357. https://doi.org/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. *Earth's Future*, *5*(11), 1169–1179. https://doi.org/10.1002/2017ef000632

Productivity Commission. (2005). Trends in Australian agriculture. Retrieved from https://www.pc.gov.au/research/completed/agriculture

Pujol, G. (2009). Simplex-based screening designs for estimating metamodels. *Reliability Engineering & System Safety*, *94*(7), 1156–1160. https://doi.org/10.1016/j.ress.2008.08.002

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., et al. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

RMCG. (2016a). *Basin plan- GMID socio-conomic impact assessment, RM consulting group*. GMID Water Leadership Forum. Retrieved from 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. Retrieved from 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. Retrieved from https://www.rmcg.com.au/app/uploads/2019/07/InsightsPaper_Finalv2_r.pdf

RPG. (2020). Goulburn Murray resilience strategy, regional partnership Goulburn. Retrieved from 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*, 216–243. https://doi.org/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. Retrieved from 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*, *32*, 100582. https://doi.org/10.1016/j.esr.2020.100582

SDG Watch Europe. (2019). Who is paying the bill? (Negative) impacts of EU policies and practices in the world. Retrieved from https://www.sdgwatcheurope.org/who-is-paying-the-bill/

Sharp, R., Douglass, J., Wolny, S., Arkema, K., Bernhardt, J., Bierbower, W., et al. (2018). InVEST user's guide, integrated valuation of ecosystem services and tradeoffs (version 3.5.0). [Software]. 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*, *247*, 135–143. https://doi.org/10.1016/j.ecolmodel.2012.08.005

Sterman, J. (2002). In *Business dynamics, system thinking and modeling for a complex world*. Massachusetts Institute of Technology.

Sterman, J., Fiddaman, T., Franck, T., Jones, A., McCauley, S., Rice, P., et al. (2012). Climate interactive: The C-ROADS climate policy model. *System Dynamics Review*, *28*(3), 295–305. https://doi.org/10.1002/sdr.1474

Szetey, K., Moallemi, E. A., Ashton, E., Butcher, M., Sprunt, B., & Bryan, B. A. (2021). Participatory planning for local sustainability guided by the Sustainable Development Goals. *Ecology and Society*, *26*, art16. https://doi.org/10.5751/ES-12566-260316

UN. (2015). *Transforming our world: The 2030 Agenda for sustainable development, A/RES/70/1*. UN General Assembly. Retrieved from https://sustainabledevelopment.un.org/content/documents/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf

van Beek, L., Hajer, M., Pelzer, P., van Vuuren, D., & Cassen, C. (2020). Anticipating futures through models: The rise of integrated assessment modelling in the climate science-policy interface since 1970. *Global Environmental Change*, *65*, 102191. https://doi.org/10.1016/j.gloenvcha.2020.102191

Van Soest, H. L., Van Vuuren, D. P., Hilaire, J., Minx, J. C., Harmsen, M. J. H. M., Krey, V., et al. (2019). Analysing interactions among sustainable development goals with integrated assessment models. *Global Transitions*, *1*, 210–225. https://doi.org/10.1016/j.glt.2019.10.004

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., et al. (2011). The representative concentration pathways: An overview. *Climatic Change*, *109*(1), 5–31. https://doi.org/10.1007/s10584-011-0148-z

Vennix, J. (1996). *Group model building: Facilitating team learning using system dynamics*. Wiley.

Ventana Systems Inc. (2021). Vensim DSS (version 8.2.1) [Software]. Ventana Systems Inc. Retrieved from https://vensim.com/

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

VSG. (2019). Victorian water accounts [Dataset]. Victoria State Government. Retrieved from 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*, *137*, 107067. https://doi.org/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*, *122*, 107232. https://doi.org/10.1016/j.ecolind.2020.107232

Wiedmann, T. (2009). A review of recent multi-region input–output models used for consumption-based emission and resource accounting. *Ecological Economics*, *69*(2), 211–222. https://doi.org/10.1016/j.ecolecon.2009.08.026

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*, *2*(4), 481–489. https://doi.org/10.1016/j.Eng.2016.04.010

References From the Supporting Information

DELWP. (2019b). *Victoria's North and Murray water resource plan, comprehensive report part 1*. Department of Environment, Land, Water and Planning, Victoria State Government. Retrieved from https://www.mdba.gov.au/sites/default/files/pubs/vic-victoria%20s-north-and-murray-comprehensive-report-part-1-30-april-2019.pdf

DELWP. (2019c). *Victoria's North and Murray water resource plan, comprehensive report part 2*. Department of Environment, Land, Water and Planning. Retrieved from https://www.mdba.gov.au/sites/default/files/pubs/vic-victoria%20s-north-and-murray-comprehensive-report-part-2-30-april-2019_1.pdf

MDBA. (2015). *Basin salinity management strategy BSM2030, Murray–darling basin authority*. Murray–Darling Basin Ministerial Council. Retrieved from https://www.mdba.gov.au/sites/default/files/pubs/D16-34851-basin_salinity_management_strategy_BSM2030.pdf

MDBA. (2023). River Murray data [Dataset]. MDBA. Retrieved from https://livedata.mdba.gov.au/