

Reflections on linking economic equilibrium models with agent-based models in the context of agricultural land use

Alena Schmidt¹, Franziska Appel², Filippo Arfini³, Robin Argueyrolles¹, Lisa Baldi³, Tatiana Filatova⁴, Robert Finger⁵, Jiaqi Ge⁶, Nastasija Grujić⁷, Thomas Heckelei⁸, Robert Huber⁵, Ahmet Ali Koç⁹, Chunhui Li⁶, Gabriele Mack¹⁰, Birgit Müller¹¹, Davit Stepanyan¹², Meike Will¹¹, and Ruth Delzeit^{1,*}

¹ University of Basel, Basel, Switzerland

² Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle (Saale), Germany

³ University of Parma, Parma, Italy

⁴ Delft University of Technology, Delft, The Netherlands

⁵ ETH Zurich, Zürich, Switzerland

⁶ University of Leeds, Worsley Building, Leeds, UK

⁷ University of Novi Sad, Novi Sad, Serbia

⁸ University of Bonn, Bonn, Germany

⁹ Akdeniz University, Konyaalti, Antalya, Turkey

¹⁰ Agroscope, Ökonomische Modellierung und Politikanalyse, Ettenhausen, Switzerland

¹¹ Helmholtz Centre for Environmental Research-UFZ inc., Leipzig, Germany

¹² Johann Heinrich von Thunen Institute, Braunschweig, Germany

Abstract

Linking computable general or partial equilibrium models with agent-based models can combine the strengths of both modeling concepts. The linking allows to trace global feedback effects while providing a flexible representation of human behavior and social interactions. This linking would facilitate the simulation of interconnected land-use and economic systems while accounting for actors' heterogeneity, their specializations, and the representation of alternative decision models. In this paper, we examine the challenges that currently hinder the realization of these potential benefits and present a roadmap outlining possible solutions for successful model linking in the context of land use change. The main challenges include: 1) conceptual misalignment between modeling concepts, 2) differences in scales and resolution, 3) difficulties in validation and calibration of linked models, 4) increased complexity in interpreting and communicating results, 5) high demands on computational infrastructure and computational costs, and 6) limited personnel and financial resources. Successfully linking different model concepts and overcoming these challenges requires the modelling communities and stakeholders to engage in long-term, platform-supported dialogue. This dialogue could facilitate the development of a shared framework for model linking, standards for model documentation, validation procedures, and appropriate approaches for communicating and evaluating results. This process will enhance the benefits and sustain the linked models while helping determine circumstances in which the advantages of linking models may outweigh the costs.

Keywords

agent-based model; computable general equilibrium model; partial equilibrium model; model integration

Correspondence:

Contact R. Delzeit at ruth.delzeit@unibas.ch

Cite this article as:

Schmidt, A., Appel, F., Arfini, F., Argueyrolles, R., Baldi, L., Filatova, T., Finger, R., Ge, J., Grujić, N., Heckelei, T., Huber, R., Koç, A.A., Li, C., Mack, G., Müller, B., Stepanyan, D., Will, M., & Delzeit, R. Reflections on linking economic equilibrium models with agent-based models in the context of agricultural land use *Socio-Environmental Systems Modelling*, vol. 8, 18872, 2026, doi:10.18174/sesmo.18872

This work is licensed under a [Creative Commons Attribution-NonCommercial 4.0 International License](https://creativecommons.org/licenses/by-nc/4.0/).



Socio-Environmental Systems Modelling

An Open-Access Scholarly Journal

<http://www.sesmo.org>

1. Introduction

Effective land-use policies must consider both local interdependencies and global market feedback to comprehensively assess their impact on biodiversity, nutrient losses, food security, and climate change (Kelly et al., 2013). New policies must account for diverse behavior of local land users. Indirect effects, such as leakages from carbon, pesticide, or nutrient policies (e.g., Finger, 2024, Fournier Gabela et al. 2024, Oita et al., 2016), as well as associated price feedback may reduce the effectiveness of these policies. These feedback mechanisms make *ex-ante* policy assessments challenging, for instance in the context of reforms to the European Union's Common Agricultural Policy (CAP) or the introduction of environmental taxes.

While market feedback is well represented in computable general equilibrium (CGE) and partial equilibrium (PE) models, local interdependencies are more effectively captured by agent-based models (ABMs). ABMs are particularly suited to represent behaviorally rich, spatially explicit and diverse agents, capturing heterogeneity, social interaction, including peer influence, information costs, social learning, and emergent properties (e.g., Huber et al., 2018, van Duinen et al., 2016). These behaviors affect land use, production intensity, farm exits, and related land sales (e.g., Nowak et al., 2017, Li et al., 2020). ABMs enable the simulation of interactions among farmers, generating insights at both the farm and regional levels. However, empirically based ABMs are typically limited to small geographical areas with little consideration of direct and indirect market feedback (Lippe et al., 2019). In contrast, CGE and PE models are well suited to capturing market feedback and cross-sectoral effects. The European Union (EU) has promoted the continued development of modeling networks such as the European Simulation Model (ESIM), the Common Agricultural Policy Regionalized Impact Modelling System (CAPRI), and the Agricultural Member State Model (AGMEMOD) due to their strengths in policy analysis (Barreiro-Hurle et al., 2024). However, these equilibrium models typically assume rational behavior by representative agents and generally lack spatial detail (Robinson et al., 2018).

Given the respective strengths of the two modeling concepts, this paper addresses the following question: What are the benefits, challenges, and feasible pathways for linking ABMs with CGE or PE models to achieve a more comprehensive assessment of land-use policy impacts? Based on a literature review, a survey of the modeling community, and workshops involving modelers from both modeling concepts, we identify key challenges and discuss potential solutions for successful model linking. Such linking could expand the analytical toolbox for assessing cross-scale impacts arising from global market feedback evaluating the equity implications of policies and examining the dynamics of land-use transitions.

Researchers have identified considerable potential in linking ABMs with CGE or PE models. This linking could represent alternative decision-making processes, spatial heterogeneity, and feedback effects involving global markets, while improving spatial, temporal and institutional resolution (Babatunde et al., 2017; Husby & Koks, 2017; Filatova et al. 2025; Müller et al., 2020; Niamir et al., 2020; Rounsevell et al., 2012). Millington et al. (2017) and Müller et al. (2020) see specific potential in linking these modeling frameworks to simulate the effects of telecoupling and bridging the micro and the macro scale of socio-environmental systems.

Despite its potential, there is currently no established standard for linking these models, and only a few documented applications exist. For instance, Möhring et al. (2016) linked the agent-based model SWISSland with a PE model for the Swiss agricultural sector, and Morgan & Daigneault (2015) implemented a soft linking in which a PE model informed an ABM in simulating impacts of climate change on farmers land-use decisions. Niamir et al. (2020) linked an ABM with a CGE model to better represent energy consumers and their behavioral changes (see Supplementary Material B for more information). Millington et al. (2017) explored the possibility of linking ABMs with CGE/PE models to represent telecoupling between China, Brazil, and the United States. They ultimately adopted a telecoupled ABM framework instead of a linked ABM–CGE/PE model (Dou et al., 2020). In a recent study, Klein et al. (2025) uses an ABM to 'agentize' a CGE model assessing the robustness of the equilibrium model's results under varying household heterogeneity. Three examples of coupling ABM with macro models, like CGE and Integrated Assessment Models (IAM), for cross-scale climate policy analysis have been recently discussed by Filatova et al. (2025).

Both, ABMs and CGE/PE models have been linked to other modeling types. ABMs have been linked to large-scale emissions models (Robinson et al., 2018) and to system dynamic models (Liu et al., 2020). In addition to linking models, there are also ABMs that directly incorporate local markets, e.g., land markets (Magliocca et al.,

2011). CGE models have been linked with bottom-up models for energy system optimization (e.g. Krook-Riekkola et al., 2017) and to models that capture innovation adoption (e.g., Lee et al., 2022). They have also been used with microsimulation models to evaluate the effects of heterogeneity on labor markets, food security, trade agreements and energy demand (e.g., Zhang et al., 2022; Boulanger et al., 2022; Akgul et al., 2016; Campagnolo & Cian, 2022). CGE models have been linked with PE models to assess regional economic impacts and international spillover of regional policies (e.g., Britz & Hertel, 2011).

Despite these efforts, the potential of linking ABMs with models that allow to simulate market feedback, such as CGEs or PEs remains underexplored. This paper contributes to the literature by reflecting on the benefits, challenges, and limitations of linking ABMs with CGE or PE models. It provides a holistic assessment of the complexities involved and outlines a conceptual roadmap for linking these models to assess complex processes, such as land-use change or climate change adaptation. The paper does not propose new mathematical model formulation but provides guidance on pathways to make the linking between ABMs and CGE/PE models more feasible and beneficial. This is particularly timely given recent advances in computational techniques, including artificial intelligence, as well as enhanced data integration frameworks that offer new opportunities for ABM-CGE/PE model linking.

In the remainder of this paper, we first outline our methodological approach, which combines a literature review, expert workshops and insights from successful and not yet successful attempts at model linking, acknowledging the limited literature available. We then describe the key characteristics of the two modeling concepts. In the results, we present and discuss when model linking is promising or rather challenging. Finally, we present a roadmap for future projects linking the two modeling approaches with a focus on land-use modeling in European countries while noting that several aspects may also be relevant in other contexts.

2. Methods

A literature review was conducted using the following keywords: “partial equilibrium”, “computable general equilibrium”, and “agent-based” on Scopus and Bielefeld Academic Search Engine (BASE). We then organized a dedicated workshop to examine the key challenges and opportunities associated with linking these two modeling concepts. Invitations were extended to researchers with demonstrated expertise in linking ABMs and CGE/PE models. Furthermore, researchers from the AGRIMODELS cluster working with CGE/PE models or ABM were also invited. The AGRIMODELS cluster aims to combine different models from ABM and CGE/PE models to better evaluate agricultural policies (see Supplementary Material C). Prior to the workshop, 24 people completed an online survey about their experience with the models, the challenges they perceived, and possible solutions (see Supplementary Material A). The survey responses were then used to define the thematic focus of the workshop sessions.

In May 2022, we held a hybrid workshop. It began with 22 participants, 77% also took part in the questionnaire, to examine the challenges of linking ABM with CGE/PE models. The workshop opened with introductory presentations by AGRIMODELS researchers on existing experiences and ideas for linking CGE models and ABMs and an input from the CGE-ABM example (see Supplementary Material B.1). This was followed by four rounds of parallel sessions during which participants selected topics based on their expertise. These discussions led to the identification of six key challenge areas and clarified the purpose and suitable contexts for linking the two modeling concepts. These challenges were first formulated in self-selected small groups and then refined through plenary discussions. A subgroup of the workshop participants subsequently developed a roadmap and recommendations for linking CGE/PE models with ABMs.

3. Overview of the two model concepts

ABMs and CGE/PE models differ significantly in their conceptual foundations and modeling priorities, while providing complementary perspectives on economic and system-level dynamics. They typically span distinct scales and resolutions. In this chapter, we provide some background to each model concept.

3.1 Agent-based models

Agent-based models simulate complex systems by starting from the “bottom up” (e.g., Brown et al., 2016). They focus on the actions and interactions of individual agents - such as people, farms, or institutions - each has its own goals and behaviors (e.g., Axtell & Doyné Farmer, 2025). Unlike models that assume uniform or representative behavior across a system, ABMs allow for diversity among agents and do not rely on predefined system-wide rules (e.g., Groeneveld et al., 2017). This flexibility makes ABMs well suited for exploring specific research questions, especially when systems are complex and outcomes are difficult to predict (e.g., Huber et al. 2018, Kremmydas et al., 2018). By modeling decisions and interactions at the individual level, ABMs can capture nonlinear dynamics and unexpected patterns (e.g., An et al., 2023).

One of the key strengths of ABMs is their ability to simulate emergent phenomena (e.g., Helbing 2012). This means that they can show how large-scale patterns, such as changes in land cover, emerge from many small-scale land-use decisions, without making assumptions about the behavior of the entire system (e.g., Armeth et al., 2014). This makes them particularly useful for studying land-use systems, which are examples of complex adaptive systems, and for understanding how land-use decisions affect regional development, environmental outcomes, or spatial markets (e.g., Möhring et al., 2016; Troost et al., 2023; Happe et al., 2006).

ABMs have been applied at various spatial, temporal and institutional levels. These range from local studies (e.g., Huber et al., 2022), to regional levels (e.g., Pitson et al., 2020), to continental levels (such as CRAFTY, see Brown et al., 2017; Millington et al., 2021). Some models focus on individual agents (e.g., Appel & Balmann, 2019), others use heterogeneous archetypal agents (e.g., Grêt-Regamey et al., 2019), and still others include organizations or institutions (e.g., Ge et al., 2021). In land-use research, ABMs have been used to study topics such as diffusion of new technologies (e.g., Coronese et al., 2023), the impact of new policies on biodiversity (e.g., Nilsson et al., 2019), climate impacts (e.g., Kreft et al., 2023), nitrogen surpluses (e.g., Schmidt et al., 2021), or the role of social networks in promoting sustainable agricultural practices (e.g., Nilsson et al., 2019).

3.2 General and partial equilibrium models

CGE/PE models are based on microeconomic theory, assuming profit-maximizing producers and utility-maximizing consumers under flexible, endogenous prices arising from market-clearing conditions (Jafari & Othman, 2016). These models represent all transactions between producers, consumers, and the government in a whole economy (CGE models) or a single sector (PE models) and commonly include bilateral trade flows. Land is one of the primary production factors that might be considered next to labor and capital. For an overview of existing CGE and PE models simulating land use see Moallemi et al. (2025).

PE models are typically preferred for disaggregated outcomes and are computationally less expensive. PE models allow analysts to depict land use in greater detail and to consider land markets (Michetti, 2012). PE models usually refer to physical units and are therefore often linked with biophysical models (Jafari & Othman, 2016). A frequently applied model in the agricultural sector to analyze international agricultural markets and policies is the CAPRI (Common Agricultural Policy Regionalized Impact) model (Gocht & Witzke, 2023). Similarly, the AGMEMOD and FAPRI (Food and Agricultural Policy Research Institute) models are applied for this purpose. Examples of PE model applications in the agricultural sector are the effects of CAP reform on farm income (e.g., Gocht et al., 2013), climate policies in the agricultural sector (e.g., Gocht et al., 2017), the impact of carbon pricing (e.g., Stepanyan et al., 2023), and carbon taxes (e.g., Jansson et al., 2023).

At the cost of sectoral detail, CGE models can represent economy-wide interactions and encompass both direct and indirect economy-wide multiplier effects induced by policy changes. For instance, biofuel production connects various sectors of the economy through intermediate input and factor markets, as well as different regions through international trade (Calzadilla et al., 2014; Heimann et al., 2023; Argueyrolles et al., 2025). Further, CGE models have been used to study food loss or insecurity, biodiversity, and climate change in relation to land-use change (e.g., Calzadilla et al., 2010; Moore et al., 2017; Philippidis et al., 2019; Zabel et al., 2019).

In the literature, several linking approaches between PE and CGE models exist (see Delzeit et al. 2020 for an overview) to inform the PE model about factor market changes (e.g., Britz & Hertel, 2011) and the CGE model about farm or product level change from external shocks such as climate change that might have economy-wide

impacts. Challenges for linking CGE with PE models are the different units and representations of concepts, distinct software, and aligning of the baselines (Delzeit et al., 2020). Nevertheless, linking two equilibrium models is conceptually more straightforward than linking an equilibrium model with ABM since they are based on compatible economic theory.

4. Results

In the results section, we present our analysis of the purpose and usefulness of model linking and the main challenges of linking the two modeling concepts. The results draw on the workshop, follow-up discussions, and relevant literature.

4.1 What is the purpose of linking?

In the literature, the following purposes of linking ABM with CGE/PE model can be found:

- Bridging the gap between local and telecoupled impacts of policies (Millington et al., 2017).
- Simulating drivers and impacts across scales (Müller et al., 2020).
- Representing behavioral change through mechanisms such as social learning, innovation diffusion, or specialization of farms (Niamir et al., 2020).
- Enabling heterogeneous and spatially explicit responses to global market feedback (Babatunde et al., 2017).
- Facilitating feedback loops across different scales to improve understanding of complex systems, such as land-use decisions involving both private and public actors (Lippe et al., 2019; Niamir et al., 2020).

During the workshop, participants stressed that linking should be motivated by research questions.

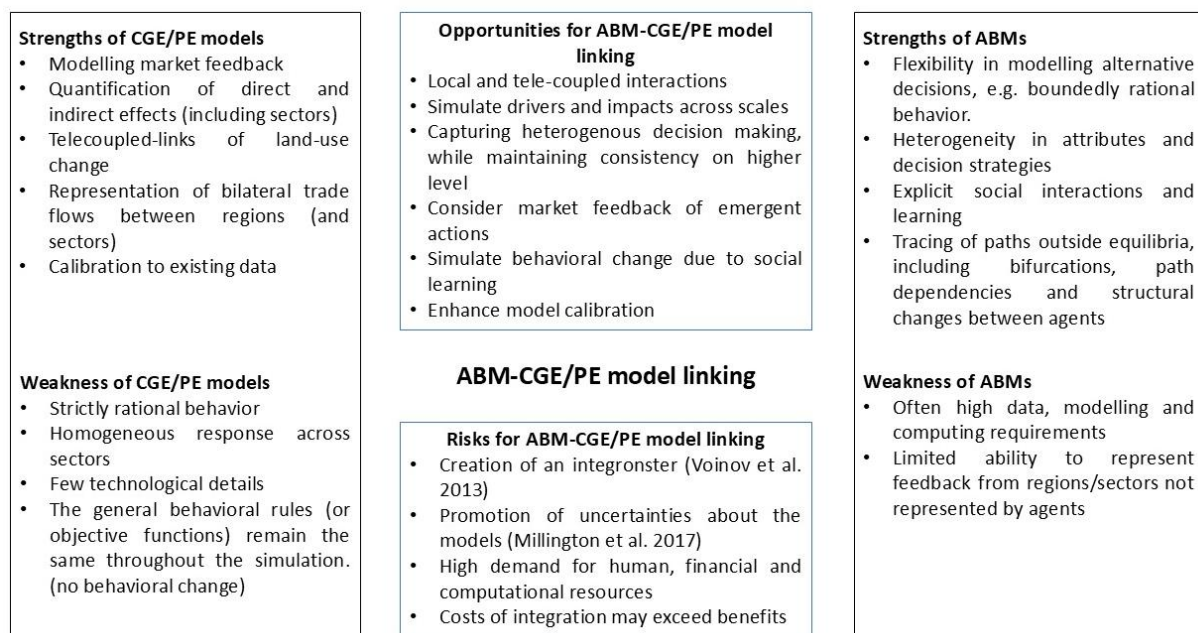


Figure 1: Strengths and weaknesses of general/partial equilibrium (CGE/PE) models and agent-based models (ABMs) and opportunities and risks for linking the two distinct concepts.

For ABM modelers, the purpose of linking to a CGE/PE model is to incorporate aspects such as responses from global markets, cross-sectoral responses, or telecoupling into their analysis.

For CGE/PE modelers, the aim is to model alternative or heterogeneous decision-making, to capture emerging structural phenomena such as changing behavior due to social learning, or to receive a spatially explicit response on land use. The participants concluded that the representation of alternative decision making could

substantially change the outcome of the model. The purpose of linking is therefore to exploit the respective strengths of the two models (see Figure 1 for a comparison).

4.2 When does linking make sense?

During the workshop, participants emphasized the importance of clearly articulating the specific circumstances in which model linking provides added value over standalone approaches. In this context, two key conditions were identified.

First, the issue being investigated must be characterized by relevant impacts that are heterogeneous and extend beyond the spatial location or sectors being researched. Second, it is expected that the results or inputs will include emergent properties, such as extremes, that cannot be captured by CGE/PE models. Simultaneously, emergent properties can cause impacts beyond the spatial boundaries of the model.

When analyzing land-use change, linking may be advantageous compared to using a standalone ABM if the land-use decision analyzed by the ABM affects land-use decisions elsewhere, for example, through global crop markets. However, the participants do not consider linking to be beneficial if the research question focuses on a specific regional and sectoral scale with no implications for other sectors or regions. Linking with an ABM may also be useful for CGE/PE models in cases where the representative farmer does not behave as a profit maximiser. This would allow for information on reactions toward policy measures simulated with an ABM to be mimicked with a CGE/PE model. For instance, from ABM, if most farmers adopt an agri-environmental measure even though it is not the most profitable decision, the more realistic adoption behavior regarding this measure could be represented in a CGE/PE through appropriate parameterization. This would also help if production sectors or households were very heterogeneous, and this heterogeneity was relevant for the aggregate outcome.

Further, the participants discussed that the combination of CGE/PE models and ABM is particularly effective in enhancing the representation of land-use change, especially in cases where there are relations of environmental impacts via trade (e.g., feed imports), as well as bifurcation processes resulting from specialization, behavioral changes (e.g., innovation diffusion or boundedly rational behavior in space), market and social interactions (e.g., social learning), or opt-outs. The dynamics induced by behavioral factors can inform CGE/PE models regarding changes in elasticities in sequential simulations across multiple time periods.

4.3 Challenges for linking ABM with CGE/PE models

We identified the challenges of model linking using the questionnaire responses from workshop participants, existing examples (see Supplementary Material B for an overview), and conceptual insights from the AGRIMODELS cluster (see Supplementary Material C). Below, we present the results for the six key challenges identified: conceptual alignment, differences in scale and resolution, calibration and validation, complexity in results interpretation, high computational demand and limited resources. However, our analysis showed that the challenges associated with linking ABMs and CGE/PE models are often interdependent and should not be addressed in isolation (see also Section 6).

4.3.1. Challenge 1: Conceptual alignment

Linking CGE/PE models with ABM faces several conceptual challenges. CGE/PE models solve for market equilibria, whereas ABMs generate macro-level outcomes from bottom-up behavioral dynamics, potentially leading to a linked model that cannot converge to a stable solution. Both approaches also incorporate path-dependence, where outcomes are strongly influenced by historical conditions or model initialization. Berger and Troost (2014) discuss this in the context of climate adaptation in agriculture, and Müller et al. (2020) in the context of food security. However, path dependence may not be straightforward when the models are combined, because their initialization procedures and temporal dynamics differ.

The two model concepts also differ in their assumptions about behavior. CGE/PE models draw on rational behavior, whereas ABMs allow for a broader range of behavioral factors (Farmer & Foley, 2009) including self-organizing processes, bounded rationality, learning, and memory effects (Nolan et al., 2009).

Workshop discussions highlighted that policy shocks or stochastic processes in ABMs can lead farmers' price responses to diverge from equilibrium conditions. For example, price signals transferred from a CGE/PE model to an ABM may trigger production decisions that differ from the assumptions underlying the equilibrium model including a consistent social accounting matrix. When these adjusted production levels are then fed back into the equilibrium model, they may no longer align with the initial equilibrium solution. This iterative feedback can introduce substantial uncertainty, propagate errors, and create oscillating ("seesaw") model outputs. As a result, the linked system may lose its effectiveness as an integrated tool, leading to what Voinov and Shugart (2013) refer to as "integronsters." In the BESTMAP example (see Supplementary Material C.1), the models could not be linked because the ABM assumed constant shadow prices across different adoption schemes, which could not reflect responses from the CGE model.

In ABMs, agents display heterogeneous behavior arising from differences in resource endowments, initial conditions, and behavioral rules, which can generate endogenous synergies, trade-offs, or conflicts. While aggregation is possible, workshop participants noted that these heterogeneous effects may not be sufficiently represented in aggregate CGE/PE models, potentially leading to biased results or requiring extensive calibration. This may also obscure emergent properties, such as regime shifts, when results are scaled up (See chapter 4.3.2.).

Finally, ABMs can also represent irreversible decisions (Müller et al., 2020). In land-use modeling, CGE/PE models typically do not account for irreversible developments such as specializations that reduce a farmer's supply price elasticity or lead to farm exit.

4.3.2. Challenge 2: Different scale and resolution

The spatial, temporal, and organizational dimensions of ABMs and CGE/PE models must be aligned to enable meaningful data exchange. A comprehensive overview of these dimensions is provided in Dressler et al. (2022). Table 1 summarizes the key characteristics of these three dimensions in CGE/PE models and ABMs.

Table 1: Resolution and scale of CGE/PE models vs. ABMs.

Scale	Dimension	CGE/PE	ABM
Resolution	Spatial	From supranational to country, to subnational regions, with PE becoming more prominent as resolution increases.	In land-use/farming context at parcel or farm level.
	Temporal	CGE: Generally yearly when recursive. Sometimes quarterly. In the case of a comparative static model, the time horizon of the model responses may cover several years. PE: comparative static / recursive dynamic / fully dynamic.	Typically, the frequency is annual; however, it is adaptable to the specific model under consideration.
	Organizational	CGE/PE models: From representative agent (aggregated firm, household, and government), regionally differentiated to heterogeneous firms or household types.	Decision makers, households, firms or institutions, in land-use context mostly individual farms. Individual (farm) agents, aggregated agents (agent types).
Extent	Spatial	CGE/PE model: global or national (sometimes regional).	Often case-study based, e.g. NUTS (Nomenclature of Territorial Units for Statistics) 2 or NUTS 3, catchments, organizational units such as districts/regions.
	Temporal	For agricultural studies, from the base year (i.e., past or current year), usually until 2030, but sometimes up to 2100.	Short-term ('Alternative Now', i.e. one time step), medium-term (e.g. one CAP-period) or long term (e.g. 50 years).
	Organizational	CGE: All government, firms, and households. PE: agricultural firms and households.	All farmers of the case study/region.

To approach common scales, it is important to increase the resolution of the CGE/PE model and/or the extent of the ABM model. However, increasing the extent of an ABM in any of the dimensions would require more data, which is often unavailable (Millington et al., 2017). Approaches such as synthetic landscapes (Uthes & Kiesel, 2020) or synthetic farm populations (Pahmeyer et al., 2021) can overcome data protection issues for the spatial dimension. However, these approaches can be computationally costly (see section 4.3.5.) and may be less accurate than using the original data. Similarly, agent typologies (e.g. Armeth et al., 2014; Rounsevell et al., 2012) could be used to support the ABM in achieving the necessary scale of a CGE model while reducing the heterogeneity between agents in the model. Experience with these approaches to address the gap between the scales is still limited. In the example of ABM-CGE linking (see Supplementary Material B.1), data upscaling often requires more data than is available.

On the CGE side, specialized models have been developed to improve the resolution of each identified dimension. For instance, GTAP-HET (Global Trade Analysis Project – Heterogeneity; Akgul et al., 2016) allows for firm heterogeneity based on productivity differences, while regional CGE models allow to analyze the impact of policy at the sub-national level (Ghaith et al., 2021). However, these improvements can have high data requirements (Giesecke & Madden, 2013) and involve computational difficulties like numerical stability (Jafari & Britz, 2018). As a result, efforts to expand the resolution of a model often come at the expense of reducing its extent in another dimension.

4.3.3. Challenge 3: Calibration and validation of linked models

A linked ABM-CGE model must be useful for policy making (Grimm et al., 2020). To ensure that the model is trustworthy, developers should follow established “best practices” in model development. There are three key concepts for validation and calibration: documentation, robustness checks, and adequate validation.

Documentation is an important first step. Any model must be fully documented including detailed technical explanations that would enable other researchers to replicate the simulations and to adhere to the FAIR (findable, accessible, interoperable and reusable) principles (see Müller et al., 2014; Zhang & Robinson, 2021). It must be clear how the model parameters are chosen (Troost et al., 2023). Good documentation builds confidence in the model, especially when there is a soft linking between the models.

The level at which the models are linked must be clearly defined, as ABMs and CGE/PE models often operate at different scales (see section 4.3.2). Combining them requires careful alignment of information across these scales (Belete et al., 2019; Lippe et al., 2019; Voinov & Shugart, 2013). This includes both a conceptual explanation and a technical description of how the models are connected, especially when there is a “hard coded” interaction between the models. This level of detail is also necessary for adequately validating the combined model (e.g., Lippe et al., 2019).

Another aspect is the robustness of the models. Both ABMs and CGE/PE models use many parameters, which can introduce a high level of uncertainty. This uncertainty can come from multiple sources, such as the input data, the assumptions about agent behavior, or even the model structure itself (Uusitalo et al., 2015; Warmink et al., 2010). When models are linked together, these uncertainties may propagate. Therefore, it is necessary to carefully understand and document these uncertainties (Millington et al., 2017).

The third key aspect is the adequate validation of the models to ensure a sensible model. This means that the modeling assumptions underlying the conclusions drawn from the simulation analyses must be systematically examined and supported within the specific context in which the model is applied (see Troost et al., 2023). This includes assessing whether the model’s results and conclusions are generalizable beyond the scope of the model. For ABMs, this can be particularly challenging. If agent behavior is based on data that does not adequately represent the real-world population, the outcomes can be biased (Troost et al., 2023).

Thus, building and linking ABMs with CGE/PE models is an iterative process that requires careful planning and transparency. Specific challenges include thorough documentation of the models, robustness checks, and adequate validation of results - essential steps to ensure that the final model is both credible and useful. The necessary work involved can be prohibitive for linking projects (e.g. MINDSTEP Supplementary Material C.2).

4.3.4. Challenge 4: Complexity of results interpretation & communication

Workshop participants agreed that the interpretation and communication of results from the two linked models can be challenging. The interpretation of results requires a proper understanding of the model outcomes. The analysis of model output in CGE/PE models is typically based on neoclassical equilibrium theory (Argueyrolles, 2025), while ABMs do not presume an equilibrium implicitly (Huber et al., 2018) (see section 4.3.1.). ABMs' emergent properties and stochastic processes can generate outcomes that are difficult to comprehend due to large amounts of data and require alternative forms of presentations (Lee et al., 2015).

Different terminology (see Box 1), coding standards (see section 4.3.5.), and data sources in the distinct modeling communities complicate the interpretation of the results. In addition, the two modeling communities meet at different conferences which reduces exchange. There are no established documentation standards for CGE/PE models.

Box 1: Differences in terminology.

Specific ABM terminology	Specific CGE terminology
Agent: an individual decision-maker, often with unique (heterogeneous across the population of agents) characteristics, not just with respect to income and demographics but also behavior (diverse preferences, perceptions, social network contacts).	Agent: an aggregate economic actor that embodies the behaviors of a larger group (e.g., households, firms).
Macro models: Models that operate on a global scale depicting the whole economy including CGE models.	Macro models: Models built on macroeconomic theory, focusing on variables like inflation and employment. Instead, CGE models are grounded in microeconomic theory, modeling the behavior of agents and market interactions at a disaggregated level.
Dynamic behavior: behavioral rules of action and interactions evolve over time as agents learn and adapt.	Recursive dynamic behavior: considering time as discrete steps rather than a continuum, where every time step's conditions are based on the previous timestep.

Finally, results need to be translated to the stakeholders to help them understand the corresponding model response to policy scenarios. Stakeholders could help improve the selection, communication, and use of information by providing different perspectives (Meuwissen et al., 2019; Voinov & Bousquet, 2010). The workshop participants think that this is specifically challenging in ABM-CGE/PE model linking as it requires communicating the model linking transparently to non-modelers and not overpromising the validity of results to stakeholders. Communication with policymakers requires the use of RACER (relevant, accepted, credible, easy, and robust) indicators that are linked to policy goals and provide information on potential trade-offs and synergies (European Commission, 2018). It is important to present the model and its limitations clearly and concisely (European Commission, 2018). However, trust will build upon a sequence of applications with understandable and useful results for the policy maker. In the SWISSland case (see Supplementary Material B.2), stakeholders first needed to understand which questions were suitable for the model and which, while logically possible, could not be answered.

4.3.5. Challenge 5: High demand for computational infrastructure and computational costs

Linking ABMs with CGE/PE models also presents computational challenges. ABMs need large computational resources due to large populations of heterogeneous agents (Lee et al., 2015). While high-performance computing (HPC) and parallel processing can speed up, these solutions may be limited (Grujić et al., 2022; Tang et al., 2011). CGE and PE models, which rely on solving systems of equations simultaneously to reach equilibrium, require numerous iterations to converge, that cannot be parallelized (Burfisher, 2021). Challenges relating to high computational costs were reported in ARULUNZ (see Supplementary Material B.2).

Beyond computational demands, the infrastructure for linking these models introduces risks of error due to the volume and complexity of data exchanged between them. Similar outputs potentially cause model

inconsistencies when calculated differently (see section 4.3.1.). The workshop participants concluded that these differences can be subtle and difficult to detect, yet they may significantly impact the robustness of integrated results.

Furthermore, input data often originates from diverse sources with varying definitions, aggregation levels, and temporal or spatial resolutions (Belete et al., 2019). Delzeit et al. (2020) provide an extensive analysis of the resulting inconsistencies. In some cases, the required data may not exist in adequate quality or resolution for either model, further complicating the process of linking (see section 4.3.2.). The workload required for the technical implementation of an interface can be considerable, as demonstrated by the MINDstep project (see Supplementary Material C.2).

4.3.6. Challenge 6: Limited personnel and financial resources

During the workshop, it became clear that for an ABM-CGE/PE linking projects to be viable, they require adequate time, financial support, skilled personnel, and infrastructure. Although adequate resources might also be a solution, sufficient resources are not currently ensured by the funding schemes and employment procedures in academia. Different projects have demonstrated that this is a key limiting factor in the development of the linked model, for example in MINDSTEP and AGRICORE (see Supplementary Material C.2 & C.3).

While contributing to such modeling projects offers substantial value to the broader research community, the individuals directly involved may not receive adequate recognition. It may even be a disadvantage as it may reduce their publication output, as noted by Bangerth and Heister (2014).

Sustaining model linking requires adequate funding and a long-term perspective, particularly as such efforts often receive limited academic recognition. Yet, financial support for the development, maintenance, and long-term operation of linked models remains scarce, as demonstrated by the existing CGE–ABM example (see Supplementary Material B.1) and the MINDSTEP project (see Supplementary Material C.2). Existing funding schemes usually prioritize model setup over the ongoing support and maintenance necessary for durable linkings.

While ABM codes are increasingly made available publicly, they are rarely maintained beyond initial release (Finger et al., 2024; Hasselbring et al., 2019). CGE model codes, on the other hand, are shared less frequently (exceptions are e.g., CGE Box, see Britz & van der Mensbrughe, 2018, or GTAP, see Corong et al., 2017). Yet, CGE models often enjoy a higher level of institutional and policy trust. Thus, the mere availability of model code does not automatically lead to greater trust or uptake.

A shortage of expertise can also limit the usability and uptake by other researchers (see Anzt et al., 2020), as knowledge on creating, maintaining, and supporting linked models is often limited to a single person or a small group (see example in Supplementary Material B.2).

Finally, the supporting infrastructure constitutes an additional layer of complexity. Collaboration between institutions can be challenging due to legal constraints, bureaucratic processes, and traditional funding and budgeting in academia, which may result in a lack of cross-organizational infrastructure. Additionally, cloud infrastructure providers and their pricing models may not align with current academic funding frameworks due to compliance issues (Anzt et al. 2020).

5. Discussion: A roadmap to advance ABM-CGE/PE linking efforts

The identified challenges presented areas for action to facilitate the linking of models and ensure their value for assessing policy impacts. After the workshop, we developed a roadmap outlining the steps required to advance efforts in linking ABM-CGE/PE models that would allow for effective and robust policy recommendations.

The roadmap involves several key actor groups, including the respective scientific communities, modelers from both concepts, funding agencies, and stakeholders who utilize model outputs, such as policymakers and public administrations. The main actions include: fostering communication between modeling communities e.g., through the establishment of an exchange platform; clearly demonstrating the benefits of model linking;

conducting model intercomparisons; developing standardized documentation; and enhancing collaboration with policy stakeholders in defining research questions and communicating results as well as funding agencies for a long-term establishment of resources. Our roadmap (see Figure 2) integrates these actions into four sequential steps, prerequisites, preparation, model actions, and results communication. In the following, these steps are discussed in more detail.

1. Prerequisites: Improving communication between different modeling communities is essential. Currently, only a few research groups have expertise in both model types. Therefore, exchanging knowledge and ideas on concepts, data generation, modeling platforms, and model documentation is vital. In particular, developing a common procedure for model validation represents an important prerequisite for successfully linking the two concepts. Moreover, substantial additional and systematic work is needed to improve the understanding of when linking is useful and how to build an appropriate basis for it. This can be achieved by modelers clearly demonstrating the benefits of model linking. Another important prerequisite is the expansion of evaluation criteria for scientific work, as advocated by the San Francisco Declaration on Research Assessment (SF DORA), which calls for a broader recognition of research outputs. Endorsed by numerous international funding organizations, the declaration encourages institutions to value contributions such as software, code, and datasets alongside peer-reviewed publications (see Anzt et al., 2020). Funding agencies can further support this by promoting and sustaining modeling environments over the long term. Moreover, integrating modeling education into university curricula could help to ensure well-equipped personnel.

2. Preparation: Model intercomparisons aimed at identifying parallels and differences in conceptualization represent an important preparatory step for linking the two modeling concepts. This process also involves defining which data is exchanged between models and how these data influence the receiving model, as illustrated by the BESTMAP example (see Supplementary Material C.1). Appropriate indicators are needed to assess which models are suitable for linking. For instance, an ABM should incorporate price dynamics to adequately respond to inputs from a CGE or PE model. Linking models can be particularly suitable when market equilibrium assumptions are empirically supported but transient dynamics are the primary focus.

In other cases, model simplification before linking them might be an alternative approach e.g., by using more aggregated information in the ABM. This could make the linking less prone to uncertainty and inconsistency, and require fewer resources. Ultimately, the specific contributions of each model type to addressing the research question must be clearly defined from the start to avoid costly misalignments that could reduce the benefits of model linking.

As data availability is one of the key issues, research on synthetic populations and upscaling or disaggregation mechanisms is needed to understand their potential and challenges. Uncertainty should be well understood as it affects how results are interpreted and how confidently they can be used for decision-making. Different types of uncertainty, such as uncertain data inputs, assumptions about behavior, and structural differences between the models, must be identified and assessed. Sensitivity analysis identifies which model components have the greatest impact on results to simplify models without sacrificing essential detail (Zadeh et al., 2017). For this process to be effective, the ABM and the CGE/PE models must adhere to the same standards for conducting sensitivity analysis. This could then form the basis for calibration of the models before linking.

It would also be important to establish a standard for model documentation, such as the ODD protocol for ABMs (Grimm et al., 2020), to facilitate model comparison exercises and ensure transparency of model assumptions (Belete et al., 2019). Such documentation should include the scope of each model, its design, the results of previous calibration efforts, and a detailed explanation of how the two models are linked (Grimm et al., 2014).

Finally, the development and reuse of a linked ABM-CGE/PE model will use more resources than a usual research call. Either some of the involved researchers need to have long-term contracts funded by e.g., a governmental research institute, or research tenders should be targeted for long term projects (one example is the Swiss SWEET program, which offers the opportunity to work on specific energy-related topics with long-term 8-year long research consortia). Additionally, international standards in funding bodies could ease the collaboration between researchers.

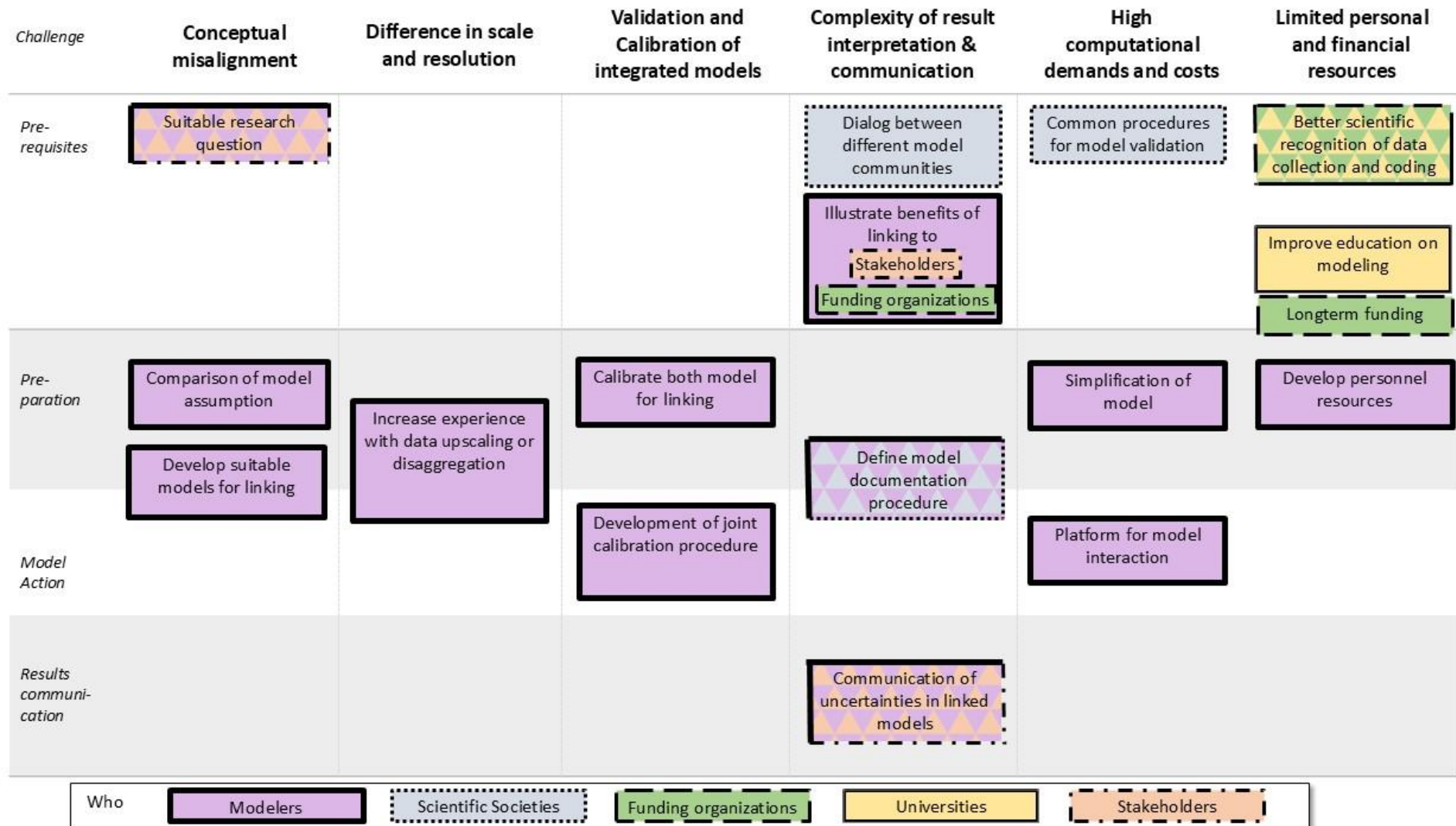


Figure 2: Different steps to overcome challenges for linking CGE/PE models with ABMs.

3. Model action: To choose the two models to be linked, it is important to consider the features, resolution, and extent of the models being linked, as some ABMs or CGE/PE models may be more suitable than others. For example, not all ABMs include price changes in decision-making, which is necessary for linking with CGE/PE models. Also, whether the more detailed PE model can be used as an intermediate model to link ABM with CGE needs to be evaluated. A forum could be constituted to facilitate and advance such discussion. With regards to scale, specialized CGE models with a finer resolution may be more suitable for linking with ABMs. Also, PE models might have a smaller, but more fitting extent facilitating the linking. All approaches come with additional cost regarding accuracy, data efforts, and computational power.

To establish a link, a common platform that coordinates the exchange between the two modeling concepts could be developed, along with joint calibration procedures. The platform could facilitate data exchange, documentation, and version control, while aligning structural, spatial and temporal model components. The platform could provide standardized application programming interface (API), common data formats, and tools for resolving discrepancies in aggregation, definitions, and resolution. It should also support high-performance computing to manage the computational demands of large-scale simulations. This will require efficient collaboration between modeling groups and experts from different fields (Horridge & Pearson, 2011; Kravari & Bassiliades, 2015). Taheripour et al. (2020) discuss solutions for maintaining physical balances in CGE models, including how to deal with land, while frameworks like Open Modelling Interface (OpenMI) or Modular Modelling System (MMS) offer partial solutions, adapting them to the specific needs of ABM-CGE/PE linking, such as maintaining agent-level detail and system-wide equilibrium. As highlighted by Horridge and Pearson (2011) and Kravari and Bassiliades (2015), interdisciplinary cooperation is key to building a consistent, scalable, and interpretable integration environment.

4. Results communication: In the last step, stakeholders should also contribute to the evaluation of the model (Heckbert et al., 2010). It is important to communicate model limitations, as linked ABM-CGE/PE models could be considered overly potent. Stakeholders should be integrated into all modeling steps and informed about the uncertainties associated with model parameters. In addition, researchers should lobby for unified data protection laws for research purposes to allow access to better data and to clarify the situation about the use of Farm Accountancy Data Network (FADN) and census data for generating synthetic populations (Wimmer & Finger, 2023).

6. Conclusion

Linking CGE/PE models with ABMs can be valuable in assessing land-use-related, complex impacts of global developments such as climate change, biodiversity loss, or new trade regimes. The linking may enhance the assessment toolbox for the analysis of cross-scale impacts from global market feedback, the equity implications of policies, and the dynamics of land-use transitions.

We outline six interrelated challenges for linking CGE/PE models with ABMs to improve policy impact models concerning land use. Linking the two model types requires long-term collaboration among various experts, adherence to common model documentation standards, and clearly formulated research questions that enable the targeted development towards a beneficial model linking exercise. These activities require an intensive exchange between the two model communities to foster a common understanding of the different concepts.

Effective collaboration requires a clear understanding of the uncertainties inherent in the models involved, as well as the development of common procedures to address the propagation of uncertainty. Additionally, resources must be aligned to enable model linking and enable the setup of a platform that provides the necessary transparency for developing models, model links, and communication of model results. Conceptual alignment, or the development of conceptually sound interfaces, seems crucial to advancing the benefits of linking ABM with CGE/PE models.

Research on upscaling of regional results and the generation and implications of synthetic agent populations deserves close attention to be put in use for model linking. In addition, model intercomparisons based on suitable indicators can facilitate the identification of relevant models for linking purposes. For an appropriate development of human resources in model linking, sufficient long-term funding and career paths for scientists involved in model development, that do not solely focus on peer-reviewed publications, are needed. Modelers should advocate for more sensible and unified data protection laws to support the integration and repeated use of existing data in complex modelling exercises.

In conclusion, extensive research and development is still required to render the linking of ABMs and CGE/PE models more feasible and beneficial. If targeted and well done this linking may contribute to more thoroughly and effectively evaluating policy impacts in the context of global and local land-use change.

Acknowledgements

Authors are thankful for the funding provided by the European Union's Horizon 2020 research and innovation program under grant agreement No 817501 (BESTMAP). TF is thankful for the support of the European Research Council under the European Union's Horizon 2020 Research and Innovation Program (grant Agreement No. 758014), FA and TH are thankful for the support of the European Research Council under the European Union's Horizon 2020 Research and Innovation Program (grant Agreement No. 817566, Mindstep) and AK, FA and LB are thankful for European Research Council under the European Union's Horizon 2020 Research and Innovation Program (grant Agreement No. 816078, Agricore). We thank Alfons Balmann, Alexander Gocht, John Helming, Abdelradi Mohammed, Sebastian Rasch, Franziska Schünemann and Guy Ziv for their contribution to the workshop and previous versions of the paper. We thank four anonymous reviewers for their time and effort that provided us with helpful comments and suggestions for this manuscript.

Supplementary Material

The Supplementary Material can be found online at: <https://sesmo.org/article/view/18872/18442>.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Deepl and ChatGPT to improve language and style. After using this tool/service, the authors reviewed the content and take full responsibility for the content of the publication.

References

- Akgul, Z., Villoria, N., & Hertel, T. (2016). GTAP-HET: Introducing Firm Heterogeneity into the GTAP Model. *Journal of Global Economic Analysis*, 1(1), 111–180. <https://doi.org/10.21642/JGEA.010102AF>
- An, L., Grimm, V., Bai, Y., Sullivan, A., Turner II, B. L., Malleson, N., Heppenstall, A., Vincenot, C., Robinson, D., Ye, X., Liu, J., Lindkvist E., & Tang, W. (2023). Modeling agent decision and behavior in the light of data science and artificial intelligence. *Environmental Modelling & Software*, 166, 105713. <https://doi.org/10.1016/j.envsoft.2023.105713>
- Anzt, H., Bach, F., Druskat, S., Löffler, F., Loewe, A., Renard, B. Y., Seemann, G., Struck, A., Achhammer, E., Aggarwal, P., Appel, F., Bader, M., Bruschi, L., Busse, C., Chourdakis, G., Dabrowski, P. W., Ebert, P., Flemisch, B., Friedl, S., . . . Weeber, R. (2020). An Environment for Sustainable Research Software in Germany and Beyond: Current State, Open Challenges, and Call for Action. *F1000Research*, 9, 295–295. <https://doi.org/10.12688/f1000research.23224.2>
- Appel, F., & Balmann, A. (2019). Human behaviour versus optimising agents and the resilience of farms-Insights from agent-based participatory experiments with FarmAgriPoliS. *Ecological Complexity*, 40, Part B, Article 100731. <https://doi.org/10.1016/j.ecocom.2018.08.005>
- Argueyrolles, R. (2025). Market power and fossil fuel subsidy reforms: Who should lead the call for change?. *Journal of Policy Modeling*, 47(1). <https://doi.org/10.1016/j.jpolmod.2025.07.007>
- Argueyrolles, R., Heimann, T., Delzeit, D. (2025). Impact of Gasoline and Diesel Subsidy Reforms on Global Biofuel Mandates. *GCB Bioenergy*, 17(1). <https://doi.org/10.1111/gcbb.70019>
- Arneth, A., Brown, C. & Rounsevell, M. D. A. (2014). Global Models of Human Decision-Making for Land-Based Mitigation and Adaptation Assessment. *Nature Climate Change*, 4, 550–557. <https://doi.org/10.1038/NCLIMATE2250>
- Axtell, R. L., & Doyne Farmer, J. (2025). Agent-based modeling in economics and finance: Past, present, and future. *Journal of Economic Literature*, 63(1), 197–287. <https://doi.org/10.1257/jel.20221319>
- Babatunde, K. A., Begum, R. A., & Said, F. F. (2017). Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review. *Renewable and Sustainable Energy Reviews*, 78, 61–71. <https://doi.org/10.1016/j.rser.2017.04.064>
- Bangerth, W., & Heister, T. (2014). Quo vadis, scientific software. *SIAM News*, 47(1), 8. <https://www.math.colostate.edu/~bangerth/publications/2014-siam-news.pdf>
- Barreiro-Hurle, J., Fellmann, T., & M'barek, R. (2024). Modelling in Support of Better Agricultural and Food Policies: the JRC's Integrated Agro-economic Modelling platform (iMAP). *EuroChoices*, 23(1), 43–53. <https://doi.org/10.1111/1746-692X.12421>

- Belete, G. F., Voinov, A., Arto, I., Dhavala, K., Bulavskaya, T., Niamir, L., Moghayer, S. & Filatova, T. (2019). Exploring Low-Carbon Futures: A Web Service Approach to Linking Diverse Climate-Energy-Economy Models. *Energies*, 12(15), Article 2880. <https://doi.org/10.3390/en12152880>
- Berger, T., & Troost, C. (2014). Agent-based Modelling of Climate Adaptation and Mitigation Options in Agriculture. *Journal of Agricultural Economics*, 65(2), 323–348. <https://doi.org/10.1111/1477-9552.12045>
- Boulanger, P., Dudu, H., Ferrari, E., Mainar-Causapé, A. J., & Ramos, M. P. (2022). Effectiveness of Fertilizer Policy Reforms to Enhance Food Security in Kenya: A Macro-Micro Simulation Analysis. *Applied Economics*, 54(8), 841–861. <https://doi.org/10.1080/00036846.2020.1808180>
- Britz, W., & Hertel, T. W. (2011). Impacts of EU Biofuels Directives on Global Markets and EU Environmental Quality: An Integrated PE, Global CGE Analysis. *Agriculture, Ecosystems & Environment*, 142(1-2), 102–109. <https://doi.org/10.1016/j.agee.2009.11.003>
- Britz, W., & van der Mensbrugge, D. (2018). CGEBox: A flexible, modular and extendable framework for CGE analysis in GAMS. *Journal of Global Economic Analysis*, 3(2), 106–177. <https://doi.org/10.21642/JGEA.030203AF>
- Brown, C, Seo, B., & Rounsevell, M (2019). Societal breakdown as an emergent property of large-scale behavioural models of land use change. *Earth System Dynamics*, 10(4), 809–845. <https://doi.org/10.5194/esd-10-809-2019>
- Brown, C., Brown, K., & Rounsevell, M. (2016). A Philosophical Case for Process-Based Modelling of Land Use Change. *Modeling Earth Systems and Environment*, 2(50), 1–12. <https://doi.org/10.1007/s40808-016-0102-1>
- Burfisher, M. E. (2021). Introduction to computable general equilibrium models. Cambridge University Press. <https://doi.org/10.1017/CBO9780511975004>
- Calzadilla, A., Delzeit, R., & Klepper, G. (2014). DART-BIO: Modelling the Interplay of Food, Feed and Fuels in a Global CGE Model. Kiel Working Paper, Article 1896. <https://www.ifw-kiel.de/fileadmin/Dateiverwaltung/IfW-Publications/fis-import/3df55738-5c59-4a9c-905f-2bfccb2c78b5-KWP1896.pdf>
- Calzadilla, A., Rehdanz, K., Betts, R., Falloon, P., Wiltshire, A., & Tol, R. (2010). Climate Change Impacts on Global Agriculture. Kiel Working Paper, Article 1617. <https://www.ifw-kiel.de/fileadmin/Dateiverwaltung/IfW-Publications/fis-import/a90d19fb-bb4f-4ae4-8a8e-46819aa1d7c5-CalzadillaKIEL1617.pdf>
- Campagnolo, L., & De Cian, E. (2022). Distributional Consequences of Climate Change Impacts on Residential Energy Demand across Italian Households. *Energy Economics*, 110, Article 106020. <https://doi.org/10.1016/j.eneco.2022.106020>
- Coronese, M., Occelli, M., Lamperti, F., & Roventini, A. (2023). AgriLOVE: Agriculture, land-use and technical change in an evolutionary, agent-based model. *Ecological Economics*, 208, Article 107756. <https://doi.org/10.1016/j.ecolecon.2023.107756>
- Corong, E. L., Hertel, T. W., McDougall, R., Tsigas, M. E., & Van Der Mensbrugge, D. (2017). The standard GTAP model, version 7. *Journal of Global Economic Analysis*, 2(1), 1–119. <https://doi.org/10.21642/JGEA.020101AF>
- Delzeit, R., Beach, R., Bibas, R., Britz, W., Chateau, J., Freund, F., Lefevre, J., Schuenemann, F., Sulser, T., Valin, H., Ruijven, B. van, Weitzel, M., Willenbockel, D., & Wojtowicz, K. (2020). Linking Global CGE Models with Sectoral Models to Generate Baseline Scenarios: Approaches, Challenges, and Opportunities. *Journal of Global Economic Analysis*, 5(1), 162–195. <https://doi.org/10.21642/JGEA.050105AF>
- Dou, Y., Yao, G., Herzberger, A., Da Silva, R., Song, Q., Hovis, C., Batistella, M., Moran, E., Wu, W., & Liu, J. (2020). Land-Use Changes in Distant Places: Implementation of a Telecoupled Agent-Based Model. *Journal of Artificial Societies and Social Simulation*, 23(1), Article 11. <https://doi.org/10.18564/jasss.4211>
- Dressler, G., Groeneveld, J., Hetzer, J., Janischewski, A., Nolzen, H, Rödig, E., Schwarz, N., Taubert, F., Thober, J., Will, M., Williams, T., Wirth, S. B., & Müller, B. (2022). Upscaling in Socio-Environmental Systems Modelling: Current Challenges, Promising Strategies and Insights from Ecology. *Socio-Environmental Systems Modelling*, 4, Article 18112. <https://doi.org/10.18174/sesmo.18112>
- European Commission. (2018). Analytical tools and models to support policies related to agriculture and food. https://cordis.europa.eu/programme/id/H2020_RUR-04-2018-2019/de
- Farmer, J. D., & Foley, D. (2009). The Economy Needs Agent-Based Modelling. *Nature*, 460, 685–686. <https://doi.org/10.1038/460685a>
- Finger, R. (2024). Europe’s ambitious pesticide policy and its impact on agriculture and food systems. *Agricultural Economics*, 55(2), 265–269. <https://doi.org/10.1111/agec.12817>
- Finger, R., Henningsen, A., Höhler, J., Huber, R., Rommel, J., & Grebitus, C. (2024). Open science in agricultural economics. *Q Open*, 5(3), Article qoae029. <https://doi.org/10.1093/qopen/qoae029>
- Filatova, T., J. Akkerman, F. Bosello, T. Chatzivasileiadis, I. Cortés Arbués, A. Ghorbani, O. Ivanova, N. Knittel, J. Kwakkel, F. Lamperti, N.R. Magliocca, G. Marangoni, S. Nabernegg, A. Pichler, A. Poujon, K. Safarzyńska, A. Taberna, M.A.E. van Sluisveld, L. Verbeek, & T. Wei. (2024). The power of bridging decision scales: Model coupling for advanced climate policy analysis. *Proc. Natl. Acad. Sci. U.S.A.* 122 (38) e2411592122, <https://doi.org/10.1073/pnas.2411592122>
- Fournier Gabela, J. G., Spiegel, A., Stepanyan, D., Freund, F., Banse, M., Gocht, A., Söder, M., Heidecke, C., Osterburg, B., & Matthews, A. (2024). Carbon leakage in agriculture: when can a carbon border adjustment mechanism help? *Climate Policy*, 24(10), 1410–1425. <https://doi.org/10.1080/14693062.2024.2387237>
- Ge, J., Polhill, J. G., Macdiarmid, J. I., Fitton, N., Smith, P., Clark, H., Dawson, T., & Aphale, M. (2021). Food and nutrition security under global trade: a relation-driven agent-based global trade model. *Royal Society Open Science*, 8(1), Article 201587. <https://doi.org/10.1098/rsos.201587>
- Ghaith, Z., Kulshreshtha, S., Natcher, D., & Cameron, B. (2021). Regional Computable General Equilibrium Models: A Review. *Journal of Policy Modeling*, 43(3), 710–724. <https://doi.org/10.1016/j.jpmod.2021.03.005>

- Giesecke, J. A., & Madden, J. R. (2013). Chapter 7 - Regional Computable General Equilibrium Modeling. *Handbook of Computable General Equilibrium Modeling*, 1, 379–475. <https://doi.org/10.1016/B978-0-444-59568-3.00007-9>
- Gocht, A., Britz, W., Ciaian, P., & Paloma, S. G. y. (2013). Farm type effects of an EU-wide direct payment harmonisation. *Journal of Agricultural Economics*, 64(1), 1–32. <https://doi.org/10.1111/1477-9552.12005>
- Gocht, A., Ciaian, P., Bielza, M., Terres, J.-M., Röder, N., Himics, M., & Salputra, G. (2017). EU-wide economic and environmental impacts of CAP greening with high spatial and farm-type detail. *Journal of Agricultural Economics*, 68(3), 651–681. <https://doi.org/10.1111/1477-9552.12217>
- Gocht, A., & Witzke, H. P. (2023). P. CAPRI Modelling system. <https://capri-model.org/>
- Grêt-Regamey, A., Huber, S. H., & Huber, R. (2019). Actors' diversity and the resilience of social-ecological systems to global change. *Nature Sustainability*, 2, 290–297. <https://doi.org/10.1038/s41893-019-0236-z>
- Groeneveld, J., Müller, B., Buchmann, C. M., Dressler, G., Guo, C., Hase, N., ... & Schwarz, N. (2017). Theoretical foundations of human decision-making in agent-based land use models—A review. *Environmental modelling & software*, 87, 39–48. <https://doi.org/10.1016/j.envsoft.2016.10.008>
- Grimm, V., Johnston, A., Thulke, H. H., Forbes, V. E., & Thorbek, P. (2020). Three Questions to Ask Before Using Model Outputs for Decision Support. *Nature Communications*, 11, Article 4959. <https://doi.org/10.1038/s41467-020-17785-2>
- Grimm, V., Augusiak, J., Focks, A., Frank, B. M., Gabsi, F., Johnston, A. S. A., Liu, C., Martin, B. T., Meli, M., Radchuk, V., Thorbek, P., & Railsback, S. F. (2014). Towards better modelling and decision support: Documenting model development, testing, and analysis using TRACE. *Ecological modelling*, 280, 129–139. <https://doi.org/10.1016/j.ecolmodel.2014.01.018>
- Grujić, N., Brdar, S., Osinga, S., Hofstede, G. J., Athanasiadis, I. N., Pljakić, M., Obrenović, N., Govedarica, M., & Crnojević, V. (2022). Combining Telecom Data with Heterogeneous Data Sources for Traffic and Emission Assessments—An Agent-Based Approach. *ISPRS Int. J. Geo-Inf.*, 11(7), Article 366. <https://doi.org/10.3390/ijgi11070366>
- Happe, K., Kellermann, K., & Balmann, A. (2006). Agent-based Analysis of Agricultural Policies: An Illustration of the Agricultural Policy Simulator AgriPoliS, Its Adaptation and Behavior. *Ecology and Society*, 11(1), Article 49. <https://doi.org/10.5751/ES-01741-110149>
- Hasselbring, W., Carr, L., Hettrick, S., Packer, H., & Tiropanis, T. (2019). FAIR and Open Computer Science Research Software. *ArXiv*, Article 908.05986. <https://doi.org/10.48550/arXiv.1908.05986>
- Heckbert, S., Baynes, T., & Reeson, A. (2010). Agent-based modeling in ecological economics. *Annals of the New York Academy of Sciences*, 1185(1), 39–53. <https://doi.org/10.1111/j.1749-6632.2009.05286.x>
- Helbing, D. (2012). Agent-based modeling. In *Social self-organization: Agent-based simulations and experiments to study emergent social behavior* (pp. 25–70). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Heimann, T., Argueyrolles, R., Reinhardt, M., Delzeit, R. (2023). Phasing out palm and soy oil biodiesel in the EU: What is the benefit?. *GCB Bioenergy*, 16(1). <https://doi.org/10.1111/gcbb.13115>
- Horridge, M., & Pearson, K. (2011). Solution software for CGE modeling. *Centre of Policy Studies*, Article G-214. <https://vuir.vu.edu.au/38903/1/g-214.pdf>
- Huber, R., Bakker, M., Balmann, A., Berger, T., Bithell, M., Brown, C., Grêt-Regamey, A., Xiong, H., Le, Q. B., Mack, G., Meyfroidt, P., Millington, J., Müller, B., Polhill, J. G., Sun, Z., Seidl, R., Troost, C., & Finger, R. (2018). Representation of Decision-Making in European Agricultural Agent-Based Models. *Agricultural Systems*, 167, 143–160. <https://doi.org/10.1016/j.agsy.2018.09.007>
- Huber, R., Xiong, H., Keller, K., & Finger, R. (2022). Bridging behavioural factors and standard bio-economic modelling in an agent-based modelling framework. *Journal of Agricultural Economics*, 73(1), 35–63. <https://doi.org/10.1111/1477-9552.12447>
- Husby, T. G., & Koks, E. E. (2017). Household Migration in Disaster Impact Analysis: Incorporating Behavioural Responses to Risk. *Natural Hazards*, 87(1), 287–305. <https://doi.org/10.1007/s11069-017-2763-0>
- Jafari, T., & Britz, W. (2018). Modelling Heterogeneous Firms and Non-Tariff Measures in Free Trade Agreements using Computable General Equilibrium. *Economic Modelling*, 73, 279–294. <https://doi.org/10.1016/j.econmod.2018.04.004>
- Jafari, Y., & Othman, J. (2016). Impact of biofuel development on Malaysian agriculture: A comparative statics, multicommodity, multistage production, partial equilibrium approach. *Food and Energy Security*, 5(3), 192–202. <https://doi.org/10.1002/fes3.84>
- Jansson, T., Malmström, N., Johansson, H., & Choi, H. (2023). Carbon taxes and agriculture: the benefit of a multilateral agreement. *Climate Policy*, 24(1), 13–25. <https://doi.org/10.1080/14693062.2023.2171355>
- Kelly, R. A., Jakeman, A. J., Barretheau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., Henriksen, H. J., Kuikka, S., Maier, H. R., Rizzoli, A. E., van Delden, H., & Voinov, A. A. (2013). Selecting Among Five Common Modelling Approaches for Integrated Environmental Assessment and Management. *Environmental Modelling & Software*, 47, 159–181. <https://doi.org/10.1016/j.envsoft.2013.05.005>
- Klein, F., van Bergh, J. den, Foramitti, J., & Konc, T. (2025). Agentizing a General Equilibrium Model of Environmental Tax Reform. *Environmental and Resource Economics*, 88(2), 459–502. <https://doi.org/10.1007/s10640-024-00937-z>
- Kravari, K., & Bassiliades, N. (2015). A survey of agent platforms. *Journal of Artificial Societies and Social Simulation*, 18(1), Article 11. <https://doi.org/10.18564/jasss.2661>
- Kreft, C., Finger, R., & Huber, R. (2023). Action-versus results-based policy designs for agricultural climate change mitigation. *Applied Economic Perspectives and Policy*. 46(3), 1010–1037. <https://doi.org/10.1002/aep.13376>

- Kremmydas, D., Athanasiadis, I. N., & Rozakis, S. (2018). A review of agent based modeling for agricultural policy evaluation. *Agricultural systems*, 164, 95-106. <https://doi.org/10.1016/j.agsy.2018.03.010>
- Krook-Riekkola, A., Berg, C., Ahlgren, E. O., & Söderholm, P. (2017). Challenges in top-down and bottom-up soft-linking: Lessons from linking a Swedish energy system model with a CGE model. *Energy*, 141, 803–817. <https://doi.org/10.1016/j.energy.2017.09.107>
- Lee, H., Lee, J., & Koo, Y. (2022). Economic Impacts of Carbon Capture and Storage on the Steel Industry – A Hybrid Energy System Model Incorporating Technological Change. *Applied Energy*, 317, Article 119208. <https://doi.org/10.1016/j.apenergy.2022.119208>
- Lee, J. S., Filatova, T., Ligmann-Zielinska, A., Hassani-Mahmoei, B., Stonedahl, F., Lorscheid, I., Voinov, A., Pollhill, G., Sun, Z., Parker, C. P. (2015). The Complexities of Agent-Based Modeling Output Analysis. *Journal of Artificial Societies and Social Simulation*, 18(4). <https://doi.org/10.18564/JASSS.2897>
- Li, F., Li, Z., Chen, H., Chen, Z., & Li, M. (2020). An agent-based learning-embedded model (ABM-learning) for urban land use planning: A case study of residential land growth simulation in Shenzhen, China. *Land Use Policy*, 95(C), 104620. <https://ideas.repec.org//a/eee/lausp/v95y2020ics0264837719303254.html>
- Lippe, M., Bithell, M., Gotts, N., Natalini, D., Barbrook-Johnson, P., Giupponi, C., Hallier, M., Hofstede, G. J., Le Page, C., Matthews, R. B., Schlüter, M., Smith, P., Teglio, A., & Thellmann, K. (2019). Using agent-based modelling to simulate social-ecological systems across scales. *Geoinformatica*, 23(2), 269–298. <https://doi.org/10.1007/s10707-018-00337-8>
- Liu, D., Zheng, X., & Wang, H. (2020). Land-use Simulation and Decision-Support System (LandSDS): Seamlessly Integrating System Dynamics, Agent-Based Model, and Cellular Automata. *Ecological Modelling*, 417, Article 108924. <https://doi.org/10.1016/j.ecolmodel.2019.108924>
- Magliocca, N., Safirova, E., McConnell, V., & Walls, M. (2011). An economic agent-based model of coupled housing and land markets (CHALMS). *Computers, Environment and Urban Systems*, 35(3), 183-191. <https://doi.org/10.1016/j.compenvurbsys.2011.01.002>
- Meuwissen, M. P. M., Feindt, P. H., Spiegel, A., Termeer, C. J. A. M., Mathijs, E., Mey, Y. de, Finger, R., Balmann, A., Wauters, E., Urquhart, J., Vigani, M., Zawalińska, K., Herrera, H., Nicholas-Davies, P., Hansson, H., Paas, W., Slijper, T., Coopmans, I., Vroege, W., ... Reidsma, P. (2019). A framework to assess the resilience of farming systems. *Agricultural Systems*, 176, Article 102656. <https://doi.org/10.1016/j.agsy.2019.102656>
- Michetti, M. (2012). Modelling land use, land-use change, and forestry in climate change: A review of major approaches. FEEM Working Paper, Article 46.2012. <http://dx.doi.org/10.2139/ssrn.2122298>
- Millington, J. D., Katerinchuk, V., da Silva, R. F. B., de Castro Victoria, D., & Batistella, M. (2021). Modelling drivers of Brazilian agricultural change in a telecoupled world. *Environmental Modelling & Software*, 139, Article 105024. <https://doi.org/10.1016/j.envsoft.2021.105024>
- Millington, J., Xiong, H., Peterson, S., & Woods, J. (2017). Integrating modelling approaches for understanding telecoupling: Global food trade and local land use. *Land*, 6(3), 56. <https://doi.org/10.3390/land6030056>
- Moallemi, E. A., Castonguay, A. C., Mason-D’Croz, D., Nelson, R., Britz, W., Allen, C., Hadjikakou, M., Battaglia, M., Bryan, A.B., Conti, C., Marcos-Martinez, R., Frank, S. Nong, D., Eker, S., Razavi, S., Navarro-Garcia, J. & Gao, L. (2025). Complexity and uncertainty in future food system transformation modelling. *Nature Food*, 1-12. <https://doi.org/10.1038/s43016-025-01257-1>
- Möhring, A., Mack, G., Zimmermann, A., Ferjani, A., Schmidt, A., & Mann, S. (2016). Agent-Based Modeling on a National Scale-Experience from SWISSland. *Agroscope Science*, 30, 1–56. www.swissland.org
- Moore, F., Baldos, U. L. C., & Hertel, T. (2017). Economic Impacts of Climate Change on Agriculture: A Comparison of Process-based and Statistical Yield Models. *Environmental Research Letters*, 12(6), Article 65008. <https://doi.org/10.1088/1748-9326/aa6eb2>
- Morgan, F. J., & Daigneault, A. J. (2015). Estimating impacts of climate change policy on land use: An agent-based modelling approach. *PLoS One*, 10(5), Article e0127317. <https://doi.org/10.1371/journal.pone.0127317>
- Müller, B., Balbi, S., Buchmann, C. M., Sousa, L. de, Dressler, G., Groeneveld, J., Klassert, C. J., Le, Q. B., Millington, J., Nolzen, H., Parker, D. C., Polhill, J. G., Schlüter, M., Schulze, J., Schwarz, N., Sun, Z., Taillandier, P., & Weise, H. (2014). Standardised and Transparent Model Descriptions for Agent-Based Models: Current Status and Prospects. *Environmental Modelling & Software*, 55, 156–163. <https://doi.org/10.1016/j.envsoft.2014.01.029>
- Müller, B., Hoffmann, F., Heckelei, T., Müller, C., Hertel, T. W., Polhill, J. G., Wijk, M. van, Achterbosch, T., Alexander, P., Brown, C., Kreuer, D., Ewert, F., Ge, J., Millington, J. D. A., Seppelt, R., Verburg, P. H., & Webber, H. (2020). Modelling Food Security: Bridging the Gap between the Micro and the Macro Scale. *Global Environmental Change*, 63, Article 102085. <https://doi.org/10.1016/j.gloenvcha.2020.102085>
- Niamir, L., Ivanova, O., & Filatova, T. (2020). Economy-wide Impacts of Behavioral Climate Change Mitigation: Linking Agent-based and Computable General Equilibrium Models. *Environmental Modelling & Software*, 134, Article 104839. <https://doi.org/10.1016/j.envsoft.2020.104839>
- Nilsson, L., Clough, Y., Smith, H. G., Olsson, J. A., Brady, M. V., Hristov, J., Olsson, P., Skantze, K., Ståhlberg, D., & Dä nhardt, J. (2019). A suboptimal array of options erodes the value of CAP ecological focus areas. *Land Use Policy*, 85, 407–418. <https://doi.org/10.1016/j.landusepol.2019.04.005>
- Nolan, J., Parker, D., Van Kooten, G. C., & Berger, T. (2009). An overview of computational modeling in agricultural and resource economics. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroéconomie*, 57(4), 417-429. HYPERLINK "<https://doi.org/10.1111/j.1744-7976.2009.01163.x>"<https://doi.org/10.1111/j.1744-7976.2009.01163.x>

- Nowak, S. A., Matthews, L. J., & Parker, A. M. (2017). A general agent-based model of social learning. RAND Corporation. https://www.rand.org/pubs/research_reports/RR1768.html
- Oita, A., Malik, A., Kanemoto, K., Geschke, A., Nishijima, S., & Lenzen, M. (2016). Substantial nitrogen pollution embedded in international trade. *Nature Geoscience*, 9(2), 111–115. <https://doi.org/10.1038/NGEO2635>
- Pahmeyer, C., Schäfer, D., Kuhn, T., & Britz, W. (2021). Data on a Synthetic Farm Population of the German Federal State of North Rhine-Westphalia. Data in Brief, 36, Article 107007. <https://doi.org/10.1016/j.dib.2021.107007>
- Philippidis, G., Sartori, M., Ferrari, E., & M'Barek, R. (2019). Waste not, want not: A bio-economic impact assessment of household food waste reductions in the EU. *Resources, Conservation & Recycling*, 146, 514–522. <https://doi.org/10.1016/j.resconrec.2019.04.016>
- Pitson, C., Bijttebier, J., Appel, F., & Balmann, A. (2020). How Much Farm Succession is Needed to Ensure Resilience of Farming Systems? *EuroChoices*, 19(2), 37–44. <https://doi.org/10.1111/1746-692X.12283>
- Robinson, D. T., Di Vittorio, A., Alexander, P., Arneith, A., Barton, C. M., Brown, D. G., Kettner, A., Lemmen, C., O'Neill, B. C., Janssen, M., Pugh, T. A. M., Rabin, S. S., Rounsevell, M., Syvitski, J. P., Ullah, I., & Verburg, P. H. (2018). Modelling Feedbacks between Human and Natural Processes in the Land System. *Earth System Dynamics*, 9(2), 895–914. <https://doi.org/10.5194/esd-9-895-2018>
- Rounsevell, M. D. A., Robinson, D. T., & Murray-Rust, D. (2012). From Actors to Agents in Socio-ecological Systems Models. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 367(1586), 259–269. <https://doi.org/10.1098/rstb.2011.0187>
- Schmidt, A., Necpalova, M., Mack, G., Möhring, A., & Six, J. (2021). A Food Tax Only Minimally Reduces the N Surplus of Swiss Agriculture. *Agricultural Systems*, 194, Article 103271. <https://doi.org/10.1016/j.agsy.2021.103271>
- Stepanyan, D., Heidecke, C., Osterburg, B., & Gocht, A. (2023). Impacts of national vs European carbon pricing on agriculture. *Environmental Research Letters*, 18(7), Article 74016. <https://doi.org/10.1088/1748-9326/acdcac>
- Taheripour, F., Zhao, X., Horridge, M., Farrokhi, F., & Tyner, W. (2020). Land Use in Computable General Equilibrium Models. *Journal of Global Economic Analysis*, 5(2), 63–109. <https://doi.org/10.21642/JGEA.050202AF>
- Tang, W., Bennett, D. A., & Wang, S. (2011). A parallel agent-based model of land use opinions. *Journal of Land Use Science*, 6(2-3), 121–135. <https://doi.org/10.1080/1747423X.2011.558597>
- Troost, C., Huber, R., Bell, A. R., van Delden, H., Filatova, T., Le, Q. B., Lippe, M., Niamir, L., Polhill, J. G., Sun, Z., & Berger, T. (2023). How to Keep it Adequate: A Protocol for Ensuring Validity in Agent-Based Simulation. *Environmental Modelling & Software*, 159, Article 105559. <https://doi.org/10.1016/j.envsoft.2022.105559>
- Uthes, S., & Kiesel, J. (2020). Creating a synthetic landscape: Spatial allocation of non-spatial single farm data. *Agricultural Systems*, 177, Article 102740. <https://doi.org/10.1016/j.agsy.2019.102740>
- Uusitalo, L., Lehikoinen, A., Helle, I., & Myrberg, K. (2015). An overview of methods to evaluate uncertainty of deterministic models in decision support. *Environmental Modelling & Software*, 63, 24–31. <https://doi.org/10.1016/j.envsoft.2014.09.017>
- van Duinen, R., Filatova, T., Jager, W., & van der Veen, A. (2016). Going Beyond Perfect Rationality: Drought Risk, Economic Choices and the Influence of Social Networks. *Annals of Regional Science*, 57, 335–369. <https://doi.org/10.1007/s00168-015-0699-4>
- Voinov, A., & Shugart, H. H. (2013). 'Integronsters', Integral and Integrated Modeling. *Environmental Modelling & Software*, 39, 149–158. <https://doi.org/10.1016/j.envsoft.2012.05.014>
- Voinov, A., & Bousquet, F. (2010). Modelling with stakeholders. *Environmental Modelling & Software*, 25(11), 1268–1281. <https://doi.org/10.1016/j.envsoft.2010.03.007>
- Warmink, J. J., Janssen, J., Booij, M. J., & Krol, M. S. (2010). Identification and classification of uncertainties in the application of environmental models. *Environmental Modelling & Software*, 25(12), 1518–1527. <https://doi.org/10.1016/j.envsoft.2010.04.011>
- Wimmer, S., & Finger, R. (2023). A note on synthetic data for replication purposes in agricultural economics. *Journal of Agricultural Economics*, 74(1), 316–323. <https://doi.org/10.1111/1477-9552.12505>
- Zabel, F., Delzeit, R., Schneider, J., Seppelt, R., Mauser, W., & Václavík, T. (2019). Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity. *Nature Communications*, 10, Article 2844. <https://doi.org/10.1038/s41467-019-10775-z>
- Zadeh, F. K., Nossent, J., Sarrazin, F., Pianosi, F., van Griensven, A., Wagener, T., & Bauwens, W. (2017). Comparison of variance-based and moment-independent global sensitivity analysis approaches by application to the SWAT model. *Environmental Modelling & Software*, 91, 210–222. <https://doi.org/10.1016/j.envsoft.2017.02.001>
- Zhang, J., & Robinson, D. T. (2021). Replication of an Agent-Based Model Using the Replication Standard. *Environmental Modelling & Software*, 139, Article 105016. <https://doi.org/10.1016/j.envsoft.2021.105016>
- Zhang, Q., Zhang, X., Cui, Q., Cao, W., He, L., Zhou, Y., Li, X., & Fan, Y. (2022). The Unequal Effect of the COVID-19 Pandemic on the Labour Market and Income Inequality in China: A Multisectoral CGE Model Analysis Coupled with a Micro-Simulation Approach. *International Journal of Environmental Research and Public Health*, 19(3), Article 1320. <https://doi.org/10.3390/ijerph19031320>