BESTMAP
BEHAVIOURAL, ECOLOGICAL & SOCIO-ECONOMIC TOOLS FOR MODELLING AGRICULTURAL POLICY

Integration guide for using common CGE/PE models with BESTMAP models

Deliverable D6.5

8th August 2022

Ruth Delzeit[1], Simone Markhof[1], Alena Schmidt[1]
Birgit Müller[2], Meike Will[2]
Chunhui Li[3], Jodi Gunning[3], Guy Ziv[3]

[1] University of Basel
[2] Helmholtz Centre for Environmental Research
[3] University of Leeds

BESTMAP

Behavioural, Ecological and Socio-economic Tools for Modelling Agricultural Policy

This project receives funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 817501.

Prepared under contract from the European Commission

Grant agreement No. 817501
EU Horizon 2020 Research and Innovation action

Project acronym:	**BESTMAP**
Project full title:	**Behavioural, Ecological and Socio-economic Tools for Modelling Agricultural Policy**
Start of the project:	September 2019
Duration:	48 months
Project coordinator:	Prof. Guy Ziv School of Geography, University of Leeds, UK http://bestmap.eu/
Deliverable title:	Integration guide for using common CGE/PE models with BESTMAP models
Deliverable n°:	D6.5
Nature of the Deliverable:	Report
Dissemination level:	Public
WP responsible:	WP6
Lead beneficiary:	UNIBAS
Citation:	Delzeit, R., Markoff, S., Schmidt, A., Müller, B., Will, M., Li, C., Gunning, J., Ziv, G. (2022). *Economic scenarios outputs based on policy workshops.* Deliverable 6.5, EU Horizon 2020 BESTMAP Project, Grant agreement No. 817501.
Due date of deliverable:	36
Actual submission date:	36

Deliverable status:

Version	Status	Date	Author(s)
1.0	Final	8th August 2022	Ruth Delzeit, Simone Markoff, Alena Schmidt, *University of Basel* Birgit Müller, Meike Will, *Helmholtz Centre for Environmental Research* Chunhui Li, Guy Ziv, Jodi Gunning, *University of Leeds*

Table of contents

Summary

This deliverable report provides an integration guide on how information gained in BESTMAP's agent-based model can be used in the standard economic model to improve the assessment of agricultural policies in the European Union. First, the models used in the BESTMAP are explained. The integration guide discusses in detail the preconditions and challenges when linking agent-based models with standard economic models such as partial and general equilibrium models. As a result of an expert workshop, six challenges are identified. The report also presents suggestions on how to make use of the finding and presents a way forward to integrate the two types of models.

1. Background

Land-use decisions are made at the local level but are driven by factors such as market prices of agricultural commodities which are influenced by global drivers including international energy or climate policies. Capturing the different spatial scales that influence decision-making and considering at the same time biophysical and socio-economic influence factors poses a challenge when modelling the impact of agricultural policies on land use (and subsequently on the provision of ecosystem services including biodiversity).

In the BESTMAP project, an alternative modelling framework has been developed to improve the state-of-the-art modelling of the impacts of agricultural policies on land use. Agricultural policies in the European Union (EU) consist of a mix of market-based instruments and voluntary schemes. While market-based instruments such as direct payments are well modelled in standard economic models, capturing the impact of voluntary schemes with modelling tools such as partial equilibrium (PE) or general equilibrium (CGE) models is a challenge. This challenge is relevant since in recent amendments to the EU's agricultural policy, voluntary schemes have gained more importance and therefore policy impact assessment is needed in this regard. A literature review on farmer's adoption of agri-environment schemes (AES) for case studies in the European Union by Ziv et al. (2022) shows that in addition to economic factors, socio-demographic factors such as land-ownership, education, age, farm size, farmers' belief and values, other policies and the social network play a role.

To address this challenge, this deliverable deals with the potential of making use of information gained in agent-based models (ABMs) in PE and CGE models taking the behaviour of farmers regarding the willingness to participate in voluntary agri-environment schemes as an example.

This deliverable first presents models developed in BESTMAP and presents potential ways to use the information gained in ABM in standard economic models (CGE and PE models). Subsequently, challenges when linking models are discussed in detail summarizing the main findings of an expert workshop. Lastly, next steps towards integrating ABMs and CGE / PE models are presented.

2. The BESTMAP modelling framework

2.1 ABM used in BESTMAP

To systematically test how farmers' decision-making under different policy designs affects the adoption rate and the resulting spatial allocation of AES, we designed an agent-based model where decisions of individual farmers on four selected schemes are explicitly included. The selected AES are flower strips, cover crops, maintaining permanent grassland, and conversion of arable land to permanent grassland. The model can be used to study the social-ecological consequences of agricultural policies at different spatial and temporal scales and, in combination with biophysical models, test the ecological implications of different designs of the EU's Common Agricultural Policy.

In the model, farmer behaviour is empirically based on data from interviews conducted in the five BESTMAP case studies. We condensed these observations into a formalized conceptual framework that covers a three-step decision process: (1) Farmers accept an AES if they are open to considering the adoption. This is an identity-driven decision based on own prior experience, intrinsic openness, and influence from advisory and/or social network; (2) they need to have suitable land available (i.e. grassland for schemes applicable on grassland and arable land for schemes applicable on arable land) and (3) agents only decide to adopt a scheme if the offered payment level (as defined in the policy regulations) exceeds their individual expected payment level (economically and value-driven decision, different depending on farm characteristics and external influences). To parameterize the expected payment level, we rely on the results of a discrete choice experiment that has been conducted in all case studies to quantify farmers' preferences for specific features of AES contracts. In combination with an additional questionnaire to capture farm and farmer characteristics, this allows to include heterogeneity between farmer types.

We use the agent-based model to critically evaluate agricultural policies and analyse how they should be designed to achieve the desired impact. Based on the design of the discrete choice experiment, we are in particular able to estimate the effect of contract duration, bureaucratic effort and advisory support on the adoption of AES. These results feed into biophysical analyses to quantify the environmental impacts of AES adoption on biodiversity, water quality, food and fodder production as well as carbon sequestration.

Farms are spatially represented by individual fields derived from IACS/LPIS data for the case studies in CZ, DE, ES and UK and from the AgroSense database for Serbia. Time is represented as discrete yearly time steps with AES adoption decisions made once a year. The temporal extent can be chosen depending on the research question that should be addressed. Since the model currently does not include other land-use decisions, changes in farm structure or ownership and abandonment, within BESTMAP, we are mainly focusing on 'alternative now' scenarios, i.e. one simulated decision based on the latest input data available.

To provide stakeholders with an effective tool for assessing the impact of future policies in EU, the model will be upscaled to other EU regions. The upscaled ABM will adopt the same farmer decision-making process discussed above. However, due to the availability of data, the spatially explicit model will be replaced by a spatially implicit version, as we will use FADN data as the main data source. The upscaled ABM will estimate the farmers' adoptions of AES in EU regions in the scenarios of varied AES designs.

2.2 CGE model used in BESTMAP

We use the Computable General Equilibrium (CGE) model DART-BIO for our analysis. The DART model is a global multi-sectoral, multi-regional recursive-dynamic CGE model. It was developed at the Kiel Institute for the World Economy and has been widely applied to analyse international climate policies (e.g. Klepper et al. 2006a, Thube et al. 2021), environmental policies (Weitzel et al. 2012), energy policies (e.g. Klepper et al. 2006b), and biofuel policies (e.g. Schuenemann & Delzeit 2022), and global mid-term scenarios (Delzeit et al. 2018). DART-BIO is a version of the DART model which has a detailed representation of the agricultural sector, land use and biofuels (see Delzeit et al. 2021 for a technical description). It has been used in interdisciplinary studies to address potential trade-offs between food security and biodiversity (Delzeit et al. 2017, Zabel et al. 2019) and the simulation of global biomass potentials via linking to a crop growth model (Mauser et al. 2015).

In BESTMAP, DART-BIO is applied to analyse the interplay between climate- and biofuel policies. Voluntary schemes are not modelled in CGE models. The usual approach is (see SUPREMA) that the second pillar is modelled in the PE model and then linked to the CGE model. Large uncertainties in national implementation of agricultural policy, which was still under reform during the project phase, such that repetition of assumption-based analysis as done in SUPREMA would have been redundant. A scenario analysis (see Deliverable 2.4) shows that by 2030, significant land-use change is caused in the EU member states if current biofuel policies (Renewable Energy Directive 2018 including a phase-out of palm-oil-based biodiesel and global biofuel quotas) are met. More rapeseed is produced, while crop and land prices rise. This changes the opportunity costs for farmers when deciding whether to participate in agri-environment schemes.

Based on the scenario analysis, DART-BIO generates for 5 EU regions (see Table 1) changes in prices and production of 10 crop categories. For example, EU and global biofuel policies lead to an increase in 49% of rapeseed production in the EU, and an increase in different types of annual crops by 6%. Further, changes in land prices and land use are simulated for the 5 regions subdivided into agri-environmental zones (see description of GTAP-AEZ database).

Table 1: List of EU regions in DART-BIO

CEU	Central European Union with Belgium, France, Luxembourg, Netherlands
DEU	Germany
MED	The Mediterranean with Cyprus, Greece, Italy, Malta, Portugal, Spain
MEE	Eastern European Union with Austria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia, Romania, Bulgaria, Croatia
NEW	North-Western European Union with Denmark, Finland, Ireland, Sweden, United Kingdom*

* Since the database includes taxes pre-Brexit, we decided to keep the UK in this region.

2.3 A concept to integrate ABM and CGE in BESTMAP

The combination of ABM and CGE can bridge the gap between complexity and realism (Babatunde et al., 2017). With the ABMs being developed from scratch, the development of a linking procedure was not intended in the project, but a concept for integrating ABMs to DART-BIO was developed.

In general, there can be information flows from the ABM to the CGE model and from the CGE model to the ABM, depending on the question at hand. For the latter, the results from the CGE analysis can be included in the ABM developed in BESTMAP where the decision to adopt agri-environment schemes depends on opportunity costs. Currently, the opportunity costs of participating in agri-environment schemes are assumed to be the same across scenarios in the ABM, but could be varied for future analysis. Changes in opportunity costs can be taken from the scenario analysis with the CGE model which shows changes in crop prices and land use under the biofuel and climate policy scenarios: depending on the policy scenario, prices of e.g. rapeseed under biofuel policies rise, causing farmers to use more land for rapeseed production. Other scenarios show changes in pasture land and prices. As these changes in land use are directly linked to changes in opportunity costs of agri-environment schemes, the CGE output can be used to analyse how farmers' decision-making on participation in agri-environment schemes is affected by changes in biofuel and climate policy.

Future research might also include an improvement of the (land) decision-making process in CGE models. They are price-driven assuming profit maximisation of farmers. Since CGE models are run at a highly aggregated level having one representative farmer per region (at the country level). A better option would be to pass the information on e.g. the participation in agri-environment schemes of farmers in different locations to agricultural sector models with a higher sectoral and spatial resolution. Since agricultural sector models miss the intersectoral feedback effects of e.g. climate policy, CGE models have a clear role in bridging the gap between aggregated and cross-sectoral impacts.

3. Integrating common PE/CGE models into the BESTMAP modelling framework

In order to discuss if, how and under which conditions a linking of ABMs and equilibrium models is useful, we organized a two-day workshop in Basel. 21 experts in ABM or CGE/PE participated in a hybrid format and discussed challenges and opportunities for linking ABM with CGE/PE. Most of the experts were part of the other AGRIMODELER cluster. During the workshop, Tatiana Filatova presented her work on linking an ABM representing consumer behaviour towards reduction of energy consumption with a regional CGE model and shared her experience with the combination of the two distinct model types Niamir et al. (2020). To the best of our knowledge, this work is the only approach where an ABM and a CGE model is linked. In addition, our colleagues from the AGRIMODELER clusters presented their approaches for model integration. Alexander Gocht presented the approaches of MINDSTEP and Filippo Arfini the approaches of AGRICORE. Meike Will explained the BESTMAP approach to the colleagues.

In the workshop, we identified six challenges for linking of ABM and CGE/PE models.

- Conceptual challenges
    - Alignment of different conceptual approaches
    - Different levels of aggregation
    - Model output interpretation and communication
- Technical challenges
    - High computational cost and challenges to linking variables
    - Model validation
    - High demand in the expertise of software development and funding

The different challenges were then further discussed and a peer-reviewed paper is in preparation. In the following, we discuss the mentioned challenges in more detail (a general discussion on challenges when linking CGE with other models is discussed in Delzeit et al. 2020).

3.1 Alignment of different conceptual approaches

The two model types have distinct basic model assumptions. While PE/CGE models rely on microeconomic theory and seek market equilibrium, ABMs include behavioural assumptions that differ from rational decision-making. Therefore, aligning the two model types causes the following challenges.

1. Assumption on macro-level: CGE/PE models are based on market-equilibrium assumptions in contrast to assumptions in ABM that macro-level patterns emerge from bottom up and there may be no equilibrium at all, a multiplicity of persistent states, both eventually related to a path-dependence meaning that the outcome strongly depends on the initialization.

2. The underlying conceptualisations on the micro-level for CGE/PE models are based on microeconomic theory while in ABMs a broader set of influence factors may be incorporated. For instance, limitations of cognitive capacities, i.e.., bounded rationality, but also social learning and memory effects can be taken into account. These mismatches affect outcomes and require at least some calibration of CGE/PE models. Otherwise, when modelling (policy) shocks, the reaction of farmers to prices might differ in the two approaches and this will corrupt a hard link between the models.

3. Agents may be heterogeneous and/or behave heterogeneously which may cause endogenous synergies and trade-offs/conflicts. Though aggregation is nevertheless possible, the effects of emerging phenomena may not be covered in aggregate CGE/PE causing biased outcomes or requiring demanding calibration.

With respect to the consideration of time, apart from the role of path-dependency mentioned above, further issues are worth to be considered:

4. ABMs are dynamic process models. They may be used to investigate transient dynamics (i.e. when a market is not at equilibrium). CGE/PE models can be comparative static or recursive-dynamic. This has to be brought in line.

5. In addition, not all developments may be reversible and regime shifts may occur (-> issue of irreversibility (see also discussion on the integration of modelling approaches in Müller et al. 2020, p.11). In land-use modelling irreversibility is not considered in PE/CGE models, posing an additional challenge when coupling ABM and CGE/PE models.

6. Stochastic processes may lead to non-equilibrium dynamics (e.g., bullwhip-effects along supply chains).

In our point of view, substantial additional and systematic work is needed to improve the understanding of when coupling makes sense and how to lay a suitable basis for it.

3.2 Different levels of aggregation

In order to analyse the EU's agricultural policy as a whole in all member states, the sectoral and regional aggregation of equilibrium models and ABM models needs to be defined in a way that either the aggregations are similar or that they can be aggregated or disaggregated consistently. For the ABMs developed in BESTMAP this implies that when e.g. integrating information on the participation of AES in CAPRI, the information needs to be available on NUTS2 level in the EU. CGE/PE models and ABM usually operate on several different scales. The most obvious difference is in the spatial extent, with often local or case study-based ABMs and CGE/PE operating globally, nationwide or at the NUTS2 level. Yet, differences in other dimensions such as temporal or organizational scales could also lead to difficulties when coupling the two approaches.

- When coupling the two types of models, the mismatch in scales poses a significant challenge and requires upscaling or downscaling/disaggregation of one of the models to meet common ground. In particular, we can distinguish three dimensions that need to be considered for upscaling (spatial, temporal and organizational) and two levels along which the dimensions differ (resolution and extent) (Dressler et al., under review). ABMs often operate on smaller extents than CGE/PE models. With respect to the spatial dimension, this involves increasing either the ABM model spatial extent or the CGE resolution. Commonly, CGE models are developed at the country level. Regional CGE (RCGE) models have been growing in popularity, but they are surrounded by many challenges (Ghaith et al., 2021). The paucity of the data especially which must be suited to the regional scale and consistent between regions was found to be a major constraint (Geisecke & Madden, 2013). This reflects the difficulty of increasing the resolution of CGE models that operate on a large spatial extent. Increasing the extent of a spatially explicit ABM to that of the respective CGE/PE would require the spatial information contained in the local ABM (such as field parcels, land use, etc.) for the larger region. However, while the underlying data such as LPIS/IACS might be available, accessibility is often limited due to data protection issues. Using synthetic landscapes (Uthes and Kiesel, 2020) or farm populations (Pahmeyer et al., 2021) could be one approach, but it involves high computational costs and limitations in prediction accuracy compared to the original data. Another attempt to circumvent these problems is to reduce the resolution of the ABM, e.g., by using gridded land-use data (Václavík et al., 2013; Malek and Verburg, 2019), linking farm data to biophysical data using statistical methods (Kempen et al., 2011; Lamboni et al., 2016) or to switch to a spatially implicit ABM. In the latter case, aggregated data such as FADN data could help to parameterize the ABM. However, any spatial influences on heterogeneity in decision-making would be neglected in that case.

- Organizational: The resolution between ABM and CGE also differs with respect to the organizational dimension, i.e. the level of the individual agents. While CGE models generally assume a single representative agent differentiated by regions, heterogeneity between actors is one of the key characteristics of ABMs. Also concerning the organizational dimension, i.e. the level of the individual agents, the resolution between ABM and CGE differs. While CGE/PE assume representative agents, heterogeneity between actors is one of the key characteristics of ABMs. To reduce heterogeneity to a manageable dimension, ABMs often apply agent typologies (Arneth et al. 2014; Rounsevell et al., 2012). While farmer types have been empirically derived in a range of local case studies (Bartkowski et al., 2022), typologies of land-use decision-making for a large spatial extent are coarse (Malek and Verburg, 2020). Developing finer typologies for large regions is difficult since behavioural and socio-demographic data is often scarce. Assuming representative agents in ABMs would, however, lead to a loss of information such as direct or indirect interaction which is a central feature of ABMs. On the other hand, heterogeneity between actors in CGE/PE can only be accounted for to a limited extent, e.g. by distinguishing income classes. For example, firm heterogeneity has been introduced based on productivity differences like in the GTAP-HET model (Akgul et al 2016) and household heterogeneity via income levels in frameworks like GTAP-WiNDC. Examples of more detailed households' characterizations also exist like the MIRAGE-HH model, but these remain scarce (Bouet et al., 2013). However, it would not be possible to represent individual actors and therefore this would not solve the problem of the lack of interaction between individual actors.

- Temporal: The way in which different temporal dimensions play a role depends on how the models are coupled. A one-way linkage where CGEs with yearly projections are used for market-level feedback in ABMs is plausible but constant re-calibration of CGEs might be computationally expensive. On the other hand, aggregating ABMs to a lower temporal resolution (e.g. by providing a yearly average instead of daily outputs) is in principle also possible. However, this would smooth out years with exceptional events such as droughts or floods when considering the environmental perspective which might be particularly interesting for policymakers (see Dressler et al., under review for additional challenges regarding temporal upscaling with respect to ABMs).

3.3 Results interpretation

Model output analysis should already be involved in the model development, especially in ABM (Lee et al. 2015). When linking ABM with CGE models, reaching the market equilibrium state might not always be possible. Therefore, it is important to know the state of the market equilibrium. In addition, stochastic processes in the ABM need to be taken into consideration while interpreting model results. The implications of the distinct approaches need to be made clear to readers of model results.

3.4 Technical challenges

ABM and CGE/PE models are often programmed in different programming languages. Therefore, the model communication can be hampered. To allow the exchange of data between the two models, not only the reading of different formats is relevant, but it is also important that the different model variables are defined in the same way.

For the linking of CGE/PE and ABM models, two mature models are needed. When developing a new (ABM) model, timing particularly in the case of linking the models is important. In BESTMAP, for example, the information needed to address different opportunity costs for farmers would have to be available before doing interviews with farmers.

The models need to be transparently calibrated and validated. The team of modellers needs to understand both models. For the validation, critical points need to be considered. In addition, sufficient data is required to calibrate the model to a larger spatial extent, which in case of ABMs is very resource intensive. Due to large efforts in data acquisition and model development, sufficient funding is needed to sustain the model linking.

3.5 How to integrate common PE/CGE models to the BESTMAP modelling framework

DART-BIO used in BESTMAP, is a CGE model which has many comparable features with the MAGNET model. They share the same theoretical background (neoclassical theory), and have the same representation of agents (producers, consumers, government). Another common feature is their recursive-dynamic character. Further, both models are based on the GTAP database which allows being flexible in the choice how of countries and sectors are aggregated. Another common feature is that they disaggregate the original GTAP sectors depending on the question at hand.

Conceptually, three ways of integrating common PE/CGE models into the BESTMAP modelling framework is possible.

From the PE/CGE model to ABM:

Model results from models such as MAGNET and CAPRI could be used in BESTMAP's ABMs to translate changes in land use or crop prices to changes in the opportunity costs of farmers when participating in AESs. This would be one-way-link (passing information from the equilibrium model to the ABM).

From the ABM to PE/CGE model:

In CGE models in general, land can be set aside (land endowment could be reduced) based on the participation of farmers in AES. But since the spatial resolution is very coarse, the detailed information gained in ABMs would be lost. A more promising way is to inform a PE model, which is more detailed with respect to the agricultural sector and agents.

The PE model CAPRI for example assumes a coefficient for farmers to participate in voluntary schemes. If available for all NUTS2 regions, this coefficient could be derived from ABMs to have a more realistic assumption on the uptake of these schemes. The impact of overall agricultural policy could be passed on to the CGE model to simulate e.g. the interplay between agricultural policy and international (or EU) climate policies.

Two-way linking:

In this way of linking, the feedback between models to reach better convergence of overlapping variables is considered using a point calibration or sequential calibration of multiple parameters (Delzeit et al. 2020). For example, the policy-induced changes in the ABM can be upscaled to the country level and change certain variables (land endowment, shares of participating farmers) in a CGE/PE model. The new results (e.g. changes in prices, opportunity costs) from the CGE/PE model are passed on to the AMB resulting in changed shares of participating farmers.

3.6 Ways forward

We recommend the following steps to move forward.

1. Clarify the objective of linking ABM and CGE/PE and provide best practices, as well as point out when it does make conceptual sense (and when not). Whether linking makes sense, strongly depends on the specific context and the underlying research question. One context-specific reason where linking may make sense could be that the equilibrium assumption of the market is empirically justified and transient dynamics are not in the focus. Furthermore, the list of examples and even more best practices are currently very short. Up to now besides the work in Niamir et al. (2020) examples are missing.

2. Provide the prerequisites regarding empirics and model design/documentation: A joint effort to establish databases, and standards in model documentation (such as the ODD protocol for ABM) is needed. Therewith the basis for exercises of model comparison and to support model coupling can be laid. In this regard insights and recommendations collected and suggested in related modelling fields (such as Open Modelling Foundation) may be of value.

3. Support and conduct concerted modelling actions/model intercomparison: There is an explicit need to organise (and financially support) concerted modelling actions including model intercomparisons of different model types and assumptions. Just to give two examples of how this may look like in our case: Firstly, an ABM representing standard economic approaches are enriched by more behavioural or spatial realism and analysed whether the outcomes are substantially different (or differences are rather neglectable) for a specific research question or context. A nice example in this regard is Lundberg et al. (2015). A second testbed could be to use a regional ABM (such as AGRIPOLIS ref),

reformulate the model rules to be consistent with the assumptions of a PE (by aggregating the farms and determining suitable elasticities), calibrate it and compare the outputs of the two model versions (original ABM version and adjusted PE version) for different policy scenarios. To our knowledge, this has not been done so far. For these exercises apart from the comparison with empirical data/patterns (which are often difficult to get) the use of synthetic farm populations may be an important basis in such a virtual laboratory (e.g. from Pahmeyer et al. 2021).

These proposed three steps are part of an iterative process, since learning from step 3 – concrete modelling exercises – may give insights into when conceptual assumptions may be aligned and when not (step 1). Concluding, to our point of view a lot of preparatory work is still necessary to increase the understanding under which conditions and how linking ABM and PE/CGE models is appropriate and valuable.

4. Acknowledgements

In addition, we thank all participants of the workshop and Jiaqi Ge for her helpful comments on this report.

5. References

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

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.

Akgul, Z., Villoria, N., Hertel, T., 2016. GTAP-HET: Introducing Firm Heterogeneity into the GTAP Model. *Journal of Global Economic Analysis* 1, 111-180.

Bartkowski, B., Schüßler, C., Müller, B., 2022. Typologies of European farmers: approaches, methods and research gaps. *Regional Environmental Change* 22, 43.

Bouet, A., Estrades, C., Laborde. D., 2013. Households heterogeneity in a global CGE model: an illustration with the MIRAGE-HH (MIRAGE-HouseHolds) model. ffhal-00780103v2f

Delzeit, R., Beach, R., Bibas, R., Britz, W., Chateau, J., Freund, F., Lefevre, J., Schuenemann, F., Sulser, T., Valin, H., van Ruijven, B., 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.

Delzeit, R., Heimann, T., Schünemann, F. & Söder, M., 2021. DART-BIO: A technical description, *Kiel Working Paper* 2195, Kiel Institute for the World Economy.

Delzeit, R., Zabel, F., Meyer, C., & Václavík, T. (2017). Addressing future trade-offs between biodiversity and cropland expansion to improve food security. *Regional Environmental Change*, 17(5), 1429-1441.

Delzeit, R., Klepper, G., Zabel, F., & Mauser, W., 2018. Global economic–biophysical assessment of midterm scenarios for agricultural markets—biofuel policies, dietary patterns, cropland expansion, and productivity growth. *Environmental Research Letters*, 13(2), 025003.

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., Upscaling in socio-environmental systems modelling: Current challenges, promising strategies and insights from ecology, under review.

Ghaith, Z., Kulshreshtha, S., Natcher, D., Cameron, B., 2021. Regional Computable General Equilibrium models: A review. *Journal of Policy Modeling*, 43(3), 710-724.

Giesecke, J. A., Madden, J. R., 2013. Regional computable general equilibrium modeling. In P. B. Dixon, & D. W. Jorgenson (Eds.), Handbook of Computable General Equilibrium Modeling: Volume 1A (1st ed., pp. 379 - 475). North-Holland. https://doi.org/10.1016/B978-0-444-59568-3.00007-9

M. Kempen, B.S. Elbersen, I. Staritsky, E. Andersen, Heckelei, T., 2011. Spatial allocation of farming systems and farming indicators in Europe. *Agric. Ecosyst. Environ*., 142, 51-62.

Klepper, G., & Peterson, S., 2006a. Emissions trading, CDM, JI, and more: the climate strategy of the EU. *The Energy Journal,* 27(2).

Klepper, G., & Peterson, S., 2006b. Marginal abatement cost curves in general equilibrium: The influence of world energy prices. *Resource and Energy Economics*, 28(1), 1-23.

Mauser, W., Klepper, G., Zabel, F., Delzeit, R., Hank, T., Putzenlechner, B., & Calzadilla, A., 2015. Global biomass production potentials exceed expected future demand without the need for cropland expansion. *Nature communications*, 6, 8946.

Weitzel, M., Hübler, M., & Peterson, S. (2012). Fair, optimal or detrimental? Environmental vs. strategic use of border carbon adjustment. Energy Economics, 34, S198-S207.

Thuebe, S. D., Delzeit, R. and Henning, C. H. C. A., 2021. Economic gains from global cooperation in fulfilling climate pledges", *Energy Policy*, 160, 112673.

Lamboni, M., Koeble, R., Leip, A., 2016. Multi-scale land-use disaggregation modelling: Concept and application to EU countries. *Environmental Modelling & Software*, 82, 183-217.

Lee, J. S., Filatova, T., Ligmann-Zielinska, A., Hassani-Mahmooei, B., Stonedahl, F., Lorscheid, I., ... & Parker, D. C. (2015). The complexities of agent-based modeling output analysis. *Journal of Artificial Societies and Social Simulation*, *18*(4).

Malek, Ž., Douw, B., Vliet, J.V., Zanden, E.H.V.D., Verburg, P.H., 2019. Local land-use decision-making in a global context. *Environmental Research Letters*, 14, 083006.

Malek, Ž., Verburg, P.H., 2020. Mapping global patterns of land use decision-making*. Global Environmental Change*, 65, 102170.

Möhring, A., Mack, G., Zimmermann, A., Ferjani, A., Schmidt, A., & Mann, S. (2016). Agent-based modeling on a national scale–Experiences from SWISSland. *Agroscope Science*, *30*(2016), 1-56.

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 and Software*, 134, 104839.

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, 107007.

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, 259–269.

Schuenemann, F., Delzeit, R. (2022): Potentials, subsidies and tradeoffs of cellulosic ethanol in the European Union. *Ecological Economics*, 195, p. 107384.

Uthes, S., Kiesel, J., 2020. Creating a synthetic landscape: Spatial allocation of non-spatial single farm data. Agricultural Systems 177, 102740.

Václavík, T., Lautenbach, S., Kuemmerle, T., Seppelt, R., 2013. Mapping global land system archetypes. *Global Environmental Change,* 23, 1637–1647.

Zabel, F., Delzeit, R., Schneider, J.M., Seppelt, R., Mauser, W., T. Václavík (2019): Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity. *Nature Communications*, 10, p.2844.

Ziv, G., Gunning, J., Václavík, T., Beckmann, M., Paulus, A., Mueller, B., 2022. Deliverable D2. 2 BESTMAP Conceptual Framework Design & Architecture. ARPHA Preprints, 3, e82404.