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An Analysis of Agricultural Systems Modelling Approaches and Examples to Support Future Policy Development under Disruptive Changes in New Zealand

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Abstract: Agricultural systems have entered a period of significant disruption due to impacts from change drivers, increasingly stringent environmental regulations and the need to reduce unwanted discharges, and emerging technologies and biotechnologies. Governments and industries are developing strategies to respond to the risks and opportunities associated with these disruptors. Modelling is a useful tool for system conceptualisation, understanding, and scenario testing. Today, New Zealand and other nations need integrated modelling tools at the national scale to help industries and stakeholders plan for future disruptive changes. In this paper, following a scoping review process, we analyse modelling approaches and available agricultural systems' model examples per thematic applications at the regional to national scale to define the best options for the national policy development. Each modelling approach has specificities, such as stakeholder engagement capacity, complex systems reproduction, predictive or prospective scenario testing, and users should consider coupling approaches for greater added value. The efficiency of spatial decision support tools working with a system dynamics approach can help holistically in stakeholders' participation and understanding, and for improving land planning and policy. This model combination appears to be the most appropriate for the New Zealand national context.

Keywords: decision-making support; integrated modelling; policy development; regional to national scale; data and skills

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1. Introduction

The future of agriculture depends on the system's responses to the global challenges of climate change adaptation, carbon emission reduction, water availability, water quality restoration, and ecosystem services' provision. Policy, technology and science have a key role to play in addressing these challenges [1–3]. Climate change, the most studied of global change challenges, is already causing major disruptions in food supply due to yield losses and subsequent chain reactions on socio-economic systems [4,5]. However, a larger range of disruptions are putting agricultural systems under pressure and could lead to major disruptions to the agro-economical system: diseases or pandemics like the Asian Swine Fever outbreak [6,7], socio economic factors (war, conflict, etc.), trade restrictions/barriers or agreements [8], new food consumption trends [9,10], and disruptive technologies such as cowless milk [11]. Technology can also be a positive factor: precision agriculture to optimise yields and minimise nutrient losses [12,13], biotechnology such as the use of seaweed for reduction of methane emissions [14,15], water/irrigation optimisation, and efficiency improvements [16], and others. The range of potential beneficial and detrimental disruptive elements highlight the urgent need to address long-term sustainability of agricultural systems [17,18].

Since the 2000s, the international community through multilateral agreements and Non-Governmental Organisations (NGOs) have advocated for countries to restore or limit their impacts on the environment, based on policy informed by science. Agricultural activity, that represents almost 40% of global land use worldwide [19], is a significant contributor to Greenhouse Gas (GHG) emissions [20,21], soil and water quality loss [22–24], biodiversity loss [25–27], and thus environmental sustainability. At the international scale, several institutions have guided recommendations, incentives, and warnings over the past two decades. The Intergovernmental Panel on Climate Change (IPCC) provides assessments of climate change, its impacts and future risks, and recommendations; the Paris Agreement was adopted by 196 countries to limit global warming; the United Nations (UN) adopted the 17 Sustainable Development Goals (SDGs) [28,29], and the Millennium Ecosystem Assessment [30], by the Aichi Biodiversity Targets were formulated for conservation and restoration of biodiversity and ecosystem services by 2020 [31]. These environmental goals need to be synergistic with agricultural productivity and food security goals and thus the Food and Agriculture Organisation (FAO) is leading international efforts to defeat hunger, and provide adequate nutrition for all people. All these international efforts link policy and science at a global scale and incentivise nations to tackle global change challenges, and national governments are the key players in setting policy to enhance sustainability, resilience, productivity, and trade opportunities. Policy implementation often requires global coordination, comprehensive, integrated, and multi-sectoral analyses to support national target-setting [32]. The national scale is thus a key scale to define policy, laws, and regulations, and also to negotiate and organise international market trade especially for food security purposes or national sustainable profitability [33,34]. Agricultural systems need to strive for more flexibility and more adaptation options to gain resilience under economic, environment, and social disruptions [35].

Modelling is a useful tool for system conceptualisation, understanding, projection of future scenarios, and hypothesis testing about the impact of disruptions in a system's overall behaviour in relation to changes in its components. Models are generally defined by two ways: (1) their approach, i.e., how the internal process is working, and (2) their thematic application, i.e., the thematic question they are being used for. The choice of approaches regarding the thematic questions is crucial for successful modelling processes. Many different modelling approaches exist and each of these have a different degree of complexity, requiring different data and application skill levels, and are not equal for system conceptualisation, analysis, prediction or prospection [36,37]. However, all the approaches provide some level of useful knowledge of agricultural systems and can help decision-making. Most agricultural models were developed from science knowledge for policy development and focus on agricultural sustainability and resilience [38–42]. Some of the available models group a wide range of indicators, such as the integrated Sustainable Development Goals model (iSDG, [40]), which is customisable for all countries, or the Integrated Valuation of Ecosystem Services and Tradeoffs (InVest), a multi-ecosystem-services modelling platform [43]. Other models only focus on one part of the system, such as crop models, water models, energy models, GHG emission calculators, or climate models. The selection of model thus depends on the application scale, the questions needing answers, system complexity, and data availability.

With more than six decades of multidisciplinary contribution to concepts and tools for agricultural systems modelling, the scientific community considers models critical to make informed agricultural decisions [39]. However, today, only few countries seem to have either appropriate agricultural systems models or decision tools to support policy development under disruptive changes (i.e., EU with their CAPRI model, [41]). In New Zealand, but also more widely in other Pacific countries, there is an urgent need for assessing the different pathways and interventions for a sustainable future of the agricultural sector under disruptive changes. Numerical and participative modelling is an option considered by the New Zealand government, and has been requested by the industry and sectoral organisations to gain in global understanding of the future of NZ agriculture and help define efficient long-term policies. As several modelling options are available, there is a need of synthesis knowledge to assist modellers and model users in selecting the most appropriate option for future application.

The aim of this paper is (1) to analyse agricultural system modelling approaches and (2) identify available model examples for thematic applications (3) to help address current NZ needs and support policy development. Agricultural system modelling knowledge is synthesised to help stakeholders with model selection and future model development. Agricultural system modelling approaches are analysed and currently available, and freely accessible (non-commercial) models are listed per thematic application. Model processes are described, as well as requirements in terms of skills and data needs, strengths, weaknesses, and the questions each is intended to answer. Discussion focuses on model usability and limitations.

2. The New Zealand Context

In New Zealand, nearly half of GHG emissions come from agriculture [44]. The main source of agricultural emissions is methane from livestock digestive systems and manure management which makes up around three quarters of the agriculture emissions. The next largest source is nitrous oxide from nitrogen added to soils. Nitrogen also leaches to groundwater and pollutes waterways through runoff. As a result of climate change and the Paris Agreement ratification, and the need to improve degraded water bodies, wetlands, streams, and groundwater, the New Zealand government has set up two major actions in the law, the Zero Carbon Amendment Act (2019), and the National Policy Statement for Freshwater Management (2020).

The NZ food and fiber export revenue represents a third of the country's total export revenue. However, with a strong market-driven agricultural system, and despite numeric environmental targets and fixed deadlines, the NZ government (i.e., Ministry of Primary Industries, regional councils, policy-makers, regulators), industries (i.e., agritech organisations, lobby groups), and sectoral stakeholders (i.e., from dairy, beef and lamb, fisheries, horticulture, crops, or forestry sectors) still struggle to have a clear vision of the future of agriculture (Figure 1).

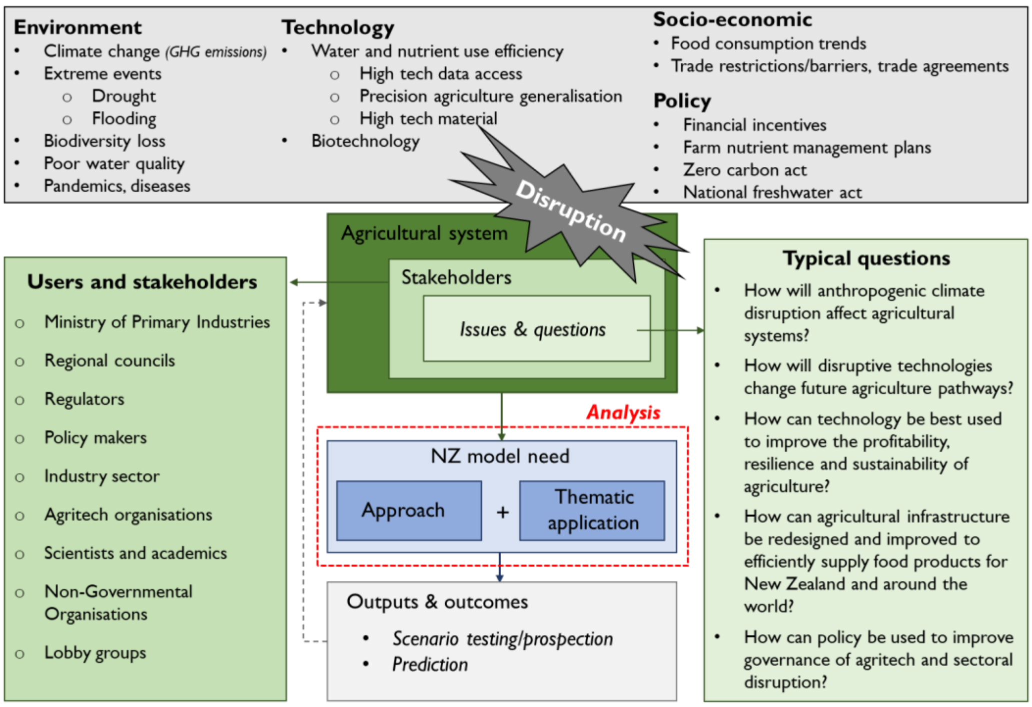

Figure 1. Flow chart from disruption of NZ agricultural system, modelling need, to solution design. Surrounding in red, where an analysis and synthesis of knowledge is proposed.

A NZ agricultural system model designed for policy-making purposes under disruptive changes should be able to address the key questions from government and industry organisations (Figure 1). For example, climate change disruptions (i.e., recurrent droughts, flooding events, or other extreme events such as storms or spring frosts) raise questions about agricultural production, mechanisms to adapt to changes, or new agricultural opportunities and actions that need to be developed to reduce anthropogenic impact on climate change. Environmental impacts of agricultural production (i.e., the reduction of water quality, the increase of food demand, the loss of biodiversity, and the increase of GHG emissions) raise questions about actions that need to be developed regarding sectoral footprints on the environment and the need for new technology or new infrastructure to address these impacts. New disruptive technologies or the generalisation (i.e., connectivity) of precision agriculture and new biotechnology raise questions on the gain in environment resilience, sustainability, and profitability that can be expected with new developments. Similarly, a model could be used to answer questions on how new policy and incentives limit environmental impacts.

3. Method

We conducted a literature-based scoping review [45], that consists in identification, selection, and synthesis of research studies to 'map' relevant knowledge and gaps in the field of interest. Here, the scoping review was conducted to synthesise knowledge about the main agricultural systems modelling approaches and available models. To this end, we identified, selected, and synthesised research studies, methods, and associated modelling tools.

For the analysis of approaches to model agricultural systems (Section 4), a search for bibliographic references was carried out using Google Scholar, ScienceDirect, Open edition, MDPI, and ResearchGate, searching for the following keywords: agricultural modelling, agricultural system modelling, agricultural national framework, and environmental modelling approaches. The following six main types of modelling approaches emerged from the literature review: participatory, deterministic, probabilistic, system dynamics, agent-based, and artificial intelligence. A search of these approaches combined with agriculture modelling in the titles, key words, or abstracts was also carried out. Article reference lists were also checked for other pertinent articles. We focused on recent publications in order to analyse the current scientific modelling knowledge.

For the analysis of existing models by thematic applications (Section 5), research was carried out online with a focus on NGOs' initiatives like the Food and Agriculture Organisation, the United Nations, the Natural Capital Initiative, or policy support organisations. Governmental websites of primary industries of developed countries were also explored (mainly in USA, Canada, Europe, Australia, and New Zealand, as these provide broad access to data and models). From a methodological point of view, we used a set of key word searches on Google Scholar (related to decision support tools, agricultural modelling, agricultural policy model, agriculture, and ecosystem model, etc.), and a wider literature review of recent agricultural modelling reviews. We focused on developed countries' model examples that contribute to define national policy developments. Model thematic applications identified through the review process were grouped as follows: Decision Support Tools (DST), crop models, water models, Greenhouse Gas emissions (GHG) calculators, climate models, and multi-ecosystem-services' modelling platforms.

4. Analysis of Approaches to Modelling Agricultural Systems

Six main modelling approaches with different levels of complexity in terms of skills and data needs were identified (Figure 2), as well as their characteristics. Each approach is further described below, highlighting requirements for application, and their strengths and weaknesses.

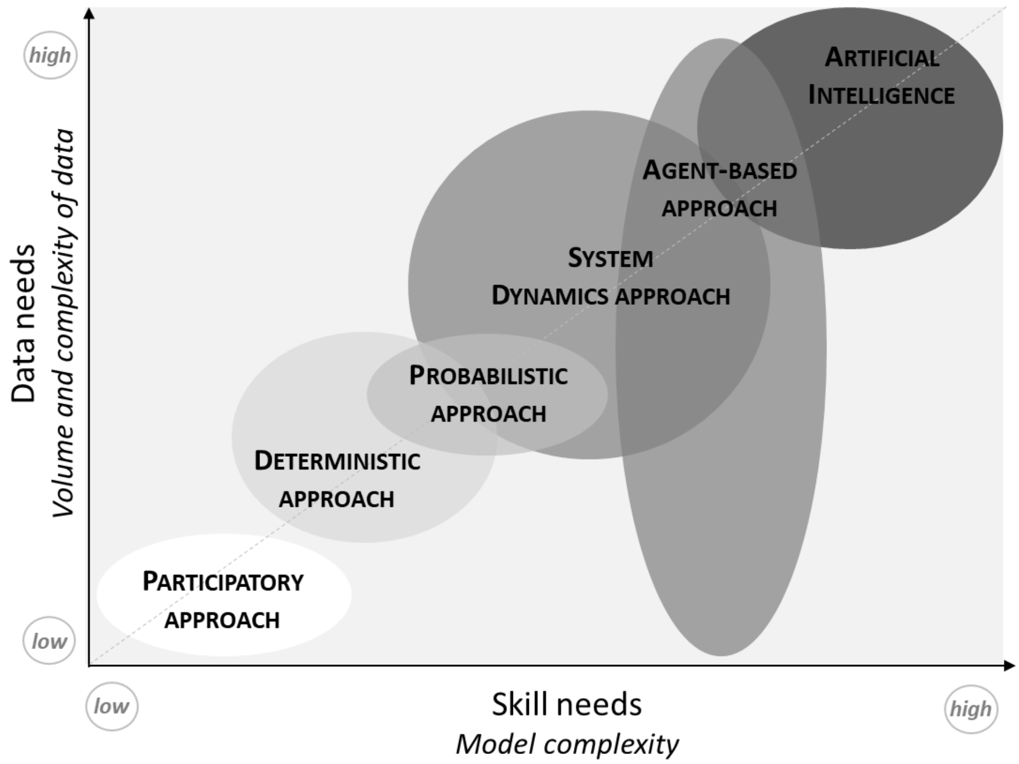

Figure 2. Modelling approaches and associated complexity.

4.1. Participatory Approach

The participatory approach is based on the active participation of experts or stakeholders. This approach is particularly useful and powerful when there is a lack of measured data (Figure 2). A conceptual framework of questions and systems thinking allows for the development of theoretical models or design concepts based on expert knowledge or stakeholders' engagement [46]. This approach is also useful to resolve conflicts of interest [47,48].

Coupling different types of expertise during the process helps strengthen the development of a conceptual model [46] or to initiate other types of more complex modelling and scenario simulations [47,49]. Participatory approaches for system modelling or scenario development are useful to bring together expert and stakeholder knowledge from academic, political, and civil sectors. Engaging stakeholders along with scientists is increasingly used in environmental research for analysing global change impacts [50] or sustainable futures [51,52]. Some tools have been developed to structure the participatory approach and to help follow scientific protocols. For example, the RIO approach (Dutch acronym for Reflexive Interactive Design) aims to structurally address complex trade-offs and to contribute by process and design to change perspectives towards sustainable development avoiding conflict [46,53,54].

While the participatory approach works very well at a fine scale to help farmers on economically viable and environmentally strong decisions related to farm management [55], it is often used as a discussion tool for structuring environmental problems and design solutions (i.e., climate change adaptation roadmap, water management, sustainability of agricultural sector) at a larger scale (regional to national) [46,56–58].

Strengths:

- At a regional to national scale, the participatory approach is well designed for policy- and decision-making if it is sustained by upstream numerical modelling.
- Expert consultation can be a quicker process than numerical modelling and it does not necessarily need data or modelling skills.

- When coupled with another approach, participatory process has a real benefit to integrate stakeholders' participation (no data can fill the "real-world" knowledge gap).
- When decision-making is the main aim, the participatory process is fundamental to gaining stakeholder buy-in.

Weaknesses:

- The participatory approach can suffer several biases, including group think, depending on the point of view of experts/stakeholders.
- It is a qualitative approach and therefore hard to quantify for coupling with other type of approaches.

4.2. Deterministic Approach

The deterministic approach consists of mathematical modelling using measured and known input parameters, with no degree of randomness. Deterministic models are based on the hypothesis that models, once calibrated, are able to project output events and magnitude of consequences (Figure 2). They are mostly based on phenomenological, mechanistic, or functional relationships between physical or biological elements.

Deterministic approaches are widely used for crop models to simulate plant growth under climate/soil/water conditions. For example, the multidisciplinary simulator for standard crops model (Simulateur mulTIdisciplinaire pour les Cultures Standard—STICS) [59,60] has been developed to simulate crop water and nitrogen balance under environmental (climate, soil) and agricultural conditions (cropping system), and to determine best sowing dates or predict yields. Deterministic models are also used in agronomy, for example, to predict sugar concentration of grapes from field observation and temperature-based models [61] that could help farmers to anticipate grape harvesting. Other agricultural-based modelling efforts have been developed using deterministic approaches for land use and crop yields' mapping [62], crop rotation modelling [63], or environment-ecosystem process simulation [64,65].

Strengths:

- At a regional to national scale, the deterministic approach is well designed for prediction that is required for decision-making and policy solution design, for example, climate change predictions and government actions [66,67].
- Many models are freely available, while some are free of charge, free of copyright, and free of restrictions for modification (see Section 5). Many of these models are already parameterised for an easier application.
- Models based on deterministic approach can be coupled with all other approaches to add stochasticity or stakeholders' involvement and be part of different scenario modelling.

Weaknesses:

- Deterministic models can be highly complex and difficult to readily adapt to specific study areas.
- It requires very specific data to develop precise and complex modelling [59,63,68].
- Upscaling or downscaling these models is a challenge and requires coupling with multiple source of data [69–71].

4.3. Probabilistic Approach

The probabilistic approach consists of adding stochastic components to a deterministic approach. This approach is based on statistical, frequentist, or Bayesian statistical models, using historical dataset to capture variability, and the use of optimisation techniques (Figure 2). Multiple linear regression, logistic regression, Poisson regression, generalised Pareto distribution, Monte Carlo simulation, weights of evidence, and geographically weighted regression are commonly used in probabilistic approaches [72,73]. Probabilistic models are less sensitive than deterministic ones to the non-stationarity of model parameters (i.e., great variations or disruptions). For example, probabilistic approaches work well for flood hazard and estimation of the 1-in-100 year flood extent where the model question is already a probability that needs mapping representation [74]. Many statistical models are developed using quantitative data table that can be coupled with a deterministic system response (i.e., crop yield, milk production, or farmers–consumers' prices) [39]. The probabilistic approach, however, lacks extrapolation power because of the data dependency for parameterisation.

The probabilistic approach is also useful for understanding statistical relationships between drivers of changes. This type of approach works well for Land Use and Land Cover Change (LULCC) modelling by coupling statistical methods like Markov chain for quantifying change over years, and to integrate probability in changes in maps [75,76], or for agricultural–economic production relationship analysis [77], historical data, and reconstruction of crop sequences [78], or allocation-optimisation based on statistical multi-criteria analysis [79].

Strengths:

- At a regional to national scale, this approach is well designed for land-use change dynamic analysis and for policy adaptation [75,80,81].
- With a large amount of data available freely, the probabilistic approach can be easily considered both for statistical and spatial trend analysis.
- Coupling deterministic and probabilistic approaches can lead to powerful modelling of the climate change adaptation for agriculture and land-use strategies.

Weaknesses:

- Statistical models are inherently unsuited to predict the impact of major disruptions because of the historical data/parameterisation dependency for this approach.
- Analysis tools are freely available (R, Q-GIS), but advanced skills in data processing are needed.

4.4. System Dynamics Approach

The system dynamics (SD) approach is a scientific framework for addressing complex and non-linear feedback systems [82]. This systems thinking approach contrasts with probabilistic and deterministic approaches by their ability to describe non-linearity of the changes in system states responding to external drivers [83] (Figure 2). SD models are usually used for energy policy development, environmental policy analysis, innovation impact evaluation, strategic planning, and public policy evaluation [84–86]. The SD process is iterative and interactive, and stakeholders can be involved at every stage of the process from question definition, to conceptual/mental model building, formal model development strategy, and scenario testing feedback. SD models are designed to address the "What if?" question of a complex problem and are useful for prospective scenario testing. Consequently, they are widely used to develop efficient Decision Support Tools (DST) to help in policy development and decision-making, and are often coupled with other types of models (see Section 4, and Table 1).

SD approach has been widely used in hydrology and water resources management [87–89], agricultural land and soil resources [90,91], or food system resilience [92–95].

Strengths:

- At a regional to national scale, the system dynamics approach is well designed for scenario testing and policy prospection.
- SD approach allows multi-disciplinary and multi-method integration. Other approaches can be coupled/linked with SD (participatory, deterministic, probabilistic approaches) to better emphasise the complexity of agricultural and natural resources issues.
- SD approach is suitable to reproduce agricultural systems' organisation and to design new strategies or to experiment management/policy scenarios [96].

Weaknesses:

- The main difficulty in SD approach is validation. Especially when modelling disruptive scenarios, and when internal (model behaviour) and external (outputs) validation possibilities are limited [97]. However, a range of tools can be used to help for validation: the use of local knowledge (participatory-expertise approach) and historical data for calibration (probabilistic approach); running sensitivity analysis of key variables, or analysing scenarios and results in comparison with expert opinions (expert modellers and expert stakeholders).
- There is a risk of formulating erroneous policy by trusting simulations of invalidated models [91].

4.5. Agent-Based Approach

The agent-based approach consists in modelling a system with autonomous decision-making entities interacting with their environment [98]. Agent-based models (ABMs) aim to reproduce real-world-like complexity (Figure 2). ABMs are usually based on a parsimonious paradigm [99] that leads to simple models with great explanatory power. This modelling approach is the only multi-level approach, allowing emergence of processes and feedback loops that mean behaviour adaptation of individuals or groups of individuals [99–102]. This makes the ABMs very useful to simulate behaviour adaptation to new incentives, or new policy, especially for scenario testing [103].

ABMs can be used as spatially explicit models. Using real (i.e., GIS layers or pixel grids) or virtual landscapes accounting for the spatial dimension, distance, and time concepts, ABMs allow coupling with LULCC models to analyse the processes causing the changes [102,104]. For example, farming decisions depend on incentives and interactions at different levels of organisation, such as interactions with other farmers, institutions, associations, markets, or other networks [100,101,104,105]. ABMs are also useful to test individual and collective adaptations to new policy, for example, GHG price effect [102], or adaptation capacity of winegrowers to climate change [106].

Strengths:

- At a regional to national scale, the ABM approach is well designed to simulate society or stakeholders' behaviour facing new policy.
- ABM approach allows coupling of models (using additional physical deterministic models like crop or climate models).
- ABM approach allows for the development of conceptual models to test simple agent behaviours or the combination of behaviours under different incentives.
- ABM approach can simulate disruptions and agent adaptation capacities to a system at different organisation levels and scales.

Weaknesses:

- Like SD, it is difficult to validate ABMs, but a range of tools can be used: the validation of the conceptual framework (by external experts or stakeholders), a robust sensitivity analysis to make sure conclusions fit with the model [104].
- ABMs are not suitable for prediction but powerful for scenario testing.

4.6. Artificial Intelligence

Artificial Intelligence (AI) is an interdisciplinary approach consisting of a set of algorithms trying to mimic human intelligence. AI is already widely used for fraud detection and prediction models, image recognition patterns, spam filters, speech and audio recognition (Google, Siri, Cortana, Alexa, etc.) and others [107]. Machine learning algorithms and deep learning tools are commonly used to automatically learn from data, such as sensor data or databases, to recognize complex patterns and make intelligent decisions based on data [108]. AI allows for analysing big data quickly [109], regardless of complexity (Figure 2). In agricultural sciences, AI is widely used for predicting crop yields [110], for precision agriculture [107], agriculture automation [111], disease detection, and weed, crop, livestock, water, soil, and irrigation management [112,113] by supporting, for example, better management practices for irrigation as well as pesticide and nutrient application.

Moreover, AI is often used to analyse multi-temporal Remote Sensing data [114], and with new satellite mission initiatives (e.g., the Trishna initiative—Thermal infraRed Imaging Satellite for High-resolution Natural resource Assessment), it is a very promising tool for more systematic use of precision agriculture and a deeper understanding of environmental processes at real-time (e.g., like monitoring water status of continental ecosystems, improving the understanding of crop water requirements and water balances). The analysis of this data has the potential for better irrigation management and earlier potential drought warnings.

Strengths:

- At a regional to national scale, the AI approach is well designed for big data exploration and sense-making from various datasets that can help to inform policy.
- AI approach is widely used for prediction and management.
- AI allows coupling various types of data and is powerful for big data analysis.
- AI techniques improve classification and prediction.

Weaknesses:

- AI modelling techniques require high skills, large datasets, and complex training procedures.
- AI approach allows for learning problems very well, but the generalisation is not possible beyond the boundaries of data and model developed (for anything untrained).

5. Analysis of Existing Models by Thematic Applications

In this section, we analyse existing models focusing on agricultural systems by main thematic applications with an emphasis on models used for agricultural policy development at the national level. The analysis focuses on an existing suite of models, skills and data needed to run the models, and how they are used to address global sustainability and adaptation challenges. A wide range of skills are needed to run the models, such as GIS knowledge, statistical or geostatistical knowledge, crop/soils/climate knowledge, and computer skills like programming. The models selected are organised into six thematic applications where DST directly informs policy and the decision-making process, and other environmental models create knowledge of environmental issues and can be used directly or as inputs of DST to inform policy of decision-making (Table 1):

- Decision Support Tools (DST) are developed to support decision-makers in addressing policy or conservation questions (Table 1). For example, the Integrated Sustainable Development Goals (iSDG) is a DST that was developed by the UN via the Millennium Institute to analyse the 17 SDG goals and impacts of changes for each country to help in the development of appropriate policies. The European Common Agricultural Policy Regionalised Impact (CAPRI) Modelling System is another DST example that was developed to support decision-making related to the Common Agricultural Policy [41]. The American Trade-Off Analysis-Multidimensional (TOA-MD) impact assessment model simulates economic, environmental, and social impacts of agricultural systems [38]. The Australian Multi-Criteria Analysis Shell (MCAS-S) for Spatial Decision Support allows stakeholders seeing the effects of land-use change decisions [115]. The American Agricultural Conservation Planning Framework (ACPF) identifies site-specific opportunities to install conservation practices across small watersheds [116–118]. The Reflexive Interactive Design (RIO) conceptual approach works as an expert consultation guideline [119,120].
- Crop models are simulation models describing the crop growth processes and development for varying weather, soil, and management conditions. Widely used crop models (Table 1) include the Agricultural Model Intercomparison and Improvement Project (AgMip) linking climate, crop, and economic modelling to improve models and project scenarios under climate change conditions for several agricultural sectors [121]. The Agricultural Production System sIMulator (APSIM) [93], the Decision Support

System for Agrotechnology Transfer (DSSAT) [122], or Aquacrop model to assess crop growth, crop yield or food security issues [123]. Other crop models not presented in Table 1 included models that are focussed on enhancing scientific understanding, more complex to use, and required a large amount of data and skills.

- General water models (Table 1) are developed to understand or manage water quality and quantity of hydrological processes under different physical and management conditions. Two water models provided by FAO are CropWat, that links crop and water modelling to calculate crop water and irrigation requirements based on soil, climate, and crop data [124], and Aquastats, which monitors the SDG 6 (ensure availability and sustainable management of water and sanitation for all), and in particular on water stress and water use efficiency [125]. Other widely used water models include WaterWorld [126], developed to understand hydrological processes and water resources, and the Soil and Water Assessment Tool (SWAT), a small watershed to river basin-scale model used to simulate the quality and quantity of surface and ground water, and predict the environmental impact of land use, land management practices, and climate change [127,128]. Additionally, many multi-service platforms provide general water modelling tools.
- Greenhouse gas emission (GHG) calculators mostly focus on deterministically estimating carbon and methane emissions (Table 1). Among GHG calculators [129], easy-to-use models that provide great added value on mitigation possibilities include the Ex-Ante Carbon-balance Value Chain Tool (Ex-ACT VC) developed by FAO to increase resilience of populations and ecosystems, and to decarbonize the global economy [130,131], the Agro Chain Greenhouse Gas Emission calculator (ACGE), which estimates total GHG emissions associated with food products [132], and the Climate Change, Agriculture and Food Security-Mitigation Options Tool (CCAFS-MOT), a mitigation options tool estimating GHG emissions from multiple crop and livestock management practices [133].
- Climate models take into account complex atmosphere–ocean–land surface–cryosphere interactions through physics-based knowledge. A full review of climate models is out of the scope of this paper, but the Climate Analogues model provided by FAO [134] caught our attention for its adaptation-focus approach (Table 1). This model identifies areas that experience statistically similar climatic conditions, but which may be separated temporally and/or spatially. The approach allows locating areas whose climate today is similar to the projected future climate of a place of interest, or vice versa. The approach allows comparing agricultural systems working in "future" climate conditions to help define adaptation strategies.
- Multi-service platforms are a shell of models related to Ecosystem Services quantification, mapping, and modelling. They group agricultural production, carbon stock, pollination, water quality, and other models together (Table 1). Multi-service platforms include the widely used Integrated Valuation of Ecosystem Services and Tradeoffs (InVest) [43], the Toolkit for Ecosystem Service Site-Based Assessment (TESSA) [135], or the Co$ting Nature platforms developed to explore how changes in ecosystems can lead to changes in the flows of many different benefits to people [136].

Table 1. Examples and thematic applications of national and regional agro-environmental models.

Model Application	Modelling Approach	Model Name	Spatial Scale	Input Data Needs	Model Aim	Skills Needed	Strengths (+)/ Weaknesses (−)	Comments	References
Decision support tool	System dynamics	Integrated Sustainable Development Goals (iSDG)	National scale, country-based model.	Worldwide data on social, economic, and environmental sectors.	Policy simulation tool designed to help policy-makers and stakeholders make sense of interconnections between the SDGs. iSDG focuses the dynamic interactions within the SDG system to reveal the best paths and progression towards achieving the SDGs.	Model open for collaboration with the iSDG team to develop own country's example.	+: Already implemented model around the 17 SDGs defined by the Millennium Institute. −: Not agricultural system model only. Wider than agricultural sector. Non-spatial modelling. Indicator scores only.	Developed first for food security issues; also used for other questions like clean energy use in the USA. Could be interested to develop for a carbon-neutral objective.	[40] https://www.millennium-institute.org/isdg (accessed on 1 December 2021)
	System dynamics	Common Agricultural Policy Regionalised Impact (CAPRI) modelling system	European Union (27) +Norway, Western Balkans, Turkey scale, NUTS2 scale (280 regions), and 10 farm types for each region.	Economic data, farm/market balance, unit value prices, policy variables. Data provided by FAOSTAT and Eurostat.	Economic model developed by EU to support decision-making related to the Common Agricultural Policy based on scientific quantitative analysis.	High skills (GIS, programmation).	+: Already developed, stable, and complete process for EU. Spatial modelling. −: Can be adapted to other countries around the world but with heavy development to plan.	Multifunctionality indicators analysis (food security, landscape, environment, rural viability), applied to the agricultural sector, with an economic model.	[41] https://www.capri-model.org/dokuwiki/doku.php (accessed on 1 December 2021)
	System dynamics	Tradeoff Analysis—Multi Dimensional impact assessment (TOA-MD)	National, regional to local scale.	Whole farm system (crops, livestock, aquaculture, income), simulating economic indicators, threshold indicators for any other quantifiable economic, environmental, or social outcome.	Model developed to improve the understanding of agricultural system sustainability and inform policy decisions. TOA-MD can be used to analyse technology adoption, payment of ecosystem services, environmental change impact, and adaptation.	Medium to high skills.	+: Already developed, stable, and complete process. Free and easy access to the full model. Model link with AgMIP crop model. Spatial modelling.	Developed by Oregon State University/USA Can be requested by registration form online.	[38] https://agsci.oregonstate.edu/tradeoffs/about-toa (accessed on 1 December 2021)
	Deterministic/Probabilistic	Multi-Criteria Analysis Shell for Spatial Decision Support (MCAS-S)	International, national, regional, and catchment scale.	GIS data/map layers.	MCAS-S informs spatial decision-making and help with stakeholder engagement. Model shows transparently how mapped information can be combined to meet an objective. Model allows stakeholders to see the effects that their decisions may have.	Medium to high GIS skills.	+: Already developed, stable, and complete process. Free and easy access to the full model. Already used for several resources management and adaptation. Spatial and multi-criteria statistical modelling.	Developed by the Australian Department of Agriculture, Water and the Environment. Download available for free.	[115] https://www.agriculture.gov.au/abares/aclump/multi-criteria-analysis (accessed on 1 December 2021)

Table 1. *Cont.*

Model Application	Modelling Approach	Model Name	Spatial Scale	Input Data Needs	Model Aim	Skills Needed	Strengths (+)/ Weaknesses (−)	Comments	References
	Deterministic/ Probabilistic	Agricultural Conservation Planning Framework (ACPF)	Watershed to regional scale.	GIS land use and soils.	ACPF informs and engages local producers in agricultural conservation. It helps in engaging with stakeholders and building conservation solutions.	Medium to high GIS skills.	+: ArcGis toolbox module. Users are able to build their own database. Spatial and multi-criteria statistical modelling.	Model available for free as an ArcGis module. Already used by conservation planners, project coordinators, agency staff etc.	[116–118] https://acpf4watersheds.org/ (accessed on 1 December 2021)
	Participatory approach	Reflexive Interactive Design (RIO)	Aspatial, conceptual process.	Expert consultation approach, need for knowledge, not data.	RIO structurally addresses complex trade-offs and contributes by process and design to change towards sustainable development.	Low skills, but high field or system knowledge needed.	+: First step to design a new system approach. Interesting for stakeholders' engagement without any skills requested. −: No quantification nor spatial analysis. Only conceptual approach.	–	[119,120] ActionCatalogue-method (accessed on 1 December 2021)
Crop Model	Physical/ Deterministic	Agricultural Model Inter-comparison and Improvement Project (AgMIP)	World to national scale.	Worldwide data on climate, crops, and economy.	AgMIP was developed to improve agricultural models for assessing impacts of climate variability and change and other driving forces on agriculture, food security, and poverty.	Medium to low computational skills.	+: Use worldwide dataset, good for country comparisons. Online model with data translator. −: Only sectoral applications, no general overview of agricultural systems.	Developed for food security issues.	[121] https://agmip.org/ (accessed on 1 December 2021)
	Physical/ Deterministic	Agricultural Production System Simulator (APSIM)	Global to local scale.	Field data and observation needed.	APSIM is a highly advanced model for modelling and simulation of agricultural systems. It contains a suite of modules that enable the simulation of systems for a diverse range of plant, animal, soil, climate, and management interactions.	High skills on crop modelling needed.	+: Very precise farming model. More than only crops. Online download available for free. −: Not easy to use. Require very precise agronomic knowledge. No spatial component.	Based on crop model, with other parameters larger than only crops (like livestock, and climate variability effects). Developed in Australia and New Zealand.	[93] https://www.apsim.info/ (accessed on 1 December 2021)
	Physical/ Deterministic	Decision Support System for Agrotechnology Transfer (DSSAT)	Aspatial model.	42 crops implemented, database management for soil, weather, crop management, experimental data.	The DSSAT crop model simulates growth, development, and yield as a function of the soil–plant–atmosphere dynamics.	High skills on crop modelling needed.	+: already implemented for 42 crops. −: Crop model only.	Online download available for free.	[122] https://dssat.net/about/ (accessed on 1 December 2021)

Table 1. *Cont.*

Model Application	Modelling Approach	Model Name	Spatial Scale	Input Data Needs	Model Aim	Skills Needed	Strengths (+)/ Weaknesses (−)	Comments	References
	Physical/ Deterministic	AquaCrop	Aspatial model.	Weather data, crop and soil characteristics, management practices.	Crop growth model developed by the Land and Water Division of FAO to address food security and to assess the effect of environment and management on crop production. Crop yield prediction model under vertical conditions.	Medium to high skills in crop modelling and agronomy.	+: Good to assist for management decisions on irrigation or on crop response to environmental changes. −: No spatial component.	Software available online for free. Provided by FAO.	[123] http://www.fao.org/aquacrop/overview/whatisaquacrop/en/ (accessed on 1 December 2021)
Water/Crop model	Physical/ Deterministic	CropWat	Aspatial, farmer to landscape resolution.	Crop, soil, climate data. Decade and daily calculation of crop water requirements.	Calculation of crop water requirements and irrigation requirements based on soil, climate, and crop data. CROPWAT can also be used to evaluate farmers' irrigation practices and to estimate crop performance under both rain-fed and irrigated conditions.	Medium agronomical skills.	+: Software freely available online. Allow the development of irrigation schedule. −: Work firstly at farm scale; can be used at small catchment scale.	Provided by FAO.	[124] http://www.fao.org/land-water/databases-and-software/cropwat/en/ (accessed on 1 December 2021)
Water/Crop model	Physical/Deterministic	Soil and Water Assessment Tool (SWAT)	Small watershed to river basin.	GIS topography, land use, soil, climate data.	Simulation of the quality and quantity of surface and ground water. Prediction of the environmental impact of land use, land management practices, and climate change.	High water, GIS and, modelling skills.	+: Spatial modelling. Already widely used in assessing soil erosion prevention and control, non-point source pollution control, and regional management in watersheds. Software available for free with a GIS connection.	Data can be provided online from available world data to help build own model.	[127,128] https://swat.tamu.edu/ (accessed on 1 December 2021)
Water	Physical/ Deterministic	AQUASTAT	Global, regional, national scale.	Worldwide data on water resources, water use, and agricultural water management.	AQUASTAT is monitoring of the Sustainable Development Goal 6 that sets out to "ensure availability and sustainable management of water and sanitation for all", and, in particular, on water stress and water use efficiency.	Medium data analysis skills to collect and bring together information.	+: Model outputs already available. −: Low resolution, but already processed.	Provided by FAO.	[125] http://www.fao.org/aquastat/en/ (accessed on 1 December 2021)

Table 1. *Cont.*

Model Application	Modelling Approach	Model Name	Spatial Scale	Input Data Needs	Model Aim	Skills Needed	Strengths (+)/ Weaknesses (−)	Comments	References
	Physical/Deterministic	WaterWorld	Large to fine scale.	Data provided from remote sensing or other global sources. Own data sources can be used.	Waterworld aims to understand the hydrological and water resources baseline and water risk factors associated with specific activities under current conditions, and under scenarios for land use, land management, and climate change.	Medium to low as default parameters and data are provided. More complicated to use with own data and precise parameterisation at a local scale.	+: Quick and relatively easy to use. Allow scenarios, spatial model, spatial outputs.	Used detailed spatial datasets at 1 km^2 and 1 ha resolution for the entire world. Spatial model for biophysical and socio-economic processes along with scenarios for climate, land use, and economic change.	[126] http://www.policysupport.org/waterworld (accessed on 1 December 2021)
GHG emission calculator	Physical/ Deterministic	Ex-Ante Carbon-balance Tool value chain (EX-ACT VC)	From local to national scale.	Worldwide data provided by FAO.	EX-ACT VC aims to develop sustainable and performant food value chain in order to eradicate poverty in rural areas, to increase resilience of populations and ecosystems, and to decarbonize our global economy.	Medium to low data skills.	+: Works as a decision support tool. Indicators like value added, employment, water use, emissions, food loss and waste, and resilience are monitored by the model.	Excel software/indicators open access and free download. Provided by FAO.	[130,131] http://www.fao.org/tc/exact/ex-act-vc/en/ (accessed on 1 December 2021)
	Physical/ Deterministic	Agro chain greenhouse gas emission (ACGE)	From world to regional scale, per agricultural production type.	Regional data, specific data on transport and packaging.	ACGE estimates total GHG emissions associated with a food product. It addresses the most common stages of "linear" agro-food chains (chains for fresh and simple processed products: canned, frozen, packaged, and other minimally processed forms).	Low skill, Excel sheet to fill.	+: Default data are already implemented. General indices. Large regional indices. −: Not easy to downscale at national scale.	Very easy to use Excel sheet. Quick to obtain indices on general GHG emission per agricultural production type. Clear guidelines provided.	[132] https://ccafs.cgiar.org/agro-chain-greenhouse-gas-emissions-acge-calculator#.Xvq6hCgzYuU (accessed on 1 December 2021)
	Physical/ Deterministic	Climate Change, Agriculture and Food Security—Mitigation Options Tool (CCAFS-MOT)	Regional to national scale.	General data on national climate, soil, crop, and grassland management.	Model estimates greenhouse gas emissions from multiple crop and livestock management practices, providing policy-makers with access to reliable information needed to make science-informed decisions about emission reductions from agriculture.	Low skill, Excel sheet to fill.	+: Easy to use. FAO data can provide all the needed inputs.	Very efficient tool providing emissions and mitigation potentials for crops, grasslands, and livestock.	[133] https://cgspace.cgiar.org/handle/10568/67027 (accessed on 1 December 2021)

Table 1. *Cont.*

Model Application	Modelling Approach	Model Name	Spatial Scale	Input Data Needs	Model Aim	Skills Needed	Strengths (+)/ Weaknesses (−)	Comments	References
Climate Models	Probabilistic	Climate Analogues	Worldwide.	Use current climate data from WorldClim aggregated to 2 degrees, (1970–2000). Future climate data come from CCAFS-Climate for all CMIP5 and RCPs.	The models identify areas that experience statistically similar climatic conditions, but which may be separated temporally and/or spatially. The approach allows locating areas whose climate today is similar to the projected future climate of a place of interest, or vice versa.	Medium to low skill.	+: Easy to use data are already implemented. Model is running with R. −: No downscaling allowed.	Very interesting to compare the future climate of a region of interest with other places in the world and what agriculture can look like. Good for building mitigation options rapidly. Provided by FAO.	[134] https://www.ccafs-analogues.org/ (accessed on 1 December 2021)
Multi-service platform	Physical/ Deterministic	Integrated Valuation of Ecosystem Services and Tradeoffs (InVest)	Local to global scale.	Spatial resolution and data input are flexible (wide range of environmental modelling).	Suite of models used to map and value the goods and services from nature that sustain and fulfill human life. It helps explore how changes in ecosystems can lead to changes in the flows of many different benefits to people.	Medium to high. Need GIS and mapping skills to build own data and analyse outputs.	+: Spatial modelling of a wide range of ES. Allow spatial inputs and outputs. Can be used with other model outputs in a GIS.	Almost 20 models available for free such as: carbon, pollination, habitat quality, reservoir hydropower, crop production, habitat risk assessment, sediment retention, water purification, etc.	[43] https://naturalcapitalproject.stanford.edu/software/invest (accessed on 1 December 2021)
	Physical/ Deterministic	Toolkit for Ecosystem Service Site-Based Assessment (TESSA)	Local to global scale.	Land-use data, default parameters provided.	TESSA aims to understand the impacts on natural capital and ecosystem services of actual and potential changes in state at individual sites. TESSA aims to promote better planning decisions to support both biodiversity conservation and ecosystem service delivery.	Medium to low: guides for non-specialist users through various methods for rapidly quantifying a range of ecosystem services.	+: Toolkit, multi-indicators, ES-based, developed for decision-making. Can be used by non-experts.	ES approach, not agricultural approach. Evaluate a range of 10 ES (nutrition, water supply, materials, energy, regulation of biophysical, flow, physico-chemical, biotic environment, 2 cultural ES).	[135] http://tessa.tools/ (accessed on 1 December 2021)
	Physical/Deterministic	Co$ting Nature	Worldwide.	Spatial datasets at 1 km^2 and 1 ha resolution for the entire world.	A web-based tool for natural capital accounting and analysing the ecosystem services provided by natural environments (i.e., nature's benefits), identifying the beneficiaries of these services, and assessing the impacts of human interventions.	Medium to low.	+: Online platform with already implemented data. −: Target Ecosystem Services, more for conservation and development, less for only agricultural purposes. No downscaling available.	Spatial models for biophysical and socio-economic processes along with scenarios for climate and land use.	[136] http://www.policysupport.org/self-paced-training/costingnature-english (accessed on 1 December 2021)

6. Discussion

6.1. Range of Model Approaches and Thematic Applications

The approaches and model examples presented in Figure 2 and Table 1 show a range of freely and easily accessible tools, which require low to high levels of input data and application skills. That means modelling of agricultural systems does not necessarily require time-consuming data collection or model development for certain levels of application, but only a few models are available for regional or national modelling applications. For example, the FAO models can be used as-is for basic scenario modelling or for feeding another model. The benefits from combined approaches and the use of spatial models for better land planning are also obvious. For example, coupling a participatory approach to a quantitative deterministic or probabilistic approach to include stakeholder engagement for scenario design or to test stakeholder behaviours on an ABM enhances the model outputs.

A range of models are available to address specific questions faced by the NZ government at a national or regional decision-level, related to agricultural systems technology, disruptions, and the environment (Figure 1), but none of the currently available models or approaches can answer all questions by themselves. A combination of several approaches and existing models can help address individual disparate issues (Table 2).

Table 2. Synthesis of example questions and modelling process options.

Question Examples	Modelling Process Options
• How will anthropogenic climate disruption affect agricultural systems?	- Deterministic approach to understand physical processes (climate, crop, milk yields models, economic models); - Probabilistic approach to define vulnerability (land-use model); - Participatory approach to draw opportunities and adaptation strategies; - Agent-based approach with Decision Support Tools to design incentives, regulations or policies. - ...
• How will disruptive technologies change future agriculture pathways?	- Systems Dynamics approach to simulate a new technology disruption (non-linear system); - Agent-based approach with Decision Support Tools to understand new technology adoption, and scaling up and out opportunities; - Multi-Criteria Analysis to spatially understand and predict consequences on land use, ecosystems, and environment. - ...
• How can technology be best used to improve the profitability, resilience and sustainability of agriculture?	- Systems Dynamics approach to simulate a new technology disruption (non-linear system); - Deterministic and probabilistic approaches to evaluate environmental consequences (GHG emission calculators, Ecosystem Services models, water models, economic models); - Multi-Criteria Analysis to spatially understand and evaluate consequences of change. - ...

Table 2. *Cont.*

Question Examples	Modelling Process Options
• How can agricultural infrastructure be redesigned and improved to efficiently supply food products for a country and around the world?	- Systems Dynamics approach to simulate a system change and its disruption; - Deterministic and probabilistic approaches to evaluate socio-economic consequences on food supply; - Artificial Intelligence to simulate demand and supply capacity in real-time. - ...
• How can policy be used to improve governance of agritech and sectoral disruptions?	- Agent-Based approach to understand behaviours against decision levels; - Decision Support Tools to design optimal changes in governance system; - Deterministic and probabilistic approaches to evaluate economic consequences on a sector disruption (economic models). - ...

Analysis of modelling approaches and model examples allows for identifying model strengths, weaknesses, data needs, and skill requirements to select the best combination for the NZ needs. A DST, based on an SD approach, can be the most suitable modelling system at a regional to national scale for modelling the agricultural systems to support policy development and anticipate main impacts. For example, the iSDG model developed by the Millennium Institute [40] aims to model the interconnections between a large number of objectives to help identify policy interventions (Table 1). This model focuses on the dynamic interactions within the objectives to reveal the best pathways towards achieving them all. The SD approach used appears to be perfectly suited to the modelling of interconnections even for non-linear relationships of the system between parameters and feedback loops. DST are even more efficient when coupling with a spatial component. For example, the CAPRI model, using an SD approach (Table 1), was specifically developed for the European agricultural system to evaluate the impacts of the Common Agricultural Policy and trade on production, income, markets, trade, and the environment from global to regional scales [41]. The model architecture is organised around a supply model of 280 European regions embedded in a global market model, and uses specific spatial and non-spatial databases. The indicators defined in the model are relevant to addressing agricultural/environmental issues related to Nitrogen and Phosphate balances, GHG emissions, animal stock density, irrigation and water consumption, and the value of nature. In addition, the spatial component from national to regional scales is ideally suited for its intended application. The model allows spatial and temporal analysis of trends and the impacts of new policies. It also takes into account the international market supply and demand chain. One negative point of the CAPRI model is its inability to transpose and calibrate the model to any other country outside the EU without restructuring the model. In comparison, the American Trade-Off Analysis-Multidimensional (TOA-MD, Table 1) impact assessment model is a smart-model easily re-usable, using an SD approach, taking into account economy, technology, policy, crop, livestock, and aquaculture subsystems to simulate adoption, outcome distributions, and impact indicators of new policy [38]. This model, which includes a spatial component, can also be used for analysing ecosystem services, the impacts of climate change, and other environmental changes. The SD approach used for DST in policy development is the most suitable approach to model complex and dynamic systems and allows coupling with other model approaches.

One complementary approach to SD is the spatial Multicriteria Analysis (MCA). Spatial MCA is based on a deterministic or probabilistic modelling approach and is used within a geographic information systems (GIS) spatial platform. Spatial MCA is of added-value for land-use planning optimisation because it allows mapping of model outputs or stakeholder choices. Widely used for quantifying multifunctionality of agriculture [137,138] or ecosystem services trade-off and bundles [139,140], MCA are quantitative and goal-oriented models. An example of this complementary approach is the Australian Multi-Criteria Analysis Shell for Spatial Decision Support (MCAS-S, Table 1), which is designed for decision-makers to combine and meet planning objectives [115]. This model helps with stakeholder engagement by showing the effects of decisions using spatial information. Only basic GIS skills are needed to apply this model because of the user-friendly interface and inbuilt GIS database. On the contrary, the Agricultural Conservation Planning Framework (ACPF, Table 1) is a GIS toolset developed for MCA and requires a high level of GIS skills. This model, however, allows engagement with stakeholders to build conservation solutions in an agricultural context [116–118].

Whatever the skills needed and methodological choices, the spatial MCA allows for the SD model to provide a spatial representation of scenarios. MCA can thus help to provide optimal allocation propositions and scenario assessments for any systems models.

6.2. Limits, Margin of Progress, and Recommendations for Future New Zealand Development

With more than six decades of multidisciplinary contribution to concepts and tools for agricultural systems modelling, the scientific community considers models critical to make informed agricultural decisions [39]. However, despite all data and models available, models often fail to inform policy. For example, the European Commission defined a strategy to halt biodiversity loss affected by the agricultural sector by 2020. Those efforts were supported by the Common Agricultural Policy (CAP) subsidies (40% of the EU budget, EUR 362.8 billion) for the 2014–2020 period. However, the agricultural reforms failed on biodiversity, mainly due to underestimation of intensive farming, increasing of chemicals, and machinery use (according to European Court of Auditors). In addition to limited modelling, other reasons for failure include the dilution of ambitions, targeting large farms only, multiple possible exemptions, and abandonment of previous working measures (e.g., reduction of permanent grassland) [27,141]. A large number of other models have been developed since 2014 to understand the failed processes [142,143] and define recommendations for the 2030 strategy. They highlighted the need for more flexibility to regional adaptations and a focus on land-use processes rather than quantity (e.g., connectivity of landscape element to support overall diversity) [141,142]. In the context of a future development of the NZ agricultural system model, the example of the European model limits are to be considered. The chosen or developed model must take into account the complexity of the whole system, but it must also maintain an expert analysis phase downstream from the modelling outputs.

The next generation of models should be led by the use of AI, and should include advances in technology, such as precision agriculture, biotech, and others. During the analysis process, we did not find any national or regional agricultural systems of DST model based on AI, as proper training of AI systems requires large volumes of data, and in a sense, AI is still in its infancy in environmental applications. However, as agricultural systems modelling has always capitalised from technology advances, operating with big data and generalising cloud computing is a major avenue of future development. The current state of agricultural system models' complexity is sufficient for powerful applications [83].

To select the ideal model or combination of models for future agricultural system modelling initiatives in NZ, modellers and users should consider the following:

1. Clearly identify the question(s) to be answered or the objectives of the modelling initiative.
2. Assess the data available for modelling (qualitative, quantitative, statistical databases, field observations, GIS maps, etc.). The data available will help refine the modelling approach to use and model thematic application, and if needed, help identify what additional data needs to be collected.
3. Evaluate existing models and their adaptation potential to address the modelling requirements. Consideration for the type of approach needed, model thematic application, and model availability will depend on items 1 and 2 above. Furthermore,

consideration should be given to a combination of modelling approaches to address all requirements, if necessary.

7. Conclusions

There is currently an urgent need for a national scale agricultural systems modelling in NZ to address key questions of the sector, due to critical global environmental, socio-economic, and technological disruptions. Although there are a number of models available for agricultural systems modelling, none are intended to be used for modelling major national or regional disruptions to agriculture, or their usability outside inbuilt geographic boundaries is low. Furthermore, most models are only intended for targeted applications for understanding the effects of land-use change, climate, or other specific changes. The FAO suite of models are freely globally accessible, provide generalised country-specific input data, and are quickly reusable for specific regional to national modelling initiatives; however, the weakness of these models is in their singular modelling approach, which limits their applicability to address a range of complex disruptions at once.

Six broad modelling approaches were identified, and each of these approaches provides for specific strengths, weaknesses, and application complexities. The participatory approach allows a great stakeholder engagement; deterministic approaches allow for a direct link with field knowledge and physical processes; probabilistic approaches provide statistical modelling to explain uncertainties; system dynamics approaches allow for modelling complex systems and include feedback loops and delay response; agent-based approaches permit behaviour reproduction and testing, and artificial intelligence allows for deep learning of any source of data to provide understanding of previous changes, which can be used as a predictive tool.

To better understand the current complex disruptions affecting the NZ agricultural sector and assess relevant policies to address future disruptions, a suite of physical crop–water–climate models (i.e., FAO models) should be linked to economic, trade, and production models (i.e., CAPRI model), ecosystem health models (i.e., InVest), and target socio-environmental global objectives (i.e., ISDG indices). An SD approach would be an ideal framework to allow for an integration of these models for both temporal and spatial analysis. Furthermore, ABM could be used to understand and test behaviour of stakeholders under various scenarios of disruptions. Free national datasets (i.e., NZ Stats, sectoral statistics Dairy NZ, Beef&Lamb, Irrigation NZ), international datasets (i.e., FAOSTAT) and maps (i.e., Global Land Cover, OurEnvironment NZ), together with data analysis of national or global datasets through Artificial Intelligence could provide for the necessary inputs to drive such models and also be used to calibrate and validate results through comparison to examples of historical disruptions to agriculture.

The complexity of the NZ agricultural system and its economic, social, and environmental implications, requires integrative approaches, particularly at the national scale for policy and decision-making. A single modelling approach has limited usefulness for modelling of complex agricultural disruptions and thus future investment is needed by the NZ government and industry in integrative modelling development. Finally, this analysis suggests the use of a spatial DST, based on an SD approach, as the most suitable modelling system at a regional to national scale for modelling the NZ agricultural system to support policy development and anticipate main impacts and future disruptions.

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