MIND STEP

MODELLING INDIVIDUAL DECISIONS TO SUPPORT THE EUROPEAN POLICIES RELATED TO AGRICULTURE

Deliverable D4.1: Protocol to link new tools in WP4

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ACRONYMS

ABM	Agent Bases Models
AES	Agri-Environmental Schemes
AgriPoliS	Agricultural Policy Simulator
CAP	Common Agricultural Policy
CAPRI	Common Agricultural Policy Regional Impact Analysis
CoESM	Collective Ecosystem Services Management
DNN	Deep Neural Network
EU	European Union
FADN	Farm Accountancy Data Network
FSS	Farm Structure Survey
GLOBIOM	Global Biosphere Management Model
IDM	Individual Decision Making
IFM	Individual Farm Modelling
KPI	Key Performance Indicator
MAGNET	Modular Applied GeNeral Equilibrium Tool
MIND STEP	Modelling INdividual Decisions to Support The European Policies related to agriculture
NEIO	New Industrial Organization
OECD	Organisation for Economic Co-operation and Development
PMP	Positive Mathematical programming

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EXECUTIVE SUMMARY

The tools developed in work package 4 of MIND STEP serve the general purpose of capturing interaction of individual farms relevant for economic and environmental outcomes of policy interventions. The objective of this deliverable is to describe the purpose and design of the different tools developed and to discuss their long-term policy relevance.

The approaches considered here comprise

- Task 4.2: The estimation of farm exit rates exemplified for Germany and Norway aiming to be the basis for integrating farm structural change into representative farm-level or equilibrium models
- Task 4.3: The investigation of farmers' preferences and related behavior regarding the participation in collective environmental schemes through computer and group experiments
- Task 4.4: the estimation of conjectural elasticities that capture market power along the supply chain and specifically (and for the first time) the power of farmers arising from contractual agreements or the formation of producer organizations. The conjectural elasticities can be incorporated in equilibrium models for a more realistic representation of price transmission along the supply chain
- Task 4.5: The training of machine-learning-based surrogate models that address the computational challenges arising when trying to incorporate detailed farm level models into representative larger scale models, here specifically into agent-based models with interaction between individual farms on the land market.

For each of these approaches, the deliverable elaborates on the basic modelling challenge addressed, the specific approach employed including the discussion of advantages and limitations, the potentially visionary or long-term perspective for the integration of IDMs and upper scale models that the tools might allow, and what is to be expected at the end of the project regarding the use of the tools in terms of integrated or complementary use.

In the long run, the approaches considered will strengthen the analysis of the type of scenarios currently foreseen in MIND STEP to show the functionality of the toolbox. For example, reducing chemical inputs in agriculture by 50% will have strong impacts on the relative profitability of farming systems and thereby on farm structural change. The farm exit model and the integration of detailed farm models in a regional agent-based model allow capturing structural change implications for the farm population and the spatial distribution of environmental outcomes.

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1. INTRODUCTION

The impact assessment of agri-environmental policies at the EU level originally mostly relied on quantitative simulation models at the market level (Heckelei et al. 2001). Representative farm, processing, and consumer agents at the EU or national level interact in a setting that determines corresponding average prices, demand, and supply quantities. The design of the models delivers relevant analyses as long as general income support policies with minimum domestic prices, trade instruments like tariffs and export subsidies, or coupled and later decoupled direct payments are at the core of the Common Agricultural Policy (CAP) of the EU.

When direct payments started to slowly replace price support and the rural development measures received increasing budgets under the second pillar of the CAP, regional differentiation of policy implementation and impact gained relevance and gave rise to spatially less aggregated model developments (Heckelei, Britz, and Others 2001). More recent policy developments respond to an increasing demand of society for improving the environmental performance of the EU agricultural sector and to tie the CAP budget more closely to this objective. Environmental performance in terms of nutrient emissions and biodiversity, for example, directly depend on biophysical conditions at the local level. Aggregated representation of production agents struggles to capture the relevant processes of such impacts and the regulatory policies addressing them. At the same time, the public became more interested in the distributional aspects of the CAP across farm households.

These developments lead researchers to think about how individual farm-level models - having long been around as normative planning tools (Hazell and Norton 1986) and more recently as behavioral models more suitable for policy analysis (Howitt 1995; Heckelei and Wolff 2003; Heckelei and Britz 2005) - could be specified such that representative analysis across larger regions would be possible (Ciaian et al. 2013). The use of template models and EU-wide FADN data in combination with PMP approaches to calibrate or estimate individual model behavior using empirical information were the basis of the EU covering IFM-CAP model (e.g., Louhichi et al. 2017). It has the advantage of modelling real farms but it suffers from the limitations of the FADN database and the lack of explicit and detailed representation of technology. FarmDyn moved towards a much richer technology specification allowing to simulate policy impacts on technological choices and thereby on related environmental indicators (e.g., Britz et al. 2016). This is made possible by letting the collection of individual farm models be representative of certain population characteristics instead of trying to model real farms for which data information is insufficient. The project MIND STEP builds upon these recent advances in representative policy analysis using individual farm models to develop a suitable generic and modular bio-economic farm model (Britz et al. 2021).

Individual farm level models take their environment as given and simulate behavioral responses to exogenous changes in this environment regarding prices, policies, or the availability of technologies. In the long run, however, the environment of farms depends on the outcome of the interaction of farm agents with each other or with other agents of the agri-food system. Land availability and land prices for individual farms strongly determine the structural development of a farm and depend on what the neighbors do (Storm, Mittenzwei, and Heckelei 2015). Farms also strategically collaborate to jointly use machines or to improve their market position as input buyers or product sellers. Certain environmental outcomes like biodiversity are not decided by individual farm behavior only but by the composition of activities at the landscape scale. Finally, the aggregate behavior of individual farms co-determines general price levels and with it short and long-term profitability of the farm population or certain farm types.

Consequently, there is a considerable benefit of connecting individual farm level models in the context of agent-based models at the landscape or regional scale or to allow for consistent feedback loops between farm-level models and existing market level models. The tools developed in work package 4

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of MIND STEP serve this general purpose of capturing interaction of individual farms relevant for economic and environmental outcomes of policy interventions.

It is the objective of this deliverable to describe the purpose and design of the different tools developed, including connections and interfaces to IDMs (WP3) and market models (WP5) in terms of input/output variables and to discuss their long-term policy relevance. For each of the four subtasks of the work package (structural change, collective action, market power, surrogate modelling), we address the following in the subsequent chapters:

1. The basic modelling challenge that each developed tool addresses with respect to capturing farm-level interaction and a consistent application of IDMs and aggregate, market level models. This includes examples for policies whose impact depends on appropriately capturing such processes.
2. The specific approach in developing the tools including the discussion of advantages and limitations.
3. The potentially visionary or long-term perspective of full integration of IDMs and upper scale models that the tools might allow.
4. What is to be expected at the end of the project regarding the use of the tools. Can they be applied in a complementary or integrated manner or is the achievement a preparatory step for further future developments?

2. STRUCTURAL CHANGE (TASK 4.2)

2.1. Basic modeling challenge addressed

The design of agricultural policies has become more farm-specific in most OECD countries over the past decades in the sense that market support is replaced by payments determined by individual farm characteristics such as land areas, endowments, production systems and intensity. Recent examples from the CAP include the Small Farmers Scheme that simplifies the Single Farm Payment requirements for small farms, and ‘greening’ and ‘capping’ agri-environmental payments under Pillar II. Consequently, the farm structure is crucial for the actual impact of policy changes at the aggregate level and modeling such impacts requires to represent the impact of policy variables and other drivers on farm structural change. The task 4.2 consists of two separate activities both aiming at a consistent inclusion of farm structural change in quantitative policy analysis of the agricultural sector.

Farm exit rates in Germany: In order to consistently include farm structural change in aggregated level policy models, empirical estimations of exit probabilities are required. For this task we focus on Germany but the challenges we have here are similar in other EU countries. To estimate exit probabilities for Germany there are at least two methodological challenges: First, the Farm Structure Survey (FSS) is often not collected on an annual basis. The interval of surveys in Germany is 3 to 4 years. While the data covers a rather long period from 1999 to 2020 it might not reveal the concrete year a farm exit or entry in the sector. Second, FSS does not provide financial data on income and subsidies. This limits opportunities to model determinants for farm exit decisions.

Estimating the effect of those explanatory variables is crucial to implement endogenous exit decisions in a simulation model, for example IFM-CAP. Being able to endogenous model farm structural change would strengthen the ability of existing models to consistently analyze the impact of drivers on both structural change and agricultural activities related to policy target variables. For example, significant changes in financial support will not only change the choice of production activities in the short to medium term but also affect the relative profitability of different production systems and thereby the share of those in the process of longer-term structural change.

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Norwegian farm structural change: In Norway, most subsidies are based on payments coupled to production activities and these payments are negatively related to farm size (i.e., crop levels, animal herds or the farm as such). Consequently, a direct farm-structural effect of these payments is expected. The methodological challenge is (1) to quantify the effect of farm structure and farm structural change on the costs of agricultural production and (2) to implement this information in larger scale agricultural sector models that do not explicitly consider the farm structure and structural change. In particular, the Agrispace model which covers the full population of Norwegian farms applying for subsidies, will be used to quantify the above-mentioned effects, and information from Agrispace will be implemented in the Norwegian supply module of the CAPRI (Common Agricultural Policy Regional Impact Analysis) model. The approach will expand the scope of forward-looking policy analysis with larger-scale agricultural sector models enabling the implementation of agricultural and environmental policies to depend on farm size (e.g., amount of land or number of animals at farm level) following current developments of the CAP.

2.2. Description of the specific approach

Farm exit rates in Germany: Most of the literature analyzing exit rates applies binary regression approaches. The dependent variable is coded as either being an active farm (0) or one that has exited (1). This approach has the advantage of being widely accepted and it revealed several explanatory factors that inform exit rates. Most important is the age of the farm holder (most for family farms) and the economic situation (income). If the farm holder retires and there is no successor, the farm has a higher probability of exiting the sector. Additional factors are usually incorporated in the analysis like environmental or climatic variables, off-farm income possibilities or neighboring effects. In this project we aim to implement all drivers into the estimation models that previous analyses identified as relevant in explaining exit rates. We will also evaluate what explanatory variables are relevant for both, the exit estimation model and typical medium-term farm-level simulation models to prepare the ground for a consistent application.

One of the challenges that need to be overcome is the problem of not having financial variables at farm level like income. Subsidies can be derived from the formulation of the regulations. Standard gross margins for different production activities can serve as a proxy for income after being made farm specific, i.e. dependent on the farm's production activities. We will compare the results with data information on the distribution of farm income across different farm types.

In terms of estimation methodology, we intend to implement machine learning approaches. Some machine learning algorithms are specifically suitable for classification problems (here stay or exit) and may improve the predictive performance of the model compared to logit regressions (Storm, Baylis, and Heckelei 2020). However, results may not be as self-explanatory as those from logit regressions given that they typically involve nonlinear functional forms. A careful evaluation of comparative advantages is foreseen to decide which approach serves best for our task. Another limitation might be the trade-off between rich estimations of exit probabilities and the implementation in the land market model, as the exit probabilities are conditional on the characteristics of the estimations (selected regions, selected variables), which maybe are not controlled for in the land market model. Therefore, it must be tested which final model of the exit estimations serves best for further use in the simulation farm models.

Norwegian farm structural change: The Agrispace model is a recursive-dynamic multi-commodity model based on Spatial Equilibrium approach that links results for each farm in Norway and results for aggregate farm types at regional level. The basic concept is to utilize information from the full population of Norwegian farms applying for direct payments in a model with explicit demand and production functions. Agrispace is inspired by the complexity of Norwegian agricultural policies, but

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in principle is applicable to any other regional, national, or European level where similar data are available. Agrispace is currently calibrated for the base year 2014. The CAPRI model is a global partial equilibrium model for the agricultural sector, with a focus on the European Union and Norway. It has been designed for ex-ante impact assessment of agricultural, environmental and trade policies. It has a supply module consisting of regional programming models for about 280 regions in Europe and detailed coverage of agricultural policies. Moreover, CAPRI has a market module extending to global agricultural markets representing bilateral trade between 44 trade regions. CAPRI is currently calibrated for the base year 2012. The supply side of the CAPRI model consists of programming models with an explicit objective function.

In a first step, all payments will be expressed as area payments for each farm. This allows us to calculate the overall average payment rate for all land and the overall marginal payment rate for the last unit of land that belongs to the farm. Aggregating this information at regional level is the basis to calculating a farm payment degressivity defined as the difference between the highest and the smallest ratio of average payment rate and the marginal payment rate in a region. The result of the first step is a regional specific number indicating the degressivity of farm payments.

In a second step, a series of structured simulations varying the degree of farm payment degressivity will be performed with Agrispace. Variations in farm payment degressivity will result in different supply responses. A measure of farm payment degressivity will be developed and linked to supply. This allows to establish a relationship between the farm payment degressivity ratio and the aggregate supply response, e.g., in terms of energy production. The relationship between the farm payment degressivity ratio and the supply response will be expressed in terms of elasticities. The hypothesis is that the farm payment degressivity ratio is negatively related to the supply response since more degressive payments delay farm structural change and lead to higher production costs.

In a final step, the farm payment degressivity ratio is implemented in CAPRI. The regional supply models are based on the ‘regional farm concept’ and do not consider an explicit farm structure. A straightforward implementation would be to add an additional term to the objective function of the regional supply models that mimic payment degressivity. The parameters of that term will be calibrated in such a way that an exogenously given farm payment degressivity leads to the same response in CAPRI as in Agrispace.

2.3. Vision/Long-term perspective

Farm exit rates in Germany: The long-term vision of this task is to extend the approach to an EU wide application. Once a prototype approach is developed that allows using empirically estimated exit probabilities within a policy model such as IFM-CAP, extending the approach to other regions is conceptually straightforward. From a practical point of view, extending to other regions might be limited by obtaining access to the micro-level FSS data, such that similar estimation can be performed as for Germany. For regions where access to those data sources is not available the use of alternative data sources such as FADN could be explored as a fall-back option. Or the relationships estimated in one country (e.g. Germany) could be used for another region, justification of such a transfer crucially depend on the comparability of the agricultural systems in the respective regions.

Norwegian farm structural change: The approach will contribute to a better representation of farm structure and payment schemes (e.g., capping of direct payments, payments with size-dependent rates) as a determining factor for aggregate supply responses in larger-scale agricultural sector models. The envisaged approach aims to improve the policy representation of the Norwegian agricultural sector within CARPI. A further integration or transfer to other regions is not foreseen within MIND STEP but it might inspire future upscaling for integrating farm structural development and aggregate agricultural sector and market models.

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2.4. Expected project outcome

Farm exit rates in Germany: We implement the estimated exit decision probabilities into the current land market model to account for structural change, developed as a prototype in IFM-CAP. We implement the developments of this task for at least ten selected regions compatible with the farm exit estimations. As the analysis is done for selected regions, this task serves as a starting point and full integration might be a task in future work depending on usefulness and generality of results and availability of data for the estimation of exit probabilities in other regions in the EU. The possibility of incorporating structural change in terms of some farms exiting the sector which has implications on the land market or other spheres like the environment. As it is the starting point with selected regions and the first trial, it is rather a preparatory step for future developments.

Norwegian farm structural change: There is currently no link between Agrispace and CAPRI. It is not planned to establish a permanent link between Agrispace and CAPRI. Results from Agrispace will be used as input to CAPRI in order to improve the representation of the Norwegian policy system. The model linkage will expand the scope of forward-looking policy analysis in terms of modeling agricultural and environmental policies that depend on farm size or the farm structure in a region.

3. COLLECTIVE ACTIONS (COLLECTIVE AGRI ENVIRONMENTAL PAYMENTS) (TASK 4.3)

3.1. Basic modeling challenge addressed

In the Netherlands, the Dutch government introduced agri-environmental schemes (AES) to support biodiversity conservation and the provision of ecosystem services. Similar approaches are also being discussed in other EU countries. However, the successful implementation of such programmes warrants collective implementation (Groeneveld, 2018). In other words, an adequate provision of ecosystem services will only happen if enough farmers convert their land to these alternative uses. Nature conservation outcomes in a region, are in the end, a combined result of the individual decisions of farmers in nature conservation (Grashof-Bokdam et al., 2017; Groeneveld, 2018; Westerink et al., 2017).

When it comes to individual decision making, farmers sharing a similar landscape are influenced by their peers in implementing alternative farming practices. Therefore, behavioral assumptions are of particular importance for activities outside the actual economic field of activity of the farms. Alternative agricultural activities (e.g. hedgerows, woodlots, flower strips, natural field edges, ditch banks, protected areas for ground-nesting) depend on many factors beyond pure economic incentives including individual attitudes, learning, collaboration, compatibility with the business concept of the farm or bureaucratic demands. For example, Agri-environmental schemes (AES) provide essential services for the farmer (e.g., water retention, natural pest regulation, pollination; Harrison et al. 2014) but also for society (e.g., aesthetic appreciation, biodiversity conservation; MAES et al. 2013). The benefits from collective AES are often more indirect compared to traditional farming activities: positive effects are often only shown in the longer term and if the network of nature elements surpasses a certain size. Moreover, effective AES measures often require adjustment on landscape levels larger than fields or farms and therefore require collective action of several participating farms in the corresponding region (biosphere). Hence, the farmer's interaction with other farmers in the landscape shows the collective dimension of AES and other types of Payments for Ecosystem Services (PES), which exhibits feedback between farmers and farmers and natural ecosystems (Groeneveld 2018).

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Our project aims to provide knowledge on managing ecosystem services and promote functional and non-functional biodiversity conservation that include the social aspects and behavioral traits of decision making. We do this by analyzing the farmers' decisions around contributing to ecosystem services beyond the farm level by using part of their land for collective AES for flower strips or as extensive pasture for creating a protected area for ground nesting birds.

3.2. Description of the specific approach

We use a two-step methodological approach to investigate the influences of farmers' decision to participate in collective AES. In a first stage (CoESM) computer agents' decisions on converting their arable land into flower strips is explored by a model framework which uses all possible land allocations and related gross margins generated by an imputation process and employs a Genetic Algorithm method (Hennen, 2009). We assign computer agents different types of characteristics, depending on their willingness to support the transition to nature inclusive agriculture following the implementation of the Reilly index (Schouten et al., 2013b).

In a second stage (FarmAgriPoliS), experiments with real people will be conducted to investigate other possible factors besides economic incentives that influence participation in collective AES and to experimentally test certain behavioral assumptions and characteristics.

CoESM:

We develop the conceptual framework CoESM (Collective Ecosystem Services Management) to model farmers' decision-making towards implementing flower strips at the farm level (Figure 1). Individual farmers must decide whether to invest in the provision of pest regulation services on their farms by converting arable land into flower strips. Farmers display different decision strategies in selecting their land allocation. They rely on recurring habits, imitating peers or role models, making deliberate comparisons, and asking friends or colleagues for advice (Kangur et al., 2017). Traditional farming optimization models looking at farming decision making have limitations incurring only static observed data and assuming perfect rational individuals (Malawska and Topping, 2016). Different models have been developed to facilitate the implementation of behavior factors in decision-making. For example, Kangur et al. (2017) argue that the Consumat model "closes the loop" by feed forwarding aggregated population behavior of farmers towards the decisional context of individual agents at the next moment in time. In other words, the Consumat model allows farmers to switch between cognitive processes when they experience (un)certainty and (dis)satisfaction, and in this way, facilitates formal modeling (Kangur et al., 2017).

To gather all the necessary data to run the model, we use the inputs from FARMDYN. FARMDYN is a dynamic single farm model and has been developed at the University of Bonn (Britz et al, 2014; Britz et al., 2016). With FARMDYN users can simulate economically optimal production and investment decisions in detail at the individual farm level taking into account restrictions related to feeding, fertilization, biophysical and environmental constraints, and farm endowment constraints (Britz et al, 2016). The optimization in FARMDYN is a mixed-integer programming problem, meaning that the variables in the model are a mixture of discrete and non-discrete variables.

Gross margin is calculated for all available crops in FARMDYN although it's likely that flower strips will be introduced in more extensive crops. In the case of the use of flower strips, the revenues are increased with the subsidy for flower strips relative to the size of the flower strip. Based on the gross margins data generated by FARMDYN, we create a database containing all possible land allocations and related gross margins to run the model. This is represented in the left box in Figure 1, and the process is further explained in the next section. In each run, farmers decide on the allocation of flower strips in their plots. The model updates the landscape composition every run via the Reilly index. The

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model uses this information as input to determine the risk of pest threats based on this index for the pest regulation dynamics. This is represented in the right box in Figure 1.

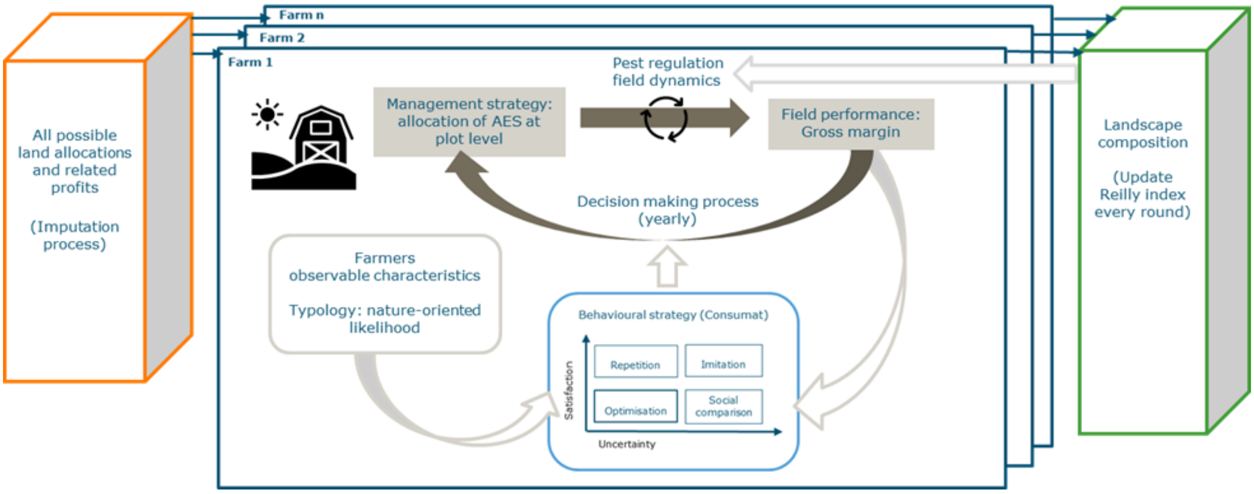

Figure 1. Conceptual framework for the CoESM (Collective Ecosystem Services Management) model. Based on Pacilly et al. 2019. Dark colored arrows represent model processes, and white arrows represent variables and frameworks used as input.

Interaction between agents

Following the Consumat approach (Jager et al., 2001; Janssen and Jager, 2001), when the farmer has experienced high-income satisfaction and a low level of uncertainty, the behavioral approach is to continue with the same strategy as the previous season and choose for “repetition”. On the other hand, when the farmer has high-income satisfaction but experiences positive levels of uncertainty, the farmer will seek for information in the nearby neighborhood and choose for “imitation” of the majority decision of the adjacent farmers with strong links. In circumstances where the farmer experiences both high uncertainty and low-income satisfaction, the farmer is encouraged to seek for information from a more extensive network of peers and to have chosen for “social comparison”, which intake a broader reference of farmers to imitate their decision. Finally, a combination of a low level of uncertainty and low-income satisfaction triggers the farmer’s individual “optimization” process at the farm level without considering the decisions of other farmers (Duinen et al. 2016). Figure 2 illustrates this process.

Furthermore, when the farmer strategy is to imitate or social comparison, we apply a farmer-nature oriented likelihood to adopt or not flower strips at the farm level. The likelihood of adoption is expressed in terms of a probability as very likely (0.9), likely (0.7), moderate (0.5), unlikely (0.3), very unlikely (0.1) and determined by farmers’ characteristics.

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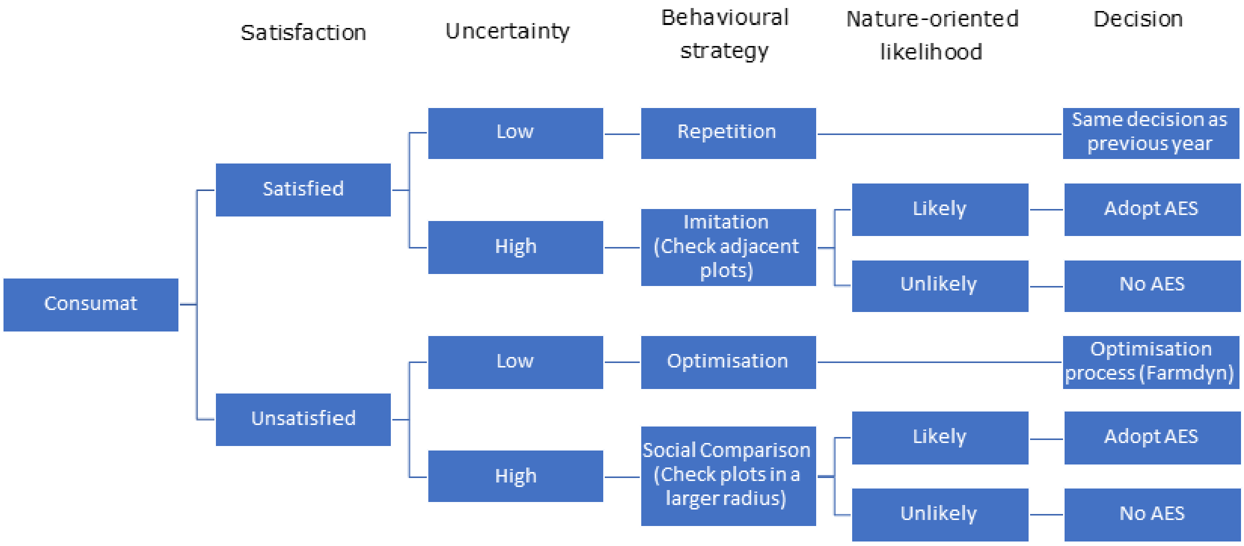

Figure 2. Illustration of assume farmers decision making following the Consumat approach (Jager et al., 2001; Janssen and Jager, 2001).

Workshop with experts

Our conceptual model has been discussed in a workshop with experts and received good feedback on how the available data is used and assumptions of farmers interaction. We gather a group of relevant policy actors and research advisors from the province of Flevoland and the ministry of agriculture. The objective of the workshop was to present our project to experts and ask input on the used model assumptions and parameters. Furthermore, the outcomes of this session will be used in the follow-up participative workshop with farmers (collective). During this workshop we proposed questions to the audience of experts in order to verify, prioritize and check underlying assumptions and parameters of the model. For this we will make use of participative methods to create interaction and get input in a structured way. In the coming year we will focus on redefining the model and include expert recommendations in the assumptions.

FarmAgriPoliS

As a methodological approach agent-based participatory modeling (Guyot and Honiden 2006) is used. In this approach, agent-based models are used to provide a context-specific environment and participants become part of the agent-based simulations. FarmAgriPoliS (Appel and Balmann 2019), derived from the ABM AgriPoliS (Happe, Kellermann, and Balmann 2006), provides participants with a software-based environment of a simulated agricultural region. Within FarmAgriPoliS, one farm is managed by a human participant. Their decisions include investments, renting land, off-farm activities and farm exits. The decisions will be made on the one hand against the background of regional conditions, prices and policy uncertainty, and the behavior of competing farms in the region on the other hand. The participant is assumed to manage this farm and to compete with computer-simulated optimizing farm agents that derive their decisions from mixed-integer short-term profit maximization (Appel et al. 2018). Thus, experiments with FarmAgriPoliS provide insights into how human participants behave in these competitive situations compared to computerized optimizing agents as used in AgriPoliS. For Task 4.3 FarmAgriPoliS will be extended to allow participants to decide on the participation in collective AES for a specific case study in Germany. The experiments with FarmAgriPoliS will provide insights on how the fact that the payment is dependent on the participation

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of other farms in the region and the overall framing of collective AES (neutral, economically or ecologically motivated) influences the farmers' willingness to participate in collective AES.

During an experiment with FarmAgriPoliS, participants have the option to participate in AES by using part of their pasture extensively for five years. Depending on the scenario they receive either a fixed or collective payment. Collective payment means that the more farms, the better the effect of the environmental measure, the higher the payment (but same expectation value as fixed payment). A further differentiation is done by different formulations of the offered AES: neutral formulation, ecological and economic motivation (see table 1).

Table 1: Scenarios planned for the experiments with FarmAgriPoliS

Scenario	Payment	Framing/ Motivation
1 (Benchmark)	Fixed	Neutral
2	Fixed	Economic
3	Fixed	Ecologic
4	Collective	Neutral
5	Collective	Economic
6	Collective	Ecologic

It is planned to organize up to ten sessions with max. 8 participants in Germany. The participants should have practical experiences in farm management. The experiment will be supplemented by a questionnaire. In addition to some general figures (age, gender, GDMS, risk preference etc.), participants are asked for their willingness to participate in collaborative AES before and after the experiment.

3.3. Vision/Long-term perspective

There is an urgent need to have insight into the contribution of the action perspective/business models at the farm and plot level to the landscape/regional level and vice versa. What are the collective benefits, incentives and governance from collaborative management of ecosystems and can payments for ecosystem services (PES) contribute by influencing the individual decision of farmers? How can regional or landscape level Key Performance Indicators (KPIs) on nature inclusiveness be connected to farm and plot level?

Agent-based models can capture emergent phenomena due to their bottom-up approach. A bottom-up approach is when the lower (sub) system-level interactions form the higher-level system properties. ABMs are both a micro and macro model, which incorporate feedback loops between the two levels (Tesfatsion 2003). ABMs like AgriPoliS/FarmAgriPoliS and CoESM therefore bridge the gap between individual farm level and sector or regional level (NUTS 3 or 2 depending on the region) and enable to address agri-environmental challenges from socio-economic and ecological perspectives. Further, the findings of behavioral experiments can be used to further improve behavioral assumptions in models such as AgriPoliS and therefore enable analysis of behavioral aspects on individual farm level as well as on sector or regional level.

3.4. Expected project outcome

By including behavioral aspects on micro-models of biodiversity transitions, we can better quantitatively support transitions to nature-inclusive agriculture. The micro-models provide essential building blocks to underpin behavior in nature-inclusive business models, and in this way, we are

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already in a better position to address questions from policy makers. The ambition is to apply the insights from the methodology developed for adapting micro-models (such as FARMDYN) aimed at biodiversity and behavior directly to current and expected projects (transitions) and thus place a consistent, scientific foundation among those projects.

4. PRICE TRANSMISSIONS (TASK 4.4)

4.1. Basic modeling challenge addressed

In most of the theoretical and empirical literature on price transmission and market power along food chains, the farm sector is assumed to be perfectly competitive (e.g., Sexton and Zhang 2001; Acharya, Kinnucan, and Caudill 2011; Assefa et al. 2017; Philippidis and Waschik 2019). However, this assumption may be implausible in modern food markets, where farmers are often able to achieve some extent of market power through the use of vertical contractual agreements and/or the creation of producers' organization (Sexton 2013; Sheldon 2017; Bonanno, Russo, and Menapace 2018). Despite the extensive and rising use of these instruments by raw agricultural commodity suppliers, contractual agreements are not adequately represented in traditional New Industrial Organization (NEIO) models (Sheldon 2017). As mentioned by Sheldon (2017), the presence of contracts and/or producers' organization may significantly affect price transmission along the food chain, as they completely or partly remove the incentives and ability of food processors to exert monopsony power towards agricultural suppliers. Therefore, extending traditional NEIO models, such as the conjectural variations approach (Appelbaum 1982), by incorporating these new features of agri-food supply chains is essential to correctly evaluate the potential effects of different policies or market shocks on market and agricultural prices and on farm incomes.

Our approach can contribute to better quantitative policy analysis in several ways. For example, by improving the understanding of price transmission mechanisms along food chains with different forms of organization and coordination, it will enable policy makers to obtain a more reliable estimate of the potential effects of policy interventions or market-shocks on farm prices and income, which is essential to design cost-effective policies to support the agricultural sector. Moreover, it will allow a comparison of market outcomes and incomes under different supply-chain organization scenarios, therefore enabling policy-makers to understand whether policies that ensure a more balanced bargaining position to farmers in the chain may result in better farm incomes. The results from this analysis can be particularly of interest considering that supporting farmers in the creation of producers' organizations is one of the actions taken by the European Commission in order to contrast unfair business practices in the food chain by strengthening their bargaining position (EC). In addition, as this intervention has proven its effectiveness for the fruit and vegetable sectors, the new CAP 2023-2027 will further extend the support for the creation of producer organizations to all agricultural sectors (Foundation Robert Schuman, 2021)

4.2. Description of the specific approach

Following Sexton and Zhang (2001) and Assefa et al. (2017), we analyze price transmission along a three-stage supply chain where farmers, f, supply agricultural raw commodities to food manufacturers, m, which, in turns, sell food products to the retail sector, r, that delivers final products to consumers. However, contrary to previous works on market power along food chains (i.e., Sexton and Zhang 2001; Weldegebriel 2004; Verreth et al. 2015; Assefa et al. 2017), our theoretical model allows for the presence of oligopoly power also at the farm level, which may derive from the use of contractual agreements or the creation of producers' organization.

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Following the framework by Sexton and Zhang (2001) and Assefa et al. (2017), it can be proven that under the assumption of constant marginal costs at all the supply chain levels (c^r, c^m, and c^f respectively), the first order conditions from the profit maximization of retailers (r), food manufacturers (m), and farmers (f) are the following:

$$P^r\left(1-\frac{\theta^{rc}}{\varepsilon^r}\right) = P^m\left(1+\frac{\theta^{rm}}{\gamma^m}\right)+\mathrm{c}^{\mathrm{r}} \tag{1}$$

$$P^m\left(1-\frac{\theta^{mr}}{\varepsilon^m}\right) = P^f\left(1+\frac{\theta^{mf}}{\gamma^f}\right)+\mathrm{c}^{\mathrm{m}} \tag{2}$$

$$P^f\left(1-\frac{\theta^{fm}}{\varepsilon^f}\right) = \mathrm{c}^{\mathrm{f}} \tag{3}$$

Where P^i, $\varepsilon^i and$ γ^i represent the final prices, the demand and supply price elasticities for each i ϵ (r,m,f) respectively, $\theta^{ij}=\frac{\partial Q^i}{\partial q^i}\frac{q^i}{Q^i}$ is the average conjectural elasticity measuring the extent of agent i's oligopoly powers with respect to the downstream sector for i,j ϵ (r,m,f), where i ≠ j, while $\theta^{kl}=\frac{\partial Q^l}{\partial q^k}\frac{q^k}{Q^l}$ is the conjectural elasticity parameter representing agent k's oligopsony power vis-à-vis the upstream sector l, for k ϵ (r,m) and l ϵ (m,f). ,

Overall, combining equation (1), (2), and (3), the relationship between retail prices and farm costs can be represented as follows:

$$P^r\left(1-\frac{\theta^{rc}}{\varepsilon^r}\right)\left(1-\frac{\theta^{mr}}{\varepsilon^m}\right)\left(1-\frac{\theta^{fm}}{\varepsilon^f}\right)$$

$$= c^f\left(1+\frac{\theta^{mf}}{\gamma^f}\right)\left(1+\frac{\theta^{rm}}{\gamma^m}\right)+c_m\left(1+\frac{\theta^{rm}}{\gamma^m}\right)\left(1-\frac{\theta^{fm}}{\varepsilon^f}\right)+c_r\left(1-\frac{\theta^{mr}}{\varepsilon^m}\right)\quad\left(1-\frac{\theta^{fm}}{\varepsilon^f}\right)$$

(4)

It is important to acknowledge that under the assumption of a perfectly competitive farm sector (i.e., $\theta^{fm}=0$ and $P^f=c^f$), equation (4) simplifies to:

$$P^r\left(1-\frac{\theta^{rc}}{\varepsilon^r}\right)\left(1-\frac{\theta^{mr}}{\varepsilon^m}\right) = P^f\left(1+\frac{\theta^{mf}}{\gamma^f}\right)\left(1+\frac{\theta^{rm}}{\gamma^m}\right)+c_m\left(1+\frac{\theta^{rm}}{\gamma^m}\right)+c_r\left(1-\frac{\theta^{mr}}{\varepsilon^m}\right) \tag{5}$$

which is equivalent to the price transmission equation obtained by Assefa et al. (2017).

Assuming that the price, cost and elasticity values at all the supply-chain levels are known, the estimated conjectural elasticities values through equation (4) and (5) can be used to compare the extent of price transmission along the food supply chain under different assumptions about the farm sector market power, thus allowing to evaluate how the presence of coordination tools at the farm level (i.e., contractual agreements, producers' organization) (4) affect farm prices and profits, compared to a situation in which farmers have no such countervailing power (5).

While price data at different stages of the supply chain are usually widely available (e.g., retail scanner data, chambers of commerce data), one challenge that one could face in estimating the conjectural elasticities parameters through equation (4) and (5) is to collect data about costs for all the market players (i.e., c_f, c_m, c_r) as these are usually not observed by the econometrician. One potential approach to overcome this issue is to collect cost data from different data sources, such as, producers' surveys, experts, or other empirical works analyzing the same supply chain. For example, Bouamra-Mechemache, Jongeneel, and Réquillart (2008) used the marginal costs estimates for the dairy industry from Moro, Nardella, and Sckokai (2005) to analyze the effects of a gradual increase in milk

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quotas on the EU dairy sector. On the other hand, one can also adopt an empirical specification that allows to indirectly estimates marginal cost, for example using widely available key inputs costs data as in Soregaroli, Sckokai, and Moro (2011), or by adopting some simplifying assumptions that enable to estimate them from the estimated price equations parameters as in Verreth et al. (2015). Similarly, market power parameters (i.e., conjectural elasticities values) and price elasticities estimated from previous empirical works for the supply chains under investigation can be used as input for the IDM behavioral equations, or these parameters can be directly estimated depending on data availability.

Finally, time-series models (e.g., Vector Autoregression Model, Vector Error Correction Model), can also be employed to investigate market power and price transmission issues when cost data are not available (e.g., Assefa et al. 2017). Even though time-series techniques have been extensively employed in empirical analysis as they are relatively easier to implement than NEIO methods, partly because of fewer data requirements, they are also often criticized as they lack a microeconomic foundation (Digal and Ahmadi–Esfahani 2002; Lloyd 2017; Cavicchioli 2018). On the other hand, despite being more difficult to estimate (e.g.., higher data requirements, rising econometric effort with the complexity of the marketing chain being analyzed), NEIO models' findings are more conclusive and reliable than those from time-series analysis, as they are rooted in economic theory and can be used for policy simulations (Digal and Ahmadi–Esfahani 2002; Lloyd 2017; Cavicchioli 2018).

4.3. Vision/Long-term perspective

The main objective of this task is to develop and implement a model of the supply chain mechanisms in modern food markets, by accounting for and parametrizing the extent of market power that raw agricultural commodities suppliers may obtain through the use of coordination tools, such as, contractual agreements and/or producers' organization. The results from this analysis will allow us to understand how different supply chain organizations affect prices and price transmission along the food-chain, therefore contributing to better policy analysis. The estimated parameters (i.e., conjectural and/or price transmission elasticities) will be used for improving the parameterization of large-scale models (i.e. CAPRI and/or MAGNET), where the issue of farmers' countervailing power has still limited representation. The general idea is the following:

a) change the equations in the market model (i.e. CAPRI/MAGNET);
b) obtain different changes in farm-level prices under different assumptions about market structure (including the presence of contracts/producer organizations);
c) use the different price levels to simulate the impact on farm income (and potentially on other target variables, such as environmental indicators) in the IDM models (IFM-CAP).

4.4. Expected project outcome

Changes in the competitive environment that characterizes agri-food industries, due for example to the development of vertical coordination tools, such as contracts between the food-processing and agricultural sectors, may reduce the predictive power of current model platforms, where there is only little representation of regional value chains and of the presence of bargaining power also from the agricultural sector. This work will contribute to integrate these features of modern agri-food markets into the classical NEIO approach, where the agricultural sector is usually assumed to be perfectly competitive (Sheldon 2017; Bonanno, Russo, and Menapace 2018), and to develop specific IDMs for the different actors within the supply chain in order to assess how differences in the supply chain organization can affect the extent of price transmission, farm prices and income. Improving the understanding of such issues is crucial to simulate questions like whether a better market integration will lead to similar or better market outcomes and incomes for the agricultural sector, and so, to assess the potential impacts of policies which enable a more balanced position of farmers in the chain. The

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results from this analysis could then be used to improve the corresponding parameters in current models and platforms referring to other agri-food chains.

5. SURROGATE MODELING (TASK 4.5)

5.1. Basic modelling challenge addressed

In task 4.5 we aim to develop novel methods to efficiently link complex IDMs that provide a detailed representation of farm technology, management, and biophysical processes, with regional level ABM that allow capturing interaction among farms, for example on (local) input/output markets (Happe, Kellermann, and Balmann 2006) or for knowledge transfer (Berger 2001). Each ABM which has farmers as the agents has an IDM model included that determines farmers' behavior. However, these IDMs are typically based on heuristics (Rasch et al. 2017) or smaller optimization models (Appel, Ostermeyer-Wiethaup, and Balmann 2016). These IDMs usually provide fewer details compared to other existing IDMs, such as "FarmDyn" (W. Britz et al. 2016), currently used for policy analysis. Increasing the complexity of IDMs used in ABMs is conceptually possible but computation demands limit either the complexity of the IDM or the number of farms and hence the regional coverage of ABMs. Currently, despite the relatively simple IDMs, applications of ABMs are typically restricted to a regional level. The limited level of details considered in the included IDMs as well as the limited regional coverage of ABM constrain the possibilities of ABMs for simulating certain policies.

One example of such a policy analysis is the simulation of a mandatory reduction in fertilizer use, including an assessment of its impacts on crop production and the environment on both farm and regional level. To simulate such a scenario, we need an IDM that is capable of modeling detailed fertilizer use decisions that differentiate between different crops, capture changes in the production mix, technology decisions as well as the environmental impacts on farm level. On the other hand, it is important to capture interactions among farms, most importantly on local land markets. Ignoring those feedbacks can lead to over/under-estimating the aggregated policy effects on a regional level.

FarmDyn (Britz et al. 2016) is an IDM model that provides the necessary details on the farm level. Previously, it has been used for a wide range of policies on single-farm level targeting the national implementations of the Nitrate and Water framework directive (Kuhn et al. 2019; Kuhn et al. 2020), the use of renewable energy (Schäfer, Britz, and Kuhn 2017), and addressed GHG abatement costs in the context of climate change policies (Lengers, Britz, and Holm-Müller 2014). The advantage for all applications was the highly detailed technology and biophysical representation which can be simultaneously linked to a number of policy measures. On the other hand, AgriPoliS (Agricultural Policy Simulator) (Happe, Kellermann, and Balmann 2006) is an established ABM model that is capable of capturing interactions between farms and market feedback. Previously, it was applied to simulate the development of regional agricultural structures over time in response to alternative scenarios of specific policies, such as biogas policy (Appel, Ostermeyer-Wiethaup, and Balmann 2016) and decoupled support (Happe, Kellermann, and Balmann 2006).

Given the complexity of FarmDyn and the computational time to solve the model, it is not possible to directly integrate FarmDyn as the IDM model in AgriPoliS. Therefore in task 4.5, we aim to develop a surrogate modeling approach where we approximate the detailed IDM model "FarmDyn" with a deep neural network (DNN). The trained DNN should be able to accurately approximate the input and output relationships of FarmDyn but with much less computation time. We then aim to use this surrogate model as the IDM model in AgriPoliS. In this way, we can run policy simulations such as a mandatory reduction in fertilizer that requires high detail in terms of technology representation or biophysical processes offered by FarmDyn but also the interaction and market feedback considered by AgriPoliS. We aim to provide an example that shows that the advantages of a highly detailed single farm-level model can be brought to the regional level through the implementation of an IDM

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surrogate model that is used in an ABM. This approach allows us to go beyond mere aggregation of single farms but also to account for structural effects including emerging phenomena from the interaction of agents in ABMs.

5.2. Description of the specific approach

Our approach links complex IDMs and large-scale ABMs using machine learning models. When conducting policy analysis related to agricultural environmental issues, complex IDMs are useful since they are highly detailed in terms of technology choices, biophysical relations, and therefore capable of providing a wide variety of environmental and economic indicators. However, IDMs are not well suited for analyzing economic and environmental impacts beyond single farms or farm types because they do not capture the interactions of heterogeneous farms and thus neglect changes in prices or other non-monetary aspects in the interactions. In contrast, ABMs are capable of simulating interactions and facilitate emerging phenomena, but the complexity of farmers' decision-making process and the number of farms in current ABMs are limited due to the computational constraints.

Directly adding new functions (more aspects/ greater detail) to the IDM of an existing ABM is possible, however, could be computationally inefficient. A complex IDM like FarmDyn can contain a lot of bio-geographical, economic and environmental information, and farmers face thousands of decisions such as investment decisions, production decisions and labor distributions under various economic and environmental constraints (Seidel and Britz 2020). When integrating such complex IDMs to large-scale ABMs, it becomes very resource demanding thus limits the applicability of such simulation models.

Using machine learning models as surrogates of complex IDMs can speed up simulations of large-scale ABMs when different policy scenarios are designed. At the same time, it allows us to fully utilize the advantages of both types of models. To be more specific, the accurate surrogate models of DNNs still capture the important details of complex IDMs, and integration of DNNs and ABMs enables us to efficiently conduct economic and environmental impact analysis of farm activities and agricultural policies from a system perspective.

Our approach requires the following steps:

1. As a trial, we first train DNNs only with data generated from FarmDyn without considering its linkages with AgriPoliS. This step helps us to gather experiences with data preparation, sampling strategies and different architectures of DNNs before the two models are aligned.
2. At the same time, we will parameterize FarmDyn and AgriPoliS for the chosen research region "Rheinisches Revier" (Germany).
3. We will define the interface between the DNN and AgriPoliS, specifying which inputs AgriPoliS provides and which outputs it requires from the DNN. In AgriPoliS, farmers make decisions at several stages: competing on the land market, investment decision, production decision, farm accounting, and exit decision. The inputs and outputs of the DNN must be clearly defined so that the DNN can take the correct inputs and produce the required outputs for AgriPoliS. We will adjust FarmDyn and AgripoliS according to the defined interface. This step needs intensive collaboration between the modelers from both sides. For example, in the current version of FarmDyn, some machines can be invested in fractions. However, in AgriPoliS, the whole machine must be invested. Thus, adjustment must be made here so that the results of farm accounting from both models are consistent, which matters a lot for farmers' exit decisions.
4. We will generate a large dataset from the adjusted FarmDyn and train DNNs of various architectures to approximate the input/output relations. One crucial feature of DNNs is that they are computationally intensive to train, while they are very efficient to run for providing

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accurate approximations of complex nonlinear input/output relations for prediction once they are trained.

5. We will replace the IDM in AgriPoliS using the well trained DNN. This step requires smooth communication between the DNN (written in python) and AgriPoliS (written in C++).
6. Lastly, when the above steps are accomplished, we will implement the policy scenario of mandatory fertilizer reduction in the research region using the integrated model.

The advantage of this approach is that it combines the strengths of both the farm-level model and the ABM without directly integrating them. The efficient surrogate model keeps all important details of FarmDyn and replaces the simple DIM in AgriPoliS. The integration of DNN and ABMs enables us to efficiently conduct economic and environmental impact analysis of farm activities and agricultural policies from a system perspective.

Despite these advantages several limitations exist. First, DNN can probably not achieve 100% accuracy in approximating the detailed farm-level model. For example, some jumpy behavior or rare events in crop production derived by the mathematical solver might be difficult for DNN to capture. Thus, we must make sure that the outputs we are interested in when conducting policy analysis should achieve a satisfying level of accuracy, which is in turn hard to set a strict threshold during evaluation. Second, since the updates from the farm-level model are not automatically transferred to the DNN, another limitation of this approach is the DNN must be retrained (partially or completely) each time when important updates are made in the detailed farm-level model.

5.3. Vision/Long-term perspective

Currently, ABMs hardly go beyond regional coverage. Hence, they primarily need to be used as complementary tools to large-scale EU or global models. The work in task 4.5 described above does not aim to go beyond a regional level, rather focusing on improving the link between complex IDMs and regional ABMs. However, the general idea of using surrogate models to link models across scales and using them for upscaling could also be used to go beyond the regional scale up to the national/EU scale. One vision in this respect would be to build a surrogate model of a regional ABM and then link those regional surrogate models together forming a new model at a national/EU scale. In such a model it would then be possible to consider further feedback mechanisms endogenously e.g. market price effects.

While conceptually such a linkage might be possible, practical obstacles need to be overcome, for example in terms of the massive data requirements necessary to adopt a regional ABM (or a surrogate model of such an ABM) to a specific region. Also building a surrogate model of a dynamic system such as an ABM might be more complex compared to the IDM model considered here.

5.4. Expected project outcome

Within this project, we aim to provide a proof of concept that building a surrogate model of a complex IDM is possible and that such a surrogate model can be used in an existing ABM. Further, at the end of the project, we expect to have an integrated model of a DNN and AgriPoliS together functioning as a modeling system to facilitate efficient simulation of complex agricultural economic and environmental scenarios capturing detailed input use on farm level, interactions among farmers, and market feedback. This integrated model is parameterized for arable farms in the region “Rheinisches Revier” (Germany) and can be used to analyze certain policy scenarios (e.g. mandatory fertilizer reduction) and their impacts on the regional environment and agricultural structural change.

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The expected output can function as a complete modeling system since it allows certain policy scenarios in an existing region in Germany. However, it functions on a relatively small scale with only arable farms involved, with limited possible policy scenarios. Thus, the outcome of this task should also be an intermediate achievement, which can be further developed. In the future, the integrated model can be extended with more farming branches and for large scale (e.g. EU level) as outlined in the previous section.

6. CONCLUSIONS

This deliverable described modeling challenges for consistently linking IDMs with landscape scale and EU/global market-level models and suggested approaches to address these challenges. It is specifically concerned with areas where the interaction between individual farms matters. For the corresponding approaches it is then presented to what extent they can be integrated in larger scale (EU/global) models or where a complementary use is envisioned.

The approaches considered here comprise (task 4.2) The estimation of farm exit rates exemplified for Germany and Norway aiming to be the basis for integrating farm structural change into representative farm-level or equilibrium models: (task 4.3) The investigation of farmers' preferences and related behavior regarding the participation in collective environmental schemes through computer and group experiments; (task 4.4) the estimation of conjectural elasticities that capture market power along the supply chain and specifically (and for the first time) the power of farmers arising from contractual agreements or the formation of producer organizations. The conjectural elasticities can be incorporated in equilibrium models for a more realistic representation of price transmission along the supply chain; (task 4.5) The training of machine-learning-based surrogate models that address the computational challenges arising when trying to incorporate detailed farm-level models into representative larger scale models, here specifically into agent-based models with interaction between individual farms on the land market.

The methodological approaches all contribute to the literature dealing with "scaling" of analytical tools to analyze developments of agricultural systems and of the policies impacting on them. They are not only about "up-" scaling of IDMs as they rather target the consistent behavior of models at different scales allowing to deal with bottom-up, top-down, or integrated scenarios to be analyzed. The approaches discussed can generally be subsumed under what Ewert et al. (2011) call "manipulation of models" and ultimate visions include the reparameterization of models (task 4.2 and 4.4) and the use of "response functions" at larger scales (task 4.5). Performing experiments to better specify individual behavior in landscape-scale models (task 4.3) may also, in the end, be seen as a "reparameterization" of models, but it goes beyond what Ewert et al. (2011) had in mind by offering an empirical approach to directly address emergent phenomena from the interaction of individual agents.

The analysis of the type of scenarios currently foreseen in MIND STEP to show the functionality of the toolbox may also benefit in the long run from the development of the tools described in here. For example, reducing chemical inputs by 50% will have strong impacts on the relative profitability of farming systems and thereby on farm structural change. The farm exit model may provide a consistent reflection of this scenario-induced outcome by changing the population (weights) of the IDM models used. A direct integration of detailed farm models in a regional agent-based model may deepen the structural change analysis by simulating land market outcomes in spatially differentiated policy settings (higher reductions in 'red areas') and the related development of environmental indicators tied to local conditions.

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