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Modélisation des systèmes agricoles complexes : Une exploration de la modélisation basée sur les agents et de l'intégration de la programmation mathématique par le biais d'une analyse systématique de la littérature

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RÉSUMÉ

Les systèmes agricoles étant de plus en plus complexes, les approches de modélisation avancées sont cruciales pour comprendre la dynamique et combler les lacunes. Cette étude systématique examine l'intégration de la modélisation basée sur les agents (ABM) et de la programmation mathématique (MP) dans les contextes agricoles. Nous avons analysé les études sélectionnées répondant aux critères d'inclusion, en caractérisant les structures des modèles, les processus de décision, les interactions entre les agents et les forces/limites comparatives. Les résultats révèlent diverses applications couvrant la gestion des ressources, l'analyse des politiques et la dynamique de la production. Les principales forces de l'intégration comprennent une meilleure représentation spatiale, l'hétérogénéité de la modélisation et les capacités d'optimisation. Les limites concernent l'intensité de calcul et les défis liés à la prise en compte de la complexité du monde réel. L'étude met également en évidence la possibilité d'améliorer le réalisme comportemental, de normaliser les méthodes et d'élargir la dynamique de la chaîne d'approvisionnement. En synthétisant les approches actuelles et en identifiant les lacunes de la recherche, ce travail vise à orienter le développement futur de modèles intégrés soutenant la prise de décision agricole durable.

Mots-clès de l'auteur

Systèmes agricoles, Programmation mathématique, Modélisation basée sur des agents, Adoption de pratiques, Décision des agriculteurs, Prise de décision, Comportement des agriculteurs, Agriculture, Analyse systématique de la littérature.

Modeling Complex Agricultural Systems: An Exploration Of Agent-Based Modeling And Mathematical Programming Integration Through Systematic Literature Review

ABSTRACT

As agricultural systems face mounting complexities; advanced modeling approaches are crucial for understanding dynamics and filling the gaps. This systematic review examines the integration of Agent-Based Modeling (ABM) and Mathematical Programming (MP) in agricultural contexts. We analysed selected studies meeting inclusion criteria, characterizing model structures, decision processes, agent interactions, and comparative strengths/limitations. Findings reveal diverse applications spanning resource management, policy analysis, and production dynamics. Key strengths of integration include enhanced spatial representation, heterogeneity of modeling, and optimization capabilities. Limitations involve computational intensity and challenges in capturing real-world complexity. The review highlights opportunities for improving behavioral realism, standardizing methods, and expanding to broader supply chain dynamics. By synthesizing current approaches and identifying research gaps, this work aims to guide future development of integrated models supporting sustainable agricultural decision-making.

Author Keywords

Agricultural systems, Mathematical programming, Agent-based modeling, Adoption of practices, Farmers' decision, Decision-making, Farmers' behaviour, Agriculture, Systematic literature review

Introduction

In the 21st century, as agriculture is moving towards industrialisation, agricultural systems are facing numerous global issues. These challenges are interlinked as population growth increases the need for food, climate variability affects the environment, and resource scarcity increases the barriers for farmers to operate sustainably (Tudi et al., 2021). In this case, tackling more efficient configurations needs looking at whole systems including other structures involved, and the decision making process produced by the decisions, on an independent and aggregate scale. Developing more sustainable practices necessitates comprehending whole-system dynamics and decision-making processes at both individual and collective levels. Thus, modeling is expected to add considerable additional advantages by permitting made up scenarios of the problems and solutions that may be encountered and the possible outcomes of agricultural systems.

The applications of agent-based modeling (ABM) and mathematical programming (MP) are helpful in the simulations and analysis of agricultural systems (Lone et al., 2019; Ravaioli et al., 2023). For instance, ABM allows for the simulation of individual agents' behaviors and interactions while providing insights into emergent patterns and system-level outcomes. Complementarily, MP provides a framework for optimising economic situations and decision-making under constraints, like enabling the identification of efficient resource allocation strategies. This study aims to examine how ABM and MP approaches are applied and integrated into agricultural systems.

Our research is categorized into several major categories such as general model information, decision-making processes, actor-environment interactions, and model evaluation. This structure allows us to systematically examine how ABM and MP are applied in agricultural systems, which decision-making mechanisms are modeled, how interactions between actors are represented, and the strengths and weaknesses of the models. The background outlined in this paper aims to provide insights into the complex linkages and interactions of ABM and MP. The selected studies address a variety of agricultural issues, such as agricultural systems management, efficient resource utilisation and climate change adaptation. Also, arranging and summarizing these approaches gives more information about the possibilities of using ABM and MP concerning problems of agriculture, the results of modelling and the recommendations accessible. They shows the advantages of integrating ABM and MP in selected agricultural studies, providing both normative and predictive insights.

This study examines how both ABM and MP modeling approaches influence agricultural activities and decision-making processes. It shows how these modeling techniques have been applied to different case scenarios, covering problems from policy regulation to agricultural resource management. The integration of ABM and MP approaches allows us to capture both the bottom-up emergent behaviors characteristic of complex agricultural systems and top-down optimisations necessary to achieve them. Also, this study aims to enhance understanding of innovative modelling techniques and their application to address complex challenges. One such challenge is the pursuit of economic efficiency in agriculture while simultaneously adopting environmentally sustainable approaches. The objective is to enhance the value of current efforts to develop more resilient, more flexible and more sustainable agricultural systems, which are required by contemporary society, by synthesising existing research and identifying areas for future research.

I. Background

1. Review of Mathematical Programming

MP is a one of the discipline of quantitative methods that involves the use of mathematical models, algorithms and equations to identify the optimal solutions to achieve a particular objective and it does so by taking into account constraints on the paths to the goal (Kaiser and Messer, 2011). One of the main objective of MP is to find the optimal solution that maximize or minimize certain objective function such as cost, profit or yield, which are crucial for the decision-making process in agricultural systems (Vajda, 2009).

The integration of MP in agricultural disciplines, began to gain momentum since the mid-20th century, particularly in the field of farm management and agricultural economics (Hazell and Norton, 1987 ; Keller, 2018). The study of McALexander and Hutton (1959), mentioned the early application of MP focused on linear programming (LP) models pioneered by Dantzig (1963), and further studies developed this method by addressing the agricultural issues, such as selecting the optimum crop rotation and profit maximisation. Brandes (1974) developed the whole-farm MP model, facilitating information sharing between farmers and extension staff. McCarl et al. (1977) introduced computer model iterations in a format that included computer model iterations presented in a way that was both realistic and understandable for crop farmers (Mössinger et al., 2022 ; Rose et al., 2017).

The background established by the pioneers in the field of MP has been evolved over time not only to fine-tuned, but also for consider a great range of constraints and variables in the modern world operations, with a face of evolving technology and increased real-world challenges in agricultural systems such as climate change, population growth, political, economic, and other issues. Advances in MP approaches have improved the efficiency of decision-making processes and led to more sophisticated optimisations in the models.

MP models consist in several common components that function cooperatively to formulate and solve optimisation problems (Bazaraa et al., 2011). Before proceeding with an analysis of the types of MP and their characteristics, it is essential to define the term "model" within the context of this study. A model is a structured representation of a system designed to facilitate the study, control and assumption-making about its behavior under different conditions. In this representation, words or mathematical formulas describe the relations between the elements of the system. In particular, decision models are the type of mathematical model that can provide the solution of the values of decision variables under the control of the manager of a system in order to achieve the optimal outcome defined by the objective function. In this context, LP is one of the most widely used techniques in agricultural studies and is a set of concepts and techniques that are related to linear decision models. Applications of MP, and especially LP, provides a structured approach to optimize various agricultural activities (Mössinger et al., 2022). As Alotaibi and Nadeem (2021) mentioned, LP can be used in many contexts in agriculture, such as feed mix optimization, crop pattern determination, crop rotation planning, land allocation and irrigation water management.

As stated in the study by Kunwar and Sapkota (2022), in any LP problem, there is typically only one optimal solution, but sometimes there can be more than one feasible solution. The problem comprises linear comprises linear equations and inequalities that represent the limitations of resources. Given that an infinite amount of resources cannot be utilized to achieve the objective, the scarce resources determine the solution space.

While LP is an effective technique for agricultural problems and linear optimization models are more frequently used, it is important to note that some non-linear structures can be involved in other agricultural challenges (Benli and Kodal, 2003 ; Sönmez and Benli, 1976). Nonlinear programming (NLP) becomes essential in complex scenarios where relationships between variables are non-linear. In addition to standard types of MP, as their sub-branches, there are other important MP techniques, which are frequently used in agricultural systems, depending on the nature of the variables of the optimization problem. Each model and technique possesses distinctive advantages and disadvantages that may facilitate its implementation in particular economic, social, and environmental contexts (Bournaris et al., 2019 ; Ewert et al., 2011 ; Moulogianni, 2022).

2. Review of ABM

Agent-based modelling has a history almost as long as computers (Hanappi, 2017). As an earlier example of ABM was the "Monte Carlo" simulation developed in the 1940s (Harrison, 2010). As Hanappi, (2017) states, in the 1940s-1950s, development of cellular automata began, most notably John von Neumann's self-replicating automata and later Conway's Game of Life (1970) (Von Neumann and Morgenstern, 1944). ABM began to be applied in agriculture in the late 1990s. As Kremmydas et al. (2018) mentioned, in practice, various issues such as farm-environment interactions, agricultural policies, land use management which are simulated to simplify the decision-making processes of agents. Early use cases of ABM in agriculture include the CORMAS model, which utilized from ABM perspective to study for management of resources, and other models combining MP with innovative elements such as farm interactions and spatial dimensions (Kremmydas et al., 2018b).

The fundamental aim of ABM in an agricultural system is to uncover the underlying patterns in the system by discovering and defining the rules and parameters that engender complex behaviour. ABM involves examining social agents as dynamic systems consisting of autonomous interacting agents and it is explores social systems from the perspective of complex adaptive systems. (Bonabeau, 2002 ; Janssen, 2005). With this sort of computational modeling, complex agricultural systems can be investigated and also to observe the behaviour that occurs within a given period. More specifically, as Ravaioli et al. (2023) mentioned, it can be observed in agricultural systems, that the ABM process which is carried out in cycles and involves the term agent and its environment being defined with some historical information and theoretical anticipation initially. Then, depending on internal characteristics and external conditions, their decision-making takes form, generally they communicate with each other and their surroundings, and state changes are made depending upon these effects and actions (Ajzen, 1991). This cycle can be performed for a predetermined period of time or until certain objectives are attained, thereby enabling evaluation of system behaviour and possible trajectories in agricultural systems. ABM is also referred to as "Multi-Agent System" (MAS) in some researches such as that conducted by Pérez-Pons et al. (2022). However, in our study, we have preferred to use the term ABM. There is no clear explanation as to why two different names are used for the same concept in agricultural research, but as we can see from many studies, this is a matter of authorial preference.

II. Material and Methods

In this section, we describe in detail the methodological framework of our research. We consider the intersections and potential integration of both ABM and MP modeling approaches within the agricultural research and practice context. We outline the systematic review process, data collection, analysis methods, and evaluation framework. A systematic literature review is a process that objectively synthesises an overview of existing knowledge, and therefore provides a better way of identifying studies relevant to research area of interest (Page et al., 2021). Beyond synthesising existing studies, this approach enables the identification of trends, gaps and beneficials. It also provides for a robust framework for understanding the complex factors shaping agricultural systems. We followed the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to enable transparency and reproducibility of the systematic literature review (Page et al., 2021). It is considered as the international standard for reporting systematic reviews and meta-analyses. The PRISMA guidelines helped structure and make openly accessible each step in the process of literature review including search for and selection of relevant studies and data extraction and synthesis of the information.

1. Review Protocol

We conducted a review of the peer-reviewed literature identified in the Web Of Science (WoS) database (*23/04/2024*). For the systematic literature review, keywords were identified under three main categories:

1. The ABM set included the terms ("agent-based model*" or "multi-agent model*" or "agent based model*" or "multiagent model*" or "ABM" or "individual-based model*"). Given the variety of terminologies that may be used in different research contexts, this inclusion was necessary to ensure that we captured all relevant work on ABM. This approach is based on the search commands of Bourceret et al. (2021) and Schulze et al. (2017) in their ABM investigations of socio-ecological systems. The use of asterisks (*) and quotation marks (" ") in our terminology allows capturing variations of a term and full expressions, respectively.

2. The terms ("mathematical programming" or "linear programming" or "operational research" or "constrained optimization" or "constrained optimisation") were used in the MP set. We have chosen these keywords to establish a balance between the different types and applications of MP.

3. Lastly, the AGRI set included the keywords (“agri*” or “farm*” or “crop*” or “culture*” or “bio*” or “environment*” or "fish*" or "livestock*" or "food*"). We have used these terms to emphasise the broad nature of agriculture, but also of food systems as well. The selected terms aim to encompass the full spectrum of the agricultural fields, from production to farming practices, crop cultivation to animal husbandry to production, biotechnology to ecological impacts (Shams et al., 2023).

2. Search Strategy and Selection Criteria

We limited the literature review to published articles and publications written in English. The articles selected include in their title, abstract, or keywords one or more terms from each of the keywords sets. In order to evaluate the ABM and MP integration in agricultural scale in a more comprehensive and systematic way, we determined certain criteria for the articles we obtained in the first stage. Each criterion helps to determine the relevance of the selected articles to our research objective. Articles that meet all these criteria are considered as studies that best represent the integrated use of ABM and MP in agricultural systems and reflect current research trends in this field.

The following criteria were taken into consideration respectively:

Criterion 1 - Fulfilling the Criteria of ABM

This criterion considers if the article uses an approach that integrates ABM.

Criterion 2 - Fulfilling the Criteria of MP

This criterion assesses whether the paper uses MP techniques.

Criterion 3 – Fulfilling the Criteria of Agricultural Focus

This criterion assesses if the paper focuses on agricultural systems and decision-making processes related to agriculture.

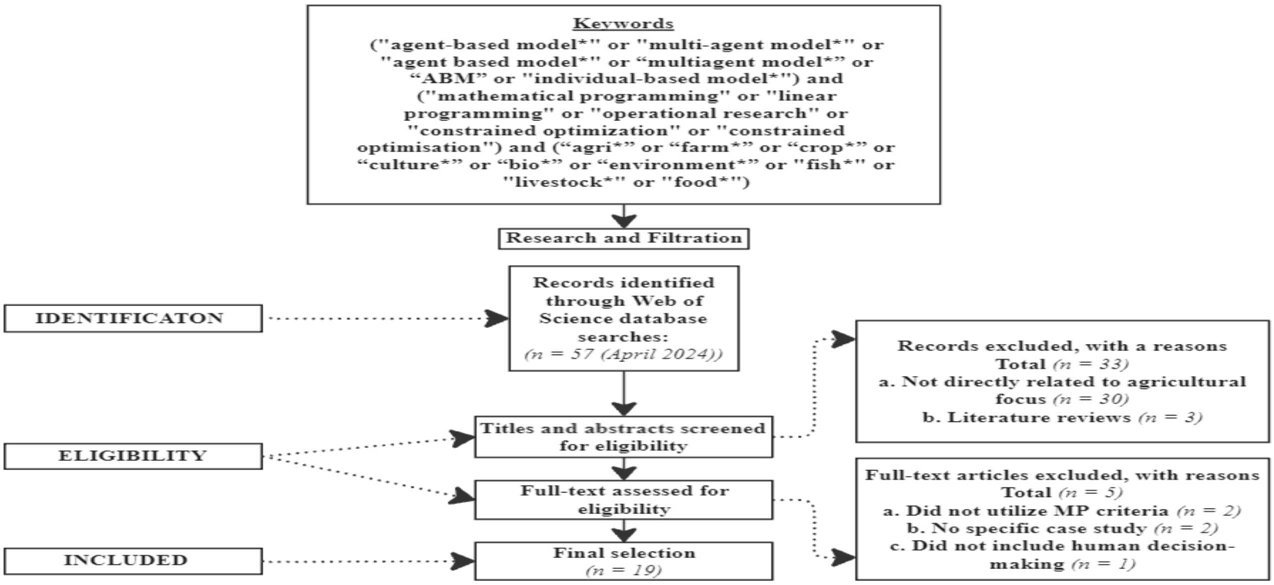
Criterion 4 – Fulfilling the Research Design

Lastly, studies are expected to include case studies or empirical applications. Review articles, framework studies, software or cyberinfrastructure descriptions were also excluded.

As a result of the search conducted on the WoS platform, 57 documents were identified and a multi-stage filtering process with given criteria was then applied. Each abstract of the 57 articles was analysed for its relevance to the keywords and the overall research theme. Papers that did not directly contribute to our primary objective of understanding the integration of ABM and MP in the agricultural theme were eliminated. Thus, 33 articles were eliminated in the first stage of abstract screening. While 30 of them were eliminated because they did not have a direct agricultural focus, 3 of them were eliminated because they were literature reviews despite having an agricultural focus and integration of ABM and MP approach.

A detailed full-text analysis was then conducted for the remaining 24 articles. This review ensured that the content, methodology and findings of these articles were in line with our research questions and objectives. This review ensured that the content, methodology and findings of these articles were in line with our research questions and objectives. As a result of this full-text review, there were 8 papers found to not meet our criteria. Specifically 2 articles were eliminated after the full-text analyses, because even if the MP wording appeared in the texts; they did not utilise MP criteria, which is a critical element for our research focus when discussing the representation and shortcomings of MP. In other words they were not aligned with our primary goal of understanding the integration of MP in agricultural contexts. Additionally, the other two articles were also eliminated after the full-text analyses because they did not include a specific case study according to our research objective. These articles mostly refer to existing literature, evaluate examples and models of ABM and MP approaches, critically examine the application of the methodologies and present their contributions. Full-text review revealed that these articles did not meet our search criteria. Lastly, another paper was eliminated because it did not directly fulfill the research topic and it was more focused on understanding and controlling the dynamics of ecological systems without human agents or human decision-making processes. At the end of the process, 19 articles were selected for the analysis. All these approaches adopted for the systematic literature review is illustrated in Figure 1 using the PRISMA four-stage flow (Moher et al., 2009 ; Utomo et al., 2018 ; Vrabel, 2015).

Figure 1: PRISMA flow diagram of the systematic literature review process



Note: A list of all articles can be found in Appendix 1, can find additionally.

3. Analyse questions addressed to literature review

The question framework in this study was based on the systematic literature review methodology used by Kremmydas et al. (2018). This approach was deemed appropriate for meeting the specific requirements of our research area and to comprehensively assess the potential and challenges of the utilisation of ABM and MP approach together.

First of all, in order to ensure that the literature review of the 19 selected articles was conducted in a structured and systematic manner, the review question matrix consisted of four main components, each with sub-questions he first category investigates the basic aspects of the studies including the specific agricultural subjects addressed, the types of decision-making processes modeled, and the key outcomes measured. It aims to find out the common trends of issues and target areas if any of the integrated ABM and MP strategies. The second category is composed of detailed examination of the decision-making processes in the models. In this context, the level of rationaliof detailedtypes of spatial and decision heterogeneity, decision-making mechanisms, optimization approaches, the influence of spatial and temporal factors, risk and uncertainty are aimed to be understood. Environmental perception and information acquisition (adaptation) processes of agents are also analysed. The third category focuses on the nature of interactions between agents, and the way in which they are modelled. Direct and indirect interactions, collective behaviour, competition and cooperation dynamics, learning (adaptation) processes are examined in detail. The place of the representation of an element such as the supply chain, which plays an important role in some agricultural systems, in the models is also evaluated. The last category addresses the comparative strengths and weaknesses of both modelling approaches. Synergies and challenges arising from the combined use of ABM and MP approaches are analysed. The applicability of this integrated approach to different issues and regions is also assessed.

4. Data Extraction and Synthesis

In the process of data collection and analysis, previously prepared question sets were used. The data collection process was carried out by 2 independent researchers to increase the reliability of the results. After the analyses of each article, we entered our findings into a standardized format of spreadsheet. To categorize the literature review responses, tables we prepared for all review question categories are in the same format, showing the responses with frequencies and percentages of the responses obtained from 19 articles. These tables show the most frequent responses and significant trends. It should be noted that common responses that were the same in all or almost all of the 19 articles and did not represent a high frequency value were not included in the table. In addition, for each question, the top 5 responses with the highest frequency are shown (no more than the top 5 are shown if there are responses with equal frequency). Finally, the percentage value that appears in the list for each response is the percentage value calculated from the frequency value of the responses of all 19 articles. (*Detailed lists of articles, responses and full frequency and percentage analyses for all categories are presented in Appendix 1. This appendix allows readers and researchers to access the full dataset and examine the analyses in detail.)* Then, crosstab analyses were meticulously performed to uncover the relationships between the questions and their answers.

III. Results

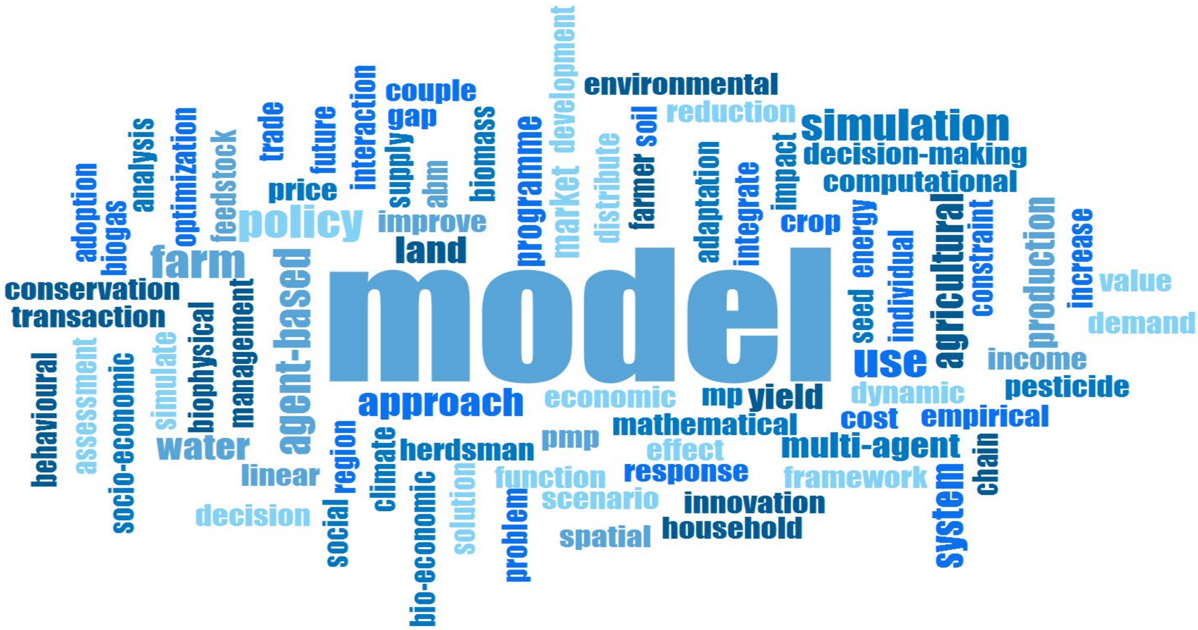
1. General Information

1.1. Bibliometric and Methodological Analysis

Initially, bibliometric analysis of the articles, revealed both the most common terms advanced in the studies (Fig. 2) and the authors' collaborative networks (Fig. 3) The full-text analyses then examined the use of the ODD (Overview, Design Concepts and Details) protocol as methodological aspect of the paper. The aim of the ODD protocol is to enable complex ecological models to be described in a more comprehensible, repeatable and transparent manner (Grimm et al., 2010 ; Müller et al., 2013). In the papers, the frequency responses of use of the ODD protocol were observed to be approximately a quarter of the papers.

Most of the study used a specific modelling framework. Regarding the model structure, all articles made their models accessible and most of the articles presented the relevant data on the model website or in the article. When the type of data is analysed, about three-quarters of the studies use secondary data, while the remaining are based on primary data. These findings indicate that the majority of studies are transparent about model and data sharing, but also the standardised documentation protocols has not yet been adopted in the majority of ecological modelling studies.

Figure 2: The word cloud of the terms that appear in the abstracts and keywords of 19 selected research articles by MAXQDA 24.



Words, such as “model”, “simulation”, “approach”, and “farm”, are suggestive for literature reviews concerning modeling and simulation of agricultural systems. The terms "multi-agent", "computational", "agent-based" and "mathematical" indicate the modelling techniques used. The words "socio-economic" and "environmental" indicate the different dimensions of the model. More words like ‘’water’’, ‘‘land’’ and ‘‘soil’’ tend to suggest the peculiar characteristics of the models that are aimed towards supporting resource management and agricultural or environmental concerns. The terms "policy", "decision-making" and "economic" emphasize that the models include economic and policy dimensions, which are necessary for solving such complex issues as advanced agriculture. Words like “conservation,” “transaction,” and “innovation” suggest that the model also addresses issues of sustainability, economic transactions, and innovation. Furthermore, it can also indicate particular focuses in the works that consider biomass in relation to the “demand” and “supply” contexts; focusing on resource-efficient production.

Figure 3. Network visualization represents the co-authorship relationships.

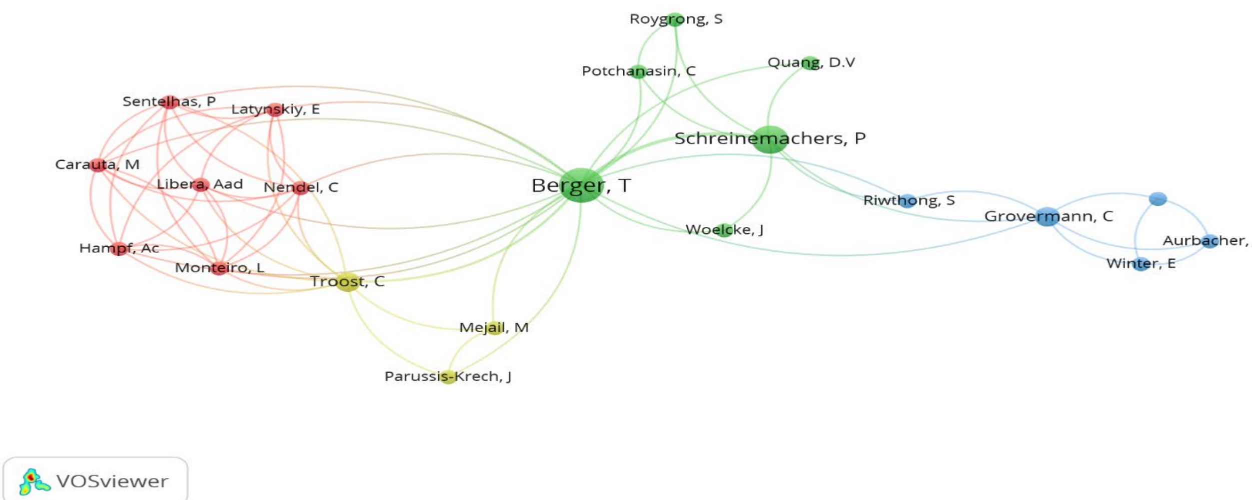


Figure 3. shows most of the cited authors and the network analysis of author citations was created in accordance bibliographic analysis (Waltman L, van Ecken NJ, 2010), based on data from the reference lists of 19 selected papers from the WoS database.

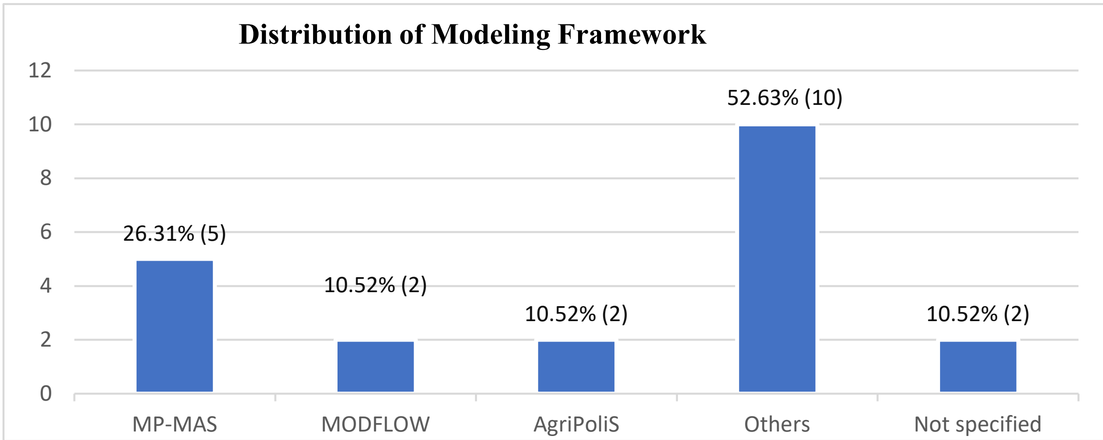
The green cluster centered around Thomas Berger, which includes authors like Pepijn Schreinemachers, Chakrit Potchanasin, Sithidech Roygrong, Johannes Woelcke, and Dang Viet Quang underscores a robust collaborative network. Evidently, they're focused on similar research themes, likely in agricultural sustainability and economic-environmental modeling. In the red cluster, Marcelo Carauta, Evgeny Latynskiy, Paulo Sentelhas, Anna C. Hampf, Affonso A.D. Libera, Leonardo Monteiro, and Nendel Claas stand out, indicating the possibility of focusing on agricultural management, climate impact in agriculture or related themes. A blue cluster includes Christian Grovermann, Suthathip Riwtong, Eva Winter, and Joachim Aurbacher, representing the researches focusing on decision-support tools, policy implications, and the impact of innovations in farming systems. Lastly, Christian Troost, Matias Mejail and Julia Parussis-Krech, form this smaller but distinct yellow cluster and they are contributing to a niche within modeling of environmental impacts on agriculture, and policy strategies to promote sustainable farming systems.

1.2. Modeling Framework

The data set we obtained shows 14 different modelling frameworks used in the papers. Occurrence in approximately quarter of the articles analysed, MP-MAS (Mathematical Programming-based Multi-Agent Systems) appeared to be the most frequently used modelling framework. The frequent recurrence of MP-MAS is likely due to the ability to combine multi-agent systems with MP, increasing the ability to address both economic and environmental aspects of complex agricultural systems (Schreinemachers et al., 2010). Quang et al. (2014) did likewise when using the MP-MAS approach to examine possible soil conservation strategies for the Vietnam mountainous area. The primary outcomes of this study were long-term effectiveness and economic acceptability of such measures in a way that all units, biological and environmental, are anticipated in order to achieve the highest response from the farmers. Hampf et al. (2018) applied MP-MAS in another setting, rather concentrating on yields gaps in Brazil, Mato Grosso. The model applied here is extended by biophysical simulations to identify the socio-economic barriers that influence crop yields; more specifically soybean, maize and cotton crops. Further, Troost et al. (2022)

turned their results on the development of surrogate modeling to the integration of agricultural decision-making in large-scale assessments with the help of the MP-MAS model. Finally, Grovermann et al. (2017) used MP-MAS to the question of integrated pest management (IPM) strategies in Northern Thailand. The research demonstrated that a composition of policies such as pesticide tax and subsidies on biopesticide would result in less pesticide application without affecting the farmers' income.

Figure 4: Distribution of modeling framework



Note: *All percentages were calculated on the basis of the total number of articles that appeared in the total number of possible responses (codes) to the questions, not on the basis of each other (as we combined some answers under one heading, duplicates or more than two repeated identical articles under the same heading were calculated as a single one).*

MODFLOW is in second place with a frequency percentage, highlighting the importance of hydrogeological factors in agricultural system modelling and in the context of agricultural modelling studies (Nouri et al., 2019, 2022). In Nouri et al. (2019), MODFLOW was connected to agent-based model and groundwater levels in Najaf Abad region of Iran are modeled in order to utilize the water resources optimally. Assessment of the consequences of such policies as diminishing water rights on the groundwater levels and agricultural production was made in this work. Again, Nouri et al. (2022) modified the approach and employed MODFLOW as an eco-component of a broader agent based modeling for analysis of long term water market development.

The AgriPoliS (The Agricultural Policy Simulator) reflects a growing interest in the simulation of the effect of agricultural policies. This clearly shows that agricultural systems modeling does not include only agronomic or ecological dimensions but also agricultural structural changes, political and economic cases Piorr et al. (2009) . Ostermeyer and Schoenau (2012), investigated the impact of production of biogas on the inter-farm competition with using the AgriPoliS model framework. They analyses the impact that biogas production has on land rents and what it means in terms of competitiveness. These studies differentiate on the impact of biogas production on agriculture, especially with regard to the restructuring of farming practices in a bid to maximize profits with a negative ripple effect on the environment. Piorr et al. (2009) performed a holistic assessment with the AgriPoliS model regarding the future implications of reforms of the Common Agricultural Policy (CAP) in this case the European Union (EU). The study estimated the likely effects from biogas production-based policies and such practices on the structure of farms and land use and also the impacts on sustainable development. The model also explored the impacts of agricultural policies at the regional economic and environmental levels which were conducted in a manner where they derived such impacts under a number of alternative scenarios for agricultural policies. The modelling frameworks on the

list, sub-categorised as "Others", each used in only one paper, represent different or other similar modeling approaches focused on specific agricultural research questions or specific agricultural systems.
The existence of different modelling frameworks in the same paper indicates that an interdisciplinary approach is adopted in agricultural systems modelling. For instance, (Hampf et al., 2018) involves MP-MAS and MONICA (MOdel for NItrogen and Carbon dynamics in Agro-ecosystems) in a strategy toward merging biophysical and socio-economic elements. While the effects of biophysical factors, such as climate conditions and soil properties, on plant productivity were modeled using MONICA, MP-MAS was used to analyze how these yield estimates affected farmers' decision-making processes. As another example, in the research of (Piorr et al., 2009), we see a different integration, especially the integration of AgriPoliS, MODAM and Geographic Information Systems (GIS) models in a hierarchical order. AgriPoliS simulates structural change as an agent-based and dynamic model. MODAM is an LP model that simulates cropping and livestock production patterns of farms and performs environmental impact assessment. In this integration approach, AgriPoliS results fed into MODAM (Multi-Objective Decision support tool for Agroecosystem Management), which then provided feedback to AgriPoliS for new simulations. This integrated approach made it possible to analyse the effects of agricultural policies from farm to regional level. Also the results sub-categorised as "Not specified" forms the rest of the results, suggesting that while ABM and MP approaches might occasionally be used, a specific name of modeling framework is left unspecified. In these studies of Liu et al. (2013) and Berger et al. (2006). ABM and MP approaches are quite clearly used, however particular model names are not specified. On the other hand, these studies were designed to assess farmers' strategies in response to climate change and the policy impacts of rural development programs, and the attempt to organize the approaches so far into conceptual modeling frameworks has been similarly open-ended and thus lacked clarity in terms of scope and definition of methods used.

1.3. Research Domain

Agricultural systems and resource management emerge as the most common research area. For instance, Nouri et al. (2019, 2022) stated the model MODFLOW for water management and crop pattern optimization, while Sapino et al. (2023) evaluated impacts of transaction costs in seeking market for water transactions in their model named APAM (AQUATOOL+PAM). This clearly shows a strong focus by researchers on sustainable agriculture and efficient resource use. Agricultural policy follows as the second most common research area, representing the studies. This significant proportion reflects the crucial role of policy in shaping agricultural practices and outcomes. According to this research domain, the RegMAS (Regional Multi Agent Simulator) model was mentioned by Lobianco and Esposti (2010) to evaluate the impact of the CAP reforms, while Baldi et al. (2023) simulated a number of policies such as carbon taxes or variations in the CAP payment systems with model framework named AGRISP.

Table 5: Frequency and percentage values of responses about research domain.

Response	Frequency Response	Percentage
Agricultural Systems And Resource Management	**7**	**36.84%**
Agricultural Policy	**6**	**31.58%**
Agricultural Production Dynamics	**3**	**15.79%**
Agricultural Decision-Making	**3**	**15.79%**
Environmental And Climate Considerations	**2**	**10.53%**

Agricultural production dynamics and agricultural decision-making each also stand out as important research domains. The strong interest in both the dynamic nature of agricultural production and farmers' decision-making processes is suggested by this balanced representation. Winter et al. (2023) evaluated interventions aimed at increasing organic seed production by the modeling framework VAL-MAS (VALue chain Multi-Agent System), while Huber et al. (2022) examined farmers' decision-making processes regarding weed control strategies. Also, Shastri et al. (2011) focused on optimizing biomass feedstock production systems, while Schreinemachers et al. (2010) examined decisions related to product choices and the adoption of new technologies and innovations. The rest of the studies focus on environmental and climate considerations. Even though this domain is not the most prevalent, this proportion clearly shows a growing awareness of agriculture's environmental impact and the need for climate adaptation strategies. Liu et al. (2013) studied how income and land surface changes of herders respond to climate change adaptation measures in ecologically vulnerable areas. Also, Troost et al. (2022) focused on developing the scalability of farm-level models and studying impacts of climate change.

2. Elements and processes of decision-making

2.1. Decision-making actors and components

The majority of studies, identified the farmer as the main decision-maker. This includes individual farmers, farm households and herders. The central role of farmers in agricultural systems and decision-making processes is underscored by this dominance. For instance, Huber et al. (2022) focused on farmers' decision-making processes regarding weed control strategies, while Schreinemachers et al. (2010) examined farmers' decisions on product choices and technology adoption. In Liu et al. (2013), the term for the agent farmers and herdsmen reflects the mixed agriculture-livestock system in the studied region. As another example, in the study of Winter et al. (2023), farmers are modeled as heterogeneous actors making decisions on seed use, crop production and technology adoption. Also, in Quang et al. (2014), the model simulates farmers' decisions on whether to adopt soil conservation practices.

The rest of the studies included other types of decision-maker agents. Study by Nouri et al. (2019) modeled institutional and policy agents as the primary decision-makers, which are regulator agents who could purchase water permits for environmental conservation purposes. Winter et al. (2023) also mentioned other main agents such as breeders and seed producers, indicating a more comprehensive approach to the agricultural value chain in the VAL-MAS model. Similarly, Kim et al. (2018) used biorefinery agents, biomass farm agents and storage facility agents to optimise the biomass supply chain in ALMANAC (Agricultural Land Management Alternative with Numerical Assessment Criteria) modeling framework. For instance, biorefinery agents place orders for biomass feedstocks, while storage facility agents control the flow of biomass.

While we also focused on other actors involved in agricultural decision-making models, it is necessary to state that these actors are not the main decision-making units, they do have important indirect roles in agriculture. In about two thirds of the papers, the authors did not explicitly model other agents. This suggests that these studies prefer to model only one type of agent (usually farmers). For the few papers, institutional and policy agents assigns a subset role of defining the regulatory and policy context in which farmers' decision get affected. It is observed that such representatives of the government bodies and its regulatory agencies within the rural and agricultural setting influence farm practices by making laws, policies or regulations, granting subsidies or providing other indirect measures (Berger et al., 2006 ; Liu et al., 2013; Nouri et al., 2022). Also, intermediate agents, the study by Lobianco and Esposti (2010) include anonymous intermediary agents that manage the land leasing process in the RegMAS model. These agents manage land allocation by collecting land released by exiting farms and auctioning it to the highest bidding farmers. Similarly, as intermediate agents, landowners mentioned by Ostermeyer and Schoenau (2012) as impact farm economics indirectly through their role in the land rental market. According to the research of Kim et al. (2018) and Shastri et al. (2011), the agents examined under the title of commercial agents, which are mostly participated particularly in supply/value chain activities represented by the models. Although these agents, such as storage facilities, transporters, and bio-energy producers, are not involved in making decisions at the farm level, their activities have a significant role on farmers' choices regarding production and marketing.

There are various cognitive factors affecting the decision-making processes of all these agents. In the economic theory, agents are supposed to be rational but in the real-world, decision makers do not always behave fully rationally, as decision-making processes are influenced by various cognitive and environmental factors (Appel and Balmann, 2019 ; Dessart et al., 2019). In our research, rational boundaries of agents refer to the cognitive limitations that agricultural agents face when making their decisions. Individual preferences are the most recurrent rationing factor which according in this case is personal and/or cultural as well as societal. Nouri et al. (2022) established how agents' selfish nature influences their actions in relation to water management. We also included the innovation level in this sub-category. Values such as self-orientation and hedonistic tendencies were found to be positively associated with innovative capabilities in farming (Walder et al., 2019). For example, Quang et al. (2014) showed that each household has a unique level of innovativeness.

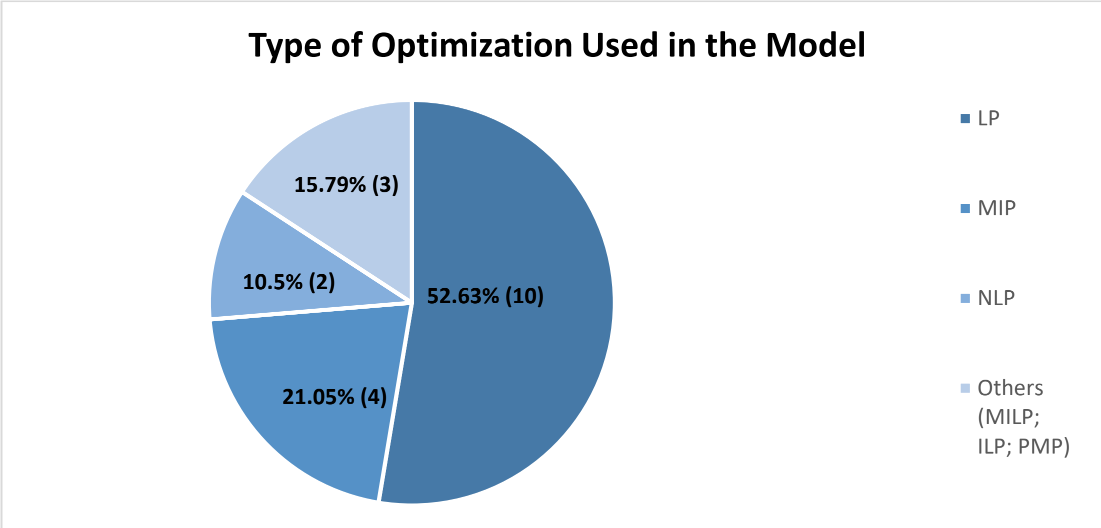
Knowledge, which appears as second majority in the studies, is a boundary that exemplifies the information level available to agents. Berger et al. (2006) highlighted how agents resolve discrepancies of individual knowledge, environmental and social knowledge by decision-making. Also, Nouri et al. (2022) emulated agents' knowledge regarding water prices and availability with socio-learning in the modeling framework. Similarly Sapino et al. (2023) noted agents' knowledge is constrained as an indicator of asymmetric information, limiting their knowledge of other possible traders in the market. In other hand, risk behavior captured one-third in the studies. This boundary is referring to agents' attempt to take part in activities resulting in uncertainty. Winter et al. (2023) enacted a scenario where a seed producer may increase production in expectation of the higher demand in the future but also bear potential losses. Lastly, by occurrence in 1 article out of 19, another boundary as tolerance level, mentioned by Huber et al. (2022), which represents agents' capacity to tolerate uncertainty and variability.

In agricultural systems, the characteristics of the model components are not uniform. Heterogeneity between agents and among model components influences the model considerably. State variables, in the context of ABM with the highest percentage, describe the current state of the agents and their environment. These factors may include time-dependent parameters such as economic status, resource endowment, land use, and so forth. Lobianco and Esposti, (2010) state this in terms of structural and spatial heterogeneity, for instance, distinguishing between small and large farms but also between lowland and mountain farming. As another example, in Baldi et al. (2023), the model accounts for differences in the size of farms, types of crops cultivated, livestock reared, and the technologies employed. The model of Grovermann et al. (2017) includes a heterogeneous population of farm agents, each with different resource endowments (e.g., land, labor, and cash). Also, behavioral heterogeneity which occurred in 14 articles out of 19, refers to differences in agents' decision-making mechanisms, preferences, strategies or patterns of behavior. Huber et al. (2022) mentioned risk preferences, farm activity preferences and social networks as examples of behavioral heterogeneity. The model in the paper of Baldi et al. (2023), also simulates the heterogeneity in the interactions between farms, particularly, for resource exchange (e.g., land, pollution quotas). Also, Grovermann et al. (2017) modeled captures heterogeneity in the adoption of Integrated Pest Management (IPM) practices, with different farm agents adopting innovations at different rates based on their propensity to innovate.

2.1. Optimization elements in model

The most used optimization method in the studies is Linear Programming (LP). The high usage rate of LP shows that it is an effective tool where linear relationships are modeled. Mixed Integer Programming (MIP) and Non-linear Programming (NLP) has used less frequently. MIP is used to solve more complex optimization problems that include non-linear decision variables and generally preferred in more complex agricultural problems, models that require more detailed allocation of resources (Ioan et al., 2021).

Figure 6: Type of optimization used in the model



2.2. Variable optimized in objective function

The variables optimised in the models can be broadly classified into two main economic approaches such as profit maximisation and cost minimisation. The profit maximisation approach stands out as the dominant approach in most of the studies. This category includes income, profit and gross margin maximisation. Profit optimisation aims to maximise farm profits by reducing costs while increasing revenues and is another high rate used variable. Gross margin optimisation represents the profit obtained after subtracting variable costs from revenue and shows how effectively businesses manage their production processes. Also, one study aimed at utility optimisation and this approach represents a more comprehensive optimisation strategy that takes into account other factors (e.g. environmental sustainability) as well as farmers' economic gains (Sapino et al., 2023). The cost minimisation approach focuses on optimising the system cost and was used in a number of the models studied. This approach aims to reduce the expenditure incurred in agricultural production processes and is generally favored in fixed output scenarios or when efficiency in resource use is a priority.

2.3.Parameters taken into account in the objective function

The output parameters of agricultural systems, that we observed with the major rate for this sub-category, are used to model the economic size of agricultural production. These parameters primarily represent revenues, though they can also capture non-monetary outputs. Many studies, such as Schreinemachers et al. (2010) and Troost et al. (2022), incorporate yield as a key output parameter and parameters that affect crop productivity and determine the maximum potential yield. In Seidel and Britz (2019) milk yield is mentioned as a parameter, also price of milk as an output included. Piorr et al. (2009) consider both crop yields and livestock productivity in their model parameters. Grovermann et al. (2017) mentioned it based on the selling prices and production quantities of the products. Especially in studies of Nouri et al. (2022) and Nouri et al. (2019), this is clearly states the price of production as the parameter. Berger et al. (2006) directly refers increases in crop prices to assess the impacts on agricultural systems. Also, Winter et al. (2023) reported that organic carrot selling prices are parameterised as an output price. We can also see that Lobianco and Esposti (2010) explained as it is refers to the gross margin of each activity. Finally, Troost et al. (2022) mentioned it as not direct prices, but coefficients showing the proportional change in prices relative to the base period. These coefficients are used for both inputs (e.g. fertilizer, fuel) and outputs (e.g. milk, wheat).

Input parameters, which are equally common with output parameters under different sub-term, represent the resources and costs associated with agricultural production. In Piorr et al. (2009), cost considered in the form of labor costs, while Grovermann et al. (2017) noted the production costs such as pesticides, labor, and other inputs are included in the model. Baldi et al. (2023) accounted the costs related to milk production such as feed, forage crop production, energy and also water cost. For the costs, Nouri et al. (2022) parameterise production costs directly. Schreinemachers et al. (2010) modeled the costs related to labor, irrigation systems and other agricultural practices, also costs related to the implementation of innovations. Transportation costs are also considered by Lobianco and Esposti (2010), reflecting the importance of logistics in agricultural economics. Input prices are another crucial aspect of parameters, representing the price coefficients for various agricultural inputs that influence economic decisions in the models. Seidel and Britz (2019) mentioned, it includes the cost of feed concentrates and the cost of crops grown for feeding livestock. We also explicitly see by Nouri et al. (2022), the terms of parameters includes the inputs required for production and the costs of these inputs. In the research of Berger et al. (2006) directly refers reduction in input prices. Lastly, we can also see water prices in the article of Nouri et al. (2022) explicitly modeled. Environmental and biophysical factors, representing natural conditions affecting agricultural systems, are present in the second majority of the studies. Troost et al. (2022) incorporated physical and climate conditions for the maximum yield. Furthermore, Piorr et al. (2009) used soil quality classes to assess its impact on productivity and environmental outcomes. In the model of Grovermann et al. (2017) considers crop water requirements, rainfall, crop yield based on production functions with damage control specifications for pesticides, pest pressure, soil properties, topography and local climatic conditions. Nouri et al. (2022) included available agricultural area as a parameter tells us that agricultural area is a factor shows biophysical conditions and local land use. Schreinemachers et al. (2010) used precipitation data and plant water requirement calculations in their research. Berger et al. (2006) incorporated nutrient balances of the soil as biophysical factors in their model. Differently, Lobianco and Esposti (2010) models the effect of altitude on production. Also there is a case about the resource allocation, such as, Baldi et al. (2023) explained the use of resources such as land, water, and nitrogen, with specific consideration of their efficient allocation under different policy scenarios (e.g., nitrogen quotas). In the study of Nouri et al. (2022) amount of water allocated for a particular crop and concerns the efficient use of water. In other study of Nouri et al. (2019), incorporated total arable land owned by agents as a parameter. Likewise, Schreinemachers et al. (2010) mentioned efficiency values for different irrigation methods. Finally, Sapino et al. (2023) shows the amount of water initially allocated for each agricultural water demand unit and the AQUATOOL model simulates water allocations for agents based on different environmental scenarios (e.g., minimum environmental flows).

Table 7: Frequency and percentage values of parameters taken into account in the objective function.

Response	Frequency Response	Percentage
Policy Instruments and Regulatory Parameters	5	26.32%
Operational and Risk Assessment Factors	3	15.79%
Environmental/Biophysical Factors	10	52.63%
Output Parameters	15	78.95%
Input Parameters	15	78.95%

Policy tools and regulatory parameters are used to model the effects of agricultural policies and regulations. For example, Grovermann et al. (2017) discussed biopesticide subsidies as part of strategies to reduce pesticide use. Also, Piorr et al. (2009) modeled various CAP policy scenarios in the study; including direct payments, single farm payments, and agri-environmental payments. As for penalties, Nouri et al. (2022) included them as a parameter, just as fines imposed for over-extraction play a role in shaping the decision-making of agricultural agents. Winter et al. (2023) shows the impact of derogations on organic seed production, highlighting the relationship between policy decisions and agricultural outcomes. Also, Nouri et al. (2019) mentioned a parameter as represents the surface water (e.g. lake, rivers) right of agricultural agent and there is also groundwater (e.g. aquifers) right of agent. Therefore, these parameters emphasize the legal and administrative aspects of water use.

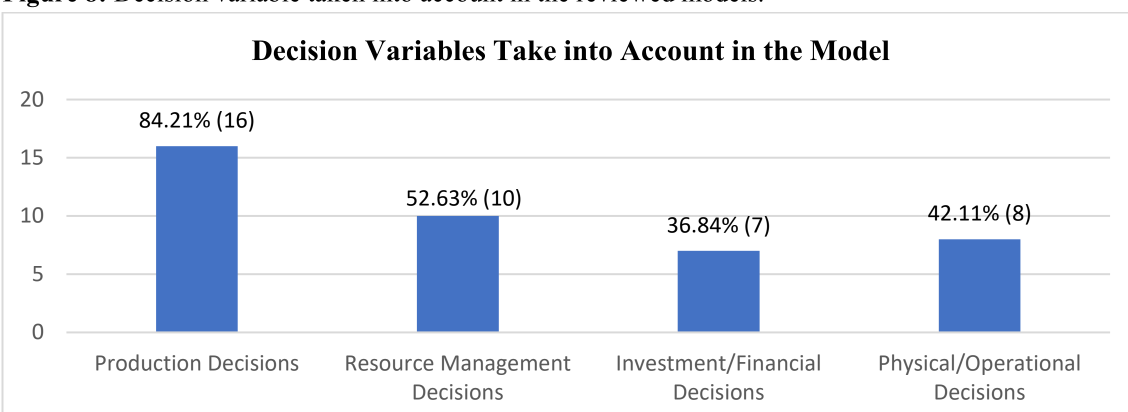
Operational and risk assessment factors reflect the complex dynamics of farmers' decision-making processes with few articles. Sapino et al. (2023) applied profit, risk and management complexity model parameters while Nouri et al. (2019) assessed productivity and production capacity evaluation performance function. Also, the Troost et al. (2022), including probability factors such as the likelihood of farm succession by a male child and the ability to hire machinery services under suitable weather conditions.

2.4. Decision variables of the models

Decision variables are critical components that represent the operational, tactical and strategic decisions of farmers and other agricultural actors. Production decisions are the most commonly optimized decision variables. These variables cover the decisions of farmers to minimize their costs or use inputs efficiently. Production decisions encompass the choices that farmers make with regards to the type of crops to plant, the techniques to be used in crop planting and the quantity of crops to produce. It also allow for agricultural operations such as changing of crops, controlling of weeds, managing livestock, applying chemicals and fertilizers. For instance, Grovermann et al. (2017) presented a model describing how farmers select pesticide type and dosage based on agricultural pest management needs, associated costs and potential tax limitations. Besides, some aspects added up to the demarcation of production decisions involve production of plants, production of milk, production of biogas etc.

Resource management decision variables include decisions, how to use the resources that form the basis of agricultural production, optimised in nearly half of the articles. This category also includes the decisions on land renting, land allocation, water use and water trading, and so forth. For example, in the model of Sapino et al. (2023), farmers' water use decisions for irrigation and how they respond to water restrictions were modeled.

Figure 8: Decision variable taken into account in the reviewed models.



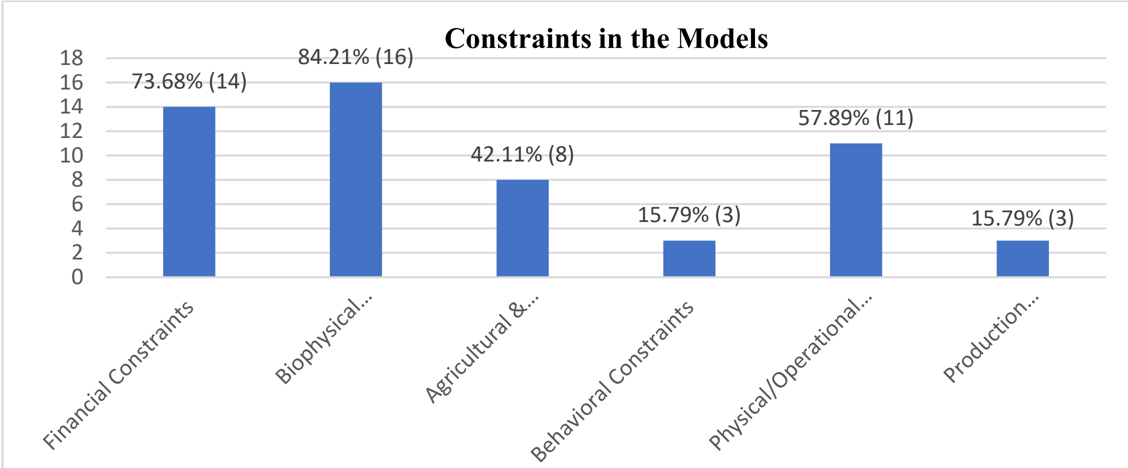
Physical and operational decisions are the variables optimised in nearly half of the articles. These decisions are associated with the operational stages of the processes including storage facilities, transportation quantities, operating schedule and biomass distribution (Huber et al., 2022 ; Kim et al., 2018 ; Shastri et al., 2011). These decisions may include, for example, the potential to increase personnel efficiency, equipment handling and management, and other activities related to operational processes (Grovermann et al., 2017b ; Hampf et al., 2018 ; Piorr et al., 2009 ; Quang et al., 2014 ; Seidel and Britz, 2019) .

Investment and also financial decisions, represent farmers' strategic decisions. This sub-category includes investments in new technologies, equipment or facilities. For example, Ostermeyer and Schoenau (2012) shows that farms can choose to invest in biogas plants of different sizes. Also in this paper, the investment costs range depending on the plant size.

2.5. Constraints in the models

This sub-category encompasses the various factors that constrain the decision-making process in the models. These constraints determine the boundaries of action which decision-makers must operate, reflecting the real-world limitations and challenges in agricultural production processes.

Figure 9: Constraints on decision-making processes in the models



Biophysical constraints are one of the most common constraints considered in agricultural models. These constraints are related to the limitations, such as water, soil and other natural resources. Lobianco and Esposti (2010) provided a notable example, modeling plots as individual resources with spatial information organized in different layers, including land typology, altimetry, and environmental constraints, which indicates that the land is modeled together with its bio-physical properties. Furthermore, financial constraints are important constraints extend to elements that restrict farmers' economic choices taken into account nearly three-quarters of the papers. This category includes well-blotted factors; such as, liquidity, capital, available investment, cost of transportation, and market conditions. For example, Baldi et al. (2023) and Grovermann et al. (2017) modeled how farmers' limited financial resources affect their investment decisions. Physical and operational constraints, considered in over half of the reviewed models, related to logistics, labor, and equipment in agricultural production processes. Kim et al. (2018) investigated the logistics challenges encountered in biomass transportation and storage operations. These constraints in particular determine farmers' production scale and efficiency and therefore the performance of agriculture enterprises. The inclusion of policy-related constraints into several models also encompassed legal framework related to agricultural and environmental policy. Seidel and Britz (2019) state that environmental regulations affect agricultural outcomes and farmers' decisions on land use pointing out that this is an issue that should be incorporated in modeling.

Although less common, behavioral constraints include limitations related to behavioral factors such as farmers' adoption of innovations and risk-taking tendencies. For instance, in the study of Grovermann et al. (2017), farmers' risk-taking behaviors and adaptations to innovative practices were discussed. Production and also stock restrictions include factors that limit the production capacity and stock management of agricultural enterprises. Kim et al. (2018) and Winter et al. (2023) were keen to focus on the performance of agricultural holdings in terms of the performance impact of constraints such as production volumes. These constraints affect farmers through production planning and market strategies.

3. Interaction between agents and their environment

The interactions and learning processes in agricultural systems reflects the complex and dynamic nature of modern agricultural modeling. The studies addressed various dimensions of these interactions to understand how agricultural decision-making processes are shaped.

In agricultural system modeling, a critical role in realistic representation is played by the interactions between agents and social dynamics. Various approaches in this regard are shown by the reviewed studies. In nearly all studies (95%), agent interactions are modeled, underscoring the increasing recognition of social and economic linkages in agricultural systems modelling. We observed that various types of interactions are modelled in the studies. In the majority of studies, non-physical interactions were modelled such as learning, market and economic interactions, while some articles addressed physical interactions such as transportation operations.

Market and economic interactions are a prominent theme in more than half of the studies which includes several behaviors in the land market, economic transactions, auctions (land rental, manure, milk delivery), and market price responses. For instance, economic transactions often involve trading in water markets and bilateral negotiations. These interactions include issues such as price formation, supply-demand dynamics and market equilibrium. For example, Sapino et al. (2023) modeled interactions in water markets and provided insights for more efficient use of water resources. Learning interactions were addressed in about a third of the studies, emphasizing the importance of understanding how farmers learn from each other and their environment. Huber et al. (2022) examined how farmers acquire and apply knowledge about weed control strategies. In addition, direct interactions, such as negotiation and agreement processes, are less frequently examined. Interactions also included logistics such as transportation operations of biomass from fields to storage facilities and refineries, and shared transportation logistics such as examined in the studies of Kim et al. (2018) and Shastri et al. (2011).

Competitive and cooperative approaches emerge as an important feature of the models. While the majority of studies model competitive interactions, few rest include cooperative behaviors. This balance reflects the complex social dynamics in agricultural systems. For example Nouri et al. (2022) examined both competition and cooperation scenarios in the use of water resources. The effects of competitive or cooperative behavior are observed in various areas. Mostly on resource allocation, also impacts on changes in agricultural activities, market balances and land allocation as quarter of the analyses.

In agricultural systems modelling, agents' learning or adaptation processes play a critical role in reflecting the dynamic nature of the system. More than half of the studies, agents' learning (adaptation) processes were explicitly modelled. The effects of learning and adaptation on decision-making processes were examined in about half of the studies. These effects were mostly observed on agricultural strategies and practices followed by resource management, response to policies and response to market signals. For example, the impact of learning on the adoption of soil conservation methods was analysed by Quang et al. (2014), illustrating how farmers acquired and applied soil conservation techniques over time, subsequently shaping their decision-making processes. Similarly, Winter et al. (2023) modeled the influence of learning in organic seed production, revealing how farmers adopt and integrate organic farming practices, consequently molding agricultural strategies.

3.1. Supply /value chain modeling

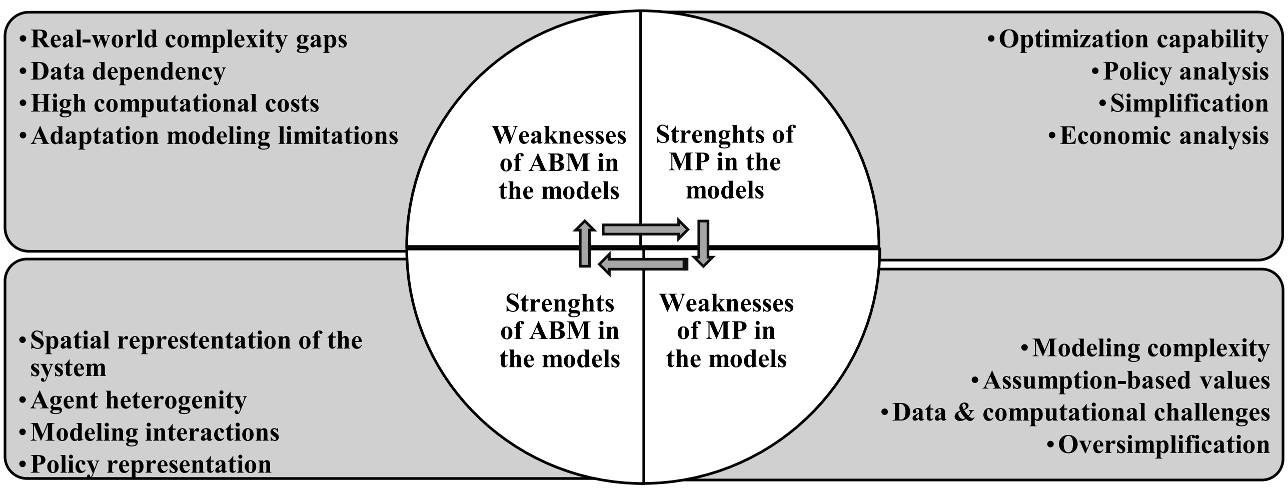
Supply and value chain modeling was explicitly represented in merely 3 of the studies, underscoring that supply chain dynamics remain an underexplored facet within agricultural systems modeling. However, important insights are offered by some studies in this domain. For instance, the biomass supply chain was modeled by Shastri et al. (2011), unveiling the intricate dynamics from agricultural production to the end user. These studies highlight the imperative to comprehend agricultural systems within a broader economic and logistical framework. The nature of social interactions and agent relationships in agricultural system modeling is revealed through this detailed examination. A wide range of interactions has been modeled, from market dynamics to learning processes, and from policy influences to supply chain management; showcasing the diversity of approaches.

4. The strengths and weaknesses of ABM and MP in modelling approaches

The most frequent strength of ABM is their ability to provide a spatial representation of systems, nearly three-quarters of the studies. Lobianco and Esposti (2010) exemplified this by capturing the geographical context of agricultural decisions by spatially modeling land types and environmental constraints in the RegMAS model. This modeling approach provides both measures of the spatial consequences of agricultural practices as well as better understand policy makers and researchers. The ability to model heterogeneity between the households and agents is found as second frequent strength of ABM. Grovermann et al. (2017) demonstrated this by modeling diverse farmer behaviours towards pesticide use, enabling more nuanced policy impact analyses. The modeling of farmer interactions, highlighted in half of the studies, was also noteworthy. Huber et al. (2022), for instance, delved into how information exchange about weed control methods shapes farmers' decision-making processes. Additional enhancing aspects of ABM include the integration of multidisciplinary approaches and policy representation, both highlighted in nearly half the studies. A smaller subset of research also pointed out ABM's capability to incorporate dynamic-stochastic elements and model environmental sustainability factors.

ABM also have some critical limitations. In almost half of the reviewed studies, the lack of understanding of all real-world behaviours and interactions emerged as a challenge. Sapino et al., (2023) found that some real-world complexity needs to be reduced in order to improve the water markets drawn in some interactions. It can limit the applicability of models, especially in terms of capturing real-world complexity. Data dependency was highlighted as another major weakness of ABM. Nouri et al. (2019) state the challenges of extensive data requirements in a water management model. This data dependency can limit the applicability of models, especially in data-constrained regions.

Figure 10: ABM and MP characteristics in agricultural modeling



The optimization capabilities of MP models is the most commending feature in the stenghts of the MP. Through the optimization of farm-level decisions, Seidel and Britz (2019) evaluated the impacts of different policy scenarios. The enhancement of policy evaluation and analysis has become to be the second most cited strength of the MP. This has been noted in more than half of the articles (12 articles). This finding further suggests MP models are vital in assessing the outcomes of agricultural policies and in coming up with policy scenarios. It confirms MP as one of the robust decision support systems for policy analysts and the policy debaters. The simplification and enhancement of economic analysis using MP models is also significant as these two aspects were highlighted in a couple of the articles. This shows the degree of MP to make complex agricultural systems more understandable and also to analyse economic impacts in detail. Other strengths, such as flexibility and extensibility, the ability to analyze adoption criteria and the competitiveness of farm activities were mentioned more less. These features show the adaptability of MP to various agricultural issues and its capacity to perform specific analyses. Especially in the field of agricultural economics, these features of MP offering valuable contributions.

The second most frequently highlighted strength of MP models is the ability to improve policy analysis, which was addressed in more than half of the studies. Winter et al. (2023) utilised by advantage of this feature of MP when analysing the effects of organic seed production policies. This ability helps policy makers to assess the potential impacts of different interventions.

MP models also have some limitations. Modeling complexity and assumption-based values were cited as weaknesses majority of the studies. Some researchers like Huber et al. (2022), emphasised that MP models can sometimes lead to oversimplifications. In such analysis there is an underestimation of the complexity of variations. This shows the limitations of the models in accurately reflecting the complexity of the real world.

Another weakness of MP model designs is that they can be based on assumptions. Some of the assumptions of MP models may not always be compatible with real world conditions as stated by Baldi et al. (2023). It was also shown that MP models may ignore some values and this can affect the results according to the study of Winter et al. (2023). In addition, difficulties related to data and computing resources were also articulated as another limitation of MP modeling approaches. Hampf et al. (2018) mentioned the high computational power required to run MP models. Sapino et al., (2023) emphasised that MP models require large amounts of data, which may not always be available. Temporal limitations and oversimplification emerged as less frequently mentioned but important weaknesses. Sapino et al., (2023) noted that MP models may struggle to capture rapid changes over time. Huber et al. (2022) also states that MP models has the risk of oversimplifying overly complex issues.

IV. Discussion

The combinaton of ABM and MP within agricultural systems research represents an important step forward in the simulation of complex farming systems.

It is evident that there is an inclination towards grant research which deals with agricultural systems and resource management, largely because of the improved efficiency of farm practices and better management of resources. As underscored by the dominance of the water models such as MODFLOW, the role of resources in agricultural modeling is critical (Nouri et al., 2019, 2022). These developments illustrate the current trends in agricultural systems modeling which can be noted to be multidisciplinary where physical, financial, social, and environmental aspects are giving room for better projections than before. Additionally, a more peculiar trend has been the use of policy evaluation in models in this area of agriculture. From the observations made, there has obviously been an increase in the measurements of these policy variables through using these models For example, the studies by Ostermeyer and Schoenau (2012) and Piorr et al. (2009) on the development of AgriPoliS demonstrates the use of these policy structures on agricultural restructuring and environmental impact policies. This trend, however, seems to hold potential advantages for policy makers as they show the anticipatory impacts of carrying out such agricultural policies.

The broadness of approaches to modeling featured in the articles reviewed highlights the depth and the multi-disciplinarity aspect of agricultural systems modeling. An interesting trend is the modeling system MP-MAS which seems to be a popular framework of application (Schreinemachers et al., 2010). Its adoption in various studies, from soil conservation strategies in Vietnam (Quang et al., 2014) to yield gap analysis in Brazil (Hampf et al., 2018), were able to assess the reasons for the yield gap not only due to biophysical reasons but also regarding social-economics by combining the two models MONICA and MP-MAS.

In the majority of the models described, the individual farmers were analysed as the key decision makers of the system. This emphasises the central role of farmers in agricultural systems. However, in some studies, policy makers, seed producers and other stakeholders were also included in the models. This avenue has enabled a better holistic understanding of the complicated relationship of the agricultural systems. For example, the VAL-MAS model of Winter et al. (2023) considered different actors of the value chain when evaluating interventions to increase organic seed production and utilisation.

The coupling of ABM and MP approaches has brought to the forefront the complementarity in their strengths and shortcomings as shown in Figure 10. In particular the spatial representation capability of ABM has been found to be useful as it gives a better understanding on how space relates to agricultural choices and their outcomes. To illustrate, Lobianco and Esposti (2010) applied this ability with in RegMAS model to study the effects of spatial land use and land use restrictions on the policy outcomes in different regions. A notable advantage of the ABM-MP integration is the modeling of heterogeneity amongst different household agents. This attribute allows capturing heterogeneity in the decision making and resource endowment structures present in actual farming systems. The integration of MP systems within the context of agricultural decision support systems, has therefore improved the effectiveness and efficiency of scenario simulations thereby adding value to policy formulation.

These integrated models, like any other practice, have their own disadvantages that should not be brushed aside. ABM can be unable to fully account for how agents behave and how interactions occur, which is also one of the reasons there remains a problem of depicting the agricultural systems in their true complexity. It implies that although these models are helpful in demonstrating certain trends, their results should be affixed with more in-depth analysis and actual evidence. Also data dependency presents another significant challenge. This problem may affect how models can be implemented especially in less data intensive areas, and could result in a slanted or incomplete analysis. Their growing popularity is weighed down by the high costs that are inherent to the running of the models. However, the simplification capabilities of MP can help mitigate some of these computational challenges.

There was a notable limitation of our study, which was related to the relatively small number of the articles that incorporate both ABM and MP within the same studying framework focusing on agricultural issues. This deficiency in literature, however, does not only represent a limitation of our analysis but suggests a very real intermediary in the current research. It points out that even though there seems to be an advantage in converging both approaches, the convergence in agriculture remains in its infancy with lots of opportunities waiting.

There is certainly a sense of some gaps in the data that need to be filled by future research in any forward-looking analysis. Computational efficiency, better methods of data collection and integration, and detailed presentation of how people make decisions in the models are factors that could improve their utility and trustworthiness. In addition, the lack of literature on supply chain dynamics in the reviewed studies represents an interesting direction for future studies, especially considering the increasing importance of studying agricultural systems in logistic context and economy.

Many options for future research are also offered. One of these is the development of more consistent and comprehensive frameworks that combine the advantages of various modeling approaches. Second is the standardisation and increased transparency of modelling approaches can improve the replicability and comparability of studies. Also, additional insights from the fields of behavioural economics could be integrated for a more realistic representation of farmer behaviour. This approach has the potential to provide valuable insights to policy makers and researchers to better understand the dynamics of agricultural systems and design more effective interventions. Future studies can continue to support the transition to sustainable agriculture by further developing these modelling approaches and expanding their application areas.

V. Conclusion

This systematic literature review on ABM and MP modeling approaches in agricultural systems can be considered as a promising but still new area to better understand the multifaceted structure of agriculture. The synthesis of these two approaches helps to fill the fundamental gaps in agricultural modeling and thus to cope with the structural complexity of agricultural systems. This synergy allows for more detailed agricultural system analysis and better prediction of agricultural system responses to various interventions.

Especially the widespread application of the MP-MAS framework in different agricultural systems makes it quite flexible and effective and explains why agricultural decision-making processes are focused on this modeling framework. However, these combined approaches require the use of complex models that require high computational effort and large amounts of data, which may be inconvenient in data-poor regions. Moreover, more researchers are focusing on the use of these tools in agricultural modeling, there are not many studies applying both ABM and MP and therefore the field is still in its infancy with high potential for growth in methods and techniques.

Consequently, as this field progresses, it has the potential to help agriculture make sound decisions that will promote better system dynamics in ever-changing conditions. Further work should aim to address existing gaps, enable broader use of these integration models, and leverage the integrative strengths of ABM and MP techniques in related fields.

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Le Bars, M; Attonaty, JM	Le Bars, M; Attonaty, JM	A multi-agent system to the common management of a renewable resource: Application to water sharing	2001	10.1109/ICTAI.2001.974447	http://dx.doi.org/10.1109/ICTAI.2001.974447
Kishore, A; Thorve, S; Marathe, M	Kishore, Aparna; Thorve, Swapna; Marathe, Madhav	Budget-constrained optimal and equitable retrofitting problems for achieving energy efficiency	2023	10.1145/3575813.3597354	http://dx.doi.org/10.1145/3575813.3597354
Higgins, AJ; Miller, CJ; Archer, AA; Ton, T; Fletcher, CS; McAllister, RRJ	Higgins, A. J.; Miller, C. J.; Archer, A. A.; Ton, T.; Fletcher, C. S.; McAllister, R. R. J.	Challenges of operations research practice in agricultural value chains	2010	10.1057/jors.2009.57	http://dx.doi.org/10.1057/jors.2009.57
Liu, YC; Zhang, T; Geng, XL; He, LS; Pang, ZG	Liu, Yingcheng; Zhang, Tao; Geng, Xiaoli; He, Liansheng; Pang, Zhiguo	Herdsmen's Adaptation to Climate Changes and Subsequent Impacts in the Ecologically Fragile Zone, China	2013	10.1155/2013/748715	http://dx.doi.org/10.1155/2013/748715

Curtis, NJ; Dortmans, PJ	Curtis, NJ; Dortmans, PJ	A dynamic conceptual model to explore technology-based perturbations to a complex system: The land force	2004	10.1142/S0217595904000345	http://dx.doi.org/10.1142/S0217595904000345
Li, XY; Epureanu, BI	Li, Xingyu; Epureanu, Bogdan, I	AI-based competition of autonomous vehicle fleets with application to fleet modularity	2020	10.1016/j.ejor.2020.05.020	http://dx.doi.org/10.1016/j.ejor.2020.05.020
Ma, TJ; Nakamori, Y	Ma, TJ; Nakamori, Y	Agent-based modeling on technological innovation as an evolutionary process	2005	10.1016/j.ejor.2004.01.055	http://dx.doi.org/10.1016/j.ejor.2004.01.055
Berger, T; Schreinemachers, P; Woelcke, J	Berger, T; Schreinemachers, P; Woelcke, J	Multi-agent simulation for the targeting of development policies in less-favored areas	2006	10.1016/j.agsy.2005.06.002	http://dx.doi.org/10.1016/j.agsy.2005.06.002

Heijnen, P; Chappin, E; Nikolic, I	Heijnen, Petra; Chappin, Emile; Nikolic, Igor	Infrastructure Network Design with a Multi-Model Approach: Comparing Geometric Graph Theory with an Agent-Based Implementation of an Ant Colony Optimization	2014		
Al Irsyad, MI; Halog, A; Nepal, R; Koesrindartoto, DP	Al Irsyad, Muhammad Indra; Halog, Anthony; Nepal, Rabindra; Koesrindartoto, Deddy Priatmodjo	Economical and environmental impacts of decarbonisation of Indonesian power sector	2020	10.1016/j.jenvman.2019.109669	http://dx.doi.org/10.1016/j.jenvman.2019.109669
Nurwidiana, N; Sopha, BM; Widyaparaga, A	Nurwidiana, Nurwidiana; Sopha, Bertha Maya; Widyaparaga, Adhika	Simulating Socio-Technical Transitions of Photovoltaics Using Empirically Based Hybrid Simulation-Optimization Approach	2022	10.3390/su14095411	http://dx.doi.org/10.3390/su14095411

El Bakali, I; Brouziyne, Y; El Mekki, AA; Maatala, N; Harbouze, R	El Bakali, Imane; Brouziyne, Youssef; El Mekki, Abdelkader Ait; Maatala, Nassreddine; Harbouze, Rachid	The impact of policies on the diffusion of agricultural innovations: Systematic review on evaluation approaches	2024	10.1177/00307270231215837	http://dx.doi.org/10.1177/00307270231215837
Parise, F; Lygeros, J; Ruess, J	Parise, Francesca; Lygeros, John; Ruess, Jakob	Bayesian inference for stochastic individual-based models of ecological systems: a pest control simulation study	2015	10.3389/fenvs.2015.00042	http://dx.doi.org/10.3389/fenvs.2015.00042
Winter, E; Grovermann, C; Messmer, MM; Aurbacher, J	Winter, Eva; Grovermann, Christian; Messmer, Monika M.; Aurbacher, Joachim	Assessing seed and breeding interventions for organic farming using a multiagent value chain approach	2023	10.1186/s40100-023-00262-x	http://dx.doi.org/10.1186/s40100-023-00262-x
Utomo, DS; Onggo, BS; Eldridge, S	Utomo, Dhanan Sarwo; Onggo, Bhakti Stephan; Eldridge, Stephen	Applications of agent-based modelling and simulation in the agri-food supply chains	2018	10.1016/j.ejor.2017.10.041	http://dx.doi.org/10.1016/j.ejor.2017.10.041

Yu, KY	Yu, Kaiyuan	Seeking the Smartest Growth	2017		
Nguyen, LN; Megiddo, IE; Howick, S	Nguyen, Le Khanh Ngan; Megiddo, Itamar E.; Howick, Susan	Hybrid simulation modelling of networks of heterogeneous care homes and the inter-facility spread of Covid-19 by sharing staff	2022	10.1371/journal.pcbi.1009780	http://dx.doi.org/10.1371/journal.pcbi.1009780
Williams, RA	Williams, R. A.	Towards an agent-based model using a hybrid conceptual modelling approach: A case study of relationship conflict within large enterprise system implementations	2022	10.1080/17477778.2022.2122741	http://dx.doi.org/10.1080/17477778.2022.2122741

Grovermann, C; Schreinemachers, P; Riwthong, S; Berger, T	Grovermann, Christian; Schreinemachers, Pepijn; Riwthong, Suthathip; Berger, Thomas	'Smart' policies to reduce pesticide use and avoid income trade-offs: An agent-based model applied to Thai agriculture	2017	10.1016/j.ecolecon.2016.09.031	http://dx.doi.org/10.1016/j.ecolecon.2016.09.031
Tonelli, F; Bruzzone, AAG; Paolucci, M; Carpanzano, E; Nicolo, G; Giret, A; Salido, MA; Trentesaux, D	Tonelli, F.; Bruzzone, A. A. G.; Paolucci, M.; Carpanzano, E.; Nicolo, G.; Giret, A.; Salido, M. A.; Trentesaux, D.	Assessment of mathematical programming and agent-based modelling for off-line scheduling: Application to energy aware manufacturing	2016	10.1016/j.cirp.2016.04.119	http://dx.doi.org/10.1016/j.cirp.2016.04.119
Ferreira, L; Borenstein, D	Ferreira, L.; Borenstein, D.	Normative agent-based simulation for supply chain planning	2011	10.1057/jors.2010.144	http://dx.doi.org/10.1057/jors.2010.144
Geng, SY; Liu, SF; Fang, ZG	Geng, Sunyue; Liu, Sifeng; Fang, Zhigeng	An agent-based algorithm for dynamic routing in service networks	2022	10.1016/j.ejor.2022.03.010	http://dx.doi.org/10.1016/j.ejor.2022.03.010

Petronijevic, J; Etienne, A; Dantan, JY	Petronijevic, Jelena; Etienne, Alain; Dantan, Jean-Yves	Human factors under uncertainty: A manufacturing systems design using simulation-optimisation approach	2019	10.1016/j.cie.2018.11.001	http://dx.doi.org/10.1016/j.cie.2018.11.001
Troost, C; Parussis-Krech, J; Mejaíl, M; Berger, T	Troost, Christian; Parussis-Krech, Julia; Mejail, Matias; Berger, Thomas	Boosting the Scalability of Farm-Level Models: Efficient Surrogate Modeling of Compositional Simulation Output	2023	10.1007/s10614-022-10276-0	http://dx.doi.org/10.1007/s10614-022-10276-0
Ostermeyer, A; Schönau, F	Ostermeyer, Arlette; Schoenau, Franziska	Effects of biogas production on inter- and in-farm competition	2012		
Kim, S; Kim, S; Kiniry, JR	Kim, Sojung; Kim, Sumin; Kiniry, James R.	Two-phase simulation-based location-allocation optimization of biomass storage distribution	2018	10.1016/j.simpat.2018.05.006	http://dx.doi.org/10.1016/j.simpat.2018.05.006

Hampf, AC; Carauta, M; Latynskiy, E; Libera, AAD; Monteiro, L; Sentelhas, P; Troost, C; Berger, T; Nendel, C	Hampf, Anna C.; Carauta, Marcelo; Latynskiy, Evgeny; Libera, Affonso A. D.; Monteiro, Leonardo; Sentelhas, Paulo; Troost, Christian; Berger, Thomas; Nendel, Claas	The biophysical and socio-economic dimension of yield gaps in the southern Amazon - A bio-economic modelling approach	2018	10.1016/j.agsy.2018.05.009	http://dx.doi.org/10.1016/j.agsy.2018.05.009
Páez-Pérez, D; Sánchez-Silva, M	Paez-Perez, David; Sanchez-Silva, Mauricio	A dynamic principal-agent framework for modeling the performance of infrastructure	2016	10.1016/j.ejor.2016.03.027	http://dx.doi.org/10.1016/j.ejor.2016.03.027
Chu, YF; You, FQ; Wassick, JM; Agarwal, A	Chu, Yunfei; You, Fengqi; Wassick, John M.; Agarwal, Anshul	Integrated planning and scheduling under production uncertainties: Bi-level model formulation and hybrid solution method	2015	10.1016/j.compchemeng.2014.02.023	http://dx.doi.org/10.1016/j.compchemeng.2014.02.023
Zylberberg, J; DeWeese, MR	Zylberberg, Joel; DeWeese, Michael Robert	How should prey animals respond to uncertain threats?	2011	10.3389/fncom.2011.00020	http://dx.doi.org/10.3389/fncom.2011.00020

Reidsma, P; Janssen, S; Jansen, J; van Ittersum, MK	Reidsma, Pytrik; Janssen, Sander; Jansen, Jacques; van Ittersum, Martin K.	On the development and use of farm models for policy impact assessment in the European Union - A review	2018	10.1016/j.agsy.2017.10.012	http://dx.doi.org/10.1016/j.agsy.2017.10.012
Rocha, ABD; Salomao, GM	da Silva Rocha, Andre Barreira; Salomao, Gabriel Meyer	Environmental policy regulation and corporate compliance in evolutionary game models with well-mixed and structured populations	2019	10.1016/j.ejor.2019.05.040	http://dx.doi.org/10.1016/j.ejor.2019.05.040
Duclos-Prévet, C; Guéna, F; Efron, M	Duclos-Prevet, Claire; Guena, Francois; Efron, Mariano	Constraint handling methods for a generative envelope design using genetic algorithms: The case of a highly constrained problem	2022	10.1177/14780771221120577	http://dx.doi.org/10.1177/14780771221120577

De Vizia, C; Patti, E; Macii, E; Bottaccioli, L	De Vizia, Claudia; Patti, Edoardo; Macii, Enrico; Bottaccioli, Lorenzo	A win-win algorithm for aggregated residential energy management: resource optimisation and user acceptance learning	2020		
Chargui, T; Bekrar, A; Reghioui, M; Trentesaux, D	Chargui, Tarik; Bekrar, Abdelghani; Reghioui, Mohamed; Trentesaux, Damien	Proposal of a multi-agent model for the sustainable truck scheduling and containers grouping problem in a Road-Rail physical internet hub	2020	10.1080/00207543.2019.1660825	http://dx.doi.org/10.1080/00207543.2019.1660825
Nouri, A; Saghafian, B; Bazargan-Lari, MR; Delavar, M	Nouri, Alireza; Saghafian, Bahram; Bazargan-Lari, Mohammad Reza; Delavar, Majid	Local water market development based on multi-agent based simulation approach	2022	10.1016/j.gsd.2022.100826	http://dx.doi.org/10.1016/j.gsd.2022.100826

Otsuki, T; Isa, ABM; Samuelson, RD	Otsuki, Takashi; Isa, Aishah Binti Mohd; Samuelson, Ralph D.	Electric power grid interconnections in Northeast Asia: A quantitative analysis of opportunities and challenges	2016	10.1016/j.enpol.2015.11.021	http://dx.doi.org/10.1016/j.enpol.2015.11.021
Piorr, A; Ungaro, F; Ciancaglini, A; Happe, K; Sahrbacher, A; Sattler, C; Uthes, S; Zander, P	Piorr, Annette; Ungaro, Fabrizio; Ciancaglini, Arianna; Happe, Kathrin; Sahrbacher, Amanda; Sattler, Claudia; Uthes, Sandra; Zander, Peter	Integrated assessment of future CAP policies: land use changes, spatial patterns and targeting	2009	10.1016/j.envsci.2009.01.001	http://dx.doi.org/10.1016/j.envsci.2009.01.001

Authors	Article Title	Publication Year	DOI	DOI Link
Huber, R; Xiong, H; Keller, K; Finger, R	Bridging behavioural factors and standard bio-economic modelling in an agent-based modelling framework	2022	10.1111/1477-9552.12447	http://dx.doi.org/10.1111/1477-9552.12447
Schreinemachers, P; Potchanasin, C; Berger, T; Roygrong, S	Agent-based modeling for ex ante assessment of tree crop innovations: litchis in northern Thailand	2010	10.1111/j.1574-0862.2010.00467.x	http://dx.doi.org/10.1111/j.1574-0862.2010.00467.x
Lobianco, A; Esposti, R	The Regional Multi-Agent Simulator (RegMAS): An open-source spatially explicit model to assess the impact of agricultural policies	2010	10.1016/j.compag.2010.02.006	http://dx.doi.org/10.1016/j.compag.2010.02.006
Baldi, L; Arfini, F; Calzolai, S; Donati, M	An Impact Assessment of GHG Taxation on Emilia-Romagna Dairy Farms through an Agent-Based Model Based on PMP	2023	10.3390/land12071409	http://dx.doi.org/10.3390/land12071409
Nouri, A; Saghafian, B; Delavar, M; Bazargan-Lari, MR	Agent-Based Modeling for Evaluation of Crop Pattern and Water Management Policies	2019	10.1007/s11269-019-02327-3	http://dx.doi.org/10.1007/s11269-019-02327-3
Sapino, F; Haer, T; Saiz-Santiago, P; Pérez-Blanco, CD	A multi-agent cellular automata model to explore water trading potential under information transaction costs	2023	10.1016/j.jhydrol.2023.129195	http://dx.doi.org/10.1016/j.jhydrol.2023.129195
Quang, DV; Schreinemachers, P; Berger, T	Ex-ante assessment of soil conservation methods in the uplands of Vietnam: An agent-based modeling approach	2014	10.1016/j.agsy.2013.10.002	http://dx.doi.org/10.1016/j.agsy.2013.10.002
Seidel, C; Britz, W	Estimating a Dual Value Function as a Meta-Model of a Detailed Dynamic Mathematical Programming Model	2019	10.13128/bae-8147	http://dx.doi.org/10.13128/bae-8147

Shastri, Y; Hansen, A; Rodríguez, L; Ting, KC	A novel decomposition and distributed computing approach for the solution of large scale optimization models	2011	10.1016/j.compag.2011.01.006	http://dx.doi.org/10.1016/j.compag.2011.01.006
Liu, YC; Zhang, T; Geng, XL; He, LS; Pang, ZG	Herdsmen's Adaptation to Climate Changes and Subsequent Impacts in the Ecologically Fragile Zone, China	2013	10.1155/2013/748715	http://dx.doi.org/10.1155/2013/748715
Berger, T; Schreinemachers, P; Woelcke, J	Multi-agent simulation for the targeting of development policies in less-favored areas	2006	10.1016/j.agsy.2005.06.002	http://dx.doi.org/10.1016/j.agsy.2005.06.002
Winter, E; Grovermann, C; Messmer, MM; Aurbacher, J	Assessing seed and breeding interventions for organic farming using a multiagent value chain approach	2023	10.1186/s40100-023-00262-x	http://dx.doi.org/10.1186/s40100-023-00262-x
Grovermann, C; Schreinemachers, P; Riwthong, S; Berger, T	'Smart' policies to reduce pesticide use and avoid income trade-offs: An agent-based model applied to Thai agriculture	2017	10.1016/j.ecolecon.2016.09.031	http://dx.doi.org/10.1016/j.ecolecon.2016.09.031
Troost, C; Parussis-Krech, J; Mejaíl, M; Berger, T	Boosting the Scalability of Farm-Level Models: Efficient Surrogate Modeling of Compositional Simulation Output	2023	10.1007/s10614-022-10276-0	http://dx.doi.org/10.1007/s10614-022-10276-0
Ostermeyer, A; Schönau, F	Effects of biogas production on inter- and in-farm competition	2012		
Kim, S; Kim, S; Kiniry, JR	Two-phase simulation-based location-allocation optimization of biomass storage distribution	2018	10.1016/j.simpat.2018.05.006	http://dx.doi.org/10.1016/j.simpat.2018.05.006

Hampf, AC; Carauta, M; Latynskiy, E; Libera, AAD; Monteiro, L; Sentelhas, P; Troost, C; Berger, T; Nendel, C	The biophysical and socio-economic dimension of yield gaps in the southern Amazon - A bio-economic modelling approach	2018	10.1016/j.agsy.2018.05.009	http://dx.doi.org/10.1016/j.agsy.2018.05.009
Nouri, A; Saghafian, B; Bazargan-Lari, MR; Delavar, M	Local water market development based on multi-agent based simulation approach	2022	10.1016/j.gsd.2022.100826	http://dx.doi.org/10.1016/j.gsd.2022.100826
Piorr, A; Ungaro, F; Ciancaglini, A; Happe, K; Sahrbacher, A; Sattler, C; Uthes, S; Zander, P	Integrated assessment of future CAP policies: land use changes, spatial patterns and targeting	2009	10.1016/j.envsci.2009.01.001	http://dx.doi.org/10.1016/j.envsci.2009.01.001

Category 1 - General Information	Sub-Category	Headings of the Questions	Answers	Frequency Response Over (x) Articles	Percentage Over (x) Articles	Number of Articles where Answers Occured
Category 1 - General Information	Research Documentation	Use of ODD protocol	Yes	5	26.32%	
			No	14	73.68%	19
	Model Structure	Available model	Yes	19	100%	
			No	0	0%	19
		Available data	Yes	18	94.74%	
			No	1	5.26%	19
	Modeling Framework	Use of modeling framework	Yes	17	89.47%	
			No	2	10.53%	19
		Name of Modelling Framework	MP-MAS	5	26.31%	
			MODFLOW	2	10.52%	
			AgriPoliS	2	10.52%	
			Others	10	52.63%	
			Not specified	2	10.52%	19

	Research Domain	Main Subject of the Study	Agricultural Systems And Resource Management	7	36.84%	
			Agricultural Policy	6	31.58%	
			Agricultural Production Dynamics	3	15.79%	
			Agricultural Decision-Making	3	15.79%	
			Environmental And Climate Considerations	2	10.53%	19

Note: **All percentages were calculated based on the total number of articles that appeared on the questions' total potential answers (codes), not on each other, as in the previous error (since we combined some answers under one heading, duplicate or more than two repeated identical articles under the same heading were calculated as a single one).**

Main Category	Sub-Category	Headings of the Questions	Answers	Frequency Response Over (x) Articles	Percentage Over (x) Articles	Number of Articles where Answers Occured
	Types of Decision-Making	**Main Decision-Making**	Farmer	18	94.74%	
			Others	3	15.79%	19
	Types of Decision-Making Agent	**Other Actors Involved in Decision-Making**	No Other Agent	12	63.16%	
			Institutional & Policy Agents	3	15.79%	
			Intermediate Agents	2	10.53%	
			Commercial Agents	2	10.53%	19
	Decision-Making Objects	**Decision-Making Object of the Agent**	Production	15	78.95%	
			Investment	9	47.37%	
			Land Use	8	42.11%	
			Conversion To Agricultural Practice	8	42.11%	

		Others	5	26.32%	19
Rationality of Agent	**Bounded Rationally of the Agent**	Yes	16	84.21%	
		No	3	15.78	19
Rationality of Agent	**The Boundaries of Agent Rationality**	Knowledge	8	42.10%	
		Individual Preferences	11	57.89%	
		Risk Behavior	7	36.84%	
		Others	1	5.30%	
		Not Specifie	5	26.30%	19
Heterogeneity	**Type of Heterogeneity**	Behavioral	14	73.68%	
		State Variables	18	94.74%	
		Information	5	26.30%	19

	Optimization Elements in Model	**Variable Optimized in Objective Function**	Income	9	47.37%	19
			Profit	4	21.05%	19
			System Cost	2	10.53%	19
			Gross Margin	3	15.79%	19
			Others	1	5.26%	19
Making Processes & Elements		**Type of Optimization**	LP	10	52.63%	
			MIP	4	21.05%	
			NLP	2	10.50%	

Category 2 - Decision-M			Others (MI	3	15.79%	19
		Optimization Approach	Maximisation	17	89.47%	
			Minimisation	2	10.52%	19
		Parameters Taken Into Account in the Objective Function	**Policy Instruments and Regulatory**	5	26.32%	19
			Operational and Risk Assessmen	3	15.79%	19
			Environmental/Biophysical Factors	10	52.63%	19
			Output/Revenue Parameters	15	78.95%	19
			Input/Costs	15	78.95%	19
	Optimization Elements in Model		Production Decisions	16	84.21%	19

		Decision Variables	Resource Management Decisions	10	52.63%	19
			Investment/Financial Decisions	7	36.84%	19
			Physical/ Operational Decisions	8	42.11%	19
		Constraints on Decision-Making	Financial Constraints	14	73.68%	19
			Biophysical Constraints	16	84.21%	19
			Agricultural & Environmental Laws And Policies Constraints	8	42.11%	19
			Behavioral Constraints	3	15.79%	19
			Physical/Operational Constraints	11	57.89%	19

		Production Constraints	3	15.79%	19
Model Calibration	**Type of Calibration**	Secondary Data	15	78.95%	
		Primary Data	5	26.32%	19
Stochasticity	**Stochasticity in the Model Structure**	Yes	16	84.210526	
		No	3	15.789474	19
Stochasticity	**Type of Stochasticity**	Initial	12	63.16%	
		Economic	9	47.37%	19
		In The Dm	5	26.32%	
		Not Specified	2	10.53%	19
Risk And Prediction Factors	**Inclusion of the Risk Factor in the Agent's Decision Rules**	No	11	57.894737	
		Yes	8	42.105263	19
Environmental Sensing	**The spatial scale of sensing of agents' environment**	Local	17	89.50%	
		Global	2	10.50%	19

Main Category	Sub-Category	Headings of the Questions	Answers	Frequency Response Over (x) Articles	Percentage Over (x) Articles	Number of Articles where Answers Occured
		Existence of agents interactions modeled in the ABM framework	Yes	18	94.74%	19
		Existence of agents interactions modeled in the ABM framework	No	1	5.26%	19
		Presented Interactions in the Model	Market & Economic Interactions	10	52.63%	19
		Presented Interactions in the Model	Information & Learning Interactions	6	31.58%	19
		Presented Interactions in the Model	Policy Influences	6	31.58%	19
		Presented Interactions in the Model	Negotiation & Agreements	2	10.53%	19
		Presented Interactions in the Model	Transportation Operation	2	10.53%	19

	Interactions	Competitive approach or cooperation between organizations	**Competitive**	11	57.89%	19
		Competitive approach or cooperation between organizations	**Cooperative**	5	26.32%	19
		Competitive approach or cooperation between organizations	**Not Applicable**	3	15.79%	19
		The effects of competitive / cooperative behaviour	Resource Allocation	7	36.84%	19
		The effects of competitive / cooperative behaviour	Changes In Agricultural Activities	5	26.32%	19
		The effects of competitive / cooperative behaviour	Market Equilibria	5	26.32%	19
		The effects of competitive / cooperative behaviour	Land Allocation	5	26.32%	19
		The effects of competitive / cooperative behaviour	Not Applicable	3	15.79%	19

Category 3 - Actors & Environmental Interactions		The effects of competitive / cooperative behaviour	Supply Chain Efficiency	2	10.53%	19
		The effects of competitive / cooperative behaviour	Others	4	21.05%	19
	Learning Processes	Effects of Learning/ Adoption on Decision-Making Process	Not Applicable	10	52.63%	19
		Effects of Learning/ Adoption on Decision-Making Process	By Agricultural Strategies/ Practices	8	42.11%	19
		Effects of Learning/ Adoption on Decision-Making Process	By Resource Management	4	21.05%	19
		Effects of Learning/ Adoption on Decision-Making Process	By Response To Policies	4	21.05%	19
		Effects of Learning/ Adoption on Decision-Making Process	By Response Market Signals	4	21.05%	19
		Effects of Learning/ Adoption on Decision-Making Process	By Investment	2	10.53%	19

		Effects of Learning/ Adoption on Decision-Making Process	**By More Information Seeking Behavior**	1	5.26%	19
	Supply Chain Representation	**Supply/Value Chain Representation in the Model**	**Yes**	16	84.21%	19
		Supply/Value Chain Representation in the Model	**No**	3	15.79%	19
		Explicit Modeling of Agent Interactions Within the Supply/Value Chain	**Yes**	3	84.21%	19
		Explicit Modeling of Agent Interactions Within the Supply/Value Chain	**No**	16	15.79%	19
		Supply/Value Chain Actors Included in the Model	**Not Applica**	16	84.21%	19
		Supply/Value Chain Actors Included in the Model	**Farmer**	2	10.53%	19
		Supply/Value Chain Actors Included in the Model	**Storage Fac**	2	10.53%	19

		Supply/Value Chain Actors Included in the Model	**Others**	6	31,58%	19

Main Category	Sub-Category	Headings of the Questions	Answers	Frequency Response Over (x) Articles	Percentage Over (x) Articles	Number of Articles where Answers Occured
		Strengths of ABM in the Model	Spatial Representation Of Systems	14	73.68%	19
			Heterogeneity Of Households/Agents	13	68.42%	19
			Modeling Farmer Interactions	11	57.89%	19
			Integration Of Multidisciplinary Approaches	9	47.37%	19
			Policy Representation	9	47.37%	19
			Heterogeneity Of Land	6	31.58%	19
	The		Include Dynamic-Stochastic Element	5	26.32%	19

	strengths of ABM in the model		**Environmental/Sustainability Representation**	4	21.05%	19
			Others	12	63.16%	19
		Strengths of ABM in the Model (Others)*	**Market Interactions**	3	15.79%	19
			Heterogeneity Of Economic	3	15.79%	19
			Representation Of Agricultural Structural Change	3	15.79%	19
			Capacity To Represent The Effects Of Information Asymmetries	2	10.53%	19
			Representation Of Value Chain Behavior	1	5.26%	19
			Failing To Capture Some Real-World Behaviors/ Interactions	11	57.89%	19

Category 4 - Model Evaluation in Terms of ABM and MP Features	Weaknesses of ABM in the Model	Weaknesses of ABM in the Model	Data Dependency	9	47.37%	19
			High Computational Costs	7	36.84%	19
			Failing To Capture Some Effects Of Agricultural Adaptation And Innovations	3	15.79%	19
			Failing To Capture System Complexity	3	15.79%	19
			Others	2	10.53%	
	Weaknesses of ABM in the Model (Others*)	Weaknesses of ABM in the Model (Others*)	Failing To Capture Policy Changes/Policy Impacts	1	5.26%	19
			Limitations Due To Assumptions And Ignored Value	1	5.26%	19
			Simulate Optimising	16	84.21%	19

	Strengths of MP in the Model	Strengths of MP in the Model	Enhancing Policy Analysis	12	63.16%	19
			Simplification	6	31.58%	19
			Enhancing Economic Analysis	6	31.58%	19
			Flexibility & Extendibility	2	10.53%	19
			Analysing Adoption Measures	2	10.53%	19
			Enables Analysis Of The Competitiveness Of Farm Activities	2	10.53%	19
			Others	2	10.53%	19
	Strengths of MP in	Strengths of MP in	Detailed Spatial Analysis	1	5.26%	19

	the Model (Others*)	the Model (Others*)	Enables Analysis Of The Cooperativeness Of Farm Activities	1	5.26%	19
	Weaknesses of MP in the Model	Weaknesses of MP in the Model	Modeling C	6	31.58%	19
			Assumption	6	31.58%	19
			Data & Con	5	26.32%	19
			Not Specifie	4	21.05%	19
			Others	2	10.53%	19
	Weaknesses of MP in the Model (Others*)	Weaknesses of MP in the Model (Others*)	Temporal L	1	5.26%	19
			Over Simpl	1	5.26%	19

We prepared sequential questions according to the content of the 19 articles we analysed, and the questions were answered objectively according to the articles. Unfortunately it is not possible to answer each question specifically, which would be both difficult to understand and time consuming. Therefore, to make the answers inclusive, we have developed generic and unified a coding pool of potential answers that we have analysed and clarified in a way that readers can understand. In order to show this in an easy way, we have prepared a table in which we have collected the comments we have prepared for the answers. It is also important to note that each question may have more than one answer also the answers might not be appliable or specified. Finally, it is important also to note that we have not only included in our definitions what we have found in existing articles, but we have also done so keeping in mind that all answers should be included when a new article appears in the future.

Category 1 - General Information

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 1 - General Information	**Modeling Framework**	**Name of Modeling Framework**	**MP-MAS**		(Grovermann et al., 2017a ; Hampf et al., 2018 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Troost et al., 2022)
			MODFLOW		(Nouri et al., 2019, 2022)
			AgriPoliS		(Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009)
			Others	1. FARMIND 2. RegMAS 3. APAM 4. FARMDYN 5. ABMSim 6. BioFeed 7. VAL-MAS 8. ALMANAC 9. MONICA	**1. FARMIND** (Huber et al., 2022) **2. RegMAS** (Lobianco and Esposti, 2010) **3. APAM** (Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023a) **4. FARMDYN** (Seidel and Britz, 2019) **5. ABMSim** (Seidel and Britz, 2019) **6. BioFeed** (Shastri et al., 2011) **7. VAL-MAS** (Winter et al., 2023) **8. ALMANAC** (Kim et al., 2018)

				10. MODAM 11. AGRISP	**9. MONICA** (Hampf et al., 2018) **10. MODAM** (Piorr et al., 2009) **11. AGRISP** (Baldi et al., 2023)
			Not Specified*		**Not Specified** (Berger et al., 2006 ; Liu et al., 2013)

** Both documents confirm the use of MAS and MP in the study of Berger et al. (2006) and also ABM and PMP in Liu et al. (2013). However, there is no information on whether the names of the modeling approaches are explicitly mentioned in these studies. Both studies include case studies where these models were used.*

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 1 - General Information	**Research Domain**	**Main Subject of the Study**	**Agricultural Decision-Making**	This subject can include but are not limited to, the choices made by farm agents resource use, crop and livestock management, and overall farm operations. For example Huber et al. (2022) was focused on farmers decision-making processes regarding to the weed control strategies. Schreinemachers et al.(2010) examined decisions regarding product choices and adoption of new technologies and innovaitons. Also, Berger et al. (2006) investigated the effects of development policies on farmer decisions.	(Berger et al., 2006 ; Huber et al., 2022 ; Schreinemachers et al., 2010).

			Agricultural Policy	Public policies impacting or aiming to regulate the agricultural sector are included in this category; such as subsidies, trade regulations, sustainability initiatives and funding for research and development. For example, Lobianco and Esposti (2010), the model which named RegMAS was developed to assess the impact of agricultural policies, especially CAP (Common Agricultural Policy) reforms. Piorr et al. (2009) conducted an integrated assessment of future CAP policies by using ABM and LP. Baldi et al. (2023) simulated different policy scenarios, including carbon taxes and changes in CAP payment systems by ABM and PMP. Berger et al. (2006) developed a MAS model for policy development in less productive areas. Grovermann et al. (2017) examined how different policy mixes could reduce the usage of pesticide without harming farm incomes. Ostermeyer and Schoenau, (2012) shows the effects of biogas production policies on inter- and in-farm competitions.	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017a ; Lobianco and Esposti, 2010 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009)
			Agricultural Systems and Resource Management	This field focuses on the efficient and sustainable use of resources; likewise land, water, soil, and biodiversity. Various issues that stand out under the framework of this topic include such as integrated agricultural systems, soil and water	(Hampf et al., 2018 ; Kim et al., 2018 ; Nouri et al., 2022, 2022 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023a ; Seidel and Britz, 2019)

				management practices, efforts to protect biodiversity for the long-term sustainability of agriculture. For example, Nouri et al., (2019, 2022) in both studies developed ABM for water management and crop pattern optimization. The potential for water trading was highlighted by Sapino et al. (2023) who evaluated the impacts of transaction costs on the water market. Also, the adoption of soil conservation methods in Vietnam's mountainous regions was examined by Quang et al. (2014). Meanwhile, a two-stage simulation-based model for optimal biomass storage location was developed by Kim et al. (2018). Seidel and Britz (2019) used a model that showed the relationship between key characteristics such as farm equipment and discounted farm household incomes. Also, Hampf et al. (2018), considered the biophysical and socioeconomic dimensions of yield gaps in the farm systems.	
			Agricultural Production Dynamics	This agricultural production dynamics examines changes in agricultural productivity over times and spaces. It helps predict future trends and make informed decisions by examining yield trends, the impact of technology, market impacts and the effects of climate	(Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023a ; Shastri et al., 2011 ; Winter et al., 2023)

				change. The approach to optimizing biomass feedstock production systems was followed by Shastri et al. (2011). Interventions aimed at increasing organic seed production and use were evaluated by Winter et al. (2023). Ostermeyer and Schoenau, (2012), simulated changes in production systems and their impact on agricultural structures.	
			Environmental and Climate Considerations	The focus of this research area is to examine how agricultural activities affects the environment and how climate change impacts agricultural systems. Adaptation to climate change can involves approaches to decrease greenhouse gas emissions, and advocate for sustainable methods that safeguard natural resources and maintain the sustainability of agriculture. The effects of climate change adaptation measures on herders' income and land surface dynamics were analysed by Liu et al. (2013). Troost et al., (2022) worked on improving the scalability of farm-level models and assessing climate change impacts.	(Liu et al., 2013 ; Troost et al., 2022)

Category 2 - Decision-Making Processes

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 2 - Decision-Making Processes			**Farmer**	Refers to individual farmers, farm households or herdsmen who make decisions on crop production, livestock management and other farming activities. In Liu et al. (2013), the term for the agent "farmers" and "herdsmen" reflects the mixed agriculture-livestock system in the studied region. The use of the term ''herdsmen'' within the term ''farmers'' emphasizes the overlapping aspects of these roles and extends the scope of the study. As another example, in the study of Winter et al. (2023), farmers are modeled as heterogeneous actors making decisions on seed use, crop production and technology adoption. Also, in Quang et al. (2014), the model simulates farmers' decisions on whether to adopt soil conservation practices.	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017a ; Hampf et al., 2018 ; Huber et al., 2022 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023a ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Shastri et al., 2011 ; Troost et al., 2022 ; Winter et al., 2023)
	Types of Decision-Making Agent	**Main Decision-Making Agent**	**Others**	**1. Institutional & Policy Agents** It includes the institutional or political actors responsible for regulating agricultural practices and policies, such government, state and parliamentary bodies. In the article of Nouri et al. (2019), there are regulator agents who	**1. Institutional & Policy Agents** (Nouri et al., 2019) **2. Breeders** Winter et al. (2023) **3. Seed Producers** Winter et al. (2023) **4. Biomass Farms** (Kim et al., 2018)

				may buy water permits for environ mental conservation purposes, we can consider them as institutional & policy decision-makers. Also the research from Winter et al. (2023), defined the Breeders and Seed Producers as actors that develop long-term strategies for seed production and breeding. ***"Seed producers and breeders are represented by two types of actors: internationally active commercial seed and breeding companies (Type I) and small companies or initiatives dedicated to organic seed (Type II)"*** **2. Breeders** Breeders and farmers play a role at different stages. Breeders develop new plant varieties to help farmers grow more productive and resilient crops. **3. Seed Producers** Seed production, along with ensuring seeds meet quality standards for purity and germination, is handled by these agents. Also, they manage the logistics of delivering seeds to the market, ensuring farmers get access to the essential seeds they need. As a different approach, Kim et al. (2018) models different actors instead of a single central decision-making agent. **'Biomass farms'** provide feedstock by producing switchgrass, **'Storage facilities'** serve as the intermediate point	**5. Storage Facilities** (Kim et al., 2018) **6. Biorefineries** (Kim et al., 2018)

				between farms and biorefineries and store biomass, and **'Biorefineries'** are the endpoint of the supply chain, converting biomass into ethanol**. '***'The AnyLogic model captures detail activities (e.g., loading, unloading, and storing feedstocks) among the actors (e.g. farms, storage facilities, and biorefineries) in the biomass supply chain.***"** **4. Biomass Farms** **5. Storage Facilities** **6. Biorefineries**	

Note 1. *Some articles may include more than one category.*

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 2 – Decision-Making Process	**Types of Decision-Making Agent**	**Other Actors Involved in Decision-Making**	**Intermediate Agents**	They are agents that mediate agricultural processes. They can play a role in various resource allocation processes (e.g. land rental) and these processes may not involve direct farmer-farmer interactions. Lobianco and Esposti (2010) mentioned anonymous intermediate agents, like *"an anonymous intermediate agent that operates in the land market collecting plots released by farms exiting the business, in addition to the initial pool of rentable plots. This*	(Lobianco and Esposti, 2010) (Ostermeyer and Schoenau, 2012)

				agent makes all these plots available to farmers through a bid where only the farm offering the highest price eventually rents the plot." In the study of, Ostermeyer and Schoenau, (2012) referred to "Land owners", which are considered as intermediary agents, as follows: *"The more money is forwarded to the land owners, the less money remains for the farmer."*	
			Commercial / Supply Chain Agents	Agents engaged in commercial activities in the agricultural supply/value chain systems such as storage facilities, distributors, transportation providers, storage facilities and biorefineries. In the paper of Shastri et al. (2011), commercial agents such as storage facilities, transportation providers and biorefineries are modeled in detail. The model optimizes the selection and sizing of these facilities and considers their interactions with farmers. Also in the model by Kim et al. (2018), commercial agents are part of the transport and distribution processes.	(Shastri et al., 2011) (Kim et al., 2018)
			Institutional & Policy Agents	Institutional or political actors responsible for regulating agricultural practices and policies. These may	(Berger et al., 2006 ; Liu et al., 2013 ; Nouri et al., 2022)

				include government bodies, regulatory agencies or other policy makers. Although, Berger et al. (2006) did not model the 'Institutional & Policy Agents' directly as main decision-makers, they are used to simulate the effects of policy interventions. For example, policy scenarios such as credit programs, fertilizer subsidies and irrigation investments are tested. Liu et al. (2013) find that government subsidies have a strong positive impact on different sizes of grazing land and livestock industry income. In Nouri et al. (2022), these agents explained as governmental bodies which regulates agricultural practices and policies.	
			Not Specified		(Baldi et al., 2023 ; Grovermann et al., 2017a ; Hampf et al., 2018 ; Huber et al., 2022 ; Nouri et al., 2019 ; Piorr et al., 2009 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023a ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Troost et al., 2022 ; Winter et al., 2023)

Main Category	**Sub-Category**	**Headings of the Questions**	**Potential Answers**	**Explanation**	**Examples**
Category 2 – Decision-Making Process	**Rationality of the Agents**	**The Boundaries of Agent Rationality**	**Knowledge**	Level of relevant and reliable information available to agents, influencing their decision-making	(Berger et al., 2006 ; Grovermann et al., 2017a ; Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Quang et al., 2014 ; Sapino et al., 2023; Troost et al., 2022 ; Winter et al., 2023)

				process. It also includes these past experiences. Berger et al. (2006) emphasize the knowledge, particularly, like***: "In this type of models, a computational agent typically represents a farm household who combines individual knowledge and values, information on soil quality and topography (the biophysical landscape environment), and an assessment of the land management choices of neighbors (the spatial social environment) to make land-use decisions."*** In the context of water management, Nouri et al. (2022) simulated agricultural agents' knowledge about water prices and availability. These terms such as ***"Sociolearning", "Sociopressure"*** show how agricultural agents make informed decisions and how these decisions are influenced by external factors such as social learning and social pressure. Similarly Sapino et al. (2023) noted agents' knowledge is constrained as a ***"proxy of asymmetric information"***, limiting their knowledge of other ***"possible traders"*** in the market.	
			Risk Behavior	Willingness to engage in several agricultural activities with uncertain outcomes, including risk-taking and risk-averse behavior. Winter et al. (2023) mention that ***"If the seed producer agents increase their***	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017a ; Huber et al., 2022 ; Troost et al., 2022 ; Winter et al., 2023)

				production according to expected future demand, accepting a higher risk of losses in case they cannot sell all seed as expected, farm agents incur only a gross margin loss of 3%." (Grovermann et al., 2017a) state ***'In reality, not all farm households are equally willing to take risk and capable to innovate. Many prefer to see others try first before adopting themselves. MPMAS was designed to capture this process and several previous studies have applied this (Berger et al., 2007; Quang et al., 2014; Schreinemachers et al., 2007).***	
			Individual Preferences	Personal preferences and priorities are influenced by cultural, social, and personal values. Openness to adopting new agricultural ideas, technologies, and practices. Again, in the context of water management, Nouri et al. (2022) describe the individual behavioral factors of agricultural agents as follows: ***"In addition, the tendency of AAs' to behave selfishly (as common pool resources) (Lopez-Corona ´ et al., 2013) led to non-cooperative response of water sellers (1, 2, 4, and 5 agents) in over-exploitation."*** **Innovativeness Level** In a study of Austrian farmers shown by Walder et al. (2019), values such as self-orientation and hedonistic	(Baldi et al., 2023 ; Hampf et al., 2018 ; Nouri et al., 2022 ; Piorr et al., 2009 ; Shastri et al., 2011 ; Troost et al., 2022 ; Winter et al., 2023) **Innovativeness Level** (Baldi et al., 2023 ; Grovermann et al., 2017a ; Hampf et al., 2018 ; Liu et al., 2013 ; Quang et al., 2014 ; Troost et al., 2022 ; Winter et al., 2023).

				tendencies were found to be positively associated with innovative capabilities in farming. On the other hand, an emphasis on economic success was less associated with innovation, suggesting that fostering creativity and autonomy may increase innovation at the farm level. For example, in our literature review, Quang et al. (2014) stated this as ***"innovativeness level of each household"***.	
			Others	**Tolerance Level** It represent the agents' capacity to tolerate uncertainty and variability. Huber et al. (2022) mention ***"Tolerance level for income change to determine information seeking behaviour"*** and ***"Tolerance level for activity dissimilarity to determine information seeking behaviour."***	**Tolerance Level** (Huber et al., 2022)
			Not Specified		**Not Specified** (Kim et al., 2018 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019)

Note 2. *Rational boundaries refers to the cognitive limitations that agricultural agents face when making their decisions. We haven't taken into account influences, such as economic factors or resource constraints as they are external limitations rather than internal cognitive considerations on the decision-making. Such constraints are factors that influence the behavior of agricultural agents but do not directly depend on their cognitive capacity.*

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples

Category 2 - Decision-Making Processes	**Heterogeneity**	**Type of Heterogeneity Exists**	**State Variables**	Within the context of an agent-based model (ABM), state variables are understood as factors delimiting the present conditions of a region/area. Such factors might be economic type, resource endowment land utilization and other such parameter that are time dependent. For example, Lobianco and Esposti, (2010) explained it as ‘***’structural and spatial heterogeneity (for instance, distinguishing between small and large farms but also between plain and mountainous farming).”.*** As another example, in Baldi et al. (2023), the model accounts for differences in the size of farms, types of crops cultivated, livestock reared, and the technologies employed. Grovermann et al. (2017) model includes a heterogeneous population of farm agents, each with different resource endowments (e.g., land, labor, and cash).	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017a ; Hampf et al., 2018 ; Kim et al., 2018 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023b ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019, 2019 ; Shastri et al., 2011 ; Troost et al., 2022 ; Winter et al., 2023)
			Behavioral	Variations in agents' decision-making mechanisms, preferences, strategies or patterns of behaviour. In the paper of Huber et al. (2022), risk preferences, farm activity preferences and social networks are examples of behavioral heterogeneity. The model in the paper of Baldi et al. (2023), also simulates the heterogeneity in the	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017a ; Huber et al., 2022 ; Liu et al., 2013 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023b ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Troost et al., 2022 ; Winter et al., 2023)

				interactions between farms, particularly, for resource exchange (e.g., land, pollution quotas). Also, Grovermann et al. (2017) modeled captures heterogeneity in the adoption of Integrated Pest Management (IPM) practices, with different farm agents adopting innovations at different rates based on their propensity to innovate.	

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 2 - Decision-Making Processes			**MIP**	**Mixed-Integer Programming**	(Lobianco and Esposti, 2010 ; Ostermeyer and Schoenau, 2012 ; Seidel and Britz, 2019 ; Troost et al., 2022)
			LP	**Linear Programming**	(Berger et al., 2006 ; Grovermann et al., 2017b ; Hampf et al., 2018 ; Huber et al., 2022 ; Nouri et al., 2019, 2022 ; Piorr et al., 2009 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Winter et al., 2023)
			NLP	**Non-linear Programming**	(Baldi et al., 2023 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023)
		Type of Optimization	**Others**	**MILP** (Mixed-Integer Linear Programming) **ILP (**Integer Linear Programming)	**MILP (Mixed-Integer Linear Programming)** (Shastri et al., 2011)

				PMP (Positive Mathematical Programming)	**ILP (Integer Linear Programming)** (Kim et al., 2018) **PMP (Positive Mathematical Programming)** (Liu et al., 2013)

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 2 - Decision-Making Processes	**Optimization Elements in Model**	**Parameters Taken Into Account in the Objective Function**	**Policy Instruments and Regulatory Parameters**	**1.1. Subsidies:** Grovermann et al. (2017b) discussed the biopesticide subsidies as part of strategies to reduce pesticide use. Also Piorr et al. (2009) modeled various CAP policy scenarios in the study; including direct payments, single farm payments, and agri-environmental payments. **1.2. Penalties** As for penalties, Nouri et al. (2022) included them as a parameter, just as fines imposed for over-extraction play a role in shaping the decision-making of agricultural agents. Winter et al. (2023) shows ***''Derogations allowing for the use of NCT seed hamper organic seed production."*** The model reflects the current policy scenario and explores changes under different	**1.1. Subsidies** (Grovermann et al., 2017b ; Piorr et al., 2009) **1.2. Penalties** (Nouri et al., 2022 ; Winter et al., 2023) **1.3. Surface Water Right of Agent** (Nouri et al., 2019) **1.4. Groundwater Right of Agent** (Nouri et al., 2019)

				scenarios, such as the phasing out of these derogations to assess their impact on organic seed production and use. **1.3. Surface Water Right of Agent** Nouri et al. (2019) mentioned this parameter as represents the surface water right of agricultural agent *i.* Surface water refers to water resources on the earth's surface, such as rivers, lakes, dams, etc. Therefore, it is a parameter emphasizing the legal and administrative aspects of water use. **1.4. Groundwater Right of Agent** Nouri et al. (2019) mentioned this parameter as represents the groundwater right of agricultural agent *i.* Groundwater refers to underground water sources such as aquifers. This parameter emphasizing the legal and administrative aspects of water use.	
			Operational and Risk Assessment Factors	**2.1. Risk** Sapino et al. (2023)**,** in the article, states as follows: ***"PMAUP considers 5 relevant attributes, namely profit, risk, and management complexity***" **2.3. Management Complexity**	**2.1. Risk** (Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023) **2.3. Management Complexity** (Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023) **2.4. Performance Function** (Nouri et al., 2019) **2.5. Probability** (Troost et al., 2022)

				2.4. Performance Function The term of ‘’performance function‘’ is mentioned in the article of Nouri et al. (2019) and is discussed under broad concepts such as efficiency and production capacity. **2.5. Probability** For example, in Troost et al. (2022) study, we see “Probability that a male child is interested in taking over the farm” and “Probability to be able to hire a machinery service provider per day with suitable weather”.	
			Environmental/Biophysical Factors	This category covers parameters related to environmental conditions and biophysical factors affecting agricultural production. **3.1. Biophysical Factors** These are parameters that represent the bio-physical and environmental conditions affecting agricultural production. As Troost et al. (2022) mentioned, it includes physical and climate conditions such as "KTBL climatic region for time slots of field work" and "Scaling parameter for the maximum wheat yield". Piorr et al. (2009) studied as parameters the soil quality is divided into classes to assess its impact on productivity and environmental outcomes. In the model of Grovermann et al.	**3.1. Biophysical Factors** (Berger et al., 2006 ; Grovermann et al., 2017b ; Lobianco and Esposti, 2010 ; Nouri et al., 2022 ; Piorr et al., 2009 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Troost et al., 2022) **3.2. Resource Efficiency** (Baldi et al., 2023 ; Nouri et al., 2019, 2022 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Schreinemachers et al., 2010) **3.3. Pesticide Impact** (Grovermann et al., 2017b ; Schreinemachers et al., 2010)

				(2017b) considers key bio-physical parameters such as crop water requirements, effective monthly rainfall, crop yield based on production functions with damage control specifications for pesticides, implicit pest pressure, soil properties, topography and local climatic conditions. In the study of Nouri et al. (2022), the parameter ‘***’Available area for AA i‘***’ tells us that agricultural area is a factor shows biophysical conditions and local land use. In the research of Schreinemachers et al. (2010), daily and monthly precipitation data, potential evapotranspiration (***ETO***) as a parameter to calculate plant water requirement and crop coefficient (***KC***) as a parameter used to determine the water requirement for each plant were reported. The article of Berger et al. (2006) uses nutrient balances for N, P, and K as biophysical factors, e.g., “***Negative nutrient balances in the current situation reveal a relatively high rate of nutrient depletion in the study*** **region (S1a in Table 2)**.” Lobianco and Esposti (2010), used the ‘***’Altitudinal coefficient (AltC)***’’, which partially satisfies this category because it models the effect of altitude on production.	

				3.2. Resource Efficiency (Resource Endowments and Allocations or Resource Allocation and Management) Baldi et al. (2023) explained the use of resources such as land, water, and nitrogen, with specific consideration of their efficient allocation under different policy scenarios (e.g., nitrogen quotas). In the study of Nouri et al. (2022), the parameter '***Allocated water for crop j and AA i***' represents the amount of water allocated for a particular crop and concerns the efficient use of water. In other study of Nouri et al. (2019), '***'Area(Ave,i)***'' represents the total arable land owned by agent ***i***. This is a basic resource or asset of the agent. Schreinemachers et al. (2010) mentioned efficiency values for different irrigation methods (e.g. 70% for conventional methods and 80% for micro sprinkler) were used as a parameter. Research conducted by Sapino et al. (2023) shows the amount of water initially allocated for each agricultural water demand unit (AWDU) and the AQUATOOL model simulates water allocations for agents based on different environmental scenarios (***e.g., minimum environmental flows***).	

				3.3. Pesticide Impact Grovermann et al. (2017b) expalined it like , efficacy of pesticides, including damage control properties captured using production functions (e.g. Cobb-Douglas production function with pesticide reduction terms). Schreinemachers et al. (2010), mentioned environmental impact quotient (EIQ) is used as a parameter to measure pesticide impact for different crops.	
			Output/Revenue Parameters	This category covers all parameters related to the value of agricultural outputs and the revenue generated. **4.1. Yield** In Seidel and Britz (2019), “milk yield per cow” is mentioned as a parameter. As mentioned in Troost et al. (2022) article, we also see parameters that affect crop productivity and determine the maximum potential yield, such as “Scaling parameter for the maximum wheat yield”. Also (Piorr et al., 2009) mentioned the crop yields and livestock productivity as Yield in the parameters. Schreinemachers et al., (2010) modelled the Litchi yield as a parameter, taking into account various factors	**4.1. Yield** (Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Hampf et al., 2018 ; Huber et al., 2022 ; Liu et al., 2013 ; Nouri et al., 2022 ; Piorr et al., 2009 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Troost et al., 2022 ; Winter et al., 2023) **4.2. Production Value** (Berger et al., 2006 ; Grovermann et al., 2017b ; Liu et al., 2013 ; Nouri et al., 2019, 2022 ; Seidel and Britz, 2019 ; Winter et al., 2023) **4.3. Gross Margin** (Lobianco and Esposti, 2010) **4.4. Price Coefficient** (Troost et al., 2022)

				(management level, water supply, age of the orchard). **4.2. Production Value** As Seidel and Britz (2019) explained, price of milk as an output included in this category. Grovermann et al. (2017b) mentioned it based on the selling prices and production quantities of the products. Especially in study of Nouri et al. (2022), this is clearly shown as '*Price of production i in period t'* as the parameter. In another study of Nouri et al. (2019) we can see the parameters under this title such as '' ***Prot, i, j is the production value of agent i from product j during period t (ton)".*** *Berger et al. (2006) directly refers to "***Output Prices***". In the paper, scenario S5 has a 50% increase in output prices (shown in Table 2). Crop prices are given as an example of output prices. Winter et al. (2023) reported that organic carrot selling prices are parameterized as an output price. **4.3. Gross Margin (maybe it is Production Value)** Lobianco and Esposti (2010) explained as it is refers to the gross margin of each activity.	

				4.4. Price Coefficient Troost et al. (2022) mentioned it as not direct prices, but coefficients showing the proportional change in prices relative to the base period. These coefficients are used for both inputs (e.g. fertilizer, fuel) and outputs (e.g. milk, wheat).	
			Production Cost/Input Parameters	This category includes all costs and prices associated with inputs used in agricultural processes. **5.1. Cost** For example, in Piorr et al. (2009) , cost considered under this heading in the form of labor costs. Also Grovermann et al. (2017b) mentioned the production costs such as pesticides, labor, other inputs are included in the model. Baldi et al. (2023) mentioned the costs related to milk production such as feed, forage crop production, energy and also water cost. For the costs, Nouri et al. (2022) included it as parameter like ***"Price of costs for crop j in period t***" represented production costs. Schreinemachers et al. (2010) modeled the costs related to labor, irrigation systems and other agricultural practices, also costs related to the implementation of innovations. Lobianco and Esposti, (2010) stated "***Transport costs***" as	**5.1. Cost** (Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Hampf et al., 2018 ; Huber et al., 2022 ; Kim et al., 2018 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Winter et al., 2023) **5.1.1 Input Prices** (Berger et al., 2006 ; Nouri et al., 2022 ; Seidel and Britz, 2019 ; Winter et al., 2023) buraya grovernman tekrar eklenebilir. **5.1.1.1. Water Prices** (Nouri et al., 2022) **5.1.1.2. Price Coefficients** (Troost et al., 2022)

				distance-related transportation costs in his research. **5.1.1 Input Prices** It represents the price coefficients for various agricultural inputs or inputs of products that influence the economic decisions of the model. Input prices refer to the costs of resources required for agricultural production. As an example, Seidel and Britz (2019) mentioned, it include the ***cost of feed concentrates*** (0.80 to 1.20 €/kg) and the cost of crops grown for feeding livestock. Also, we explicitly know that in Nouri et al. (2022) study, the expression '***Amount of inputs required for AA i and crop j***' includes the inputs required for production and the costs of these inputs. In the research of Berger et al. (2006) directly refers to "Input Prices". In the paper, it is stated that in scenario S5 there is an 80% reduction in input prices (shown in Table 2). In particular, ***fertilizer price*** is mentioned as an input price. Winter et al. (2023) reported that input prices are a parameter, especially for organic seed production. **5.1.1.1. Water Prices**	

				Nouri et al. (2022) explicitly mentioned it as ***''Water price in period t*''.** **5.1.1.2. Price Coefficient** Troost et al. (2022) mentioned it as not direct prices, but coefficients showing the proportional change in prices relative to the base period. These coefficients are used for both inputs (e.g. fertilizer, fuel) and outputs (e.g. milk, wheat).	

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 2 - Decision-Making Processes	**Optimization Elements in Model**	**Decision Variables**	**Production Decisions**	**1.1. Agricultural Activities** (Rotations, Weed Control Strategies, livestock management, farm management strategies, Application of pesticides & fertilizers, crop cultivation, dairy farming, bull fattening, pig production, and biogas production etc.) For example, (Grovermann et al., 2017b) explained it like; farmers decide the type and quantity of pesticides to use, balancing the need for pest control with costs and potential taxes, and choose the crops to grow based on profitability and availability of resources.	**1.1. Agricultural Activities** (Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Hampf et al., 2018 ; Huber et al., 2022 ; Nouri et al., 2019 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Troost et al., 2022 ; Winter et al., 2023) **1.2. Crops** (Baldi et al., 2023 ; Berger et al., 2006 ; Hampf et al., 2018 ; Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Troost et al., 2022) **1.3. Production Quantities** (Lobianco and Esposti, 2010) **1.3.1. Size and Amount of Biogas Plants** (Ostermeyer and Schoenau, 2012)

				1.2. Crops (Decisions on type of crops (also type of seed), crop production, (amount of crop?), arable crops) **1.3. Production Quantities** **1.3.1. Size and Amount of Biogas Plants** **1.3.2. Amount of Seeds** **1.3.3.Amount of Milk** **1.4. Livestock Quantities**	**1.3.2. Amount of Seeds** (Winter et al., 2023) **1.3.3.Amount of Milk** (Baldi et al., 2023 ; Seidel and Britz, 2019) **1.4. Livestock Quantities** (Liu et al., 2013 ; Piorr et al., 2009 ; Troost et al., 2022)
			Resource Management Decisions	**2.1. Land** (Land rental, allocation, arable land, grassland, etc.) **2.2. Water Usage** For example the model of Sapino et al. (2023) shows that farmers decide how to use water for irrigation. The paper simulates the effects of reducing water use and how farmers react to these restrictions. **2.3. Water Trade** **"*The agents' decisions of whether or not to trade are now dictated by the marginal utility (cost) of water for potential buyers (sellers) or shadow price of water*"** (Sapino et al., 2023) **2.4. Feed Concentrates**	**2.1. Land** (Baldi et al., 2023 ; Liu et al., 2013 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Seidel and Britz, 2019 ; Troost et al., 2022) **2.2. Water Usage** (Nouri et al., 2019, 2022 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Schreinemachers et al., 2010) **2.3. Water Trade** (Nouri et al., 2022 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023) **2.4. Feed Concentrates** (Seidel and Britz, 2019)

			Investment/Financial Decisions	**3.1. Investments** For example the study of Ostermeyer and Schoenau (2012) shows that farms can choose to invest in biogas plants of different sizes (150 kW, 450 kW, 800 kW). Also in this paper, the investment costs range from 850,000 to 2,650,000 euros depending on the plant size.	**3.1. Investments** (Baldi et al., 2023 ; Grovermann et al., 2017b ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Troost et al., 2022)
			Physical/Operational Decisions	**5.1. Storage Facilities** **5.2. Transportation Quantities** **5.3. Operating Schedule** **5.4. Biomass Distribution** **5.5. Equipment** **5.6. Holding Quantities** **5.7. Labour** (Off-farm labor, off-farm activities, amount of farm labor available etc.)	**5.1. Storage Facilities** (Kim et al., 2018 ; Shastri et al., 2011) **5.2. Transportation Quantities** (Kim et al., 2018 ; Shastri et al., 2011) **5.3. Operating Schedule** (Huber et al., 2022 ; Shastri et al., 2011) **5.4. Biomass Distribution** (Shastri et al., 2011) **5.5. Equipment** (Hampf et al., 2018 ; Shastri et al., 2011) **5.6. Holding Quantities** (Kim et al., 2018) **5.7. Labour** (Grovermann et al., 2017b ; Hampf et al., 2018 ; Piorr et al., 2009 ; Quang et al., 2014 ; Seidel and Britz, 2019)

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	

					Examples
Category 2 - Decision-Making Processes	**Optimization Elements in Model**		**Financial Constraints**	**1.1. Liquidity** **1.2. Withdrawals** **1.3. Capital** **1.4. Investment** **1.5. Transport Cost** **1.6. Pricing** **1.7. Market Demand/Dynamics***	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Hampf et al., 2018 ; Huber et al., 2022 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Troost et al., 2022 ; Winter et al., 2023)
			Physical/Operational Constraints	2.1. Labour 2.2. Equipment (Machinery, equipment capacity, equipment availability) 2.3. Operational & Logistical (*For feasibility region, attribute space and mass balance such as harvesting, storage, and transportation of biomass.*) 2.3.1. Transportation Quantities 2.3.2. Holding Quantities (This term can refer to both physical and production, or both categories as the case may be, but we have used it only in relation to transportation operations)	**2.1. Labour** (Grovermann et al., 2017b ; Hampf et al., 2018 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Ostermeyer and Schoenau, 2012 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019) **2.2. Equipment** (Hampf et al., 2018 ; Lobianco and Esposti, 2010 ; Shastri et al., 2011) **2.3. Operational & Logistical** (Kim et al., 2018 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Shastri et al., 2011) **(For ease of calculation also (2.3.1. Transportation Quantities** (Kim et al., 2018) **2.3.2. Holding Quantities** (Kim et al., 2018)**)**
		Constraints	**Behavioral Constraints**	3.1. Adoption 3.4. Innovativeness	(Grovermann et al., 2017b ; Nouri et al., 2019, 2022 ; Schreinemachers et al., 2010)

			Production/Stock Constraints	4.1. Production (Production Quantities, Production Capacities) 4.2. Livestock	(Kim et al., 2018 ; Lobianco and Esposti, 2010 ; Winter et al., 2023)
			Bio-physical Constraints	**5.1. Water** **5.2. Soil** **5.3. Resource** (In some articles ‘’*Land availability”* also considered into this category or like limited number of seed etc.). **5.4. Land** For example, the paper of Lobianco and Esposti (2010) shows with "***plots are explicitly modelled within the agents' problem as individual resources with spatial information organised in different layers (e.g. land typology, altimetry, environmental constraints, etc..)***" which is indicating that the land is modeled together with its bio-physical properties. (land allocation, rotation)* *("Land" in this category relates to operational and logistics management, such as the allocation and rotation of land or availability of Land.)*	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Hampf et al., 2018 ; Huber et al., 2022 ; Nouri et al., 2019, 2022 ; Piorr et al., 2009 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Troost et al., 2022 ; Winter et al., 2023) **2.4. Land** (Baldi et al., 2023 ; Berger et al., 2006 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Schreinemachers et al., 2010)

			Agricultural & Environmental Laws and Policies	6.1. Agricultural Policies 6.2. Environmental Regulations 6.3. Land use Regulations	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Huber et al., 2022 ; Nouri et al., 2022 ; Piorr et al., 2009 ; Seidel and Britz, 2019 ; Winter et al., 2023)

** For the Market/Demand, (Winter et al, 2023), it is included in the financial constraints.*

Note 3. *Constraints which limit or shape agents' decisions in the model, are factors that must be considered in the decision-making process. Constraints may include, but are not limited to, the elements listed in the table.*

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 2 - Decision-Making Processes	**Stochasticity**	**Stochasticity in the Model Structure**	**In The Decision-Making**	The agents' decision-making process is itself a stochastic process.	(Baldi et al., 2023 ; Huber et al., 2022 ; Nouri et al., 2022 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Seidel and Britz, 2019)
			Initial	Stochastic elements can also be introduced during the model's initialization phase, possibly involving the randomization of initial values or parameters.	(Berger et al., 2006 ; Grovermann et al., 2017b ; Hampf et al., 2018 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Schreinemachers et al., 2010 ; Troost et al., 2022)
			Economic	As the model runs, various factors might undergo random changes over time, reflecting uncertainties such as in economic conditions, environmental factors, or other model parameters.	(Baldi et al., 2023 ; Hampf et al., 2018 ; Kim et al., 2018 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Schreinemachers et al., 2010 ; Troost et al., 2022 ; Winter et al., 2023)
			Not Specified		(Liu et al., 2013 ; Shastri et al., 2011)

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 2 - Decision-Making Processes	**Model Calibration**	**Type of Calibration**	**Primary Data**		(Grovermann et al., 2017b ; Hampf et al., 2018 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Winter et al., 2023)
			Secondary Data		(Baldi et al., 2023 ; Berger et al., 2006 ; Huber et al., 2022 ; Kim et al., 2018 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Shastri et al., 2011 ; Troost et al., 2022)

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 2 - Decision-Making Processes	**Environmental Sensing**	**The spatial scale of sensing of agents' environment**	**Local**		(Baldi et al., 2023 ; Berger et al., 2006, p. 200 ; Grovermann et al., 2017b ; Huber et al., 2022 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Schreinemachers et al., 2010 ; Seidel and

					Britz, 2019 ; Shastri et al., 2011 ; Troost et al., 2022 ; Winter et al., 2023)
			Global		**Global** (Hampf et al., 2018 ; Kim et al., 2018)

Category 3 - Actors & Environmental Interactions

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 3 - Actors & Environmental Interactions	**Interactions**	**Presented Interactions in the Model**	**Transportation Operations**	**1. Transportation Operations** Interactions include logistics such as transportation operations of biomass from fields to storage facilities and refineries, and shared transportation logistics.	**1. Transportation Operations** (Kim et al., 2018 ; Shastri et al., 2011)
			Market & Economic Interactions	**2. Market & Economic Interactions** Includes competitive behavior in the land market, economic transactions, auctions (land rental, manure, milk delivery), and market price responses. For instance, economic transactions often involve trading in water markets and bilateral negotiations. *(Land Market, Trading, Economic transactions, Supply/Demand dynamics, farm exit etc.)*	**2. Market & Economic Interactions** (Grovermann et al., 2017b ; Hampf et al., 2018 ; Lobianco and Esposti, 2010 ; Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Seidel and Britz, 2019 ; Shastri et al., 2011 ; Troost et al., 2022 ; Winter et al., 2023)
			Information & Learning Interactions	**3. Information & Learning Interactions** Agents learn from each other through information networks. They share	**3. Information & Learning Interactions** (Berger et al., 2006 ; Huber et al., 2022 ; Nouri et al.,

				innovation informatiosn within human networks, compare adoption rates, and adjust their practices accordingly. *(Information networks, Learning etc.)*	2019 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Winter et al., 2023)
			Policy Influences	**4. Policy Influences** Agents respond to agricultural policy changes, influencing their competitive behavior and spatial considerations in farming operations. They also participate in eco-schemes and respond to policy interventions.	**4. Policy Influences** (Baldi et al., 2023 ; Grovermann et al., 2017b ; Liu et al., 2013 ; Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Winter et al., 2023)
			Negotiation & Agreements	**5. Negotiation & Agreements** Agents engage in bilateral negotiations, form contracts/agreements, and their behaviors adjust based on performance and interactions. *(Negotiation, Contracts, Agreements)*	**5. Negotiation & Agreements** (Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Shastri et al., 2011)

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 3 - Actors & Environmental Interactions Category 3 - Actors & Environmental Interactions	**Interactions**	**Competitive / Cooperative Approach Among Agents**	**Competitive**	Includes competitive behavior in the land market, economic transactions, auctions (land rental, manure, milk delivery), and market price responses. For instance, economic transactions often involve trading in water markets and bilateral negotiations.	(Hampf et al., 2018 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Winter et al., 2023)

				Land Market, Trading, Economic transactions, Supply/Demand dynamics, farm exit	
			Cooperative		(Baldi et al., 2023 ; Grovermann et al., 2017b ; Huber et al., 2022 ; Kim et al., 2018 ; Shastri et al., 2011)
			Not Applicables		(Berger et al., 2006 ; Liu et al., 2013 ; Troost et al., 2022)

Main Category	**Sub-Category**	**Headings of the Questions**	**Potential Answers**	**Explanation**	**Examples**
Category 3 - Actors & Environmental Interactions	**Interactions**	**The effects of competitive / cooperative behaviour**	**Resource Allocation**	Competitive or cooperative behaviour can influence how resources (e.g. *water, land, capital*) are distributed among agents.	(Baldi et al., 2023 ; Hampf et al., 2018 ; Nouri et al., 2019, 2022 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Schreinemachers et al., 2010)
			Changes In Agricultural Activities	Interactions between agents can lead to changes in agricultural activities such as cropping patterns, farming practices or the use of technology.	(Grovermann et al., 2017b ; Huber et al., 2022 ; Nouri et al., 2019 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009)
			Market Equilibria	Competitive or cooperative behaviour can shape market equilibria**.**	(Baldi et al., 2023 ; Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Winter et al., 2023)
			Land Allocation	Competitive or cooperative interactions between agents can influence how land is used and distributed.	(Baldi et al., 2023 ; Lobianco and Esposti, 2010 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023)
			Others	**Farm Exit** **Rental Prices** **Policy Effectiveness**	**Farm Exit** (Seidel and Britz, 2019) **Rental Prices** (Ostermeyer and Schoenau, 2012) **Policy Effectiveness** (Nouri et al., 2022)

			Not Applicable		(Berger et al., 2006 ; Liu et al., 2013 ; Troost et al., 2022)
			Supply Chain Efficiency	Competitive or cooperative behaviour can affect the efficiency of agricultural products from production to consumption.	(Kim et al., 2018 ; Shastri et al., 2011)

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 3 - Actors & Environmental Interactions	**Learning Processes**	**Effects of Learning/Adoption on Decision-Making Process**	**By Agricultural Strategies/Practices**	Learning and adaptation can both lead to changes in agents' agricultural strategies. These can include factors such as adopting new cropping methods, optimizing crop rotations, or implementing better pest control practices etc.	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Huber et al., 2022 ; Nouri et al., 2019, 2022 ; Schreinemachers et al., 2010 ; Winter et al., 2023)
			By Resource Management	The learning process can enable agents to enhance their resource management skills, just like making better decisions in areas such as improving soil health, increasing water use efficiency, and protecting biodiversity.	(Berger et al., 2006 ; Nouri et al., 2019, 2022 ; Quang et al., 2014)
			By Response To Policies	As agents obtain new knowledge, for instance, about agricultural policies, subsidies or regulations, they may modify their decisions to accommodate these policies.	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Winter et al., 2023)
			By Response Market Signals	Learning about market trends and signals can influence agents' decision; such as, about product choices, or marketing strategies.	(Berger et al., 2006 ; Grovermann et al., 2017b ; Nouri et al., 2022 ; Winter et al., 2023)

			By Investment	New information can influence agents' decisions on farm technologies or investments.	(Berger et al., 2006 ; Grovermann et al., 2017b)
			By More Information Seeking Behavior	The learning process can encourage agents to seek more information.	(Huber et al., 2022)
			Not Specified		(Hampf et al., 2018 ; Kim et al., 2018 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Seidel and Britz, 2019 ; Shastri et al., 2011 ; Troost et al., 2022)

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 3 - Actors & Environmental Interactions Category 3 - Actors & Environmental Interactions	**Supply/Value Chain Representation in the Model**	**Supply/Value Chain Interactions Included in the Model**	**Not Applicable**		(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Hampf et al., 2018 ; Huber et al., 2022 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Troost et al., 2022)

			Farmer		(Shastri et al., 2011 ; Winter et al., 2023)
			Storage Facilities		(Kim et al., 2018 ; Shastri et al., 2011)
			Others	**Biorefinery** **Transport Logistics** **Breeder** **Seed Producer** These two are not main decision-makers or decision makers **Biomass Farms** **Biorefineries**	**Biorefinery** (Shastri et al., 2011) **Transport Logistics** (Shastri et al., 2011) **Breeder** (Winter et al., 2023) **Seed Producer**(Winter et al., 2023) **Biomass Farms** (Kim et al., 2018) **Biorefineries** (Kim et al., 2018)

Category 4 - Model Evaluation in Terms of ABM and MP Features

Main Category	Sub-Category	Headings of the Questions	Potential Answers	Explanation	Examples
Category 4 - Model Evaluation	**Strengths and Weaknesses the ABM in the model**	**Strengths of ABM in the Model**	**Policy Representation**	This statement indicates that ABMs are powerful in representing policy changes and their effects. This title indicates that the model allows different policy scenarios to be	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Lobianco and Esposti, 2010 ; Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr

				simulated and their potential effects to be assessed. *(Representation of policy changes, Representation of policy impacts etc..)*	et al., 2009 ; Shastri et al., 2011 ; Winter et al., 2023)
			Spatial Representation of Systems	This statement indicates that ABMs have the ability to simulate large regions and spatial relationships. This suggests that the model is advantageous in representing geographic differences and spatial interactions. *(Simulate large regions, spatial rep. etc.)*	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Hampf et al., 2018 ; Huber et al., 2022 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Shastri et al., 2011)
			Include Dynamic-Stochastic Element		(Hampf et al., 2018 ; Lobianco and Esposti, 2010 ; Nouri et al., 2022 ; Piorr et al., 2009 ; Seidel and Britz, 2019)
			Modeling Farmer Interactions		(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Huber et al., 2022 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Piorr et al., 2009 ; Quang et al., 2014 ; Schreinemachers et al., 2010 ; Winter et al., 2023)
			Market Interactions	This statement implies that ABMs can simulate market negotiations and complex market interactions. *(Simulation of market negotiations, Representation of complex market interactions, Using zero-intelligence agents to simplify the representation of market behavior etc.)*	(Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023)

			Environmental / Sustainability Representation	This statement implies that ABMs can offer sustainable perspectives for the environment, represent adaptation to climate change, and capture relationships between socio-economic factors and the biophysical environment. *(Sustainable perspective for water resources management, Representation of climate change adaptation, Capturing the relationship between socioeconomics and the biophysical environment etc.)*	(Liu et al., 2013 ; Nouri et al., 2019, 2022 ; Quang et al., 2014)
			Others	*(Market Interactions, Heterogeneity Of Economic, Representation Of Agricultural Structural Change, Capacity To Represent The Effects Of Information Asymmetries, Representation Of Value Chain Behavio*r)	**Market Interactions** (Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023a) **Heterogeneity Of Economic** (Grovermann et al., 2017b ; Nouri et al., 2022 ; Quang et al., 2014) **Representation Of Agricultural Structural Change** (Berger et al., 2006 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009) **Capacity To Represent The Effects Of Information Asymmetries** (Grovermann et al., 2017b ; Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023a) **Representation Of Value Chain Behavior** (Winter et al., 2023)

			Integration of Multidisciplinary Approaches (Theoretical & Methodological Integration of Model)	This statement indicates that ABMs can combine models from different study disciplines and integrate different theoretical concepts. *(Combining geophysical and social models, Help to the simulate system rules in the form of mathematical relationships, Integrate theoretical concepts etc.)*	(Baldi et al., 2023 ; Grovermann et al., 2017b ; Huber et al., 2022 ; Kim et al., 2018 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Piorr et al., 2009 ; Shastri et al., 2011)
		Weaknesses of ABM in the Model	**Failing to capture some real-world behaviors/interactions**	This statement implies that ABMs struggle to capture some real-world behaviours and interactions. *(Failing to capture some complexity of the human decision-making process, Failing to capture some social interactions among farmers, Inability to encompass the many complexities of real-world behavior, Low and rough resolution of land use classification? etc.)*	(Baldi et al., 2023 ; Grovermann et al., 2017b ; Huber et al., 2022 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Schreinemachers et al., 2010 ; Troost et al., 2022)
			Limitations Due to Assumptions and Ignored Values	This heading recognises that ABMs are based on certain assumptions and may ignore certain values. *(Disregard certain values, Assumption-based values etc.)*	(Winter et al., 2023)
			Failing To Capture System Complexity	This statement indicates that ABMs may have difficulty capturing all aspects of system complexity. *(Failing to capture some of the farm activities; Failure to capture the whole industry; Failing to capture marginal changes; Failing to capture climate change impacts etc.)*	(Nouri et al., 2022 ; Shastri et al., 2011 ; Winter et al., 2023)

			High Computational Costs		(Berger et al., 2006 ; Kim et al., 2018 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019 ; Seidel and Britz, 2019 ; Shastri et al., 2011)
			Data Dependency		(Berger et al., 2006 ; Hampf et al., 2018 ; Huber et al., 2022 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019 ; Quang et al., 2014 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Seidel and Britz, 2019 ; Winter et al., 2023)
			Failing to capture some effects of agricultural adoption and innovations	This title indicates that ABMs may fail to capture some aspects of the adoption and impacts of agricultural innovations. *(Not including learning or adoption mechanisms etc.)*	(Grovermann et al., 2017b ; Liu et al., 2013 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023)
			Failing to capture policy changes/policy impacts	This statement indicates that ABMs may have limitations in their ability to account for or predict policy changes.	(Nouri et al., 2019)
		Strengths of MP in the Model	**Enhancing Policy Analysis**	This statement implies that MP models improve policy analysis capabilities. *(Enhancing policy impact analysis, Useful for agricultural policy evaluations etc.)*	(Baldi et al., 2023 ; Berger et al., 2006 ; Grovermann et al., 2017b ; Huber et al., 2022 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Shastri et al., 2011 ; Winter et al., 2023)
			Enhancing Economic Analysis	This title states that MP models increase the capacity for economic analysis. (Simulate the economic changes in resource availability, Strong microeconomic foundations,	(Grovermann et al., 2017b ; Hampf et al., 2018 ; Nouri et al., 2022 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco,

				Simulate the changes in farmers' revenue etc.)	2023 ; Troost et al., 2022 ; Winter et al., 2023)
			Simulate Optimising	It states that MP models have the ability to simulate optimisation behaviour. *(Simulating optimizing behavior, Iterative approaches to optimization etc.)*	(Baldi et al., 2023 ; Grovermann et al., 2017b, 2017b ; Hampf et al., 2018 ; Kim et al., 2018 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019, 2022 ; Ostermeyer and Schoenau, 2012 ; Piorr et al., 2009 ; Schreinemachers et al., 2010 ; Seidel and Britz, 2019 ; Shastri et al., 2011 ; Troost et al., 2022 ; Winter et al., 2023)
			Simplification		(Grovermann et al., 2017b ; Huber et al., 2022 ; Quang et al., 2014 ; Schreinemachers and Berger, 2011 ; Shastri et al., 2011 ; Winter et al., 2023)
			Flexibility & Extendibility	This title states that MP models have flexibility and extensibility features. *(Econometrically estimated functions for agent decisions etc.)*	(Liu et al., 2013 ; Shastri et al., 2011)

			Analytical Capabilities	This statement indicates that MP models have broad analytical capabilities. *(Enables analysis of the competitiveness of farm activities, Enables analysis of the cooperativeness of farm activities, Analyzes adaptation measures, Detailed spatial analysis etc.)*	**Detailed Spatial Analysis** (Lobianco and Esposti, 2010) **Analysing Adoption Measures** (Berger et al., 2006 ; Liu et al., 2013) **Enables Analysis Of The Competitiveness Of Farm Activities** (Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012) **Enables Analysis Of The Cooperativeness Of Farm Activities** (Nouri et al., 2022)
		Weaknesses of MP in the Model	**Assumption-Based Values**	This heading states that MP models are based on certain assumptions and simplifications. *(Profit maximization assumption, Assumption-based values etc.)*	**Assumption-Based Values** (Baldi et al., 2023 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019 ; Piorr et al., 2009 ; Schreinemachers et al., 2010 ; Winter et al., 2023)
			Data & Computational Challenges	It states that MP models have challenges in terms of data and computational intensity. *(Data and computational intensity, Require extensive data for calibration etc.)*	**Data & Computational Challenges** (Hampf et al., 2018 ; Kim et al., 2018 ; Sapino, Haer, Saiz-Santiago and Perez-Blanco, 2023 ; Shastri et al., 2011) **Data Dependency** (Quang et al., 2014)
			Temporal Limitations	This title states that MP models may have difficulty in capturing rapid changes in agents' behaviour over time. *(Not be able to capture rapid changes in agents' behavior throughout the time steps etc.)*	(Sapino, Haer, Saiz-Santiago and Pérez-Blanco, 2023a)

			Over Simplifications		**Over Simplifications** (Huber et al., 2022)
			Modeling Complexity		(Berger et al., 2006 ; Liu et al., 2013 ; Lobianco and Esposti, 2010 ; Nouri et al., 2019 ; Schreinemachers and Berger, 2011 ; Seidel and Britz, 2019)
			Not Specified		(Grovermann et al., 2017a ; Nouri et al., 2022 ; Ostermeyer and Schoenau, 2012 ; Troost et al., 2022)

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