# Building bridges between ecological and economic agent-based models of agriculture

**Daniel Vedder*[1,2,3†], Judith Rakowski*[1,3,4], Lea Kolb[1,2,3], Greta Theilen[5], Sebastian Lakner[5], Guy Pe'er[1,3]**

[1] Department of Biodiversity and People, Helmholtz Centre for Environmental Research – UFZ, Leipzig

[2] Institute of Biodiversity, Ecology, and Evolution, Friedrich-Schiller-Universität Jena

[3] German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig

[4] Department of Geographical Sciences, University of Maryland

[5] Faculty for Agricultural and Environmental Sciences, University of Rostock

* These authors should be considered joint first authors

[†] To whom correspondence should be addressed: daniel.vedder@idiv.de

## Abstract

Agriculture is a complex social-ecological system with numerous interactions and feedbacks between policies, markets, farm management, landscapes, and ecosystems. Because of these interconnections, policy changes, societal trends, and environmental crises can have widespread knock-on effects that threaten the stability of the entire system.

Agent-based models have become a valuable tool used for studying agricultural systems and providing policy advice. However, they often only consider one or few aspects of the complete social-ecological system. Here, we review 50 agent-based models and analyse which aspects of agricultural systems they include.

We find that there has been significant work done in the last decade, both in monodisciplinary and interdisciplinary models. There is a particularly robust tradition of using agent-based models for economic impact analyses of policy changes. Many models also study environmental impacts of agriculture. However, ecological and biodiversity-oriented models continue to be largely disconnected from the rest of the agricultural modelling literature.

Based on our review, we provide recommendations for future research in ecological, socio-economic, and social-ecological modelling of agriculture. Areas of possible improvement include simulating farm management and landscape dynamics in ecological models, risk management in economic models, and bidirectional human-nature interactions in social-ecological models. Building on these recommendations, we develop a concept for an integrated model that could be used to study the impacts of agricultural policy on both farms and biodiversity.

# 1. Introduction

Agriculture today faces a multitude of economic, social, and environmental challenges that urgently need to be addressed (Ambikapathi et al., 2022; Foley et al., 2011). In Europe, but also elsewhere, socio-economic challenges include volatile markets, high regulatory burden, difficult working conditions, and rural depopulation (Debonne et al., 2022). These have contributed to a shrinking number of farms, an ageing rural population, and high farmer dissatisfaction (Mohr et al., 2023; Nowack et al., 2023). On the environmental side, modern agricultural practices have led to widespread pollution from agrochemicals, soil erosion and degradation, high greenhouse has emissions, and ecosystem service losses (Campbell et al., 2017; Godfray & Garnett, 2014). They are also a leading contributor to biodiversity loss, with species in agricultural landscapes experiencing drastic declines across taxa (Rigal et al., 2023; Warren et al., 2021).

One of the worldwide largest efforts to alleviate these problems is the European Union's Common Agricultural Policy (CAP), a complex system of regulations and annual subsidies worth 55 billion Euros (European Commission, 2023). Yet, even this has repeatedly failed to bring significant improvements (Biagini et al., 2023; Pe'er et al., 2014, 2020). On the contrary, it has been criticised for primarily subsidising large-scale industrial agriculture, increasing the regulatory burden on farmers, and failing to set adequate environmental standards or incentives (Pe'er et al., 2017; Scown et al., 2020). Still, its continent-wide scope, massive financial endowment, and global market impacts make it a key policy to effect environmental, social, and economic improvements in agriculture (Pe'er & Lakner, 2020).

The numerous interactions between these different aspects of agriculture means that challenges must be addressed in a concerted manner, using a social-ecological systems approach that considers both human and natural domains (Fischer et al., 2015; Norton, 2016). Otherwise, solution attempts may overlook the positive and negative interactions between the two, thus ignoring possible synergies and trade-offs (Allen et al., 2014; Rasmussen et al., 2024) as well as feedback loops and tipping points (Brown & Rounsevell, 2021; Pörtner et al., 2022).

This close coupling of human and natural systems is also relevant for research. Traditionally, scientific study of agriculture has been segregated along disciplinary lines, looking separately at its agronomic, social, economic, political, environmental, and ecological dimensions. However, there is now a widespread agreement that the numerous interactions and feedbacks between these dimensions necessitate joint interdisciplinary study in the form of an SES approach (e.g. Ostrom, 2009; Reyers et al., 2018).

Agent-based models (ABMs[1]) are one important tool for studying social-ecological systems. They are well-established in multiple disciplines related to SES, including economics, political science, and ecology (Vincenot, 2018), as well as being used for integrated interdisciplinary analyses (M. A. Janssen & Ostrom, 2006; Schulze et al., 2017). Their approach is to represent a system as a collection of unique agents (such as farmers or animals), whose local, process-based interactions give rise to system-level patterns (Grimm & Railsback, 2005). This makes them well-suited to simulating the heterogeneity and dynamic processes in

[1]*Note that in the ecological literature, ABMs are usually referred to as individual-based models, or IBMs.*

social and ecological systems, and analysing both spatial and temporal phenomena (DeAngelis & Mooij, 2005; Heckbert et al., 2010).

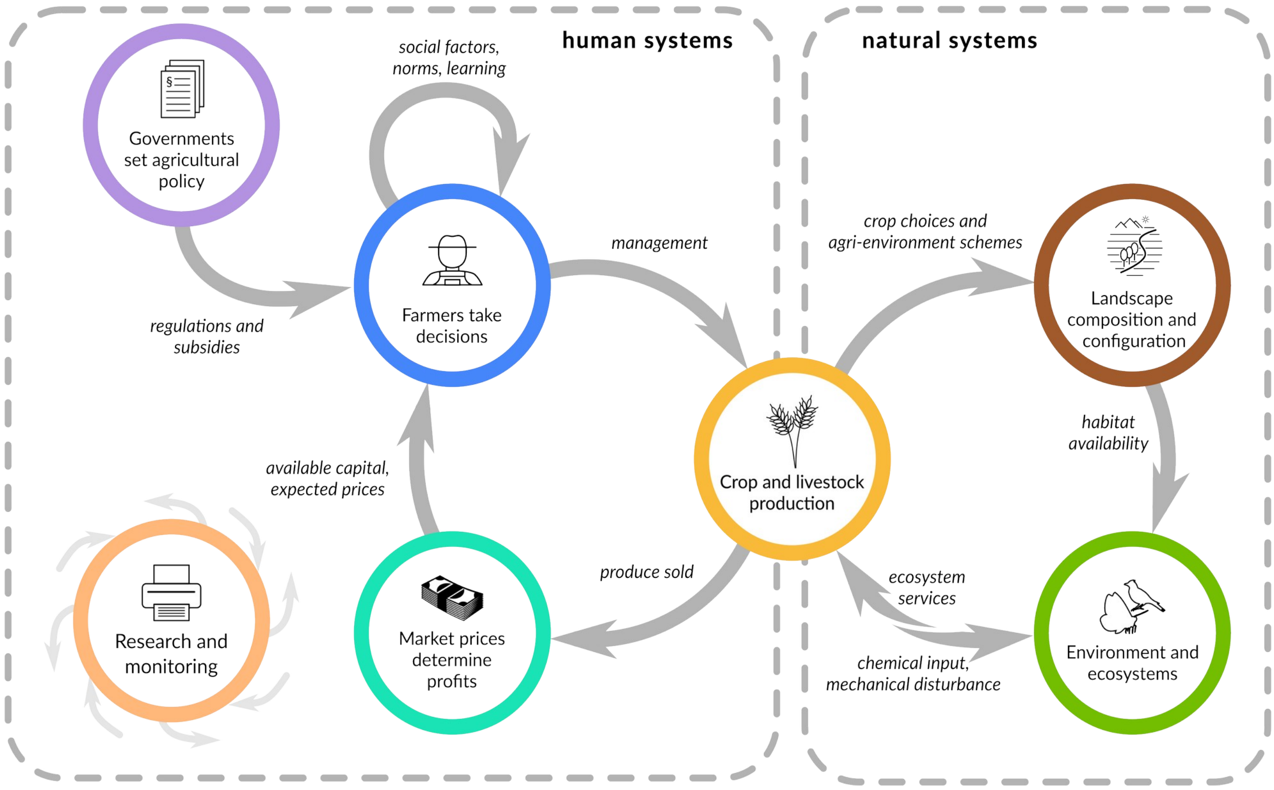


*Figure 1: Agricultural systems contain multiple subsystems (circles), that have traditionally been perceived as categories of study for dedicated disciplines. Within a social-ecological systems approach, the interrelationships (arrows) between the subsystems, and between the human and natural domains, are brought into focus. This allows a more comprehensive study of how changes to one part of the system may affect other subsystems, including the behaviour of feedback loops and tipping points.*

This suitability for SES research potentially also makes agent-based models good tools to support decision-makers in policy and management in agricultural contexts. Indeed, ABMs are frequently used for research on agricultural policy (Kremmydas et al., 2018), including for policy impact assessments in the European Union (Reidsma et al., 2018). Still, their potential for policy support is not yet achieved, with impediments including issues such as lack of data availability or infrequent contact between modellers and decision-makers (Will et al., 2021).

In this review, we want to take stock of the current state of agent-based modelling in agriculture. We want to know how existing models conceptualise and represent agricultural SES, and how the integration of different disciplines into agricultural ABMs can be improved in order to better address the multi-faceted challenges related sustainable farming systems. To this end, we analyse how different categories of study are included in a selection of 50 socio-environmental models found in the literature. We are particularly interested in models that contain a broad range of categories, which can be used to study social-ecological interactions. By this we do not imply that all models should be broad in this sense, but believe that the development of some such models is necessary for a model-based investigation of SES (Cabral et al., 2023). Based on these results, we then offer suggestions for how ecological and socio-economic ABMs of agriculture can be brought together into a joint SES modelling framework. Throughout, we keep in mind the question of how agricultural ABMs can be used to support decision-makers and provide policy-relevant research.

For the purposes of this paper, we conceptualise agricultural SES as containing a human and a natural domain, each in turn containing multiple subsystems, or categories of study (Figure 1). In the human domain, we look at agricultural policy, farmer decision-making, and market dynamics. In the natural domain, we include land use and land use change (i.e. landscape dynamics), and environments and ecosystems. The two domains are linked by agricultural practice, i.e. the production of crops and livestock, which is the point at which human and natural processes most directly interact. Finally, research and monitoring efforts produce information about the different parts of the system, which can help inform the actions of decision-makers. While this is a very simplified conceptualisation that glosses over many of the complexities of agricultural SES, it does capture the conceptual structure of most of the models that we review.

Previous reviews in this area have focussed on the use of economic and environmental modelling for agricultural policy assessment (Beaussier et al., 2019; Kremmydas et al., 2018; Reidsma et al., 2018), or the development of social-ecological models more generally (Filatova et al., 2013; Lippe et al., 2019). Our work complements these by bringing together the perspectives of agricultural SES research, agent-based modelling, and policy assessment, and provides an insight into the more recent work in this field. In addition, we develop a proposal for a new modelling framework to integrate these different strands of research. Thus, the overall aim of our review is to help build bridges between the multiple communities of agricultural agent-based modellers.

# 2. Methods

## 2.1. Literature search

We conducted a two-stage literature search for ABMs of agricultural social-ecological systems. To get an initial overview of the field, we interviewed two modelling experts about their experiences with agricultural social-ecological modelling, and searched the Web of Science Core Collection using different combinations of relevant key words. In the main search, we then queried the Web of Science Core Collection in January 2024 with the following search string:

> (agent-based OR individual-based) model AND (agric* OR farm*)
> AND (policy OR market OR econom* OR "farm management" OR "agricultural practice" OR "decision making")
> AND (landscape OR "land use" OR biodiversity OR ecosystem OR environment*)
> NOT (hydrology OR groundwater OR archaeology OR disease OR veterinary OR fish* OR forestry OR review)

We scanned the title and abstract of all publication returned by both searches to find models that were relevant to our purpose, for which we defined three core criteria:

1. The model must be at least partially an ABM/IBM.

2. It must have a direct link to agriculture.

3. It must include both human and natural processes, factors, or outcomes.

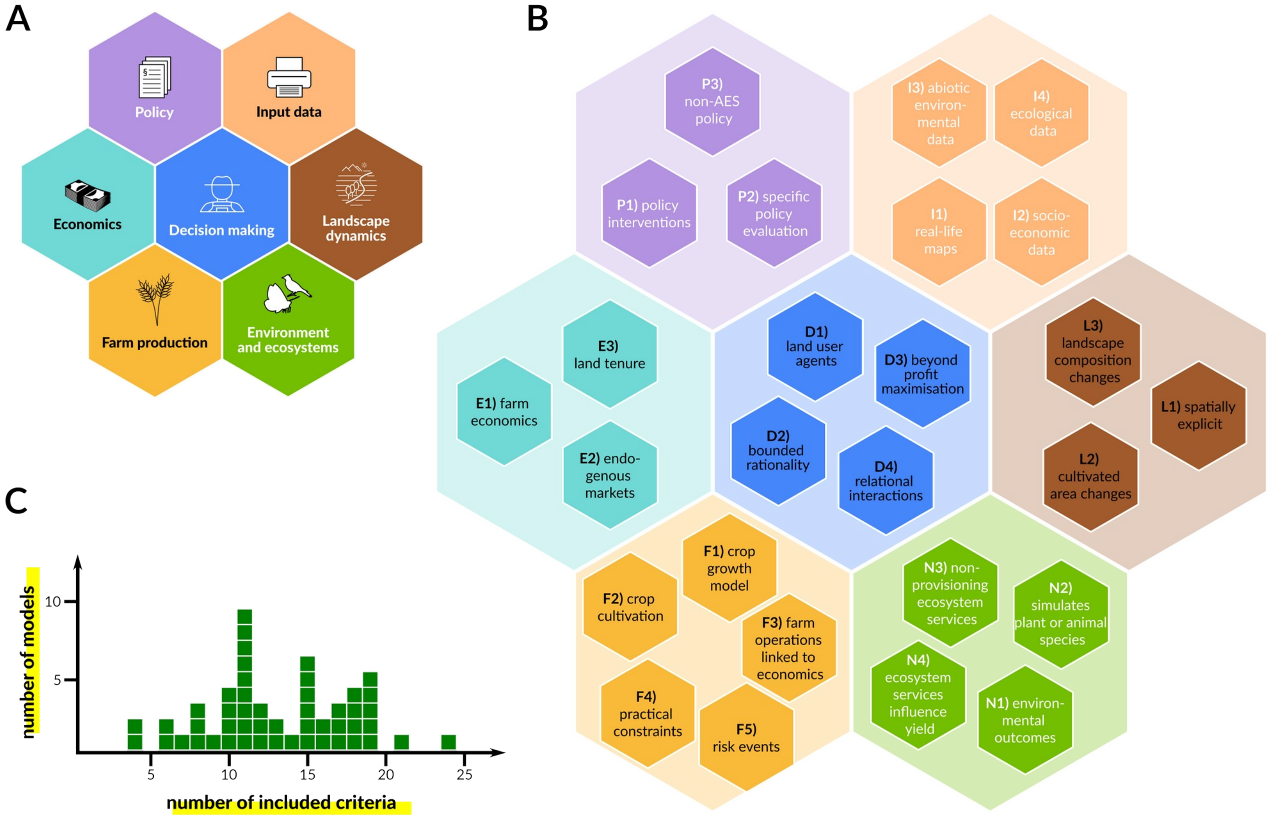


*Figure 2: A) Categories by which we assessed the comprehensiveness of models. B) Criteria that were checked within each category (colours correspond to the categories in A). C) Distribution of model comprehensiveness scores, showing how many models included how many criteria.*

We further tightened the scope by focussing on models that explicitly considered agroecosystems, i.e. terrestrial environments dominated by agricultural land use (thereby excluding studies that solely focus on forests or water resources). We tagged relevant papers by regional (e.g. Europe, Asia) and environmental focus (e.g. biodiversity, nutrients, pesticides), and identified which model was used in each publication. Finally, we used a stratified sampling approach to select models for detailed analysis, considering the distribution of regional and environmental foci and preferentially selecting models with multiple publications. If a model had been used for more than one study, we additionally tried to track down its first publication as well as any recent expansions, in order to consider the full capabilities of a given model in our analysis.

## 2.2. Model analysis

Based on the conceptual diagram of agricultural SES in Figure 1, we identified seven categories in which we compared models against each other. These include: Input Data, Policy Assessment, Economic Considerations, Agricultural Decision-Making, Farm Production, Landscape Composition and Dynamics, and Environments and Ecosystems.

We then evaluated how models implement these categories using a total of 26 yes-or-no criteria (Figure 2). The criteria were developed in an iterative process, in which the lead authors selected an initial set of criteria based on the conceptual diagram and the exploratory literature search, and then refined these in discussion with the whole author team. The aim was to develop a set of criteria that are evenly balanced among research disciplines, and can show relevant similarities and differences in the way existing model represent agricultural SES. We also wanted to look beyond established modelling approaches and include aspects that have been discussed in the wider SES literature, but are not yet commonly studied using ABMs. Overall, our review process is similar to that used by (Urban et al., 2022) for biodiversity models.

The definitions for the final set of criteria are listed in Table 1. Note that while most criteria are independent of each other, the first criteria in some categories (specifically P1, E1, D1, L1, and N1) are used as “umbrella” criteria. These are meant to show whether a model considers this category at all, with the subsequent criteria in the category addressing specific modelling approaches. For each model, we checked which criteria it fulfils based on its description in the associated papers, and counted how often each criterion appears in the reviewed models.

We specifically wanted to address the following questions:

1. Which criteria do different models cover?
2. Which criteria are frequently addressed, or overlooked?
3. Which criteria are well-connected, and where are there silos?
4. Which criteria can pose barrier for ensuring policy-relevance?

*Table 1: Models found by the literature search were evaluated across seven categories of study, to reflect all major components of agricultural SES. We used 26 yes-or-no criteria to characterise how the models implemented each category.*

| Category | Criterion | | Additional explanation |
|---|---|---|---|
| **Input data** | **I1** | The model uses real-life maps (e.g. remote sensing land cover maps, administrative field maps). | The model map is based on a real geographical area, rather than using an abstract, generated landscape. |
| | **I2** | The model uses empirical economic data (e.g. market prices, farm data). | e.g. from the EU's Farm Accountancy Data Network (FADN) |
| | **I3** | The model uses empirical data to parameterize abiotic environmental variables (e.g. weather, soil, nutrient flows). | |
| | **I4** | The model uses empirical data to parameterize ecological variables (e.g. species population sizes, green infrastructure, ecosystem service delivery). | |
| **Policy** | **P1** | The model assesses policy interventions, including hypothetical options. | Umbrella criterion (P2 and P3 necessarily include P1). |
| | **P2** | The model assesses real policy interventions, which have been or are planned to be implemented. | This includes *ex ante* or *ex post* assessments of policies such as new regulations of the CAP, or the Chinese "Grain-to-Green" programme. |
| | **P3** | The model assesses policy instruments *other than* area-based payments for environmental measures (like the CAP's AECM or ecoschemes). This includes any other payments, directives, or market instruments of relevance to agriculture (e.g. direct payments, rural development funds, anti-pollution regulations, trading agreements, labelling and certification, insurances). | |
| **Economics** | **E1** | The model considers farm economics (e.g. input and product prices, | Umbrella criterion (E2 and E3 usually include E1). |

| Category | Criterion | | Additional explanation |
|---|---|---|---|
| | | operating costs). | |
| | **E2** | The model uses endogenous input and/or output markets (i.e. uses demand and supply to calculate prices). | |
| | **E3** | The model considers land tenure (e.g. via land markets). | |
| **Decision-making** | **D1** | The model has land users as decision-making agents. | Umbrella criterion (D2, D3, and D4 usually include D1). |
| | **D2** | The model uses bounded rationality theory (i.e. farmers cannot perform absolute optimisations). | This may include satisficing, heuristic decision-making, or optimisation with a limited perception (Schlüter et al., 2017). |
| | **D3** | The model includes goals other than profit maximisation (e.g. environmental stewardship, farming as tradition, risk aversion). | |
| | **D4** | The model considers relational interactions among farmers (e.g. imitation, cooperation, social norms). | |
| **Farm production** | **F1** | The model includes a crop-growth model. | Crop growth and/or yield is calculated based on environmental and management parameters. |
| | **F2** | The model simulates crop cultivation (e.g. tillage, chemical input). | |
| | **F3** | Crop growth and/or farming operations are linked to farm costs and profits. | |
| | **F4** | The model considers practical constraints of farm operations (e.g. availability of labour force, driving distance). | |
| | **F5** | The model includes environmental and/or economic risk events. | |
| **Landscape** | **L1** | The model is spatially explicit. | Umbrella criterion (L2 and L3 usually include L1). |

| Category | Criterion | Additional explanation |
|---|---|---|
| **dynamics** | **L2** The amount of land under active cultivation changes over time (e.g. land clearing, land abandonment, crop rotation with fallows). | |
| | **L3** The landscape composition and/or configuration changes over time due to internal model processes (e.g. crop rotation, agri-environment schemes). | |
| **Environment and ecosystems** | **N1** The model includes abiotic and/or biotic environmental outcomes. | Umbrella criterion (N2, N3, and N4 usually include N1). |
| | **N2** The model simulates individuals and/or populations of non-domestic animals and/or plants. | This can include IBMs, (meta-)population models, or analytic/statistical biodiversity models based on landscape structure. |
| | **N3** The model considers non-provisioning ecosystem service delivery as an output (i.e. regulating, supporting, or cultural services). | e.g. pollination, pest control, prevention of soil erosion, water retention and filtration, landscape aesthetics |
| | **N4** The model considers feedback from regulating and supporting ecosystem services to production. | e.g. through coupling crop yield to pollinator abundance |

# 3. Results

Our main literature search yielded 432 papers, of which we classified 143 as relevant and selected 87 for further analysis, which amounted to 37 models. To this we added 13 models that we previously found in the preliminary search, bringing the total number of analysed models to 50 (Table 2). We verified that the addition of models from the preliminary search did not alter the results (see Supplementary Material). The reviewed models and which criteria they include are depicted in Figure 3, while Figure 4 shows how many models included each criterion.

In the following, we will give a general overview of the comprehensiveness of existing models of agricultural SES, before briefly summarising the current status of modelling in each category, and finally presenting the results of the multiple correspondence analysis.

## 3.1. Model comprehensiveness

Based on the number of included criteria, it is possible to divide the reviewed models into four groups, with an approximately bimodal distribution (Figure 2c, cf. Figure 3).

Only two models included more than 20 out of the total of 26 criteria. These are MPMAS (Schreinemachers & Berger, 2011) and ALMaSS (Topping et al., 2003), covering 24 and 21 criteria, respectively. To give readers a more concrete, qualitative insight into the state-of-the-art in agricultural agent-based modelling, we present these two comprehensive models in more detail (Box 1 & 2).

The second group (15-19 included criteria) contains 20 models. Most of these include criteria from all categories, and they often have a strong empirical basis (as shown by the number of criteria they include from the Input Data category).

The third group (9-14 included criteria) also has 20 models. Many of these leave out one or more categories entirely, and are often quite conceptual, usually using little or no empirical input data.

Finally, there are eight models that include eight or fewer criteria. These have a strong ecological focus, but consider few other categories, and are mostly conceptual in nature.

## 3.2. Input Data

Six models included empirical data for all four criteria: ALMaSS, AgriPoliS, SEEMS, WICM, and the models by Roeder et al. and Granco et al.. Nine models were purely conceptual and used no empirical data.

Socio-economic model components most frequently used empirical data (D2), namely in the case of two thirds of models (35 of 50). By contrast, empirical ecological data (D4) were least frequently used for model input, by around one third of models (17 of 50).

## 3.3. Policy

Two-thirds of models included some form of policy interventions (37 of 50; P1). Twenty-two models evaluated policies that actually exist or are planned to be implemented (such as policies within the framework of the CAP, rather than hypothetical policy interventions; P2). Twenty-one models included policy interventions other than agri-environment schemes (AES; P3)[2]. This included, for example, farm advisory services and forest protection (Brinkmann et al., 2021), insurance against climate risks (Choquette-Levy et al., 2021), or the abolition of CAP direct payments (Van Berkel & Verburg, 2012).

### 3.4. Economics

The majority of models (36 of 50) included farm economics (E1) using, for example, income or profit functions. The composition and complexity of the underlying economics differed depending on the models' purpose. Only few models (8 of 50) developed endogenous input and/or output markets (E2) using supply and demand to calculate prices in recurring periods. Just under half of the models (21 of 50) included land tenure (E3) or took into account underlying land markets.

### 3.5. Decision-making

Most models have farmers, or land users more generally, as decision-making agents (38 of 50; D1). The majority of these models have moved beyond simple profit-maximisation to represent more complex forms of decision-making. Common elements in this included bounded rationality (e.g. limited knowledge, heuristic decision-making; 25 of 50; D2), aims other than profit maximisation (e.g. risk aversion, landscape conservation, or farming-as-tradition; 28 of 50; D3), and relational interactions between farmers (e.g. peer learning; 24 of 50; D4).

### 3.6. Farm production

The most commonly included criterion in this category was the connection of farming operations to farm costs and profits (31 of 50; F3) - in almost all of these cases, models also considered input and product prices (E1) and vice versa.

Approximately half of the models also simulated specific crop cultivation practices such as tillage or chemical input (27 of 50; F2) and almost as many considered practical constraints such as variable availability of farm workers (22 of 50; F4).

A third of the models implemented a crop or plant growth model (18 of 50; F1). Most models that included a crop growth (sub-)model also linked this to crop cultivation (F2) and farm costs and profits (F3).

Less than a quarter of models evaluated the effect of economic or environmental risk on farm production (11 of 50; F5). Most of these based their risk assessment on IPCC climate change scenarios (e.g. ALUAM-AB, SEALM).

### 3.7. Landscape dynamics

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[2]*We here follow the normal usage in the ecological literature, where the term "agri-environment scheme" means "area-based payments for environmental measures". We recognise that in a policy context the term is sometimes used to refer specifically to a set of second-pillar payments in the CAP, and want to clarify that we use it in a broader sense, independent of any particular policy. For our precise definition, see criterion P3 in Table 1.*

Almost all models were spatially explicit (44 of 50; L1). In most models the landscape was dynamic, with its structure changing over time through endogenous land use processes such as agricultural expansion or land abandonment (21 of 50; L2), or crop rotations or other compositional changes (36 of 50; L3).

## 3.8. Environment and ecosystems

Most models evaluated environmental outcomes (43 of 50; N1). Approximately a third simulated population dynamics of non-agricultural plants and animals explicitly (19 of 50; N2) and/or modelled non-provisioning ecosystem services (19 of 50; N3). Only 20% of models included a feedback loop from regulating and supporting ecosystem services to farm production (13 of 50; N4).

Five models included all criteria in this category: CRAFTY (through its coupling with RangeShifter; Synes et al., 2019), TrophicLink, EEEworm, and the models by Granco et al. (2022) and Martinet & Roques (2022). The most detailed representation of biodiversity is found in ALMaSS (Box 2).

*Table 2: List of analysed models and their key references, sorted by the number of included criteria (most to least). Models that were not given a name by their authors are listed here under their first author's name. Only selected sources are given for models with many publications. The spatial scale is given qualitatively, in decreasing order of size: continent, country, region, landscape, field. In the environmental outcome column, GHG = green house gas emissions and ESS = ecosystem services. The purpose is classified according to (Edmonds et al., 2019).*

| **Model name** | **Source papers** | **Region** | **Spatial scale** | **Spatial resolution** | **Temporal resolution** | **Environmental outcome** | **Purpose** |
|---|---|---|---|---|---|---|---|
| MPMAS | (Carauta et al., 2021; Schreinemachers & Berger, 2011; Troost et al., 2012, 2015) | multiple | region | field | daily | hydrology, soil, nutrients, GHG | explanation |
| ALMaSS | (Malawska & Topping, 2016, 2018; Topping et al., 2003, 2019) | Europe | landscape | $1m^2$ | daily | biodiversity | prediction |
| AgriPoliS | (Happe et al., 2006; Hristov et al., 2020; Piorr et al., 2009) | Europe | region | field | annual | biodiversity, ESS, nutrients, hydrology | prediction |
| Aporia | (Guillem et al., 2015; Murray-Rust, Robinson, et al., 2014) | Europe | landscape | field | annual | biodiversity, ESS | explanation |
| LUDAS | (Le et al., 2008, 2010) | Asia | landscape | not specified | annual | land use | prediction |
| SEALM | (Brinkmann et al., 2021) | Africa | landscape | $100m^2$ | annual | land use | explanation |
| SEEMS | (Chen et al., 2023) | Asia | landscape | field | annual | biodiversity | prediction |
| ALUAM-AB | (Briner et al., 2012; Huber et al., 2017) | Europe | landscape | 1ha | annual | land use | prediction |
| Bazzana et al. | (Bazzana et al., 2022) | Africa | landscape | field | annual | none | theoretical exploration |

| Model name | Source papers | Region | Spatial scale | Spatial resolution | Temporal resolution | Environmental outcome | Purpose |
|---|---|---|---|---|---|---|---|
| SWISSLAND | (Möhring et al., 2010; Schmidt et al., 2017; Zimmermann et al., 2009) | Europe | country | farm | annual | nutrients | prediction |
| Roeder et al. | (Roeder et al., 2010) | Europe | landscape | not specified | not specified | biodiversity | prediction |
| AgriLOVE | (Coronese et al., 2023) | abstract | landscape | field | arbitrary | land use | theoretical exploration |
| PALM | (Bakam & Matthews, 2009; Brown et al., 2016; Matthews, 2006) | multiple | region | n/a | annual | GHG | explanation |
| WICM | (Van Schmidt et al., 2019) | N America | landscape | 1ha | annual | biodiversity | explanation |
| CRAFTY | (Brown et al., 2019, 2021; Murray-Rust, Brown, et al., 2014; Synes et al., 2019) | Europe | continent | various | annual | biodiversity, ESS | explanation |
| Schulze et al. | (Schulze et al., 2017) | Europe | region | 25ha | annual | biodiversity, ESS | explanation |
| Delmotte et al. | (Delmotte et al., 2016) | Europe | region | field | annual | none | social learning |
| REGMAS | (Lobianco & Esposti, 2010) | Europe | region | 25ha | annual | none | prediction |
| SERA | (Schouten et al., 2012, 2013) | Europe | region | not specified | annual | biodiversity | explanation |
| Granco et al. | (Granco et al., 2022) | N America | region | not specified | annual | hydrology, biodiversity | illustration |

| Model name | Source papers | Region | Spatial scale | Spatial resolution | Temporal resolution | Environmental outcome | Purpose |
|---|---|---|---|---|---|---|---|
| Pampas | (F. Bert et al., 2015; F. E. Bert et al., 2011; García et al., 2019) | S America | region | 25ha | annual | hydrology, land use | explanation |
| RF-MAS | (Kaye-Blake et al., 2009, 2014, 2019) | Australasia | region | not specified | annual | nutrients, GHG | explanation |
| ABM+LCA | (Bayram et al., 2023; Marvuglia et al., 2017, 2022) | Europe | region | field | monthly | GHG | explanation |
| EFForTS-ABM | (Dislich et al., 2018; Mahnken, 2018) | Asia | landscape | 0.25ha | annual | biodiversity, ESS | explanation |
| Martinet & Roques | (Martinet & Roques, 2022) | abstract | landscape | 1ha | annual | ESS | theoretical exploration |
| FARMIND | (Huber et al., 2022, 2023; Kreft et al., 2023) | Europe | region | n/a | annual | pesticides, nutrients, GHG | prediction |
| Bourceret et al. | (Bourceret et al., 2022) | abstract | landscape | arbitrary | annual | hydrology, nutrients | theoretical exploration |
| Tieskens et al. | (Tieskens et al., 2017) | Europe | landscape | 1ha | annual | none | social learning |
| Valbuena et al. | (Valbuena, Verburg, Bregt, et al., 2010; Valbuena, Verburg, Veldkamp, et al., 2010; Van Berkel & Verburg, 2012) | Europe | region | 1ha | annual | land use | explanation |
| ALABAMA | (Bartkowski et al., 2020) | abstract | landscape | 1ha | not specified | biodiversity, water | theoretical exploration |

| Model name | Source papers | Region | Spatial scale | Spatial resolution | Temporal resolution | Environmental outcome | Purpose |
|---|---|---|---|---|---|---|---|
| Choquette-Levy et al. | (Choquette-Levy et al., 2021) | Asia | region | n/a | semi-annual | none | explanation |
| Cong et al. | (Cong et al., 2014, 2016) | abstract | landscape | field | annual | ESS | theoretical exploration |
| SPASIMv1 | (Millington et al., 2008) | Europe | landscape | 0.1ha | quarterly | wildfire risk | explanation |
| AG-ADAPT | (Sanga et al., 2021) | Asia | region | 1080m | annual | none | explanation |
| AMBAWA | (Berre et al., 2021) | Africa | landscape | 1ha | half-daily | ESS | prediction |
| Drechsler | (Drechsler, 2017) | abstract | landscape | field | not specified | biodiversity | theoretical exploration |
| Gielda-Pinas et al. | (Giełda-Pinas, Dzieszko, et al., 2015; Giełda-Pinas, Ligmann-Zielińska, et al., 2015) | Europe | landscape | 25ha | annual | nutrients, soil, water, land use | explanation |
| IFM-CAP | (Espinosa et al., 2020; Louhichi et al., 2018) | Europe | continent | n/a | not specified | none | prediction |
| BEEHAVE | (Baden-Böhm et al., 2022; Becher et al., 2014) | Europe | landscape | not specified | daily | biodiversity | prediction |
| DYPAL | (Gaucherel et al., 2010, 2006) | Europe | landscape | 7m | annual | land use | explanation |
| Manson et al. | (Manson et al., 2016) | N America | region | 25ha | annual | land use | description |

| Model name | Source papers | Region | Spatial scale | Spatial resolution | Temporal resolution | Environmental outcome | Purpose |
|---|---|---|---|---|---|---|---|
| FEARLUS-SPOMM | (Gimona & Polhill, 2011; Polhill et al., 2013) | abstract | landscape | field | annual | biodiversity | theoretical exploration |
| GMSE | (Duthie et al., 2018) | abstract | landscape | arbitrary | arbitrary | biodiversity | theoretical exploration |
| TrophicLink | (Caron-Lormier et al., 2009, 2011; Raybould et al., 2011) | abstract | $100m^2$ | not specified | daily | biodiversity | theoretical exploration |
| EEEworm | (Johnston et al., 2015, 2018; Roeben et al., 2020) | abstract | 3m | $1cm^2$ | hourly | biodiversity | explanation |
| Bakam et al. | (Bakam et al., 2012) | Europe | country | n/a | annual | GHG | prediction |
| Evans et al. | (Evans et al., 2019) | abstract | $1km^2$ | $5m^2$ | second | biodiversity | prediction |
| GRASSMIND | (Schmid et al., 2022; Taubert et al., 2020a, 2020b) | multiple | field | $1m^2$ | daily | biodiversity | explanation |
| Rands & Whitney | (Rands, 2014; Rands & Whitney, 2010) | abstract | landscape | field | n/a | ESS | theoretical exploration |
| Meli et al. | (Meli et al., 2013, 2014) | abstract | $1m^2$ | $1cm^2$ | hourly | biodiversity | explanation |

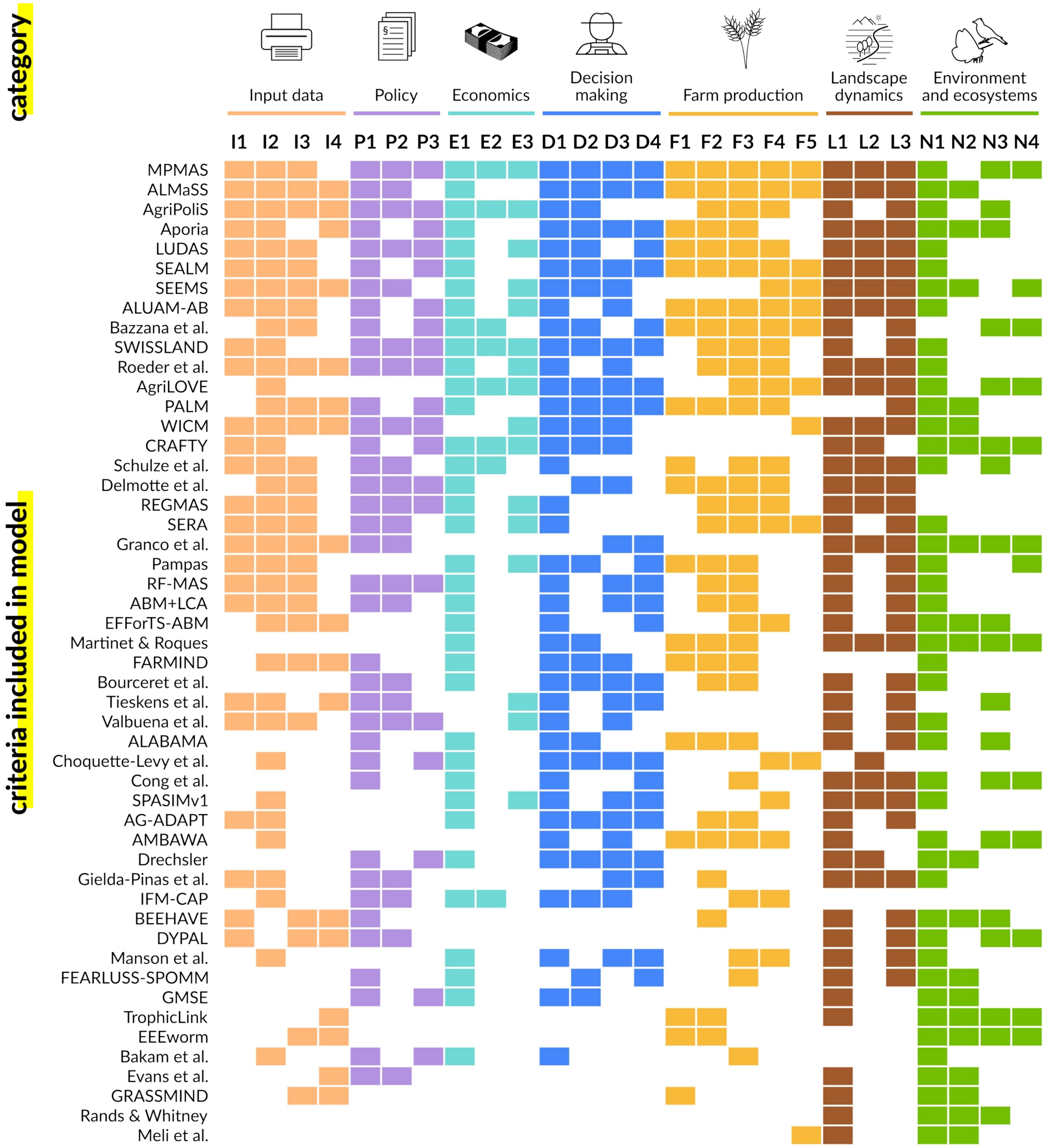


*Figure 3: Table of criteria (columns) included in each model (rows), sorted by category. A coloured tile denotes that this model includes this criterion. For criteria definitions, see Table 1.*

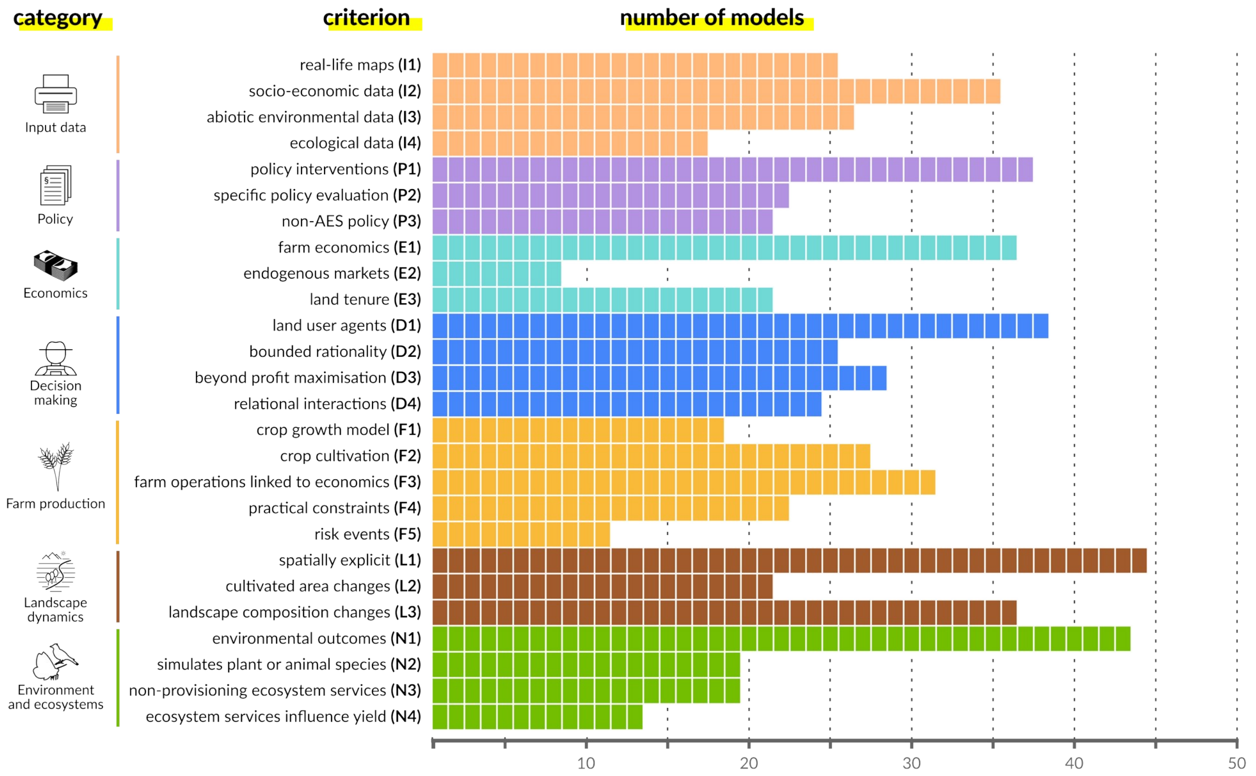


*Figure 4: Number of models including each criterion. Each coloured tile represents one model. For more detailed definitions of the criteria, see Table 1.*

### Box 1: MPMAS

MPMAS (Mathematical Programming-based Multi-Agent System) is an agricultural systems model that shares a common origin with AgriPoliS, another widely used model in our review. However, whereas AgriPoliS is explicitly an economic model (though it has been coupled to environmental modules), MPMAS was designed from the beginning to simulate the interactions between economic, social, and environmental processes (Schreinemachers & Berger, 2011).

It does so by simulating farmer households on a gridded landscape. Households are microeconomic units with individual properties (e.g. land endowment, labour supply, farm equipment, attitude to innovations) that maximise expected household income while considering additional goals. The resulting land use feeds into various biophysical submodels, which calculate crop yield, water flows, and soil quality. Different submodels are available for these tasks (both inbuilt and via model coupling), that can be selected based on the desired level of detail. The biophysical state of the landscape then feeds back into agents' decision making. Within this general framework, several socio-technical processes can be simulated, including irrigation, technology diffusion and land and water markets.

Although the main application focus of MPMAS is smallholder agriculture in developing countries, it has been applied to a broad range of case studies from across the world, including in Germany (Troost et al., 2015), Brazil (Carauta et al., 2021), Uganda, and Chile (Berger et al., 2006). Research questions include, for example, the evaluation of policies aimed at greenhouse gas reduction (Carauta et al., 2021), competition between subsidies for bioenergy and biodiversity (Troost et al., 2015), and the adaptation of farmers to climate change (Troost et al., 2012).

## Box 2: ALMaSS

ALMaSS is the most detailed biodiversity model in our review, and after MPMAS the second-most comprehensive model overall. First published by Topping et al. (2003), it contains a farm module, a landscape module, and a variety of animal modules.

The farm module simulates the production of numerous crops, considering their seasonality, crop rotations, and cultivation actions such as ploughing and harvesting. Different farm types are initialised that use different crops and follow different management plans.

The landscape module simulates a real landscape, the weather (from historical weather data), and plant growth. Plant growth is modelled for each grid cell using species-specific mathematical models dependent on the weather, season, fertiliser or pesticide application, and cutting/harvesting. The model works at a 1 $m^2$ spatial resolution and uses daily time steps.

Animal modules exist for a range of different non-domestic species from different taxa (including sky larks, roe deer, ground beetles, spiders, and voles), though only one species is simulated at a time. All modules are individual-based and use a state/transition principle, i.e. individuals exhibit certain behaviour (are in a certain state) until internal or external conditions cause them to transition to another state. Behavioural states typically include movement, territoriality, feeding, mating, and growth.

ALMaSS has been used to study species responses to pesticides (Topping & Odderskær, 2004), organic farming (Topping, 2011), and the Common Agricultural Policy (Langhammer et al., 2017; Topping et al., 2019). The farm module has been expanded to simulate more nuanced farmer decision-making (Malawska & Topping, 2016). New animal modules are also being added over time, with 17 found in the codebase as of 2023.

# 4. Discussion

## 4.1. Lessons for ecological modelling

About 60% of the models in our review considered biodiversity and/or ecosystem services in some form or another. This reflects the importance of biodiversity conservation and ecosystem health in agricultural systems research. However, we observe several issues that negatively impact the ability of these models to help us understand agroecosystems, as well as their utility for agricultural policy analyses.

First, and most importantly, many of the models are highly simplified with regards to ecology, either ignoring ecological processes or simulating very abstract systems. Several models use correlations with environmental values or indices based on landscape structure as a proxy for biodiversity or ecosystem services (e.g. Brady et al., 2012; Cong et al., 2016). Quite a few others do use process-based models such as IBMs, but are very abstract and conceptual (e.g. Caron-Lormier et al., 2011; Gimona & Polhill, 2011). Indeed, the lower part of Figure 3 shows a cluster of ecological models that are based on very little empirical data and include few other aspects of agricultural systems. This means that there are few models that can be used for applied studies of the impacts of agricultural policy and practice on the ecological processes of real landscapes and species (such as Guillem et al., 2015; Van Schmidt et al., 2019). We found this predominance of conceptual models surprising, as many IBMs in other contexts (such as forestry and fisheries) are quite detailed and tend to be highly specific to contexts and species (DeAngelis & Grimm, 2014; Stillman et al., 2015). This raises the question of why there are not more applied agroecological IBMs? Given the success of applied IBMs in other ecosystems, this strikes us as a remarkably underexplored area of ecological research.

Second, many ecological models ignore temporal landscape dynamics and crop growth/cultivation. Whereas many of the socio-economic models are spatially dynamic, only half of the reviewed ecological models simulate landscapes that change over time. This is despite extensive empirical research showing that spatio-temporal dynamics of landscapes are among the most important drivers of biodiversity change in agroecosystems (Estrada-Carmona et al., 2022; Vasseur et al., 2013). Furthermore, only a third of biodiversity models also include crop growth and/or crop cultivation. Yet this would be important for three reasons. First, because the above-mentioned landscape dynamics are the product of agricultural management. Second, because growth of crops and cultivation practices such as tillage or the application of agrochemicals play a major role in shaping biodiversity patterns (Wittwer et al., 2021). And third, a comprehensive ecological policy evaluation should be able to take into account changes in field-level yields (both gains and losses) associated with biodiversity-improving measures.

Finally, modelling the feedbacks from biodiversity and ecosystems to yields and farm economics remains a big challenge. Less than 40% of the models in our review considered non-provisioning ecosystem services as an environmental outcome, and only a quarter explicitly included a feedback of ecosystem services on yield. This is understandable, as quantitatively predicting levels of ecosystem service provision is notoriously hard and remains an active research question (Alexandridis et al., 2021, 2022). However, being able to link crop growth models with landscape-scale biodiversity models could be a decisive step towards a better understanding of biodiversity-yield relationships (Seppelt et al., 2020), and would be a major step forward in making ecological models attractive and useful for policy makers and practitioners.

### 4.2. Lessons for socio-economic modelling

There is a robust tradition of using economic farm models in agricultural policy assessments. A particularly influential model in this tradition is AgriPoliS (Happe et al., 2006), but there are several other highly elaborated economic models, such as SWISSland (Möhring et al., 2010) and CRAFTY (Murray-Rust, Brown, et al., 2014).

The biggest gap we see is the low representation of economic and environmental risks. Most models that do include risk events mainly cover the effects of climate change (e.g. Coronese et al., 2023; Huber et al., 2017; Troost et al., 2012). However, risks and risk management are an important area of study with regards to agricultural SES, for two reasons. First, the combination of climate change and environmental degradation entails a likely increase in the frequency and severity of shocks, both locally and globally, to which farmers have to respond (Maire et al., 2022). Secondly, the reduction of risk through greater yield stability is an important argument for more environmentally-friendly diversified farming systems, though one which remains poorly explored (Rosa-Schleich et al., 2019). Therefore, given the importance of risk management for social-ecological transformations in at least some agricultural contexts (e.g. Choquette-Levy et al., 2021), this is an important area for future models to expand on.

An area that has seen a lot of work is the study of decision-making processes by land users, especially farmers. An increasing number of economics studies are going beyond the classical profit-maximising, fully-rational agent (*homo oeconomicus*) to better understand the complexities of human decision-making (e.g. Drechsler, 2021; Schaub et al., 2023). This is also reflected in the agent-based modelling literature of the last years (e.g. Huber et al., 2018; Wijermans et al., 2023). Our review reveals widespread consideration of complex decision-making processes, as well as the interconnections among behavioural and economic aspects of agricultural SES. Different nuances and components of decision-making, including relationships and social networks, learning and farmers' backgrounds, are taken into account by about half of the models in our review (cf. Schlüter et al., 2017). Comparing this to the findings of prior reviews, it seems that there has been significant recent progress in the modelling of farmer decision-making (Filatova et al., 2013; Kremmydas et al., 2018).

Still, we see two directions in which this can profitably be improved. The first is a more detailed study comparing the relative importance of different factors of decision-making under different conditions (Thompson et al., 2023). Some such studies have already been carried out, for example using FARMIND (Huber et al., 2024) or ALMaSS (Malawska & Topping, 2016). As including more decision factors in a model also raises its susceptibility to error, further research into the dynamics of decision-making should help social-ecological modellers achieve a suitable level of complexity (Wijermans et al., 2023). The second direction is to look at whether and how environmental processes feed back into farmer's decision-making, e.g. through adaptation to increasing droughts or in response to pest cycles (e.g. Eisele et al., 2021). This would help to better recognise and explore the intricate interconnections between social and ecological processes in agriculture in a way that is so far only done very rarely (cf. Norton, 2016; Vogt et al., 2015).

The role of markets has been modelled to very different degrees. While land markets are well-represented in the existing socio-economic models (at least partly due to the influence of AgriPoliS and MPMAS), markets for agricultural goods and products are rarely explicitly modelled. Land markets play an important role in mediating structural change in agriculture, as farms grow or shrink in size or cease operation altogether. ABMs play to their strengths here, representing the individual decisions of many different farmers to study a large-scale phenomenon (e.g. F. E. Bert et al., 2011; Möhring et al., 2010). Endogenous markets for other goods and services are much rarer in our reviewed models. However, expanding models to also simulate markets for agricultural inputs and outputs, or linking farm models to relevant market models, could enable larger-scale studies of entire food systems (e.g. Brady et al., 2017), and the exploration of sustainability pathways (e.g. Brown et al., 2019).

### 4.3. Implications for SES modelling

With our paper we want to highlight the importance of large social-ecological models, by which we mean models that include a broad range of categories and work with different types of empirical input data. As stated in the Introduction, this does not mean that every model needs to be large in this sense. The question of adequate model complexity has been discussed extensively before (e.g. O'Sullivan et al., 2016; Sun et al., 2016; Topping et al., 2015; Troost et al., 2023). There are many research questions to which smaller models (i.e. that include fewer categories or are more conceptual in nature) are better suited than a large model would be. Still, there are several open areas of research that require such larger models.

First, we observe that the critical influence of feedback loops on system resilience and tipping points has been accepted by SES researchers but is still rarely implemented in agent-based modelling (Farahbakhsh et al., 2022). Rather than just studying uni-directional effects of socio-economic processes on ecological systems (or vice versa), we need models that can explore bi- or multidirectional interactions (e.g. Chen et al., 2023; Martinet & Roques, 2022). Other authors have called for a better integration of climate change, land use, and biodiversity models (Cabral et al., 2023; Harfoot et al., 2014; Urban et al., 2016); this needs to be applied to agriculture, too. We posit that this will entail paying more detailed attention to crop and livestock production, as this is the nexus point linking farm management and its related socio-economic processes to the environmental processes in the natural world (Figure 1).

Secondly, modellers can only provide useful policy advice if their models can provide a reasonably realistic representation of the system and the policy in question (Kremmydas et al., 2018; Sun et al., 2016). It is notable, though not surprising, that most of the reviewed models that evaluated specific policies (P2) also included much empirical input data (I1-I4). Social-ecological systems research has a valuable contribution to make to the study of agricultural systems (Allen et al., 2014; Norton, 2016), but SES models are still not well utilised in policy-making (Elsawah et al., 2020). One part of the problem is the lack of exchange between modellers and decision-makers (Will et al., 2021). Another challenge is the (perceived or actual) low reliability of ABM results, which requires rigorous validation of models intended to be used in policy (An et al., 2020; Filatova et al., 2013). Lastly, it is regrettable that although biodiversity conservation has long been a stated goal of agricultural policies such as the CAP, this is not yet reflected in the available models: in our review, only five out of 22 models that evaluated specific policies also simulated species (cf. Malawska et al., 2014).

We do recognise that building such large models is not easy. One big difficulty lies in the disciplinary differences between the different modelling traditions. Although this has long been recognised (Wätzold et al., 2006), it continues to be a challenge (Elsawah et al., 2020). One practical aspect of this is a frequent mismatch in the spatial and temporal scales of analysis (Lippe et al., 2019). For instance, it is notable that the vast majority of economic models in our review use annual time steps (Table 2), a temporal resolution that makes sense from an economics perspective but that is much too coarse for many ecological processes. A second aspect lies in the need to develop and use indicators that are relevant and meaningful to both disciplines (Pe'er et al., 2020). Finally, on a deeper level, the societal value debates surrounding land use ("environmental protection versus economic productivity") can spill over into academic discourses and impede interdisciplinary collaboration.

The second big difficulty in building large models comes from the technical challenges of building large software. Here, it can be instructive to consider the examples of MPMAS and ALMaSS, as the two most comprehensive models in our review (Box 1 & 2). Both were designed from the beginning to take a broad systems approach to studying agriculture, even though their background and main focus was recognisably economics and ecology, respectively. In implementing their conceptual design, they chose different technical approaches. ALMaSS is a very large, single code base, containing all features that have been added over the 20+ years of its use. This gives the advantage of all parts of the model integrating seamlessly with each other, at the cost of a very high technical complexity of the software. MPMAS on the other hand worked with model coupling from the beginning, implementing a small economic core model and linking this to a suite of already available biophysical models. This gives it flexibility to switch between different biophysical models for different research questions and reduces the programming work for the core development team, but means that the main model has to work within the constraints and limitations of the coupled models.

While both approaches can work well, we encourage social-ecological modellers to work more with model coupling, as this is one of the quickest routes to creating truly social-ecological models (S. Janssen et al., 2011). Several studies already do so, coupling multiple existing models in order to study the interlinkages between processes from different domains (e.g. Brady et al., 2017; Gimona & Polhill, 2011; Synes et al., 2019). This technique has been used to great effect in other modelling disciplines, such as climate modelling (Edwards, 2011), and is thus a promising avenue to pursue in future. However, doing so will require a greater degree of code sharing among modellers (Barton et al., 2022). It also requires a thorough understanding of the modelling issues to consider (Belete et al., 2017), and a knowledge of appropriate software engineering practices (Vedder et al., 2024).

### 4.4. A new model concept

Based on these lessons for ecological, socio-economic, and SES modelling, we develop a concept for a possible new social-ecological model of agriculture. This is guided by the question: "What could an integrated social-ecological model look like that can be used to investigate the interactions between agriculture and biodiversity, and the impact of policy on agricultural SES?"

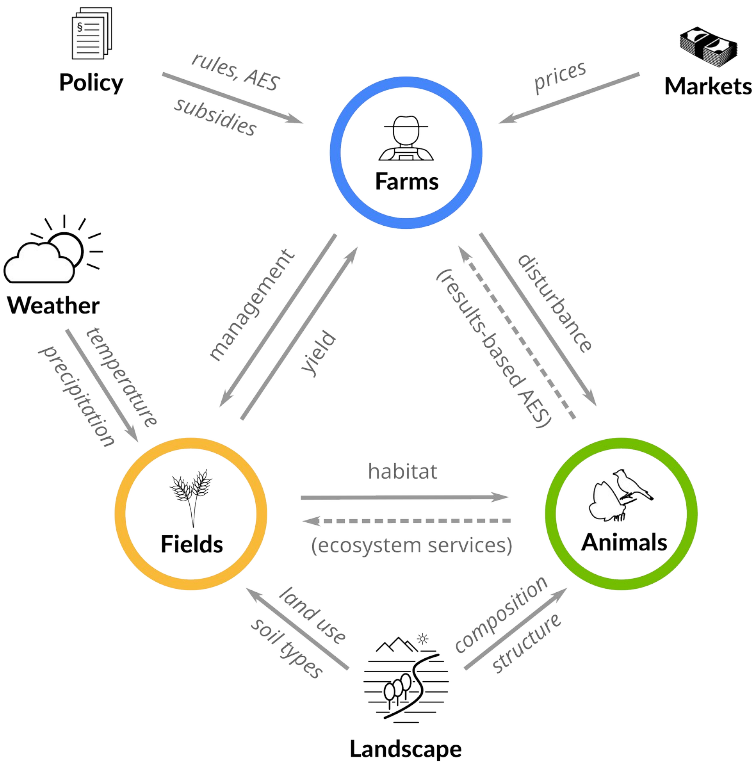


*Figure 5: A proposed structure for a social-ecological model to investigate the influence of agricultural policy and practice on farms and biodiversity. The model includes three components, or entities (in circles), which mutually interact. External inputs (arrows with italicised text) are provided by policy regulations, market prices, weather, and landscape properties. Dashed arrows with text in parentheses denote possible extensions to the core model concept. See Table 3 for further details.*

In Figure 5, we present a schematic of the model concept, showing what we propose would be the main entities and data sources and their interactions. Table 3 lists a selection of state variables, processes, and output variables that could be used in such a model, as well as suggestions for existing models that may form useful components for model coupling.

Our aim with this concept is to present a model design whose implementation would complement the existing range of models, which is broad enough to capture social-ecological dynamics, but compact enough to be scientifically and technically feasible. (We note that a very similar concept was already proposed by (Dent et al., 1995), but despite significant progress in modelling over the past 30 years it remains a worthwhile research target.)

The proposed model would include three main entities: farmers, fields, and wildlife animals. Farmers are agents that each cultivate a collection of fields, choosing crop rotations and management actions, and responding to external inputs from markets and policies. Fields represent instances of a process-based crop model, which calculates plant growth and the resulting yield for a given location over time, as determined by environmental inputs (e.g. weather, soil type) and management actions (e.g. tillage, fertilisation, grazing). Wildlife animal species (such as birds, butterflies, or wild bees) are represented either by individual-based models or spatially-explicit population models. The species' movement behaviour and life cycle is simulated on a land cover map, which is regularly updated with habitat information (e.g. plant height and cover) from the cropped fields. In addition to the indirect, habitat-mediated impact of farming on biodiversity, farmers' management actions (e.g. harvest or pesticide application) may cause direct mortality.

To achieve bidirectional feedback, the farmer submodel could respond to species dynamics using mechanisms such as result-based AES, or the animal submodel could calculate levels of ecosystem service delivery (e.g. pollination) for the field submodel. However, as particularly the latter is scientifically challenging, this may be developed as a possible extension of the main model concept.

A model like this could be used for scenario analyses by analysing the response of the modelled system to different conditions. An obvious application is to vary the policy regulations that affect farmers' behaviour, but scenarios can also include running the model over different landscapes, with different market prices, or with different weather patterns (e.g. to simulate climate change). It could also be used as a model framework for more theoretical studies, for instance to test landscape ecological hypotheses.

Overall, we envision a model that is based on empirical data to the extent possible, i.e. using remote sensing maps, real crop and animal species, etc. We believe that such a model is best suited to understanding existing agricultural SES and providing specific policy advice. Still, it would also be possible to implement the model concept in a more conceptual way, using abstract landscapes and "virtual" species. Which option is preferable will depend on the study question as much as on the available development resources.

From an ecological perspective, we see as particularly important the ability to model both the direct and indirect effects of farm management on biodiversity, i.e. through disturbance as well as through landscapes that change over time. As noted above, the spatio-temporal dynamics of agricultural management have generally received too little attention in the ecological literature (Vasseur et al., 2013), and are rarely represented in our reviewed ecological models. In this context, modelling crop growth is key, as it forms an important nexus point between human and natural domains (Figure 1). It is responsible not only for the economically important yield production that farmers work for, but also shapes the habitat of farmland species, providing (or not) forage, cover, breeding places, and connectivity (Fahrig et al., 2011).

Beyond considering the effects of farming on biodiversity, our model concept also lends itself to studying bidirectional coupling, by allowing the integration of direct and indirect effects of biodiversity and ecosystem services on farmers' behaviour. As stated above, reliable ecosystem service predictions in farmland are currently difficult to achieve, but given the current research interest in this question, our concept provides a possible modelling approach in this direction (cf. Seppelt et al., 2020).

In general, our model concept seeks to give each of its three main components equal weighting. This follows the principle that all important factors should be modelled at a similar level of detail and precision (Saltelli et al., 2020). It is also intended to simulate real landscapes and species, intentionally sacrificing some generality for increased realism and precision in the interest of providing relevant advice to decision-makers (Levins, 1966). In view of the non-trivial complexity of our concept, integrating one or more existing models in an implementation of it (e.g. those suggested in Table 3) could greatly reduce development time and provide the benefit of building on previous scientific work.

*Table 3: Details of entity types in the proposed social-ecological model concept (cf. Figure 5). State variables characterise individual entities; processes are simulated for all affected entities; output refers to model-level results for further analysis. Possible models are existing software that are potentially usable to simulate this entity within a coupled integrated model. All listed entries should be taken as examples that are neither exhaustive nor prescriptive, but reflect possible implementation choices for the model concept.*

| Entity | State variables | Processes | Output | Possible models |
|---|---|---|---|---|
| **Farms** | Fields | Crop selection | Annual profit | APORIA (Murray-Rust, Robinson, et al., 2014) |
| | Capital (e.g. financial, labour) | AES selection | Economic choices | FARMIND (Huber et al., 2022) |
| | Production (e.g. crop types, livestock) | Remain/Quit | | REGMAS (Lobianco & Esposti, 2010) |
| | Behavioural factors (e.g. values, relationships) | | | |
| **Fields** | Crop type | Plant growth | Yield | AquaCrop (Steduto et al., 2009) |
| | Crop properties (e.g. height, biomass) | Mowing/Harvest | Landscape structure | BODIUM (König et al., 2023) |
| | Soil properties | Other management (e.g. fertilisation, tillage) | | APSIM (Holzworth et al., 2014) |
| **Animals** | Habitat requirements | Reproduction | Population size | Skylark (Guillem et al., 2015) |
| | Location/home range | Dispersal | Movement patterns | Meadow brown (Evans et al., 2019) |
| | Mate | Mortality | Spatial distribution | BEEHAVE (Becher et al., 2014) |
| | Offspring | | Ecosystem service delivery | Biocontrol (Martinet & Roques, 2022) |

### 4.5. Limitations

We recognise that in this study we have only been able to review a portion of social-ecological models related to agriculture, specifically sampling agent-based models that are relevant to agroecosystems. We also acknowledge that our criteria definitions (Table 1) leave some room for interpretation, and leave out other factors that can also be relevant to agricultural SES (e.g. technological advance or governance structures). Despite these caveats, we believe our literature review does offer a representative overview of the current state of agricultural agent-based modelling, and illuminates recent trends and topics in the field. Still, we encourage our readers to look beyond our brief summaries and read the original publications to better understand how individual models work (Table 2).

On a more fundamental level, we want to address two scientific concerns related to the development of large, integrated models. First, we want to reiterate our previous statement that large models are not, by mere virtue of their increased complexity, better than small models. Every model serves a specific purpose, with different purposes imposing different requirements and constraints on the developers (Edmonds et al., 2019). Thus, model quality must be judged by adequacy for purpose, and not by comprehensiveness (Troost et al., 2023). Therefore, while we concur with other authors that the study of SES will require some integrated models (and as we argue here, more than we currently have), we do not want to denigrate the scientific importance of "small" models.

Secondly, we are aware of the pitfalls and problems associated with large, integrated models. The larger the model, the more care must be taken with its design, parameterisation, and validation, in order to deal with the rapidly increasing levels of uncertainty (Voinov & Shugart, 2013). Where model coupling is used, this must be done with an awareness of the scientific and technical issues involved (Belete et al., 2017; Vedder et al., 2024). An open and transparent discussion of modelling choices and uncertainty is particularly vital where, as we advocate, model results are used to advise decision makers (Saltelli et al., 2020; Will et al., 2021).

Finally, we emphasise that agent-based models are just one methodology among many for studying social-ecological systems. While they have particular strengths that fit in well with certain properties of SES (e.g. heterogenous, interacting agents), they also have weaknesses that must be accounted for (e.g. the difficulty of quantitative validation) (Schulze et al., 2017). Therefore, they can only ever be one approach among several for the scientific study of SES and the providing of advice to decision makers, and must be complemented in the SES literature by studies using other empirical and theoretical methods.

## 5. Outlook

In this review, we have analysed how agent-based models represent social-ecological systems in agriculture. Looking at the current state of the field, we offer the following main recommendations for future work:

1. Develop more applied agroecological models that can be used to evaluate the impacts of policy on biodiversity and ecosystem services in specific contexts.

2. Integrate agricultural management practices and spatio-temporal landscape dynamics into agroecological models.
3. Explore risk management strategies in the context of climate change and environmental degradation in socio-economic farm models.
4. Use model coupling to study bidirectional interactions between the human and natural domains of agriculture, such as the possible effects of biodiversity and ecosystem services on agricultural production and farmers' decision-making.

The model concept we propose in this paper provides a stimulus for how these recommendations could be implemented.

By their nature, social-ecological systems span across disciplinary boundaries. We encourage modellers to learn to navigate the different modelling traditions that have grown up around agriculture, and to form collaborations that can help do so, in order to more holistically approach the social, economic, and environmental problems we face. We hope that this review helps to build some of the bridges needed to do so.

## Author contributions

DV, JR, and GP conceptualised the study. DV, JR, and LK conducted the literature search; DV, LK, and GT carried out the literature analysis. DV created the figures and led the writing. GP and SL provided supervision and acquired funding. All authors co-developed the methodology, contributed critically to drafts and approved submission.

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## Declaration of interests

The authors declare no competing interests.

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