ARPHA Preprints

Project Report

Author-formatted document posted on 11/12/2024

Published in a RIO article collection by decision of the collection editors.

DOI: https://doi.org/10.3897/arphapreprints.e144085

D4.1 Agent-Based Models for each case study

Gabriela Popova, Meike Will, Birgit Mueller, Chunhui Li, Jiaqi Ge, Nastasija Grujic

Ref. Ares(2024)3555248 - 16/05/2024

Agent-Based Models for each case study

Deliverable D4.1

28 February 2023

Meike Will[1], Birgit Müller[1], Chunhui Li[2], Jiaqi Ge[2], Nastasija Grujić[3]

[1]*Helmholtz Centre for Environmental Research - UFZ*
[2]*University of Leeds*
[3]*Biosense Institute*

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.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

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:	54 months
Project coordinator:	Prof. Guy Ziv School of Geography, University of Leeds, UK http://bestmap.eu/
Deliverable title:	Agent-Based Models for each CS
Deliverable n°:	D4.1
Nature of the deliverable:	Other
Dissemination level:	Public
WP responsible:	WP4
Lead beneficiary:	Palacký University Olomouc
Citation:	Will, M., Müller, B., Li, C., Ge, J. & Grujić, N. (2023). *Agent-Based Models for each CS*. Deliverable D4.1 EU Horizon 2020 BESTMAP Project, Grant agreement No. 817501.
Due date of deliverable:	Month n°42
Actual submission date:	Month n°42

Deliverable status:

Version	Status	Date	Author(s)
1.0	Final	28 February 2023	Meike Will[1], Birgit Müller[1], Chunhui Li[2], Jiaqi Ge[2], Nastasija Grujić[3] [1]*Helmholtz Centre for Environmental Research - UFZ* [2]*University of Leeds* [3]*Biosense Institute*

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Table of contents

Preface

This deliverable provides a report on the agent-based models (ABMs) for each of the case studies, developed in the Work Package 4 (WP4) – Agent-Based Modelling and Analysis of BESTMAP. In particular, it includes a description of how the models can be accessed and which input data is needed. This document is accompanied by a description of each case study model in a structured form (see Appendix) which follows the ODD+D protocol (Müller et al., 2013). Deviations from the main processes as described in Milestone M6 (First versions of ABMs for CS) are discussed for each case study.

Summary

This document presents the agent-based models (ABMs) that were developed in the H2020 project BESTMAP for each of the project's five case studies (CS). The deliverable is based on the work done in Work Package 4 (WP4) – Agent-Based Modelling and Analysis of BESTMAP and an extension of Milestone M6 (First versions of ABMs for CS). While in the Milestone the main processes that should be included in all CS versions of the ABMs were presented, this deliverable comprises a description of the particular implementation for each CS including a discussion of how and why the CS-specific models differ from the baseline version described in Milestone M6. The links to the model codes on GitLab are provided. Furthermore, data requirements and potential limitations with respect to data accessibility are outlined. Each model code is accompanied by a model description in a structured form following the ODD+D protocol (Müller et al., 2013) in the Appendix. The deliverable focuses on the model development. As an outlook, research questions that can be answered with the models, model limitations and potential further extensions are discussed. First model outcomes for each CS are furthermore included in Deliverable D4.4 'Systematic analysis of the case studies'.

1. Research goals

Agent-based models (ABMs) are process-based simulations that allow representing decisions of individual farmers and their interactions with others as well as the environment (Schulze et al., 2017; Huber et al., 2018). In BESTMAP, the purpose of the ABM (BESTMAP-ABM) is to determine the adoption and spatial allocation of four selected groups of agri-environmental schemes (AES) by individual farmers in five case studies across Europe (South Moravia in Czech Republic, Mulde River Basin in Germany, Bačka region in Serbia, Catalonia in Spain, Humber region in the United Kingdom). The selected types of AES are flower strips, cover crops, maintaining permanent grassland and conversion of arable land to permanent grassland. These four AES were chosen (i) as they existed, with roughly similar implementations, in most CSs, (ii) according to the relative importance in terms of spatial coverage of AES across CSs and (iii) were seen as relevant for future AES implementations of the European Common Agricultural Policy (e.g. conversion of arable land to permanent grassland). For some of the selected schemes, several offered schemes were grouped into the same overarching category (see Table 1 for an overview of the respective groupings in the CS).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Table 1: Overview of existing AES per AES group in each CS. Serbia is not included in the table because, as a non-EU member state, it does not offer AES.

AES group	CZ	DE	ES	UK
Buffer strips/areas	10.1.6.1, 10.1.6.2	AL5a,b,c,d	Currently not offered as AES	SW1, SW2, SW3, SW4, SW11, AB1, AB3, AB8, WT2
Cover crops	Currently not offered as AES	AL4	AES_367	SW6
Maintaining permanent grassland	10.1.4.1, 10.1.4.2, 10.1.4.3, 10.1.4.4, 10.1.4.5, 10.1.4.6, 10.1.4.7, 10.1.4.8, 10.1.4.9, 10.1.4.10	GL5a,b,c,d,e	AES_363, AES_368	GS2, GS5, GS6, GS7, GS9
Conversion of arable land to permanent grassland	10.1.5.1, 10.1.5.2, 10.1.5.3, 10.1.5.4, 10.1.5.5, 10.1.5.6	Currently not offered as AES	Currently not offered as AES	SW7

With the model, the effect of different scenarios of policy design on patterns of adoption can be investigated. In particular, the following contract characteristics can be varied:

- Contract duration (1, 5 and 10 years) for each AES
- Fraction of farmers with access to advisory support
- Level of administrative effort for the farmer to implement and monitor each AES (low, medium and high)
- Compensation per hectare enrolled in the proposed contract per year for each AES

Based on these variations, the model can be used to study the social-ecological consequences of agricultural policies at different spatial and temporal scales. In combination with biophysical models, this allows us to test the ecological implications of different designs of the EU's Common Agricultural Policy. By implementing a model version for Serbia, i.e. a non-EU member state, we can also project the acceptance of AES if these measures are offered in the context of possible EU accession in the future. The model results could then help to design the measures appropriately. An overview of potential research questions that can be addressed with the model is outlined in section 4.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

2. Case study specific ABM implementation

The model consists of three main entities: (i) Agents representing individual farmers, (ii) the spatial environment representing individual fields with each farmer managing a fixed set of fields and (iii) AES contracts. Farmers decide whether and where to adopt AES with each AES contract entity representing an AES applied on a specific field, i.e. a farmer can have several contracts for the same AES type. It is assumed that an AES is applied to the whole field and that only one AES can be selected per field. Time is represented as discrete yearly time steps with AES adoption decisions made once a year. While the temporal extent is in principle freely selectable, we decided to simulate only one time step, since developments for example in farm structure or land markets that would have to be taken into account when simulating longer time steps are not included in the model. This includes that we omit changes in farm structure such as abandonment of farms due to economic conditions or handing over to a successor which might influence decisions on AES uptake especially when long term commitments are involved. Furthermore, without markets and corresponding price developments, farmers' considerations of AES as additional income cannot be related to economic developments. This also restricts other modeling features such as collective learning, which would require a temporal development to be represented in the model. All of these aspects offer potential for future analyses. However, the model in its current form aims at a first basic evaluation of the model structure and implications of policy design. We therefore leave such extensions to later model versions, which can build on this general understanding.

The decision-making framework of the ABM is structured as a three-step procedure in which choices are made at different spatial levels. We propose this hierarchical decision-making in the context of AES because our own interview campaign (see Deliverable D3.4 'Summaries of data, obstacles and challenges from interview campaigns') and other empirical studies (e.g. Lienhoop and Brouwer, 2015) have shown that some farmers are not at all open to considering a specific AES and therefore do not enter into in-depth deliberations. The different processes that are run in one time step include:

1. **Openness to specific AES:** Decision-making at farm level on whether at all the farmer is open to consider adoption of a specific AES
2. **Subset suitable fields:** Selection of fields that are available for AES adoption
3. **Economic deliberation and spatial selection**: Deliberation on which AES to adopt on which field based on expected and offered payment level

The main structure of the ABM, as described in Milestone M6, is the same across the CS. Due to differences in the availability of data for parameterizing and calibrating the model as well as different existing policies and regulations, some parts of the model are adapted to specific local conditions. Furthermore, specific requirements for the models for the UK due to Brexit and for Serbia as a non-EU member state are considered. A description of each case study model in a structured form which follows the ODD+D protocol (Müller et al., 2013) can be found in the Appendix. In the following subsections, we describe the general ideas for the three decision steps. Table 2 summarizes the three steps, the level of decision-making and the influence factors considered in each step. More details and technical implementations for each CS can be found in the respective ODD+D.

Table 2: Summary of the three-step decision-making framework with the level of decision-making and the influence factors for farmers' decision-making

Step	Openness to specific AES	Subset suitable fields	Economic deliberation and spatial selection
Decision level	Farm level	Field level	Field level
Influence factors	Prior experience, intrinsic openness, influence from advisory support and/or influence through social network	Current AES contracts, Ecological Focus Areas, field size, land use	Expected payment level (depending on contract characteristics), biophysical characteristics of fields (depending on CS implementation)

Openness to specific AES: In the first step, farmers individually decide whether they are at all open to think about applying a specific AES. This consideration is rather driven by the personality of a farmer, in contrast to the actual AES decision which is designed to be strongly based on economic factors. We decided to include this separate decision step as it was observed that some farmers have general aversions against some AES and never consider applying for those. This includes, for example, when farmers see themselves as farmers and not as foresters and therefore are not willing to convert their arable land to woodland (Lienhoop and Brouwer, 2015). Furthermore, as it was stated in the interviews, some farmers are reluctant because of their own negative experience or rumors about AES, e.g. including sanctions due to actions that were not the farmers' faults. Additionally, for some farmers their reluctance might simply be based on missing knowledge about specific AES, the long timeframe that some AES impose which might not be in accordance with the business plans of the farm or because they do not see the environmental benefits. In the model, the probability for being open depends on farmers' previous experience with specific AES, their access to advisory support, their intrinsic openness, and the previous experience of other farmers.

Subset of suitable fields: The second step operates at field level and determines the fields that are in general available for specific AES applications. Farmers exclude fields that have ongoing AES contracts as those are not eligible for new schemes. Additionally, farmers decide on which fields they apply Ecological Focus Areas (EFAs) and exclude those as well. To comply with the rules for the minimum field size needed for application of specific AES, farmers furthermore exclude fields that are too small. Finally, for each specific AES, farmers consider only those fields that are under the appropriate land use (see Table 4). After this step, farmers have for each AES a set of fields in their selection list, on which it can potentially be applied.

Deliberation and spatial selection: In the third step, farmers decide whether they consider the adoption of AES profitable. This calculation is done separately for each AES. The central

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

element of the decision-making is the payment level that farmers require for a specific AES. Crucial elements that we consider when calculating the expected payment level of individual farmers are: contract length, administrative effort and advisory support. In the model, it is assumed that farmers adopt a specific scheme if their individually expected payment level is exceeded by the offered payment level denoted in the contract details. To parameterize the expected payment level given these various influence factors, a discrete choice experiment (DCE) where respondents are presented with choices between alternatives of concrete AES contracts has been conducted in the five case studies (for Spain, however, the number of responses was too low to perform an objective analysis and therefore, this case study was not included in further evaluation). The results of the DCE can be summarized in a so-called "willingness to accept" for each AES which directly relates to the payment level a farmer accepts for a specific AES. It is assumed that the willingness to accept differs with different contract designs, e.g. that farmers accept a lower compensation if the contract duration is one instead of five years.

To analyze the heterogeneity among farmers, farmer types can be used to represent diversity between farmers while keeping a meaningful number of different behavioral types (Arneth et al., 2014; Bartkowski et al., 2022). Within BESTMAP, a generalized typology of farming systems (Farming System Archetypes, FSA) that are assumed to have similar response to policy change has been developed (see Deliverable D3.5 'Farming System Archetypes for each CS'). While in principle the results from the DCE can include differences between such farmer types, we have encountered difficulties to get statistically significant results for "willingness to accept" of these sub-groups. Since a statistically sound analysis of a DCE requires a substantial number of responses (especially if more detailed analyses such as latent class analysis (Hagenaars & McCutcheon, 2002) are to be conducted to uncover hidden clusters among farmers), the low number of completed responses that we obtained (sample sizes ranging from 69 for the Czech Republic to 131 for Serbia) limits the practical use of the DCE for parameterization. Given these difficulties we had to resort to alternative approaches such as pattern-oriented modeling (Grimm et al. 2005) (see section 2.1 for an explanation of the approaches taken in different CS).

With respect to the final decision on where to implement a scheme, we assume that biophysical characteristics are the primary factors given the importance of biophysical factors in the interviews (Deliverable D3.4 'Summaries of data, obstacles and challenges from interview campaigns') and the results from regression analyses conducted for the Mulde CS (Paulus et al. 2022). Following the field-level logistic regression models derived in Paulus et al. (2022), a probability is calculated for each field to determine the order in which fields are selected for AES. Depending on the data availability, this calculation is performed slightly differently for each CS (see below and in the CS ODD+Ds in the Appendix).

2.1. Differences in data availability for parameterization and calibration

2.1.1. Parameterization of expected payment level

Since the sample size of the survey was too small to obtain statistically significant results for the expected payment level of different farmer types, for those CS where AES already exist (i.e. all CS except Serbia), we developed a workaround approach to parameterize the expected payment level by deriving a mean expected payment level with which the current

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

adoption rates can be reached (see below for data augmentation analyses that were performed instead for Serbia). We assume that the expected payment levels of all farmers of the same farmer type (i.e. farmers belonging to the same FSA) are normally distributed, i.e. the mean expected payment level is the mean of the normal distribution of expected payment levels (see Figure 1 for a graphical representation of an exemplary distribution of expected payment levels). From the available data, we can derive the current adoption rates for a specific scheme per farmer type (10.9% in the exemplary calculation, highlighted in green) and the offered payment level (755€/ha in the example). For the standard deviation, assumptions have to be taken, e.g. based on results from other discrete choice experiments, or a sensitivity analysis has to be performed with which the effect of different standard deviations can be analyzed. In the example, a standard deviation of 100€/ha is assumed which results in a mean expected payment level of 878€/ha.

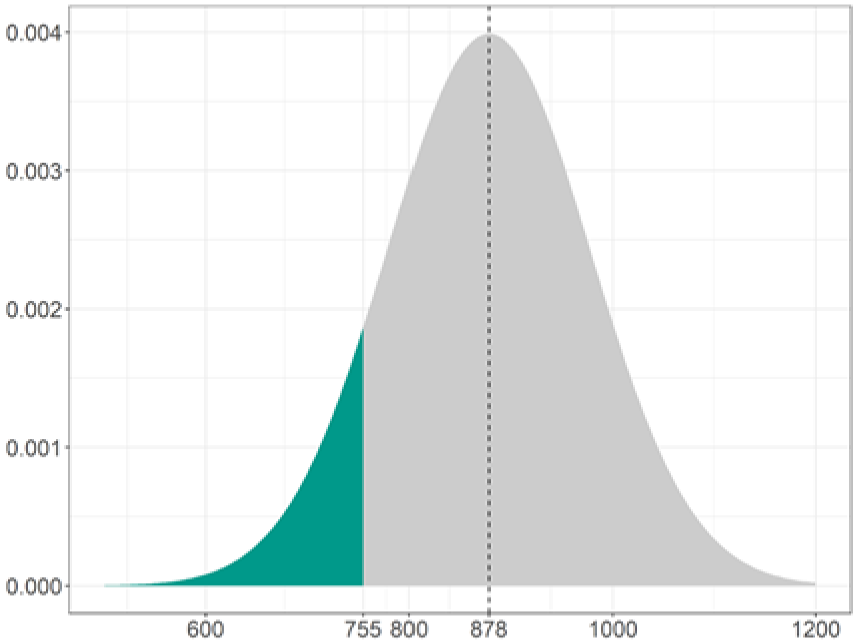

Figure 1: Exemplary distribution of expected payment levels for a scheme with adoption rate 10.9% (highlighted in green), offered payment level 755€/ha and standard deviation of 100€/ha. The resulting mean expected payment level is 878€/ha.

For schemes that are currently not offered, further assumptions on a reasonable offered payment level and the expected adoption rates have to be taken. As a consequence, in DE and CZ at the moment only those schemes are simulated that are currently offered in the respective CS (see Table 1).

For the Spanish CS, no historical data for payments for buffer strips and conversion of arable land to grassland are available. Therefore, the average offered payment levels of other CS, where buffer strips and arable land conversion to grassland are available, are used as the status quo setting for the AES designs.

Without AES being currently offered, no historical data on AES adoption is available for Serbia. Therefore, calibrating the expected payment level to match current adoption rates is not possible and more effort was taken to derive reliable information from the DCE results.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Thus, the analysis of the DCE was extended using several approaches to augment the data which resulted in statistically significant outcomes for the expected payment levels of different farmer types. In the model, it is possible to choose between three different ways of calculating the expected payment level (see Serbia's ODD+D for more details on the applied algorithms and difficulties of the individual approaches).

2.1.2. Statistical analyses included in the CS ABMs

Expected payment levels for individual farmers are drawn from a normal distribution, which is determined separately for the different farmer types. However, within the farmer types, we do not include further specification on which farmers are more likely to participate (i.e. which farmer has a lower expected payment level) than others. To reduce the resulting randomness, we decided to include results from statistical analyses based on what has been developed in Paulus et al. (2022) for the Mulde CS in Germany. In that study, a regression approach has been used to determine the probability for participation in AES based on selected farm and landscape characteristics. The general idea of how to use this approach in the ABM is to sort farmers by their predicted probability and assign a higher expected payment level the less likely they are to participate in AES. The second regression model developed in Paulus et al. (2022) determines the percentage of farm area that is enrolled under AES. In the model, this can be used to calculate the area a farmer envisions for AES. Finally, the probability for fields to be selected for AES can be calculated following the logistic regression models at field level derived in Paulus et al. (2022). Depending on the data availability, these regression approaches are incorporated to a different extent in the different CS ABMs (see Table 3 for an overview and below for more explanations).

Table 3: Overview of regression models derived in Paulus et al. (2022) to predict (1) the participation in AES, (2) the percentage of area under AES and (3) the selection of fields for specific AES based on farm and landscape characteristics.

Level	Response	Modeling Approach	Case study ABM application
Farm	Participation in AES	Logistic GLM	CZ, DE, UK
Farm	Percentage of area under AES	Beta regression	CZ, DE
Field	AES presence on field (AES specific)	Logistic GLM	DE

For the CZ ABM, the data needed for the regression on field level was not available. Therefore, only the farm level regression analyses were performed (participation in AES and percentage of area under AES). For the selection of fields under AES, low soil quality and small field sizes is used as a proxy.

For the DE ABM, all three regression approaches are applied. In contrast to the calculation in Paulus et al. (2022), the beta regression on the percentage of area under AES is only performed on the selected AES that are modeled in the ABM. Since there was a large mismatch between predicted area under AES following the beta regression and the actual

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

area under AES as in the data of 2019, a scaling factor was included with which the total area under AES could be reduced. For the regression analysis on AES presence on a field, the AES specific models are selected but farm level variables that are included in the models in Paulus et al. (2022) are excluded since they do not vary within a farm and the analysis is not used for comparison between farms.

For the UK ABM, three options can be chosen at the model initialization stage with increasing importance of the farm-level regression analysis (see UK ODD+D for more details on the differences between the approaches). The regression on the percentage of area under AES is not included. Instead farmers' envisioned area for AES is initialized with the average of the historic proportion of AES area in a farm. Also for the selection of fields under AES, the regression approach is not considered but a simplified proxy with farmers preferring to put fields with lower soil quality and smaller sizes under AES is applied.

As the current AES design in ES is substantially different from what is offered in the other CS, the ES data was excluded from the regression analysis. Therefore, the ES ABM does not include such statistical analyses. Instead, in the ES model, individual farmers' expected payment levels are drawn from a normal distribution, similar to other CS models, however, the expected payment levels are not ranked based on probabilities of adoptions produced by the regression analysis. Once a farmer has decided to participate in an AES, fields with smaller sizes and lower soil quality are prioritized to be put under the AES. A farmer's envisioned area is parameterised by either the average proportion of the farm area under an AES in a farm (according to historic adoption data for cover crops and grassland management) or the average of the measure (i.e., the average proportion of the farm area under an AES in a farm) in other CS where buffer strips and arable land conversion to grassland exist.

Since these analyses heavily rely on the current adoption data, they cannot be performed for the Serbian CS. The area that farmers envision to enroll under AES was therefore approximated using data from a question after each choice card in the choice experiment where farmers were asked to denote which fraction of their suitable land they would enroll under the chosen scheme. The fields on which AES are applied are selected based on soil quality and field size.

2.1.3. Survey data used for model parameterization

To parameterize the first step of the decision-making process, we rely on results from the questionnaire that was part of the online survey conducted in the case studies (see Deliverable D1.8 'Guidelines and protocols harmonizing activities across case studies (Update)' for more details on the content of the survey). In particular, we parameterize the fraction of farmers with access to advisory support based on the question on the frequency of different types of consultation (see Figure 2). We assume that all farmers that indicated getting consultation specific to AES at least 1-2 times a year have access to advisory support that influences their AES decision.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

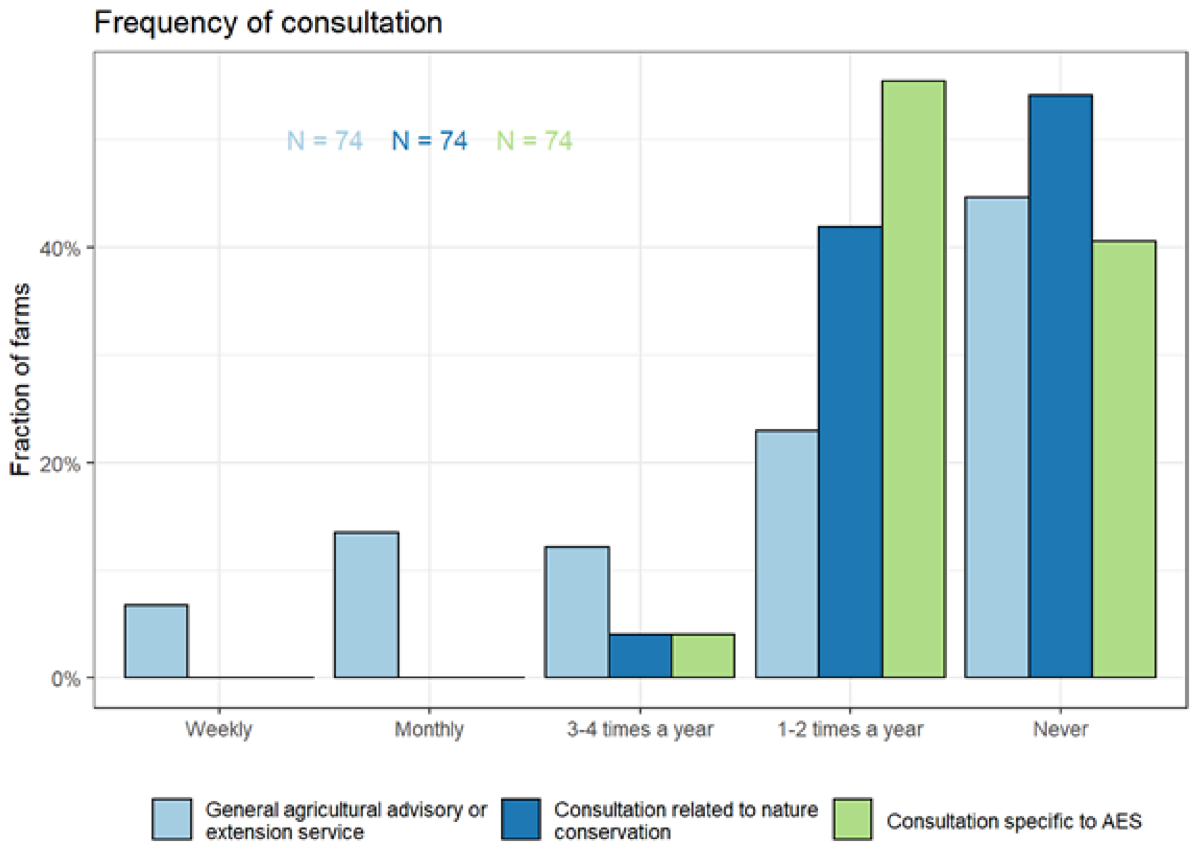

Figure 2: Frequency of consultation support for farmers in the German case study. To parameterize the fraction of farmers with access to advisory, we consider all farmers that get consultation specific to AES (light green) at least 1-2 times a year. The resulting proportion of farmers with advisory support is 59% in the German case study.

Furthermore, we include results from the question on the general openness to participate in a selected scheme. This question was shown to farmers that had not yet participated in the scheme before but indicated that they know that the scheme exists. To parameterize the intrinsic openness and the openness due to advisory support, we distinguish the responses for farmers with and without consultation specific to AES (see Figure 3).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

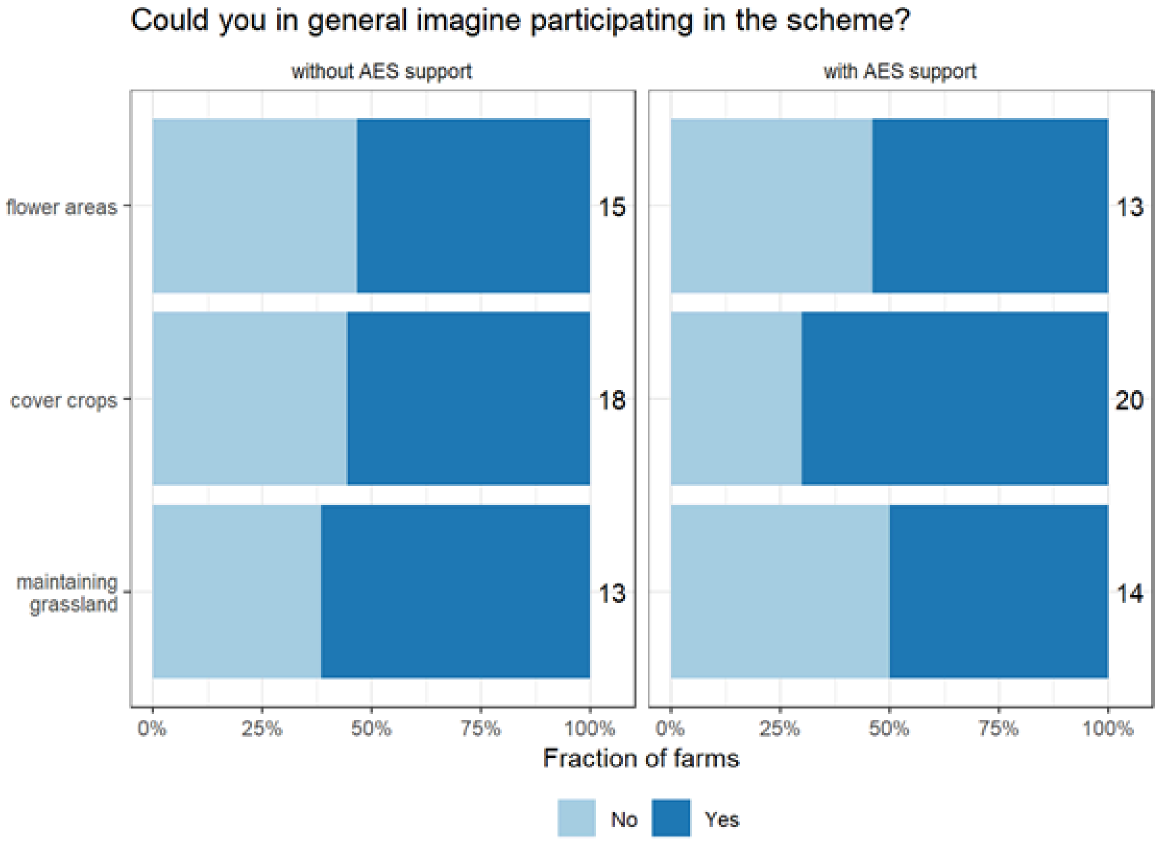

Figure 3: General openness to participate in a specific scheme for farmers with and without advisory support in the German case study. Numbers on the right indicate the number of survey respondents that answered the question for the particular scheme.

For the CZ case study, the survey data is used in the same way as for the German case study (see ODD+D for the Czech CS for the resulting parameter values).

In the ES and UK models, the survey data was not used for different reasons. For the ES model, there is no reliable survey data available since the number of respondents was too small. For the UK model, because the respondents of the survey are not representative of the UK farmer population, with a large proportion of the respondents being farmers who are either certified organic or in transition to fully organic (in total more than 50% of all respondents), we decide not to use this data for the model. Instead, we parametrize these variables based on the historic AES adoption data, the Eurostat data of Agri-environmental indicator - farmers' training and environmental farm advisory services[1] and assumptions that will be varied in sensitivity analyses. In both CS, the calculation of openness (decision step 1) therefore slightly differs from the other CSs. For ES and UK, openness due to advisory support is considered separately from intrinsic openness whereas for CS that use the survey data for farmers with advisory support, intrinsic openness and openness due to advisory

[1] Eurostat Agri-environmental indicator - farmers' training and environmental farm advisory services available at:
https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:Agri-environmental_indicator_-_farmers%E2%80%99_training_and_environmental_farm_advisory_services&oldid=227049

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

support are not disentangled and for farmers without advisory support only intrinsic openness plays a role (see the flow charts in the respective ODD+Ds for details).

Since AES are not currently offered in Serbia, the survey included a question asking farmers whether they would participate if offered a subsidy for the particular agroecological practice. Farmers that answered “yes” are considered open towards the respective practice. For the model, the openness of organic and conventional farmers is considered separately (see ODD+D for the Serbian CS for details).

2.2. Differences due to different AES regulations

Because AES regulations are developed at the member state level or even below, the specific contract details differ slightly in the CS considered. These include which areas are considered appropriate for the selected AES, how Ecological Focus Areas must be taken into account when selecting fields for AES, and whether multiple AESs can be applied to the same parcel. The following section discusses the differences between CS implementations due to these different AES regulations.

Suitable land for specific AES: Based on the requirements for existing AES, the land types (i.e. arable land, grassland, horticulture or other land) on which a specific AES can be applied differ between CS. Table 4 summarizes the resulting restrictions to land suitable for the selected AES that are assumed in the model.

Table 4: Suitable land types for the selected AES in each CS. For AES that are currently not offered, the respective land type is given in italics.

	CZ	DE	ES	RS	UK
Buffer strips/areas	arable land	arable land	*arable land*	*arable land*	arable land and grassland
Cover crops	*arable land*	arable land	horticulture	*arable land*	arable land
Maintaining permanent grassland	grassland	grassland	grassland	*grassland*	grassland
Conversion of arable land to permanent grassland	arable land	*arable land*	*arable land*	*arable land*	arable land

Excluding EFA fields for AES adoption: In the model version for the UK, the second model step for selecting suitable fields had to be slightly modified as in this CS, AES and EFA can be put on the same parcel. Instead, it is considered that environmental stewardship schemes (ESS) and countryside stewardship schemes (CSS) (to which the selection of simulated schemes belongs) cannot be applied on the same fields.

Multiple AES on the same parcel: In the model version for the UK, the assumption that only one AES per plot is allowed had to be changed since in reality it is possible to implement multiple AES on the same parcel. In the model, a farmer decides on the proportion of the field area that is put under AES, ranging from minimum required area (depending on AES designs) to 100% of a field. If less than 100% of a field is occupied by one AES, the remaining area can be used for additional AES.

Applying several AES to the same field is also possible in other CS, but only under limited conditions (e.g., only certain AES can be combined), which are omitted for simplicity.

2.3. Specific implementations for Serbia as a non-EU member state

As Serbia is a non-EU member state, data availability for that CS is slightly different compared to the other CS considered in BESTMAP. This includes that there is no data available from the standardized Land Parcel Identification System (LPIS). Instead, parcel information of farms which are registered to the locally administered AgroSense platform is used. However, as the registration to this platform is voluntary, the available fields do not cover the complete CS area but only a subset of farmers which is not necessarily representative of all farmers in the region.

Furthermore, since there are no AES offered in the CS, the first step in the decision-making process had to be adapted since previous experience with AES could not have been considered. Instead, it is assumed that in the first simulated time step, organic farmers are more likely to be open to AES adoption. The probability for being open is extracted from the survey data. In later simulated time steps, prior experience with specific AES is additionally based on the simulated participation in these AES. For social influence, a similar concept is considered. In the first simulated time steps, only organic farmers positively influence the openness of others to apply AES. In subsequent time steps, simulated participation in specific AES determines if one influences the openness of other farmers in the network.

Regarding the selection of suitable fields for AES adoption in the second step of the decision making process, it has to be taken into account that there are no regulations on EFA in Serbia. Although a proxy for EFA exists, this applies only to state property and does not affect a farmers's selection of suitable fields for AES. Therefore, this restriction in the selection of fields in the second model step is omitted.

3. Model accessibility and data requirements

The source codes of the CS model versions are publicly available on the UFZ GitLab Service (https://git.ufz.de/bestmap/bestmap-abm). The specific case study models can be found with the following links:

- CZ: https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-CZ
- DE: https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-DE
- ES: https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-ES
- RS: https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-SRB
- UK: https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-UK

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

For each of the ABMs that will be used for publications, we will also consider making the source code available on CoMSES Net (https://www.comses.net/) where it might be easier to find for the ABM community.

While the complete source code is publicly accessible, model usage is limited by data accessibility due to privacy issues for all CS. Spatially explicit information on individual fields was derived from the LPIS databases of the respective case studies, which are part of the EU-wide Integrated Administration and Control System (IACS) (see CS-specific ODD+Ds for for more details on the sources of the data that was used for the models). These data sets contain confidential information and can thus not be made publicly available. Unfortunately, this means that the BESTMAP-ABM cannot be operated by users that are not part of the BESTMAP project. However, the data can be requested from the respective agencies in the case studies for research purposes. The scripts to prepare the data to be used as input for the ABMs are available upon request from the authors of the individual CS ABMs.

4. Outlook

In this deliverable, we have focused on the reasoning behind the formalization of the decision-making ABM and its technical implementation. To conclude, we would like to give an outlook on areas of application and potential overarching research questions that can be addressed with the model.

1. **Scheme design aspects:**
   How does the AES adoption change with…
   - … higher or lower payment levels for AES?
   - … reduced or increased administrative effort for farmers?
   - … longer or shorter contract durations?
2. **Scheme promotion/roll-out aspects:**
   How does the AES adoption change…
   - … if a referral program (“word-of-mouth” marketing) is adopted to get more farmers to participate in one type of AES?
   - … if more farmers have access to advisory support?
   - … if advisory support is more targeted at AES?
3. **Social-economic developments:**
   How does the AES adoption change…
   - … if farmers are more willing to take actions than before (e.g. due to societal discussions related to climate change)?
   - ... if more farmers decide to switch to organic farming?
4. **Optimization and trade-offs:**
   How can the AES design be optimized to reach…
   - … the highest adoption with lowest payments?
   - … the adoption with the highest/minimally required ecological impact?
   - … adoption of schemes/patterns which are assumed to be ecologically favorable?

   Are there trade-offs between…
   - … the optima for different biophysical impacts?

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

- … the biophysical and the financial optimum (limited available budget for AES funding)?

5. **Introduction of new schemes**
   - How must AES be designed so that their introduction has the desired effect? (especially relevant for Serbia as a non-EU member state but also related to the introduction of new schemes)
   - How are newly introduced schemes adopted? Do they "compete" with existing schemes?

Furthermore, coupling the ABMs with the biophysical models developed in the project is planned (see Deliverable D3.3 'Ecosystem service, biodiversity and socio-economic models for each case study'). The output of the ABMs should thereby serve as input for the biophysical models. This allows us to analyze the impact of different policy scenarios on the simulated ecosystem services (biodiversity, food and fodder, carbon sequestration and water quality) and therefore to disentangle the feedback between individual farmer behavior and its impact on the environment.

While we believe that the model will be a valuable tool to address these research questions, we also see limitations of the model and aspects with which the model could be extended.

First, we admit that the model in its current form comprises only a few characteristics of a "classical" ABM. While time is represented as discrete yearly time steps with AES adoption decisions made once a year and the temporal extent is in principle freely selectable, we decided to simulate only one time step ("alternative now") instead of a longer time period. This neglects the potential of ABMs to draw conclusions from developments over time. However, changes, for example, in farm structure or land markets that would have to be considered when simulating longer time steps are not included in the model. Instead, in our case, interaction between farmers would be responsible for the majority of the dynamics that emerge over time. Given that existing empirical studies place varying degrees of importance on social interaction between farmers and that structural changes are likely to be more important to farmers' decisions, simulating longer time steps with the current model implementation might lead to unreliable results if such structural change processes are of high importance also in the medium term. To include influences by changes in farm structure and land markets, coupling our ABM with models that include farm dynamics such as AGRIPOLIS (Happe et al., 2011) or FARMDYN (Britz et al., 2014) might be an interesting approach. Similarly, with longer simulated time periods, changes in opportunity costs of participating in AES would need to be considered. As outlined in Deliverable D2.4 'Economic scenarios outputs based on policy workshops', biofuel and climate policy scenarios lead to changes in land use and varying prices for yields which are directly linked to changes in opportunity costs of participation in AES. For the application in BESTMAP, simulating only one time step is justified in the sense that the ABMs match the temporal scale of the biophysical models developed in the project.

Moreover, our model focuses only on a small part of decisions with respect to AES. We consider only four measures out of a pool of many more AES that could be applied. Thus, we neglect decisions in which trade-offs between schemes play a role. We also group different AESs together, although in reality different influencing factors could play a role even for these very similar applications. However, we have already learned during the evaluation of the DCE conducted for the four selected measures that it can be difficult to draw meaningful conclusions - especially with small sample sizes. Thus, parameterization would become much more difficult with even more AES.

We hope that our ABMs nevertheless provide a good basis for the analysis of AES adoption under different policy scenarios. The model is conceptualized in a way that it could be transferred to other regions or implemented with different AES if required. Furthermore, the main ideas of the implementation will be upscaled to the EU level (see upcoming Deliverable D5.3 ‘ABM at the European-scale’).

5. Acknowledgements

We thank all data providers for granting access to the IACS data and the data used in the regression models and the FSA classification; these are listed in deliverable D3.1 ‘Case Study Base Layer dataset for each of the case studies’ and D3.5 ‘Farming System Archetypes for each CS’.

6. References

Britz W., Lengers, B,.Kuhn, T. and Schäfer, D. (2014). A highly detailed template model for dynamic optimization of farms - FARMDYN, University of Bonn, Institute for Food and Resource Economics.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W.M., Railsback, S.F., Thulke, H.-H., Weiner, J., Wiegand, T., DeAngelis, D.L. (2005). Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology. Science 310, 987–991.

Hagenaars J.A., McCutcheon A.L., 2002. Applied latent class analysis. Cambridge University Press.

Happe, K., Hutchings, N.J., Dalgaard, T., Kellerman, K. (2011). Modelling the interactions between regional farming structure, nitrogen losses and environmental regulation. Agricultural Systems, 104, 281–291.

Huber, R., Bakker, M., Balmann, A., Berger, T., Bithell, M., Brown, C., Grêt-Regamey, A., Xiong, H., Le, Q.B., Mack, G., Meyfroidt, P., Millington, J., Müller, B., Polhill, J.G., Sun, Z., Seidl, R., Troost, C., Finger, R. (2018). Representation of decision-making in European agricultural agent-based models. Agricultural Systems 167, 143-160.

Lienhoop, N. & Brouwer, R. (2015). Agri-environmental policy valuation: Farmers' contract design preferences for afforestation schemes. Land Use Policy, 42, 568-577.

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., & Schwarz, N. (2013). Describing human decisions in agent-based models –ODD + D, an extension of the ODD protocol. Environmental Modelling & Software, 48, 37–48.

Paulus, A., Hagemann, N., Baaken, M.C., Roilo, S., Alarcón-Segura, V., Cord, A.F., Beckmann, M. (2022). Landscape context and farm characteristics are key to farmers' adoption of agri-environmental schemes. Land Use Policy, 121, 106320.

Schulze, J., Müller, B., Groeneveld, J., Grimm, V. (2017). Agent-Based Modelling of Social-Ecological Systems: Achievements, Challenges, and a Way Forward. Journal of Artificial Societies and Social Simulation 20, 8.

Appendix

ODD+D for South Moravia (CZ)

Corresponding author: Meike Will, Helmholtz Centre for Environmental Research - UFZ

1. Overview

1.1. Purpose

What is the purpose of the study?

The purpose of the BESTMAP-ABM-CZ is to determine the adoption and spatial allocation of four selected agri-environmental schemes (AES) by individual farmers in the South Moravia region located in the southeastern part of the Czech Republic. The selected AES are flower strips, cover crops, maintaining permanent grassland and conversion of arable land to permanent grassland. While the flower strips, maintaining permanent grassland and conversion of arable land to permanent grassland is currently offered in the case study area, cover crops is a hypothetical scheme designed to test the impact of potential policy changes. For the first model analyses, only the currently offered schemes are considered.
With the model, the effect of different scenarios of policy design on patterns of adoption can be investigated. In particular, 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. The model was developed in the BESTMAP project (Ziv et al., 2020) as one of five case study-specific models with the same core processes.

For whom is the model designed?

The model is designed for policymakers and stakeholders responsible for agricultural policies to assess the impact of future policy designs. In addition, the model can be used by scientists to build upon the existing model structure and address further research questions in the context of farmer behavior.

1.2. Entities, state variables, and scales

What kinds of entities are in the model?

The model consists of three main entities: Agents representing individual farmers (734 farmers), the spatial environment representing individual fields (14876 fields) with each farmer managing a fixed set of fields and AES contracts. Farmers decide whether and where to adopt AES with each AES contract entity representing an AES applied on a specific field, i.e. a farmer can have several contracts for the same AES type. It is assumed that an AES is applied to the whole field and that only one AES can be selected per field.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Farmers belong to one of twelve farmer types based on the Farming System Archetypes (FSA) developed in the project[2]. Farming System Archetypes are distinguished by their farm specialization (general cropping ('P1'), horticulture ('P2'), permanent crops ('P3') and grazing livestock ('P4') or 'mixed' if not at least 2/3^{rds} of the total farm area is dedicated to one of the corresponding land use types) and economic size (four groups: <2000 EUR, small, medium and large). For the Czech case study ABM, only P1, P4 and mixed farmers are considered since P2 and P3 farmers with mostly horticulture and permanent crops do not have (much) suitable land available to apply AES. The distribution of FSA is shown in Figure 1.

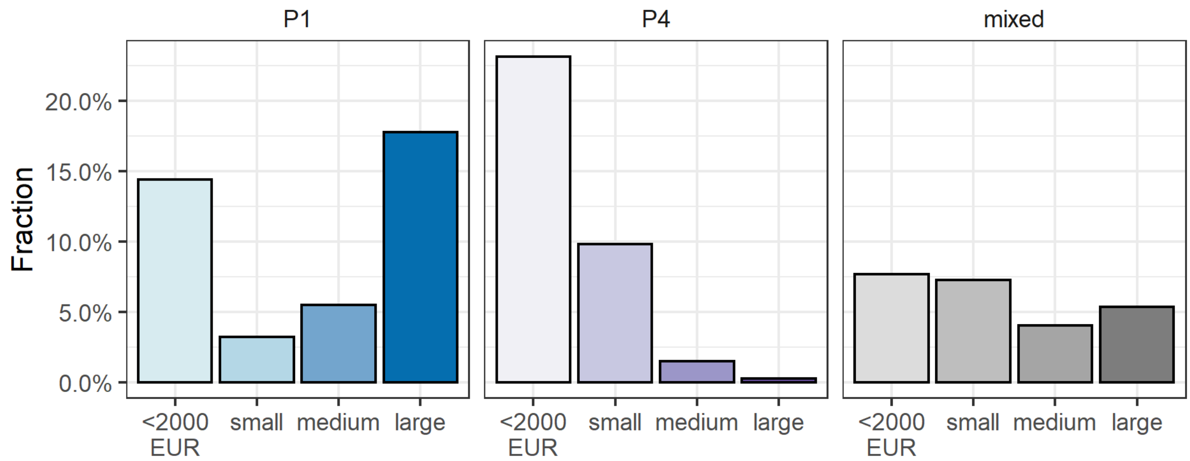

Figure 1: Distribution of farms to farming system archetypes (FSA) according to farm specialization (P1, P4, mixed) and economic size.

By what attributes (i.e. state variables and parameters) are these entities characterized?

Constant farmer state variables

	NetLogo variable	**Possible values**	**Unit**
Farmer ID	p-farmer-id	-	-
Farmer type depending on available land and farm size	p-farmer-type	All combinations of farm specialization (P1, P4, mixed) and economic size (<2000 EUR, small, medium, large)	-
Size of farm (sum of field sizes)	p-farm-area	>0	ha
Fields a farmer owns	p-property-set	-	NetLogo agentset
Access to advisory support	p-advisory	0/1	

[2] More details on the implementation of the Farming System Archetypes in all five BESTMAP project case study regions is publicly available (CC BY 4.0) as part of the publication of the EU Horizon 2020 BESTMAP Project Report *"Deliverable 3.5: Farming System Archetypes for each CS"* at: https://bestmap.eu/about.php?storyid=2732

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Farmers in social network	p-social-network	Depending on social network type	NetLogo agentset
Probability for participation in each AES calculated using logistic regression (Model 1 in Paulus et al., 2022)	p-probability-aes-list	[0,1] (4 items)	-
Intended proportion of farm area under AES calculated using beta regression (following Model 2 in Paulus et al., 2022)	p-envisioned-aes-area	[0,1] (4 items)	-
Variables to calculate probability for participation in each AES and proportion of farm area under AES following regression models developed in Paulus et al. (2022)	p-econ-int p-farmspec-arable p-farmspec-grassland p-mean-fieldsize p-crop-div p-dist-fields p-elevation-farm p-erosion-risk-farm p-organic-carbon	Depending on variables (scaled and mean centered)[3]	€/ha T/F ha T/F T/F ha - m m.a.s.l. - -

Farmer state variables varying over time

	NetLogo variable	Possible values	Unit
Prior experience with each AES (list)	v-prior-experience-list	0/1 (4 items)	-
Openness towards each AES (list)	v-open-to-aes-list	0/1 (4 items)	-
Expected payment level for each AES (list)	v-accepted-payment-list	(4 items)	EUR/ha
Acceptance and availability of land for each AES (list)	v-accepted-aes-list	0/1 (4 items)	-
Share of land used for each accepted AES (list)	v-aes-fraction-list	[0,1] (4 items) (Σ = 1)	-
Fields suitable for each AES (list)	v-suitable-fields-list	(4 items)	NetLogo agentset

[3] More details on the available data is publicly available (CC BY 4.0) as part of the publication of the EU Horizon 2020 BESTMAP Project Report *"Deliverable 3.1: Case Study Base Layer dataset for each of the case studies"* at: https://bestmap.eu/about.php?storyid=2732

Total area under AES for each AES (list)	v-contract-area-list	(4 items)	ha
Number of AES contracts for each AES (list)	v-nr-aes-fields-list	(4 items)	-

Constant field state variables

	NetLogo variable	Possible values	Unit
Field ID	p-field-id	-	-
Owner ID (farmer)	p-owner-id	-	-
Land use	p-land-use	Arable land, grassland	-
Field size	p-area	>0	ha
Ecological focus areas (EFA) status	p-EFA-field	0/1	-
Soil quality	p-soil-quality	[0,100]	-

Field state variables varying over time

	NetLogo variable	Possible values	Unit
AES currently applied (list)	v-aes-list	0/1 (4 items)	-
Number of AES contracts previously applied (list)	v-aes-hist-list	(4 items)	-

Constant AES contract state variables

	NetLogo variable	Possible values	Unit
AES type	v-aes-nr	0: Buffer strip/area 1: Catch crops 2: Maintaining permanent grassland 3: Conversion of arable land to permanent grassland	-
Duration since AES adoption	v-aes-contract-year	[1,10]	years
Field on which AES is applied	v-aes-field	-	NetLogo agentset
Farmer who owns the field	v-aes-owner	-	NetLogo

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

			agentset
Size of AES contract (field size)	v-aes-size	>0	ha

Convention for NetLogo names: g - global variables, i - variables defined via interface, p - variables set via input files (exogenous), v - variables changed in the model procedures (endogenous)

What are the exogenous factors / drivers of the model?

The AES contract design, in particular the payment level, contract duration and administrative effort, is exogenously given. Whether a farmer has access to advisory support is randomly assigned. Spatially explicit information on individual fields was derived from IACS/LPIS (Integrated Administration and Control System / Land Parcel Identification System) data provided by the Ministry of Agriculture of the Czech Republic in January 2020 for the year 2019. Data sources for further field characteristics used in the regression analyses following those derived in Paulus et al. (2022) are summarized in '*Deliverable 3.1: Case Study Base Layer dataset for each of the case studies*' of the EU Horizon 2020 BESTMAP Project[4].

What are the temporal and spatial resolutions and extents of the model?

Space is explicitly represented at field level with each farm consisting of several fields. The case study region in South Moravia covers an area of 2,089 km^2 with individual fields with up to 305 ha.

Time is represented as discrete yearly time steps with AES adoption decisions made once a year. While the temporal extent is in principle freely selectable, we decided to simulate only one time step, since developments for example in farm structure or land markets that would have to be taken into account when simulating longer time steps are not included in the model.

1.3. Process overview and scheduling

The following processes occur in each time step:

- Update prior knowledge based on own experience
- Remove AES contracts that exceed contract duration and update state variables of farmers and fields related to AES adoption
- **Decision Making Step 1** - Check openness to specific AES: Decide for each AES separately if a farmer can in general (independent of specific contract details) imagine applying the scheme
- **Decision Making Step 2** - Select suitable fields: Compile a set of fields suitable for AES adoption by excluding fields with ongoing AES contracts, fields used as Ecological Focus Area (EFA) or fields which do not meet the required minimum field size or the required land use (i.e. depending on AES arable land or grassland)
- **Decision Making Step 3** - Deliberation and site selection: Check for each farmer and AES whether the offered payment exceeds the expected payment and select fields where AES should be adopted

[4] Publicly available at: https://bestmap.eu/about.php?storyid=2732

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

2. Design concepts

2.1. Theoretical and Empirical Background

Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?

The underlying assumption is that the adoption of AES changes with changing policy conditions, i.e. farmers are more or less willing to adopt AES depending on what they have to comply with and what is offered. The model can be used to examine the effects of different policy design scenarios on adoption patterns. Furthermore, it is assumed that not all farmers are open to the adoption of AES, some have identity-driven barriers against the adoption which cannot be overcome by financial means.

On what assumptions is/are the agents' decision model(s) based?

- Farmers accept an AES if they are open to consider the adoption. Openness is based on own prior experience, intrinsic openness, influence from advisory and/or social network (decision making step 1).
- Farmers need to have suitable land available (i.e. grassland for schemes applicable on grassland and arable land for schemes applicable on arable land) (decision making step 2).
- Farmers decide to adopt AES if the adoption is financially profitable, i.e. the offered payment level (as defined in the policy regulations) needs to be equal to or exceed their individual expected payment level. The level at which the adoption of AES is considered profitable varies depending on the characteristics of the schemes (duration, administrative effort) but also farmer characteristics (e.g. farm specialization and farm size) and external factors (access to advisory, influence of social network) (decision making step 3).

Why is a/are certain decision model(s) chosen?

The decision model is based on empirical observations from an interview campaign that was conducted in all case studies of the BESTMAP project at the beginning of 2020 (Wittstock et al., 2022, Bartkowski et al., under review). Themes and questions addressed in the interviews were derived from the literature including reviews that specifically focus on AES (Lastra-Bravo et al. 2015, Brown et al. 2020) and others that give a general overview on factors affecting the adoption of sustainable farming practices (Dessart et al. 2019) and agricultural soil management (Bartkowski and Bartke 2018).
A key observation from the interviews was that farmers face a sequence of decision making elements for AES participation. To account for this sequential process in the ABM, we follow the heuristic framework for interpreting farmers' decision making developed in Wittstock et al. (2022). Due to missing data, we could not, however, include all aspects considered relevant in that framework (e.g. we had to exclude aspects on tenant-owner relationship and the duration of tenure contracts since we did not have access to tenure data).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from? At which level of aggregation was the data available?

The conceptual framework for the decision model is based on empirical data from the interview campaign conducted with individual farmers in all case studies of the BESTMAP project. To inform the decision model with quantitative data, a follow-up survey consisting of mostly closed-ended questions and a discrete choice experiment (DCE) was conducted. Results from the survey were used to parameterize how many farmers have access to advisory (*i-g-access-to-advisory*), the probability for openness of farmers with access to advisory (*p-g-prob-advisory-open-list*) and the probability for intrinsic openness of farmers without access to advisory (*p-g-prob-intrinsic-open-list*).

By using a combination of the results of the DCE and the survey questions, the aim was furthermore to derive the expected payment level ("willingness to accept" from the DCE) for each AES and farmer type depending on contract characteristics (contract duration, administrative effort) and access to advisory. These values could then directly be used to parameterize the expected payment level in the third step of the decision making framework. However, the sample size was too small to get statistically sound results including a differentiation for case studies and farmer types. Therefore, an alternative approach was taken with respect to parameterizing the expected payment level. It was assumed that the expected payment levels within a group of farmers of the same farmer type are normally distributed. Based on the current adoption rates for a specific AES, the offered payment level and an estimated standard deviation of the normal distribution based on existing empirical data, the mean expected payment level could then be derived.

Spatially explicit information on individual fields was derived from the IACS/LPIS database of the Czech Republic. The probability that a farmer takes part in a particular AES (*p-probability-aes-list*) and the area that a farmer intends to put under AES (*p-envisioned-aes-area*) are calculated using the regression models following those developed in Paulus et al. (2022) and the data sources summarized in '*Deliverable 3.1: Case Study Base Layer dataset for each of the case studies*' of the EU Horizon 2020 BESTMAP Project[5].

2.2. Individual Decision Making

What are the subjects and objects of decision making? On which level of aggregation is decision making modelled? Are multiple levels of decision making included?

Individual farmers are the *subject* of decision making. Farmers decide whether and where to adopt AES, i.e. the adoption of AES contracts at field level is the *object* of decision making. There are *three levels of decision making* included, (1) the determination of general openness towards the adoption of specific AES, (2) the selection of suitable fields for each AES, and (3) the deliberation and site selection for each AES.

What is the basic rationality behind agents' decision making in the model? Do agents pursue an explicit objective or have other success criteria?

- **Decision Making Step 1:** Some farmers have general aversions or aversions due to

[5] Publicly available at: https://bestmap.eu/about.php?storyid=2732

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

lacking prior experience, lacking advisory or lacking experience in social network against some AES and never consider applying for those.

- **Decision Making Step 2:** Not all fields are available for AES adoption due to limitations in the contractual requirements or because they are already occupied by other AES or used as Ecological Focus Area.
- **Decision Making Step 3:** Farmers only apply AES if they consider it profitable for them, the individual threshold for profitability depends on farm and farmer characteristics as well as external circumstances. The choice of fields for AES depends on soil quality and field size.

How do agents make their decisions?

Decision Making Step 1: Farmers are open to specific AES with a probability calculated based on their own prior experience, potential influence from advisory support and their intrinsic openness and/or influence through their social network (see Figure 2 for a flowchart).

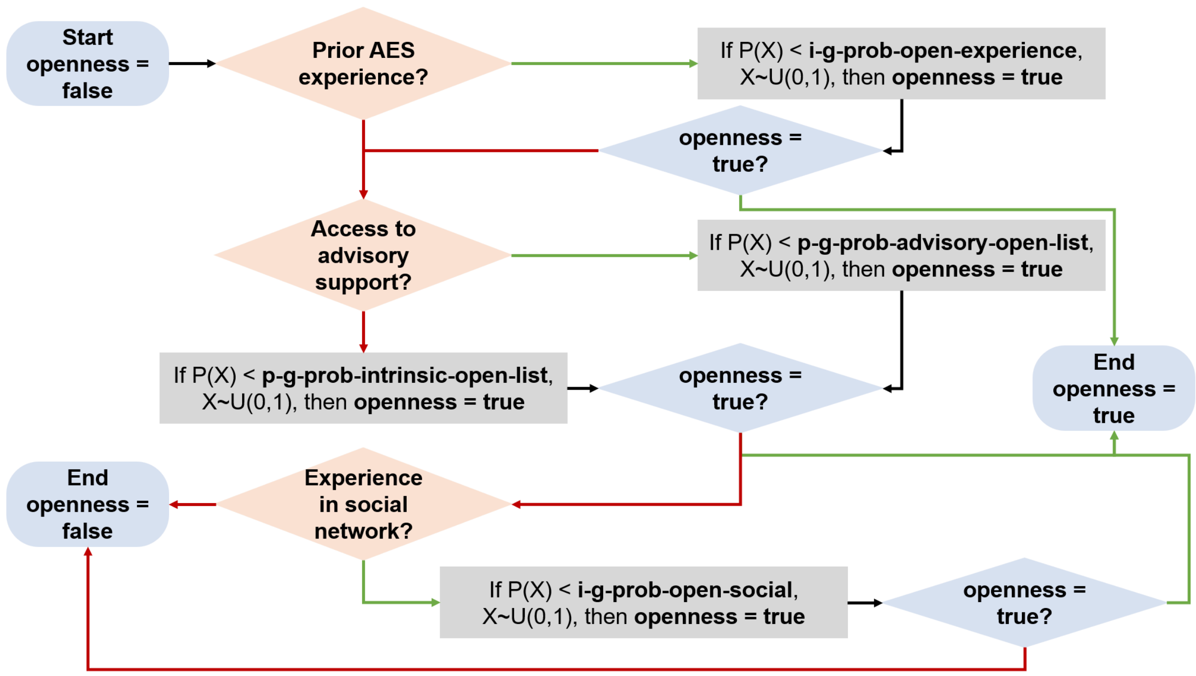

Figure 2: Flowchart of Step 1 in the decision making framework for a selected AES. Green arrows indicate “true”/yes, red arrows indicate “false”/no.

Decision Making Step 2: Farmers compare field characteristics with AES requirements and select those as suitable which fulfill the requirements.

Decision Making Step 3: Farmers compare their individual expected payment level with the offered payment level. The higher the probability for taking part in an AES as derived using the logistic regression model developed in Paulus et al. (*p-probability-aes-list*), the lower is a farmer’s expected payment level. If the offered payment level reaches or exceeds their expected payment level, farmers decide to adopt the specific AES. Farmers select fields on which to adopt AES according to the envisioned area (which is derived from input data and calculated following the beta regression derived in Paulus et al., 2022). Fields are selected

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

with increasing soil quality (*p-soil quality*). If several fields have the same soil quality, the smallest field is selected. If several fields also have the same soil quality, one of them is selected at random.

Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?

Farmers' expected payment level depends on the policy design (contract duration, administrative effort) and the share of farmers with access to advisory which can be exogenously varied to test the effect of different policy scenarios. Furthermore, farmers adapt their openness to a specific AES based on prior experience with that AES in their social network (see below).

Do social norms or cultural values play a role in the decision making process?

Social aspects are included through the influence of prior experience with a specific AES in the social network on the openness towards that AES.

Do spatial aspects play a role in the decision process?

Spatial aspects at field level are included in the probability to participate in AES and the decision how much area a farmer devotes to AES. The calculation for the probability to participate in AES follows a logistic regression as derived in Paulus et al. (2022). The area for AES is calculated using a beta regression. Both regression models include field level characteristics such as size, soil organic carbon and elevation (for a complete list of included parameters see the respective table in section 1.2). Furthermore, the decision where to apply a selected AES is based on spatial properties of the fields with farmers preferring fields with low soil quality and small size for AES.
The social network is based on spatial aspects since it consists of all farms with fields inside of a certain radius around a farmer's fields.

Do temporal aspects play a role in the decision process?

Previous experience with AES (own adoption and adoption in the social network) influences the openness towards the adoption of AES (Decision Making Step 1).

To which extent and how is uncertainty included in the agents' decision rules?

Farmers do not know how other farmers will decide in the current period, they only know their adoption from previous periods.

2.3. Learning

Is individual learning included in the decision process? How do individuals change their decision rules over time as a consequence of their experience?

Farmers who have adopted AES in previous time steps (or in the year reflected in the data used for initialization) have a high probability of being open to consider AES in subsequent decisions. Collective learning is not considered in the model.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Is collective learning implemented in the model?

Collective learning is not considered in the model.

2.4. Individual Sensing

What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Farmers can sense the state of all their fields, i.e. they know the properties of their land. Furthermore, farmers know the contract characteristics of all AES that they need to consider when deciding whether or not to adopt a scheme. Farmers remember their own previous AES adoption. The sensing process is not erroneous.

What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?

Farmers know the previous adoption of other farmers in their social network. Social networks are determined based on spatial characteristics (i.e. they include farmers with fields in a specified radius around a farmer's fields). The sensing process is not erroneous.

What is the spatial scale of sensing?

Farmers are aware of the adoption of AES on their own fields and on fields of farmers who have fields next to theirs (i.e., the neighborhood social network).

Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?

There is no explicit process of information gathering included, i.e., farmers are simply assumed to know these variables.

Are the costs for cognition and the costs for gathering information explicitly included in the model?

Costs for cognition or gathering information are not explicitly included in the model. Implicitly, it is assumed that missing knowledge about a specific AES can be a barrier for farmers to not be open towards the adoption of AES in general (Decision Making Step 1).

2.5. Individual Prediction

Which data do the agents use to predict future conditions? What internal models are agents assumed to use to estimate future conditions or consequences of their decisions? Might agents be erroneous in the prediction process, and how is it implemented?

Farmers do not predict future conditions.

2.6. Interactions

Are interactions among agents and entities assumed as direct or indirect? On what do the interactions depend?

Interactions between farmers are indirect. Farmers perceive the actions of others only through the state of AES adoption on fields of farmers in their social network which can influence their openness towards specific AES (Decision Making Step 1).

If the interactions involve communication, how are such communications represented? If a coordination network exists, how does it affect the agent's behaviour? Is the structure of the network imposed or emergent?

Communication between farmers is not explicitly modelled. The network structure is imposed and based on the spatial distance between farmers.

2.7. Collectives

Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation? How are collectives represented?

Collectives are not explicitly represented in the model. Farmers belong to a social network which is based on neighborhood and can influence the openness towards specific AES.

2.8. Heterogeneity

Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

All farmers, fields and AES contracts have the same set of state variables and processes, respectively. A fixed proportion of farmers has access to advisory. The agents and the landscape is heterogeneous with farmers differing in farm size and available land (defining their farmer type), advisory support, the social networks as well as farm characteristics used in the regression analyses based on those derived in Paulus et al. (2022). Fields differ in field size, ownership, EFA status and land use as well as characteristics used in the regression analyses derived in Paulus et al. (2022).

Are the agents heterogeneous in their decision making? If yes, which decision models or decision objects differ between the agents?

Only farmers who have passed the first step of decision making (general openness to AES) make decisions in the following two steps (selection of suitable fields, deliberation and site selection).

2.9. Stochasticity

Stochasticity is included in the following processes:

1. *General openness:* General openness (Decision Making Step 1) is calculated based on probabilities influenced by prior experience, advisory support, intrinsic openness and social influence (for details see section 3.4).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

2. *Availability of fields and openness:* Farmers can only be open to as many AES as suitable fields are available on the farm. If farmers are open to more AES than they have fields available, the maximum number of AES a farmer can be open to is calculated and for the surplus AES (randomly selected among all AES a farmer is open to) it is assumed that the farmer is not open to adopt.
3. *Expected payment level:* The mean expected payment level for a specific AES is calculated based on empirical input data for the specific policy design. To take into account aspects not considered in the factors to derive the expected payment level (contract duration, administrative effort, availability of advisory support) but also include additional differences in attitudes between farmers, the individual expected payment level for each farmer is drawn from a normal distribution around the calculated mean (see section 2.1 for the calculation of the mean). Changes in the expected payment due to deviations in contract characteristics from the baseline (five years contract, medium bureaucratic effort, no advisory support) are also normally distributed (for details see section 3.4).
4. *AES distribution:* If a farmer accepts several AES, the order in which AES are distributed to fields is random.

2.10. Observation

Observations can include effects of different model inputs on the adoption rates of AES. Data can be collected at the level of *individual farms* as well as *aggregated across all farms*. Furthermore, the spatial adoption patterns can be collected. Data can be collected at *each time step* or *aggregated over all simulation steps*.
State variables for these observations include for each AES the total area under AES (*v-contract-area-list*) or the number of AES contracts (*v-nr-aes-fields-list*) at farm level and the AES currently applied (*v-aes-list*) or the AES previously applied (*v-aes-hist-list*) at field level.

3. Details

3.1. Implementation Details

How has the model been implemented? Is the model accessible, and if so where?

The model has been implemented in NetLogo 6.2.1. The model source code is publicly available at https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-CZ.

3.2. Initialization

What is the initial state of the model world, i.e. at time t=0 of a simulation run?

- AES contract characteristics are defined based on the selected policy design.
- The landscape characteristics are imported from a GIS vector file. Field agents are created based on the input data.
- Farmers are initialized with their characteristics imported from empirical data. Access to advisory is randomly assigned.
- The social network is set up depending on *i-g-social-network-type* (either “none” or “neighbors”).
- Mean (derived based on current adoption and offered payment level, see section 2.1)

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

and standard deviation for the calculation of the individual expected payment levels is imported.

Is initialization always the same, or is it allowed to vary among simulations?

Variations can include the policy design, i.e. specifications of AES contracts, the availability of advisory support and its importance, the importance of social networks or changes in general openness. Furthermore, the effect of the standard deviation for the calculation of the expected payment level and the approach to calculate the openness can be analyzed.

Are the initial values chosen arbitrarily or based on data?

Initial values for landscape characteristics were derived from the IACS/LPIS database of the Czech Republic. Data sources for further field characteristics used in the regression analyses following those derived in Paulus et al. (2022) are summarized in '*Deliverable 3.1: Case Study Base Layer dataset for each of the case studies'* of the EU Horizon 2020 BESTMAP Project[6].
Results from the survey were used to parameterize how many farmers have access to advisory (*i-g-access-to-advisory*), the probability for openness of farmers with access to advisory (*p-g-prob-advisory-open-list*) and the probability for intrinsic openness of farmers without access to advisory (*p-g-prob-intrinsic-open-list*).
Baseline values for offered payment levels were taken from the Ministry of Agriculture of the Czech Republic (Ministry of Agriculture of the CR, 2019).

3.3. Input Data

The model does not use any external input files to represent processes that change over time.

3.4. Submodels

<u>Setup processes</u>
Function name: setup

Field setup
Function name: setup-landscape
Fields are created based on GIS input data (filenames: *\data\landscape\CZ-2019\field-file.shp* and *\data\landscape\CZ-2019\field-file.prj* - data not publicly accessible) including information on field characteristics.

Farmer setup
Function name: setup-farmers
Farmers are created based on input data in csv-format (*load-farmers*) (filename: *\data\landscape\CZ-2019\farmers.csv* - data not publicly accessible). The data include information on farm characteristics and variables used to calculate the probability for participation in AES and the percentage of farm area under AES (following Model 1 and Model 2 in Paulus et al. 2022). The probability p (*t-probability-aes*) for participation in AES

[6] Publicly available at: https://bestmap.eu/about.php?storyid=2732

based on farm attributes x_i is calculated following a logistic regression with coefficients β_j, $j = 0, 1, ..., m$ derived in Paulus et al. (2022) (filename: *\data\input\est_coefficient_mod1_CZ.txt*):

$$p = (1 + exp(-(\beta_0 + \sum_{i=1}^{m} \beta_i x_i)))^{-1}$$

The probability for participation in AES is adjusted according to the available land (arable or grassland) (*p-probability-aes-list*), i.e. farmers only have a probability of $p > 0$ for a specific AES if they have suitable land available (i.e. arable land for buffer areas, cover crops and conversion of arable land to grassland and grassland for maintaining grassland). The envisioned percentage of farm area under AES $perc$ (*p-envisioned-aes-area*) is calculated using the same farm attributes x_i as for the probability of participation in AES except the farm attributes on farm specialization (*p-farmspec-arable* and *p-farmspec-grassland*) since different coefficients based on farm specialization are used. The regression is not performed for each farmer type (i.e. distinguishing by economic size in addition to farm specialization) since the remaining subsets of farms participating in AES would be too small to perform a regression analysis. The regression coefficients β_j, $j = 0, 1, ..., m$ were derived from a beta regression following the method in Paulus et al. (2022) (filenames: *\data\input\est_coefficient_mod2_CZ_*farm_specialization*_*economic_size*.txt*):

$$perc = (1 + exp(-(\beta_0 + \sum_{i=1}^{m} \beta_i x_i)))^{-1}$$

For a list of attributes x_i that are included in the calculations for p and $perc$, see the table for constant farmer state variables in section 1.2. The set of fields that a farmer owns (*p-property-set*) is determined by comparing the farmer ID with the owner ID of the fields.

When all farmers are created, further farmer attributes are set (*set-farmer-attributes*). This includes initializing the contract area under each AES (*v-contract-area-list*), the number of fields with a specific AES (*v-nr-aes-fields-list*) and the openness to each AES (*v-open-to-aes-list*) to zero and the the expected payment level (*v-accepted-payment-list*) to 99999 (i.e. a value larger than a realistically offered payment level). A randomly chosen fraction of farmers has access to advisory support (*p-advisory*). In the baseline scenario, the fraction of farmers with advisory support is based on survey results. Furthermore, for each farmer the distribution of AES land is read based on each farmer type (filename: *data\input\fraction_AES_CZ_*farm_specialization*_ *economic_size*.csv*). These values are derived from the actual distribution of land under AES on the selected AES, i.e. the four values sum up to 1 for each farmer type.

Social network setup

Function name: setup-social-network

The type social network is defined by *i-g-social-network-type* which can be either “none” or “neighbors”. For the former option, the social network (*p-social-network*) is set to an empty turtle agentset. If the “neighbors” option is chosen, owners of fields in a radius *i-g-social-network-radius* around each field of a farmer are added to the agentset of farmers that influence the farmer.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Expected payment setup

Function name: setup-wta-specifics

AES contract characteristics are defined based on the input for duration, administrative effort and offered payment (*setup-aes-constants*).

For each farmer type (*p-g-farmer-type-list*) and AES, the mean expected payment level and its standard deviation for the baseline version of an AES contract (5 years duration, medium bureaucratic effort, no advisory support), the mean difference (*p-g-wta-mean-advisory-list*) and standard deviation (*p-g-wta-sd-advisory-list*) in expected payment when advisory is available, when contract duration is longer or shorter than five years (*p-g-wta-mean-duration-list*, *p-g-wta-sd-duration-list*) and when administrative effort is higher or lower than in the baseline case (*p-g-wta-mean-admin-list*, *p-g-wta-sd-admin-list*) are loaded from input files in csv-format (filenames: *\data\input\WTA_CZ_*farm_specialization*_*economic_size*.csv*). The following table gives an overview of the values that are considered in the simulations and references to empirical data with results that justify the chosen values. However, the differences in expected payment levels are only aligned with these studies and do not explicitly map any results. Assumptions for the standard deviations are not drawn from empirical data.

NetLogo variable	Baseline value	Source
p-g-wta-mean-advisory-list	-5%	Hasler et al. 2019, Espinosa-Goded et al. 2010
p-g-wta-sd-advisory-list	1%	-
p-g-wta-mean-duration-list	-10% (1 year contract) +40% (10 years contract)	Hasler et al. 2019, Latacz-Lohmann & Breustedt 2019, Christensen et al. 2011, Ruto & Garrod 2009, Santos et al. 2015
p-g-wta-sd-duration-list	2% (1 year contract) 4% (10 years contract)	-
p-g-wta-mean-admin-list	-5% (low bureaucracy) +5% (high bureaucracy)	Ruto & Garrod 2009
p-g-wta-sd-admin-list	1% (low bureaucracy) 1% (high bureaucracy)	-

<u>Processes in every time step</u>

Function name: go

Update world

Function name: update-world

- For each AES, it is checked whether the farmer has applied the AES before. If this is the case, the experience with this AES is set to 1 (*update-prior-knowledge*).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

- For each AES, the number of contract years is increased by one year. If the number of contract years then exceeds the contract duration, the AES is deleted (*update-aes*).

Check openness (Decision Making Step 1)

Function name: check-openness-to-aes

Openness is calculated as an individual value for each farmer and AES (*v-open-to-aes-list* equal to 0 or 1 for the respective AES). There are two options of how to calculate the openness (*i-g-openness-calculation*): “distributed” or “aggregated”.

If the option “distributed” is chosen, the calculation for each AES is conducted in the following steps (see also Figure 2). Each step is performed only if openness to the specific AES is not yet set to 1.

- Farmers with prior knowledge of the specific AES: Openness is set to 1 with probability *i-g-prob-open-experience*
- Farmers with advisory support: Openness is set to 1 with probability *p-g-prob-advisory-open-list* loaded from input data based on survey results (the probability differs between AES) (filename: *\data\input\openen_advisory_CZ.csv*)
- Farmers without advisory support: Openness is set to 1 with probability *p-g-prob-intrinsic-open-list* loaded from input data based on survey results (the probability differs between AES) (filename: *\data\input\openen_intrinsic_CZ.csv*)
- Farmers with prior experience in their social network (i.e. at least one of the farmers in their social network has prior experience with the specific AES): Openness is set to 1 with probability *i-g-prob-open-social*

If the option “aggregated” is chosen, each farmer has an aggregated probability of being open. For each AES, the aggregated probability is calculated based on the probability for being open with prior experience (*i-g-prob-open-experience*), the probability for being open with advisory support (*p-g-prob-advisory-open-list*) and the probability for being intrinsically open (*p-g-prob-intrinsic-open-list*). The probabilities for the four possible combinations compose as follows:

	Prior experience	**No prior experience**
Advisory support	*i-g-prob-open-experience + (1 - i-g-prob-open-experience) * p-g-prob-advisory-open-list*	*p-g-prob-advisory-open-list*
No advisory support	*i-g-prob-open-experience + (1 - i-g-prob-open-experience) * p-g-prob-intrinsic-open-list*	*p-g-prob-intrinsic-open-list*

To ensure that farmers from all farmer types are equally open, the subset of open farmers is drawn for each farmer type separately (*set-subset-farmers-open*). The number of open farmers is calculated based on the number of farmers in a specific group (farmer type, access to advisory, prior experience) times the aggregated probability for being open (based on the calculation as described in the table above, rounded to the next largest integer). Farmers are sorted by decreasing probability for participation in AES (*p-probability-aes-list*).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Starting from farmers with the highest probability, farmers are chosen to be open until the calculated number of open farmers is reached.

For the “aggregated” calculation of openness to AES, the influence of the social network is not taken into account.

Select suitable fields (Decision Making Step 2)
Function name: select-suitable-fields
Starting from the whole property set of fields, suitable fields are selected according to the following criteria:

- Ecological Focus areas: Fields without EFA are suitable
- Other AES: Fields not yet used for any AES are suitable
- Minimum size: Fields larger or equal to the required minimum size (*i-g-area-min*) are suitable
- Land-use: For each AES, fields with the respectively required land use are suitable (i.e. arable land fields for buffer areas, cover crops and conversion of arable land to grassland and grassland fields for maintaining grassland). The suitable fields are stored separately for each AES (*v-suitable-fields-list*).

Farmers’ envisioned area (*p-envisioned-aes-area*), i.e. the area they aim to put under AES, is converted to an area in hectares by multiplying the percentage value calculated with the beta regression by the sum of the area of all suitable fields.

Farmers’ openness is adapted to AES for which fields are available, i.e. a farmer is not open to AES for which no suitable fields are available. Furthermore, if the farmer is open to more arable AES than suitable arable land fields are available, the number of surplus AES (i.e. the number of AES for which not at least one field would be available) is calculated based on the difference between the sum of fields and the sum of AES a farmer is open to. The AES that cannot be covered with fields (based on the calculated difference) are randomly selected and the openness for these fields is set equal to zero (*adapt-openness-to-number-of-available-fields*).
Since only one grassland AES is considered, this step is not relevant for grassland.

AES decision (Decision Making Step 3)
Function name: make-aes-decision
The AES decision is composed of three parts: (1) decide which AES to adopt, (2) select fields where each AES should be adopted and (3) create AES.

1. **Choose accepted AES**

Function name: calculate-farmer-wta
For each farmer type and AES, as many values for the expected payment level for the baseline contract (five years contract duration, medium administrative effort, no advisory support) are drawn from a normal distribution as there are open farmers for a specific AES. Mean and standard deviation for the expected payment level are taken from the variables defined in the setup procedure. The distribution of expected payment levels is sorted starting from the lowest value. For each AES, open farmers are sorted according to their probability

for participating in AES (see setup farmers) and assigned an expected payment level, whereas farmers with the highest probability of participation are assigned the lowest expected payment level. Farmers that are not open are assigned an expected payment level of 99999 (i.e. a value larger than a realistically offered payment level).

If a farmer has access to advisory, a normally distributed value (with mean and standard deviation as defined in the setup procedure) is drawn and added to the baseline expected payment. The same is done if the contract duration deviates from the duration of five years (i.e. shorter contracts of one year duration or longer contracts of 10 years duration) or the bureaucratic effort is different from "medium" (baseline) (i.e. "high" or "low").

For each AES a farmer is open to, a farmer compares the individually calculated expected payment with the offered payment defined as input for each AES. If the offered payment is larger as or equal to the expected payment level, a farmer accepts the specific AES.

2. Select fields

Function name: distribute-aes, create-aes-on-fields

The total area envisioned for AES (*p-envisioned-aes-area*) is distributed among the AES based on the individual distribution (*v-aes-fraction-list*). The distribution is rescaled so that the ratios between AES areas are maintained, but only AES for which a farmer is open are considered.

Among the accepted AES, the order in which the AES are distributed to fields is randomly chosen. Suitable fields for a specific AES are sorted by increasing soil quality (*p-soil-quality*). If several fields have the same soil quality, the smallest field is selected first. If several fields also have the same soil quality, one of them is selected at random. For the sorted list of fields, the cumulative field sizes are calculated. The number of fields to select is derived by minimizing the difference between the cumulative field sizes and the envisioned area for the specific AES. Additional constraints for the selection are (i) that at least one field has to be selected (i.e. at least the one with the lowest soil quality) and (ii) that for AES on arable land at least one field needs to remain for each of the other accepted AES. Starting from the field with lowest soil quality, the determined number of fields is selected for the specific AES.

3. Create AES

Function name: setup-aes

On each selected field, the respective AES is created and AES characteristics AES type, contract year, AES area (field size), field ID and owner ID are initialized.

Model parameters

Parameter	NetLogo variable	Parameter range	Baseline value	Unit
Simulated time period	i-g-years	Yearly steps (1,2, …)	1	years
Minimum required	i-g-area-min	≥0	0	ha

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

field size for AES				
Contract duration for specific AES	i-g-duration-buffer-strips i-g-duration-catch-crops i-g-duration-grassland i-g-duration-conversion	1, 5, 10	5	years
Administrative effort for specific AES	i-g-admin-buffer-strips i-g-admin-catch-crops i-g-admin-grassland i-g-admin-conversion	"low", "medium", "high"	"medium"	-
Offered payment level for specific AES	i-g-payment-buffer-strips i-g-payment-catch-crops i-g-payment-grassland i-g-payment-conversion	Depending on policy scenario	630.5 - 240.9 367.67	EUR/ha
Probability that a farmer has access to advisory	i-g-access-to-advisory	[0,1]	0.35	-
Type of social network	i-g-social-network-type	"none", "neighbors"	"none"	-
Radius around fields in which other field owners are considered as belonging to social network ("neighbors")	i-g-social-network-radius	5, 10	-	km
Probability that a farmer with prior knowledge of a specific AES is open towards considering its application	i-g-prob-open-experience	[0,1]	1	-
Probability that a farmer with access to advisory is open towards considering application of a specific AES	p-g-prob-advisory-open-list	[0,1] (4 items)	BS: 0.62 CC: - MG: 0.57 CNV: 0.47	-
Probability of being intrinsically open towards	p-g-prob-intrinsic-open-list	[0,1] (4 items)	BS: 0.63 CC: - MG: 0.45	-

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

considering application of specific AES			CNV: 0.41	
Probability that a farmer with positive social influence is open towards considering application of a specific AES	i-g-prob-open-social	[0,1]	0.1	-
Choice of approach to calculate openness (see section 3.4)	i-g-openness-calculation	"distributed", "aggregated"	"distributed"	-

BS: Buffer strip/area, CC: Cover crops, MG: Maintaining permanent grassland, CNV: Conversion of arable land to permanent grassland
Convention for NetLogo names: g - global variables, i - variables defined via interface, p - variables set via input files (exogenous), v - variables changed in the model procedures (endogenous)

References

Bartkowski, B., Bartke, S., 2018. Leverage Points for Governing Agricultural Soils: A Review of Empirical Studies of European Farmers' Decision-Making. Sustainability 10, 3179.

Bartkowski, B., Beckmann, M., Bednář, M., Biffi, S., Domingo-Marimon, C., Mesaroš, M., Schüßler, C., Šarapatka, B., Tarčak, S., Václavík, T., Ziv, G., Wittstock, F. Adoption and potential of agri-environmental schemes in Europe: Cross-regional evidence from interviews with farmers. Under review.

Christensen, T., Pedersen, A.B., Nielsen, H.O., Mørkbak, M.R., Hasler, B., Denver, S., 2011, Determinants of farmers' willingness to participate in subsidy schemes for pesticide-free buffer zones — A choice experiment study. Ecological Economics, 70, 1558-1564.

Espinosa-Goded, M., Barreiro-Hurlé, J., Ruto, E., 2010. What Do Farmers Want From Agri-Environmental Scheme Design? A Choice Experiment Approach. Journal of Agricultural Economics, 61, 259-273.

Hasler, B., Czajkowski, M., Elofsson, K., Hansen, L.B.; Konrad, M.T., Nielsen, H.Ø., Niskanen, O., Nõmmann, T., Pedersen, A.B., Peterson, K., Poltimäe, H., Svensson, T.H., Zagórska, K., 2019. Farmers' preferences for nutrient and climate-related agri-environmental schemes: A cross-country comparison. Ambio, 48, 1290-1303.

Latacz-Lohmann, U. & Breustedt, G., 2019. Using choice experiments to improve the design of agri-environmental schemes. European Review of Agricultural Economics, 46, 495-528.

Ministry of Agriculture of the CR, 2019. Methodology for the implementation of Government Regulation No. 75/2015 Coll., on the conditions for the implementation of agri-environment-climate schemes and on the amendment of the follow-up Government Regulation No. 79/2007 Coll., valid for 2019, https://eagri.cz/public/web/mze/dotace/program-rozvoje-venkova-na-obdobi-2014/opatreni/m10-agroenvironmentalne-klimaticke/metodika-aeko-2019.html.

Paulus, A., Hagemann, N., Baaken, M.C., Roilo, S., Alarcón-Segura, V., Cord, A.F., Beckmann, M., 2022. Landscape context and farm characteristics are key to farmers' adoption of agri-environmental schemes. Land Use Policy 121, 106320.

Ruto, E. & Garrod, G., 2009. Investigating farmers' preferences for the design of agri-environment schemes: a choice experiment approach. Journal of Environmental Planning and Management, 52, 631-647.

Santos, R., Clemente, P., Brouwer, R., Antunes, P., Pinto, R., 2015. Landowner preferences for agri-environmental agreements to conserve the montado ecosystem in Portugal. Ecological Economics, 118, 159-167.

Wittstock, F., Paulus, A., Beckmann, M., Hagemann, N., Baaken, M.C., 2022. Understanding farmers’ decision-making on agri-environmental schemes: A case study from Saxony, Germany. Land Use Policy 122, 106371.

Ziv, G., Beckmann, M., Bullock, J., Cord, A., Delzeit, R., Domingo, C., Dreßler, G., Hagemann, N., Masó, J., Müller, B., Neteler, M., Sapundzhieva, A., Stoev, P., Stenning, J., Trajkovic, M., Václavík, T., 2020. BESTMAP: Behavioural, Ecological and Socio-economic Tools for Modelling Agricultural Policy. Research Ideas and Outcomes 6, e52052.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

ODD+D for Mulde region (DE)

Corresponding author: Meike Will, Helmholtz Centre for Environmental Research - UFZ

1. Overview

1.1. Purpose

What is the purpose of the study?

The purpose of the BESTMAP-ABM-DE is to determine the adoption and spatial allocation of four selected agri-environmental schemes (AES) by individual farmers in the Mulde River Basin located in Western Saxony, Germany. The selected AES are flower strips, cover crops, maintaining permanent grassland and conversion of arable land to permanent grassland. While the first three schemes have already been offered in the case study area, the latter scheme is a hypothetical scheme designed to test the impact of potential policy changes. For the first model analyses, only the currently offered schemes are considered.
With the model, the effect of different scenarios of policy design on patterns of adoption can be investigated. In particular, 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. The model was developed in the BESTMAP project (Ziv et al., 2020) as one of five case study-specific models with the same core processes.

For whom is the model designed?

The model is designed for policymakers and stakeholders responsible for agricultural policies to assess the impact of future policy designs. In addition, the model can be used by scientists to build upon the existing model structure and address further research questions in the context of farmer behavior.

1.2. Entities, state variables, and scales

What kinds of entities are in the model?

The model consists of three main entities: Agents representing individual farmers (3114 farmers), the spatial environment representing individual fields (61604 fields) with each farmer managing a fixed set of fields and AES contracts. Farmers decide whether and where to adopt AES with each AES contract entity representing an AES applied on a specific field, i.e. a farmer can have several contracts for the same AES type. It is assumed that an AES is applied to the whole field and that only one AES can be selected per field.

Farmers belong to one of twelve farmer types based on the Farming System Archetypes (FSA) developed in the project[7]. Farming System Archetypes are distinguished by their farm specialization (general cropping ('P1'), horticulture ('P2'), permanent crops ('P3') and grazing livestock ('P4') or 'mixed' if not at least 2/3[rds] of the total farm area is dedicated to one of the corresponding land use types) and economic size (four groups: <2000 EUR, small, medium

[7] More details on the implementation of the Farming System Archetypes in all five BESTMAP project case study regions is publicly available (CC BY 4.0) as part of the publication of the EU Horizon 2020 BESTMAP Project Report *"Deliverable 3.5: Farming System Archetypes for each CS"* at: https://bestmap.eu/about.php?storyid=2732

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

and large). For the German case study ABM, only P1, P4 and mixed farmers are considered since P2 and P3 farmers with mostly horticulture and permanent crops do not have (much) suitable land available to apply AES. The distribution of FSA is shown in Figure 1.

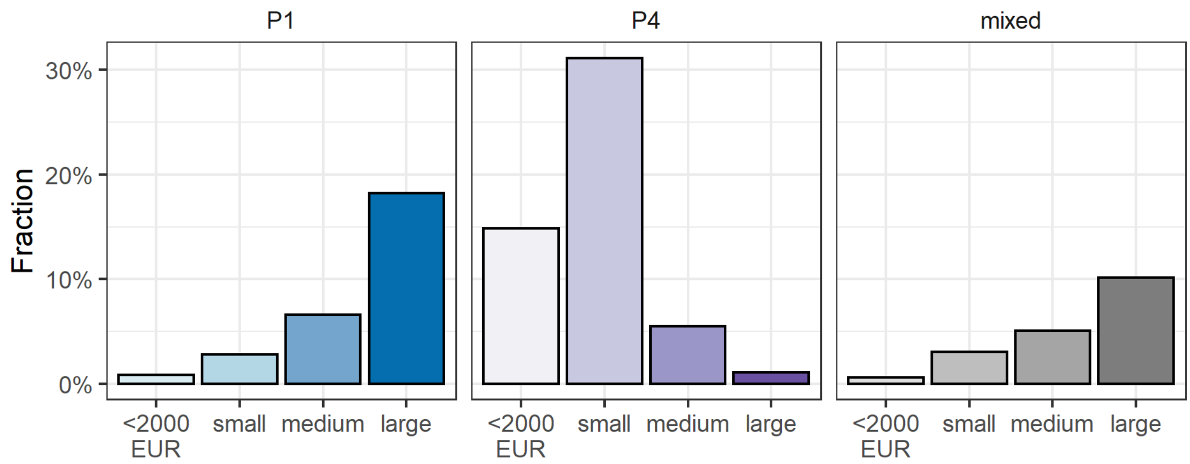

Figure 1: Distribution of farms to farming system archetypes (FSA) according to farm specialization (P1, P4, mixed) and economic size.

By what attributes (i.e. state variables and parameters) are these entities characterized?

Constant farmer state variables

	NetLogo variable	Possible values	Unit
Farmer ID	p-farmer-id	-	-
Farmer type depending on available land and farm size	p-farmer-type	All combinations of farm specialization (P1, P4, mixed) and economic size (<2000 EUR, small, medium, large)	-
Size of farm (sum of field sizes)	p-farm-area	>0	ha
Fields a farmer owns	p-property-set	-	NetLogo agentset
Access to advisory support	p-advisory	0/1	
Farmers in social network	p-social-network	Depending on social network type	NetLogo agentset
Probability for participation in each AES calculated using logistic regression (Model 1 in Paulus et al., 2022)	p-probability-aes-list	[0,1] (4 items)	-

Intended proportion of farm area under AES calculated using beta regression (Model 2 in Paulus et al., 2022)	p-envisioned-aes-area	[0,1] (4 items)	-
Variables to calculate probability for participation in each AES and proportion of farm area under AES derived in Paulus et al. (2022)	p-econ-int p-EFA-farm p-farmarea-transformed p-farmspec-arable p-farmspec-grassland p-mean-fieldsize p-organic p-shannon-crop p-ANC-farm p-elevation-farm p-erosion-risk-farm p-forest-edge-farm p-natura2000-farm p-nitrate-risk-farm p-nr-SWF-farm p-soil-fertility-farm p-waterbody-farm p-water-prot-area-farm	See Paulus et al. (2022)	€/ha T/F ha T/F T/F ha T/F - % m.a.s.l. T/F % % % - - % %
Scaling factor to overcome mismatch between predicted area under AES (beta regression) and observed area under AES (as of LPIS data 2019)	p-aes-area-scaling	Depending on farm specialization: P1: 1.36 P4: 1.13 Mixed: 1.29	-

Farmer state variables varying over time

	NetLogo variable	Possible values	Unit
Prior experience with each AES (list)	v-prior-experience-list	0/1 (4 items)	-
Openness towards each AES (list)	v-open-to-aes-list	0/1 (4 items)	-
Expected payment level for each AES (list)	v-accepted-payment-list	(4 items)	EUR/ha
Acceptance and availability of land for each AES (list)	v-accepted-aes-list	0/1 (4 items)	-
Share of land used for each accepted AES (list)	v-aes-fraction-list	[0,1] (4 items) (Σ = 1)	-
Fields suitable for each	v-suitable-fields-list	(4 items)	NetLogo

AES (list)			agentset
Total area under AES for each AES (list)	v-contract-area-list	(4 items)	ha
Number of AES contracts for each AES (list)	v-nr-aes-fields-list	(4 items)	-

Constant field state variables

	NetLogo variable	Possible values	Unit
Field ID	p-field-id	-	-
Owner ID (farmer)	p-owner-id	-	-
Land use	p-land-use	Arable land, grassland	-
Field size	p-area	>0	ha
Ecological focus areas (EFA) status	p-EFA-field	0/1	-
Probability for fields being under each AES calculated using logistic regression (Models 4 in Paulus et al., 2022)	p-desirability-list	[0,1] (4 items)	-
Field specific variables to calculate probability for fields being under each AES derived in Paulus et al. (2022)	p-fieldarea-transformed p-ANC p-elevation p-erosion-risk p-forest-edge p-natura2000 p-nitrate-risk p-nr-SWF p-soil-fertility p-waterbody p-water-prot-area	Depending on specific variables	Different

Field state variables varying over time

	NetLogo variable	Possible values	Unit
AES currently applied (list)	v-aes-list	0/1 (4 items)	-
Number of AES contracts previously applied (list)	v-aes-hist-list	(4 items)	-

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Constant AES contract state variables

	NetLogo variable	Possible values	Unit
AES type	v-aes-nr	0: Buffer strip/area 1: Catch crops 2: Maintaining permanent grassland 3: Conversion of arable land to permanent grassland	-
Duration since AES adoption	v-aes-contract-year	[1,10]	years
Field on which AES is applied	v-aes-field	-	NetLogo agentset
Farmer who owns the field	v-aes-owner	-	NetLogo agentset
Size of AES contract (field size)	v-aes-size	>0	ha

Convention for NetLogo names: g - global variables, i - variables defined via interface, p - variables set via input files (exogenous), v - variables changed in the model procedures (endogenous)

What are the exogenous factors / drivers of the model?

The AES contract design, in particular the payment level, contract duration and administrative effort, is exogenously given. Whether a farmer has access to advisory support is randomly assigned. Spatially explicit information on individual fields was derived from the InVeKoS database of Saxony (SMEKUL, 2020), which is part of the EU-wide Integrated Administration and Control System (IACS). Further field characteristics are taken from Paulus et al. (2022) and the data sources used there.

What are the temporal and spatial resolutions and extents of the model?

Space is explicitly represented at field level with each farm consisting of several fields. The Mulde River Basin covers an area of 5,814 km^2 with individual fields with up to 153 ha.
Time is represented as discrete yearly time steps with AES adoption decisions made once a year. While the temporal extent is in principle freely selectable, we decided to simulate only one time step, since developments for example in farm structure or land markets that would have to be taken into account when simulating longer time steps are not included in the model.

1.3. Process overview and scheduling

The following processes occur in each time step:

- Update prior knowledge based on own experience
- Remove AES contracts that exceed contract duration and update state variables of farmers and fields related to AES adoption

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

- **Decision Making Step 1** - Check openness to specific AES: Decide for each AES separately if a farmer can in general (independent of specific contract details) imagine applying the scheme
- **Decision Making Step 2** - Select suitable fields: Compile a set of fields suitable for AES adoption by excluding fields with ongoing AES contracts, fields used as Ecological Focus Area (EFA) or fields which do not meet the required minimum field size or the required land use (i.e. depending on AES arable land or grassland)
- **Decision Making Step 3** - Deliberation and site selection: Check for each farmer and AES whether the offered payment exceeds the expected payment and select fields where AES should be adopted

2. Design concepts

2.1. Theoretical and Empirical Background

Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?

The underlying assumption is that the adoption of AES changes with changing policy conditions, i.e. farmers are more or less willing to adopt AES depending on what they have to comply with and what is offered. The model can be used to examine the effects of different policy design scenarios on adoption patterns. Furthermore, it is assumed that not all farmers are open to the adoption of AES, some have identity-driven barriers against the adoption which cannot be overcome by financial means.

On what assumptions is/are the agents' decision model(s) based?

- Farmers accept an AES if they are open to consider the adoption. Openness is based on own prior experience, intrinsic openness, influence from advisory and/or social network (decision making step 1).
- Farmers need to have suitable land available (i.e. grassland for schemes applicable on grassland and arable land for schemes applicable on arable land) (decision making step 2).
- Farmers decide to adopt AES if the adoption is financially profitable, i.e. the offered payment level (as defined in the policy regulations) needs to be equal to or exceed their individual expected payment level. The level at which the adoption of AES is considered profitable varies depending on the characteristics of the schemes (duration, administrative effort) but also farmer characteristics (e.g. farm specialization and farm size) and external factors (access to advisory, influence of social network) (decision making step 3).

Why is a/are certain decision model(s) chosen?

The decision model is based on empirical observations from an interview campaign that was conducted in all case studies of the BESTMAP project at the beginning of 2020 (Wittstock et al., 2022, Bartkowski et al., under review). Themes and questions addressed in the interviews were derived from the literature including reviews that specifically focus on AES (Lastra-Bravo et al. 2015, Brown et al. 2020) and others that give a general overview on

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

factors affecting the adoption of sustainable farming practices (Dessart et al. 2019) and agricultural soil management (Bartkowski and Bartke 2018).
A key observation from the interviews was that farmers face a sequence of decision making elements for AES participation. To account for this sequential process in the ABM, we follow the heuristic framework for interpreting farmers' decision making developed in Wittstock et al. (2022). Due to missing data, we could not, however, include all aspects considered relevant in that framework (e.g. we had to exclude aspects on tenant-owner relationship and the duration of tenure contracts since we did not have access to tenure data).

If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from? At which level of aggregation were the data available?

The conceptual framework for the decision model is based on empirical data from the interview campaign conducted with individual farmers in all case studies of the BESTMAP project. To inform the decision model with quantitative data, a follow-up survey consisting of mostly closed-ended questions and a discrete choice experiment (DCE) was conducted. Results from the survey were used to parameterize how many farmers have access to advisory (*i-g-access-to-advisory*), the probability for openness of farmers with access to advisory (*p-g-prob-advisory-open-list*) and the probability for intrinsic openness of farmers without access to advisory (*p-g-prob-intrinsic-open-list*).
By using a combination of the results of the DCE and the survey questions, the aim was furthermore to derive the expected payment level ("willingness to accept" from the DCE) for each AES and farmer type depending on contract characteristics (contract duration, administrative effort) and access to advisory. These values could then directly be used to parameterize the expected payment level in the third step of the decision making framework. However, the sample size was too small to get statistically sound results including a differentiation for case studies and farmer types. Therefore, an alternative approach was taken with respect to parameterizing the expected payment level. It was assumed that the expected payment levels within a group of farmers of the same farmer type are normally distributed. Based on the current adoption rates for a specific AES, the offered payment level and an estimated standard deviation of the normal distribution based on existing empirical data, the mean expected payment level could then be derived.
Spatially explicit information on individual fields was derived from the IACS database of Saxony (SMEKUL, 2020). The probability that a farmer takes part in a particular AES (*p-probability-aes-list*), the area that a farmer intends to put under AES (*p-envisioned-aes-area*) and the probability that a farmer dedicates a field to a particular AES (*p-desirability-list*) are calculated using the regression models developed in Paulus et al. (2022) and the data sources used there (see section 3.4 for details).

2.2. Individual Decision Making

What are the subjects and objects of decision making? On which level of aggregation is decision making modelled? Are multiple levels of decision making included?

Individual farmers are the *subject* of decision making. Farmers decide whether and where to adopt AES, i.e. the adoption of AES contracts at field level is the *object* of decision making. There are *three levels of decision making* included, (1) the determination of general

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

openness towards the adoption of specific AES, (2) the selection of suitable fields for each AES, and (3) the deliberation and site selection for each AES.

What is the basic rationality behind agents' decision making in the model? Do agents pursue an explicit objective or have other success criteria?

- **Decision Making Step 1:** Some farmers have general aversions or aversions due to lacking prior experience, lacking advisory or lacking experience in social network against some AES and never consider applying for those.
- **Decision Making Step 2:** Not all fields are available for AES adoption due to limitations in the contractual requirements or because they are already occupied by other AES or used as Ecological Focus Area.
- **Decision Making Step 3:** Farmers only apply AES if they consider it profitable for them, the individual threshold for profitability depends on farm and farmer characteristics as well as external circumstances. The choice of fields for AES depends on several field characteristics (including size, soil quality, proximity to water bodies, and number of small woody features).

How do agents make their decisions?

Decision Making Step 1: Farmers are open to specific AES with a probability calculated based on their own prior experience, potential influence from advisory support and their intrinsic openness and/or influence through their social network (see Figure 2 for a flowchart).

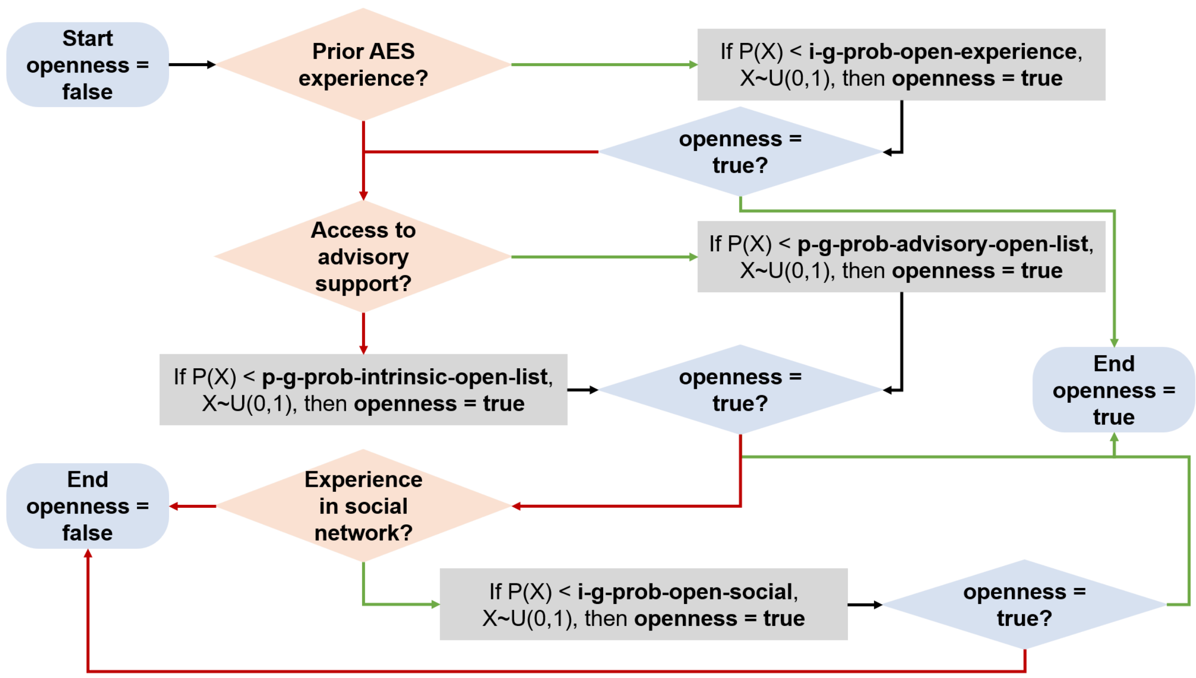

Figure 2: Flowchart of Step 1 in the decision making framework for a selected AES. Green arrows indicate "true"/yes, red arrows indicate "false"/no.

Decision Making Step 2: Farmers compare field characteristics with AES requirements and select those as suitable which fulfill the requirements.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Decision Making Step 3: Farmers compare their individual expected payment level with the offered payment level. The higher the probability for taking part in an AES as derived using the logistic regression model developed in Paulus et al. (*p-probability-aes-list*), the lower is a farmer's expected payment level. If the offered payment level reaches or exceeds their expected payment level, farmers decide to adopt the specific AES. Farmers select fields on which to adopt AES according to the envisioned area (which is derived from input data and calculated following the beta regression derived in Paulus et al., 2022). Fields are selected with decreasing probability (*p-desirability-list*) which is calculated following the logistic regression models at field level derived in Paulus et al. (2022).

Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?

Farmers' expected payment level depends on the policy design (contract duration, administrative effort) and the share of farmers with access to advisory which can be exogenously varied to test the effect of different policy scenarios. Furthermore, farmers adapt their openness to a specific AES based on prior experience with that AES in their social network (see below).

Do social norms or cultural values play a role in the decision making process?

Social aspects are included through the influence of prior experience with a specific AES in the social network on the openness towards that AES.

Do spatial aspects play a role in the decision process?

Spatial aspects at field level are included in the probability to participate in AES, the decision how much area a farmer devotes to AES and the decision where to apply a selected AES. The calculation for the probability to participate in AES and to use a specific field for a particular AES follows logistic regressions as derived in Paulus et al. (2022). The area for AES is calculated using a beta regression. All regression models include field level characteristics such as size, soil quality, proximity to water bodies, and number of small woody features (for a complete list of included parameters see the respective table in section 1.2).
The social network is based on spatial aspects since it consists of all farms with fields inside of a certain radius around a farmer's fields.

Do temporal aspects play a role in the decision process?

Previous experience with AES (own adoption and adoption in the social network) influences the openness towards the adoption of AES (Decision Making Step 1).

To which extent and how is uncertainty included in the agents' decision rules?

Farmers do not know how other farmers will decide in the current period, they only know their adoption from previous periods.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

2.3. Learning

Is individual learning included in the decision process? How do individuals change their decision rules over time as a consequence of their experience?

Farmers who have adopted AES in previous time steps (or in the year reflected in the data used for initialization) have a high probability of being open to consider AES in subsequent decisions. Collective learning is not considered in the model.

Is collective learning implemented in the model?

Collective learning is not considered in the model.

2.4. Individual Sensing

What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Farmers can sense the state of all their fields, i.e. they know the properties of their land. Furthermore, farmers know the contract characteristics of all AES that they need to consider when deciding whether or not to adopt a scheme. Farmers remember their own previous AES adoption. The sensing process is not erroneous.

What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?

Farmers know the previous adoption of other farmers in their social network. Social networks are determined based on spatial characteristics (i.e. they include farmers with fields in a specified radius around a farmer's fields). The sensing process is not erroneous.

What is the spatial scale of sensing?

Farmers are aware of the adoption of AES on their own fields and on fields of farmers who have fields next to theirs (i.e., the neighborhood social network).

Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?

There is no explicit process of information gathering included, i.e., farmers are simply assumed to know these variables.

Are the costs for cognition and the costs for gathering information explicitly included in the model?

Costs for cognition or gathering information are not explicitly included in the model. Implicitly, it is assumed that missing knowledge about a specific AES can be a barrier for farmers to not be open towards the adoption of AES in general (Decision Making Step 1).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

2.5. Individual Prediction

Which data do the agents use to predict future conditions? What internal models are agents assumed to use to estimate future conditions or consequences of their decisions? Might agents be erroneous in the prediction process, and how is it implemented?

Farmers do not predict future conditions.

2.6. Interactions

Are interactions among agents and entities assumed as direct or indirect? On what do the interactions depend?

Interactions between farmers are indirect. Farmers perceive the actions of others only through the state of AES adoption on fields of farmers in their social network which can influence their openness towards specific AES (Decision Making Step 1).

If the interactions involve communication, how are such communications represented? If a coordination network exists, how does it affect the agent's behaviour? Is the structure of the network imposed or emergent?

Communication between farmers is not explicitly modelled. The network structure is imposed and based on the spatial distance between farmers.

2.7. Collectives

Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation? How are collectives represented?

Collectives are not explicitly represented in the model. Farmers belong to a social network which is based on neighborhood and can influence the openness towards specific AES.

2.8. Heterogeneity

Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

All farmers, fields and AES contracts have the same set of state variables and processes, respectively. A fixed proportion of farmers has access to advisory. The agents and the landscape is heterogeneous with farmers differing in farm size and available land (defining their farmer type), advisory support, the social networks as well as farm characteristics used in the regression analyses derived from Paulus et al. (2022). Fields differ in field size, ownership, EFA status and land use as well as characteristics used in the regression analyses derived from Paulus et al. (2022).

Are the agents heterogeneous in their decision making? If yes, which decision models or decision objects differ between the agents?

Only farmers who have passed the first step of decision making (general openness to AES) make decisions in the following two steps (selection of suitable fields, deliberation and site selection).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

2.9. Stochasticity

Stochasticity is included in the following processes:

1. *General openness:* General openness (Decision Making Step 1) is calculated based on probabilities influenced by prior experience, advisory support, intrinsic openness and social influence (for details see section 3.4).
2. *Availability of fields and openness:* Farmers can only be open to as many AES as suitable fields are available on the farm. If farmers are open to more AES than they have fields available, the maximum number of AES a farmer can be open to is calculated and for the surplus AES (randomly selected among all AES a farmer is open to) it is assumed that the farmer is not open to adopt.
3. *Expected payment level:* The mean expected payment level for a specific AES is calculated based on empirical input data for the specific policy design. To take into account aspects not considered in the factors to derive the expected payment level (contract duration, administrative effort, availability of advisory support) but also include additional differences in attitudes between farmers, the individual expected payment level for each farmer is drawn from a normal distribution around the calculated mean (see section 2.1 for the calculation of the mean). Changes in the expected payment due to deviations in contract characteristics from the baseline (five years contract, medium bureaucratic effort, no advisory support) are also normally distributed (for details see section 3.4).
4. *AES distribution:* If a farmer accepts several AES, the order in which AES are distributed to fields is random.

2.10. Observation

Observations can include effects of different model inputs on the adoption rates of AES. Data can be collected at the level of *individual farms* as well as *aggregated across all farms*. Furthermore, the spatial adoption patterns can be collected. Data can be collected at *each time step* or *aggregated over all simulation steps*.
State variables for these observations include for each AES the total area under AES (*v-contract-area-list*) or the number of AES contracts (*v-nr-aes-fields-list*) at farm level and the AES currently applied (*v-aes-list*) or the AES previously applied (*v-aes-hist-list*) at field level.

3. Details

3.1. Implementation Details

How has the model been implemented? Is the model accessible, and if so where?

The model has been implemented in NetLogo 6.2.1. The model source code is publicly available at https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-DE.

3.2. Initialization

What is the initial state of the model world, i.e. at time t=0 of a simulation run?

- AES contract characteristics are defined based on the selected policy design.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

- The landscape characteristics are imported from a GIS vector file. Field agents are created based on the input data.
- Farmers are initialized with their characteristics imported from empirical data. Access to advisory is randomly assigned.
- The social network is set up depending on *i-g-social-network-type* (either "none" or "neighbors").
- Mean (derived based on current adoption and offered payment level, see section 2.1) and standard deviation for the calculation of the individual expected payment levels is imported.

Is initialization always the same, or is it allowed to vary among simulations?

Variations can include the policy design, i.e. specifications of AES contracts, the availability of advisory support and its importance, the importance of social networks or changes in general openness. Furthermore, the effect of the standard deviation for the calculation of the expected payment level and the approach to calculate the openness can be analyzed.

Are the initial values chosen arbitrarily or based on data?

Initial values for landscape characteristics were derived from the IACS database of Saxony (SMEKUL, 2020). Further field characteristics used in the regression models are taken from Paulus et al. (2022) and the data sources used there.
Results from the survey were used to parameterize how many farmers have access to advisory (*i-g-access-to-advisory*), the probability for openness of farmers with access to advisory (*p-g-prob-advisory-open-list*) and the probability for intrinsic openness of farmers without access to advisory (*p-g-prob-intrinsic-open-list*).
Baseline values for offered payment levels were taken from SMEKUL (2015).

3.3. Input Data

The model does not use any external input files to represent processes that change over time.

3.4. Submodels

<u>Setup processes</u>
Function name: setup

Field setup
Function name: setup-landscape
Fields are created based on GIS input data (filenames: *\data\landscape\DE-2019\field-file.shp* and *\data\landscape\DE-2019\field-file.prj* - data not publicly accessible) including information on field characteristics and variables used to calculate allocation of AES (Paulus et al. 2022, Model 4) (*load-fields*) (filename: *\data\input\est_coefficient_mod4.txt*). The desirability d (*p-desirability-list*) for each field to be chosen for a specific AES based on its attributes x_i is calculated following a logistic regression with coefficients β_j, $j = 0, 1, ..., m$ derived in Paulus et al. (2022):

$$d = (1 + exp(-(\beta_0 + \sum_{i=1}^{m} \beta_i x_i)))^{-1}$$

The desirability is calculated individually for each AES with coefficients β_j varying between AES. For a list of attributes x_i that are included in the calculation, see the table for constant field state variables in section 1.2. Farm level variables are excluded from the original model in Paulus et al. (2022) since they do not vary within a farm.

Farmer setup

Function name: setup-farmers

Farmers are created based on input data in csv-format (*load-farmers*) (filename: *\data\landscape\DE-2019\farmers.csv* - data not publicly accessible). The data include information on farm characteristics and variables used to calculate the probability for participation in AES and the percentage of farm area under AES (following Model 1 and Model 2 in Paulus et al. 2022). The probability p (*t-probability-aes*) for participation in AES based on farm attributes x_i is calculated following a logistic regression with coefficients β_j, $j = 0, 1, ..., m$ derived in Paulus et al. (2022) (filename: *\data\input\est_coefficient_mod1_DE.txt*):

$$p = (1 + exp(-(\beta_0 + \sum_{i=1}^{m} \beta_i x_i)))^{-1}$$

The probability for participation in AES is adjusted according to the available land (arable or grassland) (*p-probability-aes-list*), i.e. farmers only have a probability of $p > 0$ for a specific AES if they have suitable land available (i.e. arable land for buffer areas, cover crops and conversion of arable land to grassland and grassland for maintaining grassland). The envisioned percentage of farm area under AES $perc$ (*p-envisioned-aes-area*) is calculated using the same farm attributes x_i as for the probability of participation in AES except the farm attributes on farm specialization (*p-farmspec-arable* and *p-farmspec-grassland*) since different coefficients based on farm specialization are used. The regression is not performed for each farmer type (i.e. distinguishing by economic size in addition to farm specialization) since the remaining subsets of farms participating in AES would be too small to perform a regression analysis. The regression coefficients β_j, $j = 0, 1, ..., m$ were derived from a beta regression following the method in Paulus et al. (2022) (filenames: *\data\input\est_coefficient_mod2_DE_*farm_specialization*_*economic_size*.txt*):

$$perc = (1 + exp(-(\beta_0 + \sum_{i=1}^{m} \beta_i x_i)))^{-1}$$

For a list of attributes x_i that are included in the calculations for p and $perc$, see the table for constant farmer state variables in section 1.2. The set of fields that a farmer owns (*p-property-set*) is determined by comparing the farmer ID with the owner ID of the fields.

When all farmers are created, further farmer attributes are set (*set-farmer-attributes*). This includes initializing the contract area under each AES (*v-contract-area-list*), the number of fields with a specific AES (*v-nr-aes-fields-list*) and the openness to each AES (*v-open-to-aes-list*) to zero and the the expected payment level (*v-accepted-payment-list*) to

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

99999 (i.e. a value larger than a realistically offered payment level). A randomly chosen fraction of farmers has access to advisory support (*p-advisory*). In the baseline scenario, the fraction of farmers with advisory support is based on survey results. Furthermore, for each farmer the distribution of AES land is read based on each farmer type (filename: *data\input\fraction_AES_DE_*farm_specialization*_ *economic_size*.csv*). These values are derived from the actual distribution of land under AES on the selected AES, i.e. the four values sum up to 1 for each farmer type. Finally, a scaling factor (*p-aes-area-scaling*) is set which was included since a mismatch between the actual area under the selected AES (as in the LPIS data of 2019) and the predicted area (beta regression) was observed (filename: data/input/scaling_DE_**farm_specialization**_ **economic_size**.txt*).

Social network setup

Function name: setup-social-network

The type social network is defined by *i-g-social-network-type* which can be either “none” or “neighbors”. For the former option, the social network (*p-social-network*) is set to an empty turtle agentset. If the “neighbors” option is chosen, owners of fields in a radius *i-g-social-network-radius* around each field of a farmer are added to the agentset of farmers that influence the farmer.

Expected payment setup

Function name: setup-wta-specifics

AES contract characteristics are defined based on the input for duration, administrative effort and offered payment (*setup-aes-constants*).

For each farmer type (*p-g-farmer-type-list*) and AES, the mean expected payment level and its standard deviation for the baseline version of an AES contract (5 years duration, medium bureaucratic effort, no advisory support), the mean difference (*p-g-wta-mean-advisory-list*) and standard deviation (*p-g-wta-sd-advisory-list*) in expected payment when advisory is available, when contract duration is longer or shorter than five years (*p-g-wta-mean-duration-list*, *p-g-wta-sd-duration-list*) and when administrative effort is higher or lower than in the baseline case (*p-g-wta-mean-admin-list*, *p-g-wta-sd-admin-list*) are loaded from input files in csv-format (filenames: *\data\input\WTA_DE_*farm_specialization*_*economic_size*.csv*). The following table gives an overview of the values that are considered in the simulations and references to empirical data with results that justify the chosen values. However, the differences in expected payment levels are only aligned with these studies and do not explicitly map any results. Assumptions for the standard deviations are not drawn from empirical data.

NetLogo variable	Baseline value	Source
p-g-wta-mean-advisory-list	-5%	Hasler et al. 2019, Espinosa-Goded et al. 2010
p-g-wta-sd-advisory-list	1%	-
p-g-wta-mean-duration-list	-10% (1 year contract) +40% (10 years contract)	Hasler et al. 2019, Latacz-Lohmann &

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

		Breustedt 2019, Christensen et al. 2011, Ruto & Garrod 2009, Santos et al. 2015
p-g-wta-sd-duration-list	2% (1 year contract) 4% (10 years contract)	-
p-g-wta-mean-admin-list	-5% (low bureaucracy) +5% (high bureaucracy)	Ruto & Garrod 2009
p-g-wta-sd-admin-list	1% (low bureaucracy) 1% (high bureaucracy)	-

Processes in every time step
Function name: go

Update world
Function name: update-world
- For each AES, it is checked whether the farmer has applied the AES before. If this is the case, the experience with this AES is set to 1 (*update-prior-knowledge*).
- For each AES, the number of contract years is increased by one year. If the number of contract years then exceeds the contract duration, the AES is deleted (*update-aes*).

Check openness (Decision Making Step 1)
Function name: check-openness-to-aes
Openness is calculated as an individual value for each farmer and AES (v-open-to-aes-list equal to 0 or 1 for the respective AES). There are two options of how to calculate the openness (i-g-openness-calculation): “distributed” or “aggregated”.
If the option “distributed” is chosen, the calculation for each AES is conducted in the following steps (see also Figure 2). Each step is performed only if openness to the specific AES is not yet set to 1.
- Farmers with prior knowledge of the specific AES: Openness is set to 1 with probability *i-g-prob-open-experience*
- Farmers with advisory support: Openness is set to 1 with probability *p-g-prob-advisory-open-list* loaded from input data based on survey results (the probability differs between AES) (filename: *\data\input\open_advisory_DE.csv*)
- Farmers without advisory support: Openness is set to 1 with probability *p-g-prob-intrinsic-open-list* loaded from input data based on survey results (the probability differs between AES) (filename: *\data\input\open_intrinsic_DE.csv*)
- Farmers with prior experience in their social network (i.e. at least one of the farmers in their social network has prior experience with the specific AES): Openness is set to 1 with probability *i-g-prob-open-social*

If the option “aggregated” is chosen, each farmer has an aggregated probability of being open. For each AES, the aggregated probability is calculated based on the probability for being open with prior experience (*i-g-prob-open-experience*), the probability for being open with advisory support (*p-g-prob-advisory-open-list*) and the probability for being intrinsically open (*p-g-prob-intrinsic-open-list*). The probabilities for the four possible combinations compose as follows:

	Prior experience	**No prior experience**
Advisory support	*i-g-prob-open-experience + (1 - i-g-prob-open-experience) * p-g-prob-advisory-open-list*	*p-g-prob-advisory-open-list*
No advisory support	*i-g-prob-open-experience + (1 - i-g-prob-open-experience) * p-g-prob-intrinsic-open-list*	*p-g-prob-intrinsic-open-list*

To ensure that farmers from all farmer types are equally open, the subset of open farmers is drawn for each farmer type separately (*set-subset-farmers-open*). The number of open farmers is calculated based on the number of farmers in a specific group (farmer type, access to advisory, prior experience) times the aggregated probability for being open (based on the calculation as described in the table above, rounded to the next largest integer). Farmers are sorted by decreasing probability for participation in AES (*p-probability-aes-list*). Starting from farmers with the highest probability, farmers are chosen to be open until the calculated number of open farmers is reached.

For the “aggregated” calculation of openness to AES, the influence of the social network is not taken into account.

Select suitable fields (Decision Making Step 2)
Function name: select-suitable-fields
Starting from the whole property set of fields, suitable fields are selected according to the following criteria:

- Ecological Focus areas: Fields without EFA are suitable
- Other AES: Fields not yet used for any AES are suitable
- Minimum size: Fields larger or equal to the required minimum size (*i-g-area-min*) are suitable
- Land-use: For each AES, fields with the respectively required land use are suitable (i.e. arable land fields for buffer areas, cover crops and conversion of arable land to grassland and grassland fields for maintaining grassland). The suitable fields are stored separately for each AES (*v-suitable-fields-list*).

Farmers’ envisioned area (*p-envisioned-aes-area*), i.e. the area they aim to put under AES, is converted to an area in hectares by multiplying the percentage value calculated with the beta regression by the sum of the area of all suitable fields. The resulting area is divided by the scaling factor (*p-aes-area-scaling*) which was introduced to overcome the observed mismatch between the predicted and actual area under the selected AES.

Farmers’ openness is adapted to AES for which fields are available, i.e. a farmer is not open to AES for which no suitable fields are available. Furthermore, if the farmer is open to more

arable AES than suitable arable land fields are available, the number of surplus AES (i.e. the number of AES for which not at least one field would be available) is calculated based on the difference between the sum of fields and the sum of AES a farmer is open to. The AES that cannot be covered with fields (based on the calculated difference) are randomly selected and the openness for these fields is set equal to zero (*adapt-openness-to-number-of-available-fields*).
Since only one grassland AES is considered, this step is not relevant for grassland.

AES decision (Decision Making Step 3)
Function name: make-aes-decision
The AES decision is composed of three parts: (1) decide which AES to adopt, (2) select fields where each AES should be adopted and (3) create AES.

1. **Choose accepted AES**

Function name: calculate-farmer-wta
For each farmer type and AES, as many values for the expected payment level for the baseline contract (five years contract duration, medium administrative effort, no advisory support) are drawn from a normal distribution as there are open farmers for a specific AES. Mean and standard deviation for the expected payment level are taken from the variables defined in the setup procedure. The distribution of expected payment levels is sorted starting from the lowest value. For each AES, open farmers are sorted according to their probability for participating in AES (see setup farmers) and assigned an expected payment level, whereas farmers with the highest probability of participation are assigned the lowest expected payment level. Farmers that are not open are assigned an expected payment level of 99999 (i.e. a value larger than a realistically offered payment level).

If a farmer has access to advisory, a normally distributed value (with mean and standard deviation as defined in the setup procedure) is drawn and added to the baseline expected payment. The same is done if the contract duration deviates from the duration of five years (i.e. shorter contracts of one year duration or longer contracts of 10 years duration) or the bureaucratic effort is different from “medium” (baseline) (i.e. “high” or “low”).

For each AES a farmer is open to, a farmer compares the individually calculated expected payment with the offered payment defined as input for each AES. If the offered payment is larger as or equal to the expected payment level, a farmer accepts the specific AES.

2. **Select fields**

Function name: distribute-aes, create-aes-on-fields
The total area envisioned for AES (*p-envisioned-aes-area*) is distributed among the AES based on the individual distribution (*v-aes-fraction-list*). The distribution is rescaled so that the ratios between AES areas are maintained, but only AES for which a farmer is open are considered.

Among the accepted AES, the order in which the AES are distributed to fields is randomly chosen. Suitable fields for a specific AES are sorted by decreasing desirability for the specific AES (*p-desirability-list*). For the sorted list of fields, the cumulative field sizes are calculated. The number of fields to select is derived by minimizing the difference between the cumulative field sizes and the envisioned area for the specific AES. Additional constraints for the selection are (i) that at least one field has to be selected (i.e. at least the one with the highest desirability) and (ii) that for AES on arable land at least one field needs to remain for each of the other accepted AES. Starting from the field with highest desirability, the determined number of fields is selected for the specific AES.

3. Create AES

Function name: setup-aes

On each selected field, the respective AES is created and AES characteristics AES type, contract year, AES area (field size), field ID and owner ID are initialized.

Model parameters

Parameter	NetLogo variable	Parameter range	Baseline value	Unit
Simulated time period	i-g-years	Yearly steps (1,2, …)	1	years
Minimum required field size for AES	i-g-area-min	≥0	0	ha
Contract duration for specific AES	i-g-duration-buffer-strips i-g-duration-catch-crops i-g-duration-grassland i-g-duration-conversion	1, 5, 10	5	years
Administrative effort for specific AES	i-g-admin-buffer-strips i-g-admin-catch-crops i-g-admin-grassland i-g-admin-conversion	“low”, “medium”, “high”	“medium”	-
Offered payment level for specific AES	i-g-payment-buffer-strips i-g-payment-catch-crops i-g-payment-grassland i-g-payment-conversion	Depending on policy scenario	755 78 305.2 -	EUR/ha
Probability that a farmer has access to advisory	i-g-access-to-advisory	[0,1]	0.59	-
Type of social network	i-g-social-network-type	“none”, “neighbors”	“none”	-
Radius around fields in which other field owners are considered as belonging to social network	i-g-social-network-radius	5, 10	-	km

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

(“neighbors”)				
Probability that a farmer with prior knowledge of a specific AES is open towards considering its application	i-g-prob-open-experience	[0,1]	0.8	-
Probability that a farmer with access to advisory is open towards considering application of a specific AES	p-g-prob-advisory-open-list	[0,1] (4 items)	BS: 0.54 CC: 0.7 MG: 0.5 CNV: -	-
Probability of being intrinsically open towards considering application of specific AES	p-g-prob-intrinsic-open-list	[0,1] (4 items)	BS: 0.53 CC: 0.56 MG: 0.62 CNV: -	-
Probability that a farmer with positive social influence is open towards considering application of a specific AES	i-g-prob-open-social	[0,1]	0.1	-
Choice of approach to calculate openness (see section 3.4)	i-g-openness-calculation	“distributed”, “aggregated”	“distributed”	-

BS: Buffer strip/area, CC: Cover crops, MG: Maintaining permanent grassland, CNV: Conversion of arable land to permanent grassland

Convention for NetLogo names: g - global variables, i - variables defined via interface, p - variables set via input files (exogenous), v - variables changed in the model procedures (endogenous)

References

Bartkowski, B., Bartke, S., 2018. Leverage Points for Governing Agricultural Soils: A Review of Empirical Studies of European Farmers’ Decision-Making. Sustainability 10, 3179.

Bartkowski, B., Beckmann, M., Bednář, M., Biffi, S., Domingo-Marimon, C., Mesaroš, M., Schüßler, C., Šarapatka, B., Tarčak, S., Václavík, T., Ziv, G., Wittstock, F. Adoption and potential of agri-environmental schemes in Europe: Cross-regional evidence from interviews with farmers. Under review.

Christensen, T., Pedersen, A.B., Nielsen, H.O., Mørkbak, M.R., Hasler, B., Denver, S., 2011,

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Determinants of farmers' willingness to participate in subsidy schemes for pesticide-free buffer zones — A choice experiment study. Ecological Economics, 70, 1558-1564.

Espinosa-Goded, M., Barreiro-Hurlé, J., Ruto, E., 2010. What Do Farmers Want From Agri-Environmental Scheme Design? A Choice Experiment Approach. Journal of Agricultural Economics, 61, 259-273.

Hasler, B., Czajkowski, M., Elofsson, K., Hansen, L.B.; Konrad, M.T., Nielsen, H.Ø., Niskanen, O., Nõmmann, T., Pedersen, A.B., Peterson, K., Poltimäe, H., Svensson, T.H., Zagórska, K., 2019. Farmers' preferences for nutrient and climate-related agri-environmental schemes: A cross-country comparison. Ambio, 48, 1290-1303.

Latacz-Lohmann, U. & Breustedt, G., 2019. Using choice experiments to improve the design of agri-environmental schemes. European Review of Agricultural Economics, 46, 495-528.

Paulus, A., Hagemann, N., Baaken, M.C., Roilo, S., Alarcón-Segura, V., Cord, A.F., Beckmann, M., 2022. Landscape context and farm characteristics are key to farmers' adoption of agri-environmental schemes. Land Use Policy 121, 106320.

Ruto, E. & Garrod, G., 2009. Investigating farmers' preferences for the design of agri-environment schemes: a choice experiment approach. Journal of Environmental Planning and Management, 52, 631-647.

Santos, R., Clemente, P., Brouwer, R., Antunes, P., Pinto, R., 2015. Landowner preferences for agri-environmental agreements to conserve the montado ecosystem in Portugal. Ecological Economics, 118, 159-167.

SMEKUL, 2015. Sächsisches Staatsministerium für Energie, Klimaschutz, Umwelt und Landwirtschaft, Förderrichtlinie Agrarumwelt- und Klimamaßnahmen – FRL AUK/2015. Available at: https://www.smekul.sachsen.de/foerderung/download/Foerderrichtlinie-Agrarumwelt-und-Klimamassnahmen-.pdf .

SMEKUL, 2020. Integriertes Verwaltungs- und Kontrollsystem (InVeKoS) Sachsen.

Wittstock, F., Paulus, A., Beckmann, M., Hagemann, N., Baaken, M.C., 2022. Understanding farmers' decision-making on agri-environmental schemes: A case study from Saxony, Germany. Land Use Policy 122, 106371.

Ziv, G., Beckmann, M., Bullock, J., Cord, A., Delzeit, R., Domingo, C., Dreßler, G., Hagemann, N., Masó, J., Müller, B., Neteler, M., Sapundzhieva, A., Stoev, P., Stenning, J., Trajkovic, M., Václavík, T., 2020. BESTMAP: Behavioural, Ecological and Socio-economic Tools for Modelling Agricultural Policy. Research Ideas and Outcomes 6, e52052.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

ODD+D for Catalonia (ES)

Corresponding author: Chunhui Li, University of Leeds

1. Overview

1.1. Purpose

What is the purpose of the study?

The BESTMAP-ABM-ES is a member of the BESTMAP-ABM model suite focusing on the case study area of Catalonia, Spain. The purpose of the BESTMAP-ABM is to determine the adoption and spatial allocation of four selected agri-environmental schemes (AES) by individual farmers in five countries across the EU (Ziv et al., 2020). The selected AES are flower strips, cover crops, maintaining permanent grassland and conversion of arable land to permanent grassland. In particular, the model investigates the effect of different scenarios of policy design on patterns of adoption. 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.
We group relevant scheme options available in Catalonia into the four selected types according to the characteristics of the scheme designs, shown in the table below. Notably, flower strips and conversion of arable land to permanent grassland currently are not offered in Catalonia. We include these two schemes in the model as we believe the results will offer an insight for the future policy designs of similar AES. More details of the AES options can be found on the Catalonia government website[8].

AES typologies in BESTMAP-ABM-ES

AES types	AES option codes
Cover crops	AES_367
Grassland management	AES_363, AES_368

For whom is the model designed?

The model is designed for policymakers and stakeholders responsible for agricultural policies to assess the impact of future policy designs. In addition, the model can be used by scientists to build upon the existing model structure and address further research questions in the context of farmer behaviour.

1.2. Entities, state variables, and scales

What kinds of entities are in the model?

The model consists of these entities:

- Farmer agents representing individual farmers;

[8] https://agricultura.gencat.cat/ca/ambits/desenvolupament-rural/pla-estrategic-pac-2023-2027/

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

- Field agents representing the spatial environment. Each farmer agent manages a fixed set of fields;
- AES contracts agents representing the contracts, when farmer agents decide to adopt an AES and apply it on one of their fields. A farmer agent can have multiple AES contracts for the same AES type. 100% of the field area is put under AES when a field is put under AES
- Social networks of farmer agents representing farmer groups that farmer agents can influence each other on the openness towards the available AES

By what attributes (i.e. state variables and parameters) are these entities characterised?

The table below lists the attributes of the agents, i.e., farmers, fields, AES contracts and the social networks. The naming conventions of the NetLogo variable are designed as follows: *g* for global variables; *i* for variables defined via interface; *p* for exogenous variables; *v* for endogenous variables.

Constant farmer state variables

	NetLogo variable	Possible values	Unit
Famer ID	*p-farmer-id*	A string	
Fields a farmer owns	*p-property-set*	-	NetLogo agentset
Size of farm (sum of field sizes)	*p-farm-area*	>0	ha
Farm specialisation*	*p-fsa-spec*	P1, P2, P3, P4, mixed	-
Economic farm size	*p-fsa-size*	<2000, small, medium, large	-
Farm intensity (organic)	*p-eco*	0/1	-
Probability for intrinsic openness towards each AES (list)	*p-intrinsic-open-prob-list*	A list of 4 ‘0/1’ values	-
Access to advisory support	*p-advisory*	0/1	-
Accepted payment levels for all AES	*p-accepted-payment-list*	A list of 4 ‘0/1’ values	EUR
Area percentages of the total farm area that a farmer is willing to use for each AES	*p-envisioned-area-list*	A list of 4 items	%
Farmers in social network	*v-social-network*	Depending on social network type	NetLogo agentset

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

The GIS feature list of a farmers' fields	*p-gis-feature-list*	Input spatial data	GIS shapefile
The list of a farmer's envisioned area (in ha) for the four AES	*p-envisioned-area-ha-list*	A list of 4 items	ha
The list of a farmer's farming area, and breakdown in land uses (i.e., total farm area, arable area, grassland area and horticulture area)	*p-stats-farm-area-list*	A list of 4 items	ha

*Farming system archetypes (FSA): General cropping (P1), Horticulture (P2), Permanent crops (P3), Grazing livestock and forage (P4), mixed. Full details of FSA are available in the BESTMAP Deliverable 3.5 Farming System Archetypes for each CS at https://bestmap.eu/about.php?storyid=2732.

Farmer state variables varying over time

	NetLogo variable	Possible values	Unit
Openness towards each AES	*v-open-to-aes-list*	A list of 4 '0/1' values	-
Prior experience with each AES (list)	*v-prior-experience-list*	A list of 4 '0/1' values	-
Fields suitable for each AES	*v-suitable-fields-list*	A list of 4 items	NetLogo agentset
Total area under AES for each AES	*v-contract-area-list*	A list of 4 items	ha
Number of AES contracts for each AES	*v-nr-aes-fields-list*	A list of 4 items	-

Constant field state variables

	NetLogo variable	Possible values	Unit
Owner ID (farmer)	*p-owner-id*	-	-
Land use	*p-land-use*	Arable land, grassland, horticulture, other	-
Size	*p-area*	>0	ha
Ecological focus area (EFA) status	*p-EFA*	0/1	-
Soil quality	*p-soil-quality*	[0,14]	-

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Field state variables varying over time

	NetLogo variable	Possible values	Unit
AES currently applied	v-aes-list	A list of 4 ‘0/1’ values	-
Number of AES contracts previously applied	v-aes-hist-list	A list of 4 items	-

Constant AES contract state variables

	NetLogo variable	Possible values	Unit
AES type	v-aes-name	buffer strip, catch crops, grassland, conversion	-
The ID of the modelled AES	v-aes-nr	0 for buffer strip, 1 for catch crops, 2 for grassland, 3 for conversion	
Duration since AES adoption	v-aes-contract-year	[1,10]	years
Field on which AES is applied	v-aes-field	-	NetLogo agentset
Farmer who owns the field	v-aes-owner	-	NetLogo agentset
Size of AES contract (field size)	v-aes-size	>0	ha

Constant state variables of farmer social networks

	NetLogo variable	Possible values	Unit
Social network types	*i-g-social-network-type*	“None”, “neighbours”, ”FSA”	-
The radius of neighbourhood	*i-g-social-network-radius*	≥1	-

What are the exogenous factors / drivers of the model?

The AES contract design, in particular the payment level, contract duration and bureaucratic effort, is exogenously given. In addition, the eligible field land use types for the four AES are exogenously defined and fixed in the model. In the BESTMAP-ABM-ES, buffer strips and arable land conversion to grassland can be applied on arable lands, grassland management

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

can be applied on grasslands, and cover crops can be applied on horticultural lands.
Farms are spatially represented by individual fields derived from the database of Declaració unificada agraria (Agrarian Unified Declaration) (DUN) and also categorised into different FSA and economic sizes. Farms' fields are characterised by land use types, field sizes and soil conditions. Soil organic carbon is used as the soil quality measure in the model.
Farmers' prior AES experiences are initialised based on the adoption data of 2018 in Catalonia (available in). Whether a farmer has access to advisory support and farmers' intrinsic openness towards an AES are randomly assigned. The influences from prior AES experiences, intrinsic openness, advisory services and the social network on a farmer's openness are probability-based and randomly assigned.
A farmer's expected payment for an AES is influenced by the normal distribution of farmers' willingness to accept (WTA) for the AES and the impact on WTA by offered AES designs.

What are the temporal and spatial resolutions and extents of the model?

Space is explicitly represented at field level with each farm consisting of several fields. The ES model includes 1,095,275 agricultural fields of the Catalonia region, covering around 1,290,000 ha agricultural area that belongs to 50,728 farmers.
Time is represented as discrete yearly time steps with AES adoption decisions made once a year. The model is capable of simulating multiple-year experiments, however, due to lack of data simulating the dynamics of the farms' and environmental changes, the BESTMAP-ABM-ES has been used for 1-tick simulations representing "alternative now". The temporal extent can be updated when we have multi-years of input data, for example, field ownership changes and field land use changes over multiple years.

1.3. Process overview and scheduling

The following processes occur in each time step:

- Update prior knowledge based on own experience
- Remove AES contracts that exceed contract duration
- Update state variables of farmers and fields related to AES adoption
- **Decision Making Step 1** - Check openness to specific AES: Decide for each AES separately if a farmer can in general (independent of specific contract details) imagine applying the scheme
- **Decision Making Step 2** - Select suitable fields: Compile a set of fields suitable for AES adoption by excluding fields with ongoing AES contracts, fields used as EFA or fields which do not meet the required minimum field size or the eligible land use type
- **Decision Making Step 3** - Deliberation and site selection: Check for each farmer and AES whether the offered payment equals to or exceeds the accepted payment and select fields where AES should be adopted

2. Design concepts

2.1. Theoretical and Empirical Background

Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?

The underlying assumption is that farmers' adoption decisions are affected by the agricultural policy conditions, i.e. farmers are more or less willing to adopt AES depending on what they have to comply with and what is offered. The model can be used to examine the effects of different policy design scenarios on adoption patterns. Furthermore, it is assumed that adoption of AES or not is not a purely economic decision. Some farmers are open to AES adoptions due to identity-driven barriers, personal situations (e.g., near retirement age) and so on.
The conceptual framework of the model is described in detail in the BESTMAP Deliverable 2.5 Conceptual framework and architecture (Update) available at https://bestmap.eu/about.php?storyid=2732.

On what assumptions is/are the agents' decision model(s) based?

Farmers accept an AES if they are open to consider the adoption. This is an identity-driven decision based on own prior experience, intrinsic openness, influence from advisory and/or social network.
In addition, they need to have suitable land available, which means grassland for schemes applicable on grassland and arable land for schemes applicable on arable land. In particular, cover crops type of AES in ES are applied on horticulture land.
Furthermore, agents only decide to adopt a scheme if the offered payment level (as defined in the policy regulations) equals to or exceeds their individual accepted payment level (economically and value driven decision, different depending on farm characteristics and external influences).

Why is a/are certain decision model(s) chosen?

The decision model is based on empirical observations from an interview campaign that was conducted in all case studies of the BESTMAP project at the beginning of 2020 (Wittstock et al., 2022, Bartkowski et al., under review). Themes and questions addressed in the interviews were derived from the literature including reviews that specifically focus on AES (Lastra-Bravo et al. 2015, Brown et al. 2020) and others that give a general overview on factors affecting the adoption of sustainable farming practices (Dessart et al. 2019) and agricultural soil management (Bartkowski and Bartke 2018).
A key observation from the interviews was that farmers face a sequence of decision making elements for AES participation. To account for this sequential process in the ABM, we follow the heuristic framework for interpreting farmers' decision making developed in Wittstock et al. (2022). Due to missing data, we could not, however, include all aspects considered relevant in that framework (e.g. we had to exclude aspects on tenant-owner relationship and the duration of tenure contracts since we did not have access to tenure data).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from? At which level of aggregation were the data available?

- The decision model is based on empirical data from an interview campaign that was conducted in all case studies of the BESTMAP project at the beginning of 2020. The interviews were conducted with individual farmers.
- The field-level spatial information for the ES model comes from the DUN data.
- The soil data is sourced from the soil map publicly available[9].
- The AES adoption data of the DUN database is used to inform the model baseline of AES adoption.

2.2. Individual Decision Making

What are the subjects and objects of decision making? On which level of aggregation is decision making modelled? Are multiple levels of decision making included?

Individual farmers are the *subject* of decision making. Farmers decide whether and where to adopt AES, i.e. the adoption of AES contracts at field level is the *object* of decision making. There are *three levels of decision making* included, (1) the determination of general openness towards the adoption of specific AES, (2) the selection of suitable fields for each AES, and (3) the deliberation and site selection for each AES.

What is the basic rationality behind agents' decision making in the model? Do agents pursue an explicit objective or have other success criteria?

- **Decision Making Step 1:** Some farmers have general aversions against some AES and never consider applying for those.
- **Decision Making Step 2:** Not all fields are available for AES adoption due to limitations in the contractual requirements or because they are already occupied by other AES or used as Ecological Focus Area.
- **Decision Making Step 3:** Farmers only apply AES if they consider it profitable for them, the individual threshold for profitability depends on farm and farmer characteristics as well as external circumstances. Farmers prioritise fields with lower soil quality and smaller size for AES contracts.

How do agents make their decisions?

Decision Making Step 1: Farmers are open to specific AES with a probability calculated based on their own prior experience with this AES, their intrinsic openness towards the specific AEs as well as potential influence from advisory support independent of the specific AES and/or influence through their social network with respect to this specific AES. (see also Figure 1).

9 https://www.icgc.cat/Administracio-i-empresa/Serveis/Geoinformacio-en-linia-Geoserveis/WMS-Geoindex/WMS-Sols

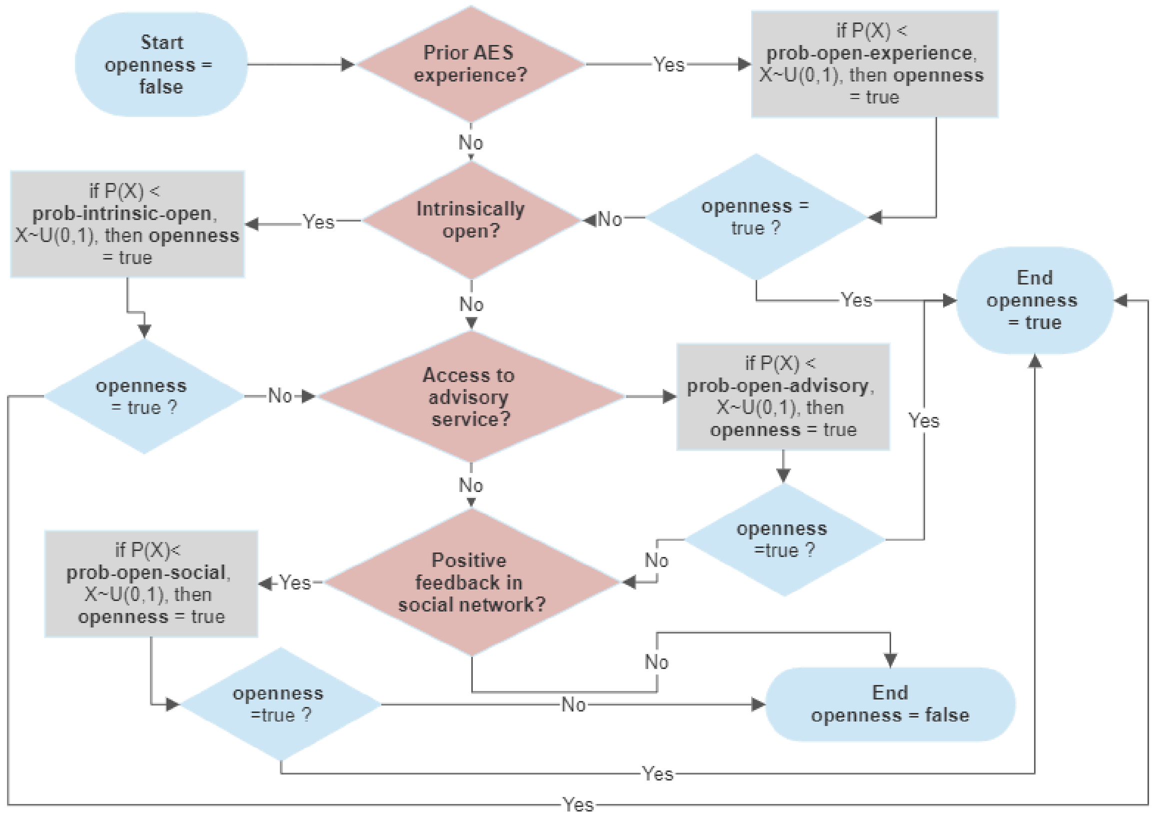

Figure 1: The flowchart of Step 1 in the decision making framework for a selected AES. Farmers' openness status (true or false) is decided by four factors – whether a farmer agent has prior experience, whether it is intrinsically open to the four types of AES, whether it has access to advisory service, whether other farmer agents in its social network have positive experience. The impact of the four factors are set to be four probabilities: "prob-open-experience", "prob-intrinsic-open", "prob-open-advisory" and "prob-open-social", subject to standard uniform distribution U(0,1). At the end of this process, the farmer agent either goes into the next step (if openness is true) or exits the decision-making process (if openness is false)

Decision Making Step 2: Farmers compare field characteristics with AES requirements and select those as suitable which fulfill the requirements.

Decision Making Step 3: Farmers compare their individual accepted payment level with the offered payment level. If their accepted payment level exceeds the offered payment level for a specific AES, farmers select fields on which to adopt the specific AES.
For the order in which the fields for accepted AES are selected, several options are implemented. Farmers could first decide on where to apply schemes with the highest offered payment, the highest difference between offered and accepted payment, the highest ratio between offered and accepted payment or the largest envisioned area. If this selection condition is equal for several accepted schemes, i.e. if for example the offered payment is equal for several schemes, one of them is selected randomly to be applied first. Since we don't have data to support which option is the Humber farmers' favoured choice in their deliberation process, we keep all options in the model for other model users to explore. In our simulation experiments of ES case study, we use "the highest ratio between offered" as the default setting.
The envisioned area of adoption given as % of total suitable area is determined by input data

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

depending on farm and farmer characteristics. Farmers select fields on which to adopt the specific AES by minimising an objective function (e.g. by selecting fields with an optimal combination of smallest field size and lowest soil quality).

Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes, how?

A farmer's openness towards specific AES is influenced by their own prior experience, i.e. prior adoption of this AES, and by their social network, i.e. the prior adoption of other farmers (endogenous state variable). Therefore, the average openness of farmers population is improving due to the increase of farmers' adoption in the region in a multi-year simulation. Farmers' openness and their accepted payment levels are influenced by the availability of advisory support (exogenous state variables). Farmers' accepted payment level depends on the contract characteristics such as duration and bureaucratic effort (exogenous state variables).

Do social norms or cultural values play a role in the decision making process?

Social norms or cultural values are included inexplicitly in the openness step (i.e. Decision Making Step 1) in the model: 1) Farmers' intrinsic openness is partially influenced by the social norms and values they believe in. 2) Farmers' openness is influenced by other farmers in their social network.

Do spatial aspects play a role in the decision process?

Spatial aspects at field level are included in the decision where to apply a selected AES (e.g. based on soil quality, distance of fields to farmstead, field size) and potentially also influence the payment level a farmer considers as profitable (e.g. a farmer with low soil quality might accept a lower payment level for a specific AES).
The social network is based on spatial aspects if it is defined by neighbourhood (i.e. the social network consists of all farms with fields inside of a certain radius around a farmer's fields). If the social network is based on similar farming types (e.g. according to economic farm size or specialisation), spatial aspects do not play a role.

Do temporal aspects play a role in the decision process?

Previous experience with AES (own adoption and adoption in the social network) influences the openness towards the adoption of AES (Decision Making Step 1).

To which extent and how is uncertainty included in the agents' decision rules?

Farmers do not know how other farmers will decide in the current period, they only know their adoption from previous periods.

2.3. Learning

Is individual learning included in the decision process? How do individuals change their decision rules over time as a consequence of their experience?

Farmers who have adopted AES in previous time steps (or in the year reflected in the data used for initialization) have a high probability of being open to consider AES in subsequent

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

decisions.

Is collective learning implemented in the model?

Collective learning is not considered in the model.

2.4. Individual Sensing

What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Farmers have the full knowledge of all their fields, i.e. they know the properties of their land. Furthermore, farmers are aware of the contract characteristics of all AES that they need to consider when deciding whether or not to adopt a scheme. Farmers remember their own previous AES adoption.
Sensing is not erroneous and there is no explicit process of information gathering included, i.e., farmers are simply assumed to know these variables. *What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?*
Farmers know the adoption of other farmers in their social network. Social networks can be determined based on spatial characteristics (including farmers with fields in a specified radius around a farmer's fields) or based on similar farming types (e.g. according to economic farm size or specialisation). The sensing process is not erroneous.

What is the spatial scale of sensing?

Farmers are aware of their own fields and the farmers who have fields next to theirs (i.e., the neighbourhood social network).

Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?

Individuals are assumed to know these variables without any explicit mechanisms.

Are the costs for cognition and the costs for gathering information explicitly included in the model?

Costs for cognition or gathering information are not explicitly included in the model. Implicitly, it is assumed that missing knowledge about a specific AES can be a barrier for farmers to not be open towards the adoption of AES in general (Decision Making Step 1).

2.5. Individual Prediction

Which data do the agents use to predict future conditions? What internal models are agents assumed to use to estimate future conditions or consequences of their decisions? Might agents be erroneous in the prediction process, and how is it implemented?

Farmer agents don't predict future condition changes. In reality, the environment conditions (e.g., climate, ownership of lands, economy, markets etc.) that farmers operate in are changing over time, however, due to lack of data we do not model these changes.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

2.6. Interactions

Are interactions among agents and entities assumed as direct or indirect? On what do the interactions depend?

Interactions between farmers are indirect. Farmers perceive the actions of others only through the state of AES adoption on fields of farmers in their social network which can influence their openness towards specific AES (Decision Making Step 1).

If the interactions involve communication, how are such communications represented? If a coordination network exists, how does it affect the agent's behaviour? Is the structure of the network imposed or emergent?

Communication between farmers is not explicitly modelled. The network structure is imposed and based on the spatial distance between farmers (if the social network is defined by neighbourhood) or on similar farming types, i.e., farm economic size and farm specialisation.

2.7. Collectives

Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation? How are collectives represented?

Collectives are not explicitly represented in the model. Farmers belong to a social network which is based on neighbourhood or similar farming types and can influence each other's openness towards specific AES.

2.8. Heterogeneity

Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

The agents in the model are heterogeneous. The farmer agents differ in the farm size, FSA, the managed fields, the access to advisory support, the prior AES experiences, the intrinsic openness, their expected payment level for the four AES and their social network. The field agents differ in their location, the land use type, the size, the owner, the soil condition and the AES implementation situation. The AES contract agents differ in the owners, the location, the size of the AES area and the type of AES.
All farmers, fields and AES contracts have the same set of state variables and processes, respectively.

Are the agents heterogeneous in their decision making? If yes, which decision models or decision objects differ between the agents?

The farmer agents are heterogeneous in their decision-making. Even though the farmer agents share the same decision models, their decisions are made based on the state variables that are varied across the population, which leads to different decision results.

2.9. Stochasticity

What processes (including initialisation) are modelled by assuming they are random or partly random?

Stochasticity is included in the following processes:

1. *General openness:*
    a. Farmers with their own *prior experience* have a higher chance of being open towards the adoption of AES.
    b. Farmers are *intrinsically open* to consider the adoption of each AES with different probabilities depending on farm characteristics.
    c. A randomly chosen fraction of farmers has *access to advisory support*. Farmers with influence from advisory support have a higher chance of being open to consider the adoption of AES.
    d. Farmers with influence through their *social network* have a higher chance of being open to consider the adoption of AES.
2. *Willingness to accept:* The mean willingness to accept for a specific AES is calculated based on the input data for the specific policy design and farmer characteristics. We assume farmers' WTA is subject to a normal distribution with the mean value differed in different AES policy designs of contract duration, bureaucratic effort and availability of advisory support.
3. *Order of AES selection:* Farmers sign up AES in an order according to their preferences of the accepted AES when they accept more than one type of AES. Several preference options are implemented to generate the order: the highest offered payment, the highest difference between offered and accepted payment, the highest ratio between offered or accepted payment or the largest envisioned area. Farmers endeavour to achieve the envisioned area for the accepted AES. The more favoured AES get field allocation first. Therefore, the order of AES selection influences the AES field-level pattern.

2.10. Observation

Observations can include effects of policy design, i.e. specifications of AES contracts, the availability of advisory support and its importance as well as the importance of social networks or the importance of land-use intensity (i.e the fraction of organic/conventional farms) on AES adoption rates.

Data can be collected at the level of *individual farms* as well as *aggregated across all farms*. Furthermore, the spatial adoption patterns can be collected. Data can be collected at *each time step* or *aggregated over all simulation steps*.

State variables for these observations include for each AES the total area under AES (*v-contract-area-list*) or the number of AES contracts (*v-nr-aes-fields-list*) at farm level and the AES currently applied (*v-aes-list*) or the AES previously applied (*v-aes-hist-list*) at field level.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

3. Details

3.1. Implementation Details

How has the model been implemented? Is the model accessible, and if so where?

The model has been implemented in NetLogo 6.2.1. The model source code is publicly available at https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-ES.

3.2. Initialization

What is the initial state of the model world, i.e. at time t=0 of a simulation run?

- AES contract characteristics are defined based on selected policy design.
- The landscape and soil characteristics are imported from GIS vector files including ownership, land use, and AES adoption. Field agents are created based on the input data.
- Farmers are initialised with the input data containing their characteristics, including FSA, economic sizes, farm areas, and prior AES experience (i.e., AES adoption data of 2018). A farmer's openness due to prior AES experience, intrinsic openness, the influence from advisory services or the influence from the social network is randomly assigned.
- Farmers' envisioned area for AES is initialised with the historic adoption data, which is the average of the proportion of AES area in a farm.
- Data for the calculation of accepted payment levels is imported. The accepted payment level and for each AES is calculated depending on contract details (contract duration, bureaucratic effort) and explicit farmer (access to advisory) as well as implicit (translated in random distribution around mean) farmer characteristics. Details of the calculation are described in Section 3.4.
- The social network is defined based on the selected type (no social network, neighbourhood or FSA).
- Farmers' reasoning on the order of preferred AES is defined according to the selection of the options implemented in the model (*i-g-site-selection*).

Is initialization always the same, or is it allowed to vary among simulations?

Farmer characteristics are the same, however, the probabilities of farmers being open to AES adoption due to prior AES experiences, advisory services and intrinsic openness, the probability of having access to advisory and the design of the social network and farmers' reasoning preferences can be varied between scenarios.
The individual accepted payment levels and envisioned areas for AES adoption are derived from input data. Please see Section 3.4 for more details.
AES contract characteristics (duration, bureaucratic effort, offered payment level) are varied between scenarios representing different policy designs.
Different landscapes can be set up: (1) The whole Catalonia dataset including all farms and fields (2) a sample containing 1% of all Catalonia farms and fields. Figure 2 shows the comparison of the whole dataset and the sample dataset in fields of different land use types. The purpose of having a sampled input data is for the efficiency of running a large number of

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

simulations. Using the sample landscape the model runs faster and produces representative results of the region.

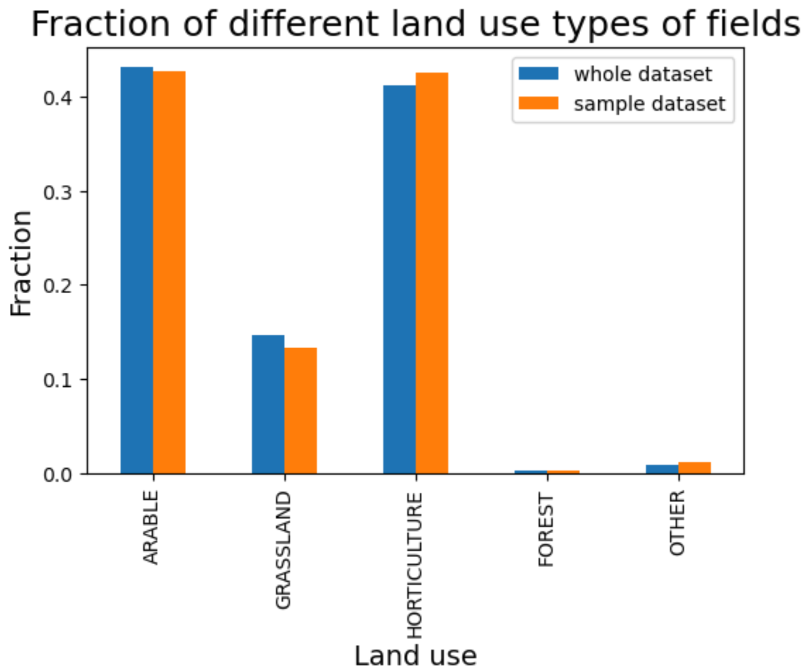

Figure 2: The proportion of fields in each land use type category in the whole dataset and the sample dataset. Five types of land uses in ES are arable, grassland, horticulture, forest and other. In the whole dataset, these five types of fields account for 43.1%, 14.6%, 41.1%, 0.25% and 0.92% respectively. In comparison, the sample dataset contains 42.7%, 13.3%, 42.6%, 0.29% and 1.15% respectively for the five land use types.

Are the initial values chosen arbitrarily or based on data?

Initial values for landscape, farmer characteristics and envisioned area are based on DUN data of 2018. Initial values for accepted payment level are set through calibration based on the model baseline, which is the AES adoption data in 2018. AES designs are composed within ranges assumed to be suitable for ES. In particular, for the baseline the values for AES designs are set according to the current AES designs.
These initial values are chosen arbitrarily because we don't have reliable data for them: A farmer's openness due to prior AES experience, intrinsic openness, the influence from advisory services or the influence from the social network is randomly assigned.

3.3. Input Data

Does the model use input from external sources such as data files or other models to represent processes that change over time?

The model does not use any external input files to represent processes that change over time.

3.4. Submodels

What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'? What are the model parameters, their dimensions, and reference values?

How were submodels designed or chosen, and how were they parameterized and then tested?

Model initialisation

Model initialization sets up the model parameters using input file data, input values in the model interface. Below is the table of model parameters and their reference values that are set in the initialisation.

Model parameters

Parameter	NetLogo variable	Baseline values	Possible values	Unit
Simulated time period	*i-g-years*	1	1-20	years
Minimum required field size for specific AES	*i-g-area-min-buffer-strips* *i-g-area-min-catch-crops* *i-g-area-min-grassland* *i-g-area-min-conversion*	0.1 0.3 0.1 0.1	Any value depending on policy designs	ha
Contract duration for specific AES	*i-g-duration-buffer-strips* *i-g-duration-catch-crops* *i-g-duration-grassland* *i-g-duration-conversion*	1, 5, 10	1, 5, 10	years
Bureaucratic effort for specific AES	*i-g-bureaucracy-buffer-strips* *i-g-bureaucracy-catch-crops* *i-g-bureaucracy-grassland* *i-g-bureaucracy-conversion*	“medium” “medium” “medium” “medium”	“low”, “medium”, “high”	-
Offered payment level for specific AES	*i-g-payment-buffer-strips* *i-g-payment-catch-crops* *i-g-payment-grassland* *i-g-payment-conversion*	661 162 168 367	Any value depending on policy designs	EUR/ha
Offered free advisory services for specific AES	*i-g-advisory-BS?* *i-g-advisory-CC?* *i-g-advisory-MG?* *i-g-advisory-CVN?*	false fasle false false	true/false	
Order of site selection for accepted AES	*i-g-site-selection*	"highest-payment-ratio"	"highest-payment”, "highest-payment-diff", "highest-payment-ratio", "largest-area"	-
Probability that a farmer has access to advisory	*i-g-access-to-advisory*	0.8	Low 20% | High 80%	-

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Type of social network	*i-g-social-network-type*	“none”	“none”, “neighbours”, “FSA”	-
Radius around fields in which other field owners are considered as belonging to social network (“neighbours”)	*i-g-social-network-radius*	5	5, 10	km
Probability that a farmer with prior knowledge of a specific AES is open towards considering its application	*i-g-prob-open-experience*	95%	10%-95%	-
Probability that a farmer with access to advisory is open towards considering application of a specific AES	*i-g-prob-open-advisory*	50%	10%-90%	-
Probability that a farmer with positive social influence is open towards considering application of a specific AES	*i-g-prob-open-social*	10%	10%-90%	-
Probability of being intrinsically open towards considering application of specific AES	*p-g-prob-intrinsic-open-list*	Data read from an input file	0-1	-

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

(depending on selected grouping, see 2.8, we might chose different probabilities for different farmer types)				

These submodels are initialised In the initialisation stage: Social networks and farmers' WTA calculation.

Social networks

The type social network is defined by *i-g-social-network-type* which can be either "none", "neighbours" or "FSA". The social network (*v-social-network*) is set to an empty turtle agentset if "none" is chosen. The owners of fields in a radius i-g-social-network-radius around each field of a farmer are added to the social network of a farmer, If the "neighbours" option is chosen; The farmers with the same FSA and economic size are added to the social network of a farmer If the "FSA" option is chosen.

WTA calculation

WTA calculation is implemented in the NetLogo function *r-calculate-farmer-DCE*. This process calculates WTA mean value of an AES for the farmer population based on the contract length *c* (1, 5 or 10 years), the bureaucratic effort *b* (low, medium or high) and the availability of advisory support *a* (yes or no) of the AES as specified in the policy design of the respective simulation run. The calculation is based on the reference value for a five years contract with medium bureaucratic effort and without advisory support *WTA (5,* medium, no*)* (status quo) and the differences for a different contract length, bureaucratic effort or availability of advisory Δ*WTA(c,b,a).*

In total, the calculation is composed as follows:

$$WTA(c,b,a) = WTA(5,\text{medium},\text{no}) + \begin{cases} \Delta WTA(1,\text{medium},\text{no}) & \text{if } c = 1 \\ \Delta WTA(10,\text{medium},\text{no}) & \text{if } c = 10 \end{cases} + \begin{cases} \Delta WTA(5,\text{low},\text{no}) & \text{if } b = \text{low} \\ \Delta WTA(5,\text{high},\text{no}) & \text{if } b = \text{high} \end{cases} + \begin{cases} \Delta WTA(5,\text{medium},\text{yes}) & \text{if } a = \text{yes} \\ 0 & \text{if } a = \text{no} \end{cases} \tag{1}$$

In farmer agent initialisation *setup-farmers*, the WTA for a type of AES of an individual farmer *i*, noted as WTA_i, is drawn randomly based on the normal distribution:

$$WTA_i \sim N\,(\mu,\ \sigma^2) \tag{2}$$

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Where $\mu = WTA(c, b, a)$ and $\sigma^2 = 0.1 * \mu$.

Update prior knowledge based on own experience

In this process, the model updates farmers' prior AES experience (*v-prior-experience-list*) based on the AES adoption history (*v-aes-hist-list*) in the NetLogo function *update-prior-knowledge*. The AES adoption history is updated when a farmer signs up for an AES in the Decision Making Step 3.

Remove AES contracts that exceed contract duration and update state variables of farmers and fields related to AES adoption

AES contracts are updated in the NetLogo function *update-aes*. As the simulation progresses, the contract year of an AES contract (*v-aes-contract-year*) is increased by one. If the contract year is larger than the AES contract duration (*i-g-duration-xxx,* whose value is stored in *p-g-duration-list*), the model removes the AES contract and updates the field and farmer agents' status. Field agents' variable - the list of AES on a field (*v-aes-list*) and farmer agents' variables - the total area under AES for each AES (*v-contract-area-list*) and the number of AES contracts (*v-nr-aes-fields-list*) are updated.

Openness (Decision Making Step 1)

Calculate openness for each AES individually (see also Figure 1):

- Check prior experience: For farmers with prior knowledge set openness to this AES to 1 with probability *i-g-prob-open-knowledge*
- Check intrinsic openness: For farmers without prior experience set openness to 1 with probability *p-g-prob-intrinsic-open-list*
- Check advisory support: For farmers not intrinsically open but with access to advisory support set openness to 1 with probability *i-g-prob-open-advisory*

Check social network: For farmers not open after advisory support or farmers without access to advisory support check social network. If at least one member of the social network has previously applied the AES, set openness to 1 with probability *i-g-prob-open-social*.

Selection of fields (Decision Making Step 2)

Farmers select suitable fields for the AES that they are open to in the NetLogo function *select-suitable-fields*. Only fields that are the eligible types of land use, larger than the minimum required area and not having ESS on are selected (stored in *v-suitable-fields-list*) and passed to the Decision Making Step 3 for further consideration.

Deliberation (Decision Making Step 3)

In the deliberation process (the NetLogo function *deliberate-aes-decision*), farmers compare WTAs with the offered payments in the NetLogo function *r-compare-payment* and get the profitable AES list (*p-accepted-aes-list*). Then farmers select fields for the AES that they are open to and update *v-suitable-fields-list* according to the field eligibility and whether their envisioned area has achieved. Farmers also produce an order of their favoured AES according to the model setting of *i-g-site-selection*, which is implemented in the NetLogo function *get-aes-decision-order*.

Farmers then select fields based on the soil quality and the size of the field to realise the AES contracts (the NetLogo function *select-aes-fields*). Fields with lower soil quality and smaller size are prioritised to be put under AES. In the ES case study area, farmers put a whole field for their selected AES in the model and also can sign multiple fields up for AES to achieve the envisioned area.

4. Discussions for future work on the model

The BESTMAP-ABM-ES model can be improved further in the future when we have more data. The current version of the model suffers from lack of data. Firstly, because two of the four types of AES we aim to model, i.e., buffer strips and arable land conversion to grassland, do not exist in the current agricultural policy, we don't have a baseline to tune the relevant parameters for. Secondly, the discrete choice experiment was not successful in Catalonia due to the low number of respondents. This leads to lacking WTA and social-behavioural data for different farm types. Given that we are short of other means (e.g. a regression model) to justify WTA values for different FSA farms, the model is not fine-tuned.

Another obstacle we encountered is the technical challenge of running a NetLogo model with more than 11 million agents. In the future, the model can be re-implemented in other platforms that are more capable of handling large models, for example, Repast HPC.

References

Bartkowski, B., Bartke, S., 2018. Leverage Points for Governing Agricultural Soils: A Review of Empirical Studies of European Farmers' Decision-Making. Sustainability 10, 3179.

Bartkowski, B., Beckmann, M., Bednář, M., Biffi, S., Domingo-Marimon, C., Mesaroš, M., Schüßler, C., Šarapatka, B., Tarčak, S., Václavík, T., Ziv, G., Wittstock, F. Adoption and potential of agri-environmental schemes in Europe: Cross-regional evidence from interviews with farmers. Under review.

Paulus, A., Hagemann, N., Baaken, M.C., Roilo, S., Alarcón-Segura, V., Cord, A.F., Beckmann, M., 2022. Landscape context and farm characteristics are key to farmers' adoption of agri-environmental schemes. Land Use Policy 121, 106320.

Wittstock, F., Paulus, A., Beckmann, M., Hagemann, N., Baaken, M.C., 2022. Understanding farmers' decision-making on agri-environmental schemes: A case study from Saxony, Germany. Land Use Policy 122, 106371.

Ziv, G., Beckmann, M., Bullock, J., Cord, A., Delzeit, R., Domingo, C., Dreßler, G., Hagemann, N., Masó, J., Müller, B., Neteler, M., Sapundzhieva, A., Stoev, P., Stenning, J., Trajkovic, M., Václavík, T., 2020. BESTMAP: behavioural, Ecological and Socio-economic Tools for Modelling Agricultural Policy. Research Ideas and Outcomes 6, e52052.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

ODD+D for Bačka region (RS)

Corresponding author: Nastasija Grujić, Biosense Institute

1. Overview

1.1. Purpose

What is the purpose of the study?

BESTMAP-ABM-SRB is an agent-based model to determine the adoption and spatial allocation of agri-environmental schemes (AES) by individual farmers in the Backa region located in Vojvodina, Serbia. The selected AES are flower strips, cover crops, maintaining grassland, and conversion of arable land to grassland. In particular, the model investigates the effect of different scenarios of policy design on patterns of adoption. Since the AES is yet to be introduced in Serbia, the model at first-time step focuses on investigating the effect of the introduction of AES to farmers, while at the later stages, it is assumed that farmers are already familiar with the concept. 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. The model was created as one of five case study-specific models with the same fundamental processes as part of the BESTMAP project (Ziv et al., 2020).

For whom is the model designed?

The model is designed for policymakers and stakeholders responsible for agricultural policies to assess the impact of future policy designs. In addition, the model can be used by scientists to build upon the existing model structure and address further research questions in the context of farmer behavior.

1.2. Entities, state variables, and scales

What kinds of entities are in the model?

The model consists of three main entities: Agents representing individual farmers (1,376), the spatial environment representing individual fields (14,222) with each farmer managing a fixed set of fields, and AES contracts. Farmers decide whether and where to adopt AES with each AES contract entity representing an AES applied on a specific field, i.e. a farmer can have several contracts for the same AES type. It is assumed that an AES is applied to the whole field and that only one AES can be selected per field.

By what attributes (i.e. state variables and parameters) are these entities characterized?

Constant farmer state variables

	NetLogo variable	Possible values	Unit
Farmer's unique identification number	p-farmer-id	-	-
Fields a farmer owns	p-property-set	-	NetLogo

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

			agentset
Size of farm (sum of field sizes)	p-farm-area	>0	ha
Farm specialization*	p-fsa-spec	P1, P2, P3, P4, P5	-
Economic farm size	p-fsa-size	<2000, small, medium, large	-
Farm intensity (organic)	p-eco	0/1	-
Access to advisory support	p-advisory	0/1	-
GIS feature list of all fields a farmer owns	p-gis-feature-list	vector polygons	-
List of villages ID where a farmer has fields	p-gis-villages-list	-	-
Farmers in social network	v-social-network	Depending on social network type	NetLogo agentset
Probability for intrinsic openness towards each AES (list)	p-prob-intrinsic-open-list	0-1 (4 items), see model parameters in 3.4	-
Probability of being open to each AES due to advisory support	p-prob-advisory-open-lis t	0-1 (4 items), see model parameters in 3.4	-
Accepted payment levels for all AES (list)	p-accepted-payment-list	(4 items)	EUR
Area a farmer is willing to use for each AES (list)	p-envisioned-area-list	(4 items)	ha

*Farm System Archetype (FSA): General cropping (P1), Horticulture (P2), Permanent crops (P3), Grazing livestock and forage (P4), mixed (P5)

Farmer state variables varying over time

	NetLogo variable	Possible values	Unit
Openness towards each AES (list)	v-open-to-aes-list	0/1 (4 items)	-
Prior experience with each AES (list)	v-prior-experience-list	0/1 (4 items)	-
Fields suitable for each AES (list)	v-suitable-fields-list	(4 items)	NetLogo agentset
Total area under AES for	v-contract-area-list	(4 items)	ha

each AES (list)			
Number of AES contracts for each AES (list)	v-nr-aes-fields-list	(4 items)	-
Numbers indicating whether a farmer accepted AES (list)	p-accepted-aes-list	0/1 (4 items)	-

Constant field state variables

	NetLogo variable	Possible values	Unit
Field's unique identification number	p-field-id	-	-
Owner ID (farmer)	p-owner-id	-	-
Land use	p-land-use	arable_land, grasslands, fruits_and_vineyards	-
Size	p-area	>0	ha
Soil quality	p-soil-quality	0-3.55	-

Field state variables varying over time

	NetLogo variable	Possible values	Unit
AES currently applied (list)	v-aes-list	0/1 (4 items)	-
Number of AES contracts previously applied (list)	v-aes-hist-list	(4 items)	-

Constant AES contract state variables

	NetLogo variable	Possible values	Unit
AES type	v-aes-name	buffer strip, catch crops, grassland, conversion	-
Duration since AES adoption	v-aes-contract-year	[1,10]	years
Field on which AES is applied	v-aes-field	-	NetLogo agentset
Farmer who owns the field	v-aes-owner	-	NetLogo agentset
Size of AES contract (field size)	v-aes-size	>0	ha

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Convention for NetLogo names: g - global variables, i - variables defined via interface, p - variables set via input files (exogenous), v - variables changed in the model procedures (endogenous)

What are the exogenous factors / drivers of the model?

The AES contract design, in particular the payment level, contract duration, and administrative effort, is exogenously given. Whether a farmer has access to advisory support is randomly assigned. Farms are spatially represented by individual fields derived from the AgroSense database for Serbia. Fields are characterized by field size, soil condition, and land use.

What are the temporal and spatial resolutions and extents of the model?

Space is explicitly represented at the field level, with each farm consisting of several fields. The selected case study is the Backa region, with an area of 8,218 km^2, of which 84% is agricultural land. We use data from the AgroSens database, which is a voluntary digital agricultural platform (https://agrosens.rs/#/app-h/welcome) in Serbia, launched in October 2017. It is free of charge and enables farmers to use and monitor their crops by combining processed Sentinel pictures with meteorological data (historical data and forecasts) and on-the-ground information received through various measurements and farmers' inputs. We used data from 2018–2021 which cover approximately 15% of the agricultural area in the CS. The data set contains around 14K parcels with 1K+ users. The field size distribution is depicted in Figure 1. For more details on AgroSens data, please refer to section 3.5.1.

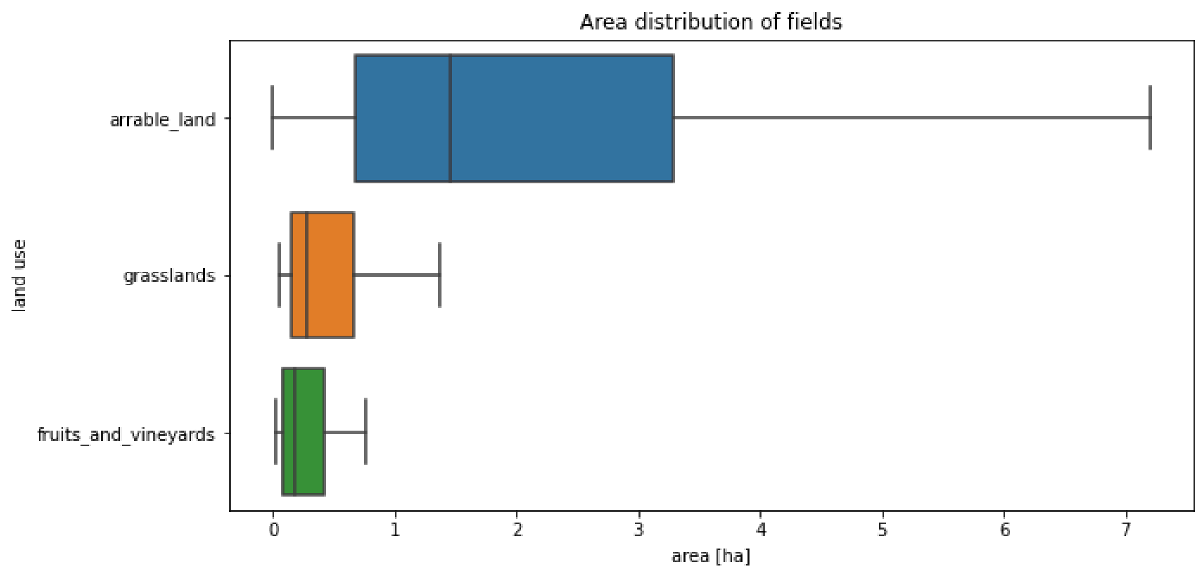

Figure 1: Distribution of field size in Backa CS. Please note: for the sake of a clearer plot, outliers were removed.

Time is represented as discrete yearly time steps with AES adoption decisions made once a year. The temporal extent can be between one and ten years depending on the research question that should be addressed.

1.3. Process overview and scheduling

The following processes occur in each time step:

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

- Update prior knowledge based on own experience
- Remove AES contracts that exceed contract duration
- Update state variables of farmers and fields related to AES adoption
- **Decision Making Step 1** - Check openness to specific AES: Decide for each AES separately if a farmer can in general (independent of specific contract details) imagine applying the scheme
- **Decision Making Step 2** - Select suitable fields: Compile a set of fields suitable for AES adoption by excluding fields with ongoing AES contracts or fields which do not meet the required minimum field size or the required land use (i.e. depending on AES arable land or grassland)
- **Decision Making Step 3** - Deliberation and site selection: Check for each farmer and AES whether the offered payment exceeds the expected payment and select fields where AES should be adopted

2. Design concepts

2.1. Theoretical and Empirical Background

Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?

Farmers accept an AES if they are open to consider the adoption. This is an identity-driven decision based on own prior experience in agro-ecological practices, such as organic farming or participation in specific AES[10], intrinsic openness, influence from advisory and/or social networks. In addition, farmers need to have suitable land available (i.e. grassland for schemes applicable on grassland and arable land for schemes applicable on arable land). Furthermore, 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). Farmers' expected payment level is determined by farm characteristics (FSA specialization farm type), contract characteristics (duration and administrative effort), and external influences (access to advisory, social network influence).

On what assumptions is/are the agents' decision model(s) based?

The underlying assumptions are embedded in 3 levels of steps of the decision-making processes.
Decision Making Step 1: Not all farmers are open to the adoption of AES, some have identity-driven barriers against the adoption which cannot be overcome by financial means.
Decision Making Step 2: Farmers compare field characteristics with AES requirements and select those as suitable which fulfill the requirements.
Decision Making Step 3: Farmers decide to adopt AES if the adoption is financially profitable, i.e. the offered payment level needs to be equal to or exceed their expected payment level. The level at which the adoption of AES is considered profitable depends on the characteristics of the schemes (duration, level of bureaucracy) but also farmer characteristics (farm specialization) and external factors (access to advisory, influence of social network).

[10] Since there is no AES in Serbia yet, this part is related to simulation in the model (i.e., experience in participation in AES in the model)

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Why is a/are certain decision model(s) chosen?

The decision model is based on empirical observations from an interview campaign that was conducted in all case studies of the BESTMAP project at the beginning of 2020 (Wittstock et al., 2022, Bartkowski et al., under review). Themes and questions addressed in the interviews were derived from the literature including reviews that specifically focus on AES (Lastra-Bravo et al. 2015, Brown et al. 2020) and others that give a general overview on factors affecting the adoption of sustainable farming practices (Dessart et al. 2019) and agricultural soil management (Bartkowski and Bartke 2018).
A key observation from the interviews was that farmers face a sequence of decision making elements for AES participation. To account for this sequential process in the ABM, we follow the heuristic framework for interpreting farmers' decision making developed in Wittstock et al. (2022). Due to missing data, we could not, however, include all aspects considered relevant in that framework (e.g. we had to exclude aspects on tenant-owner relationship and the duration of tenure contracts since we did not have access to tenure data).

If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from? At which level of aggregation were the data available?

The conceptual framework of the decision model is based on empirical data from an interview campaign that was conducted with individual farmers in all case studies of the BESTMAP project at the beginning of 2020. It served to identify the main factors that affect farmers' decision-making processes when considering applying for an AES across the case studies. In addition, a follow-up survey, including a discrete choice experiment (DCE), was conducted to inform the decision model. The survey consisted of questions divided into 5 sections: (1) background information on the farm; (2) the DCE; (3) personal attitudes towards (not) participation in each AES and personal views; (4) experience with organic farming; and (5) sociodemographic background. Using the DCE and questionnaire, which mostly consisted of close-ended questions, the aim was to derive the expected payment level ("Willingness to Accept", WTA) for each AES and farmer type (FSA size and specialization) depending on contract features (duration, administrative effort), and the availability of free advisory support. With these results, farmers' expected payment levels in the third step of the decision-making framework could be parametrized. Unfortunately, in the survey, we could only differentiate farmers by FSA farm specialization type (P1, P3, and P5 farmers). Due to the small sample size and the variability in the results, we were unable to obtain statistically significant results for farmers' expected payment levels differentiated by existing farmer types. Instead, we created three different data sets that rely on the DCE and literature:

1. A data set based on the DCE data that does not distinguish FSA specialization farmer types;
2. A augmented DCE data set using the SMOTE algorithm (Chawla, N. et al 2002), which distinguishes between FSA specialization farmer types;
3. A data set that was created as a combination of the second data set and conclusions from the literature

For more details on the creation of the DCE data sets, please refer to section 3.5.4.
The input variables such as the probabilities of being open due to previous experience in agro-ecological practices (*p-g-prob-open-experience*), being open with access to advisory support (*p-g-prob-advisory-open-list*) and being intrinsically open without access to advisory support (*p-g-prob-intrinsic-open-list*) are extracted from the survey. Also, the percentage of farmers who have access to advisory support was used in the model (*i-g-access-to-advisory*), as well as the area percentage on which a farmer would apply a certain AES (*p-g-area-list*) is drawn from the survey. This information is available at farm level. The obtained results and concrete information on the extraction of these parameters can be seen in section 3.5.3.
Spatial data come from the AgroSense database for Serbia. Soil quality in the model is approximated using a soil organic particulate matter map, which reflects the amount of organic matter in the soil (see section 3.5.2).

2.2. Individual Decision Making

What are the subjects and objects of decision making? On which level of aggregation is decision making modelled? Are multiple levels of decision making included?

Individual farmers are the *subject* of decision making. Farmers decide whether and where to adopt AES, i.e. the adoption of AES contracts at field level is the *object* of decision making. There are *three levels of decision making* included, (1) the determination of general openness towards the adoption of specific AES, (2) the selection of suitable fields for each AES, and (3) the deliberation and site selection for each AES.

What is the basic rationality behind agents' decision making in the model? Do agents pursue an explicit objective or have other success criteria?

- **Decision Making Step 1:** Some farmers have general aversions against some AES and never consider applying for those.
- **Decision Making Step 2:** Not all fields are available for AES adoption due to limitations in the contractual requirements or because they are already occupied by other AES.
- **Decision Making Step 3:** Farmers only apply AES if they consider it profitable for them, the individual threshold for profitability depends on farm and farmer characteristics as well as external circumstances.

How do agents make their decisions?

Decision Making Step 1: Farmers are open to the adoption of specific AES with certain probabilities that depend on (1) prior experience in agro-ecological practices (such as organic farming or participation in specific AES, which is present later in the simulation and not in the first time step), (2) their intrinsic openness towards the specific AES, (3) their openness towards different AES when having advisory support, and (4) influence through their social network. In the first simulation step, when farmers are introduced to AES for the first time, it is assumed that farmers with experience in agro-ecological practices (organic farming) would have the dominant social influence on someone adopting the schemes, while after the introduction of schemes (after the first model year), it is assumed that farmers with actual experience with a particular AES would influence the others to adopt (see also Figure

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

2).

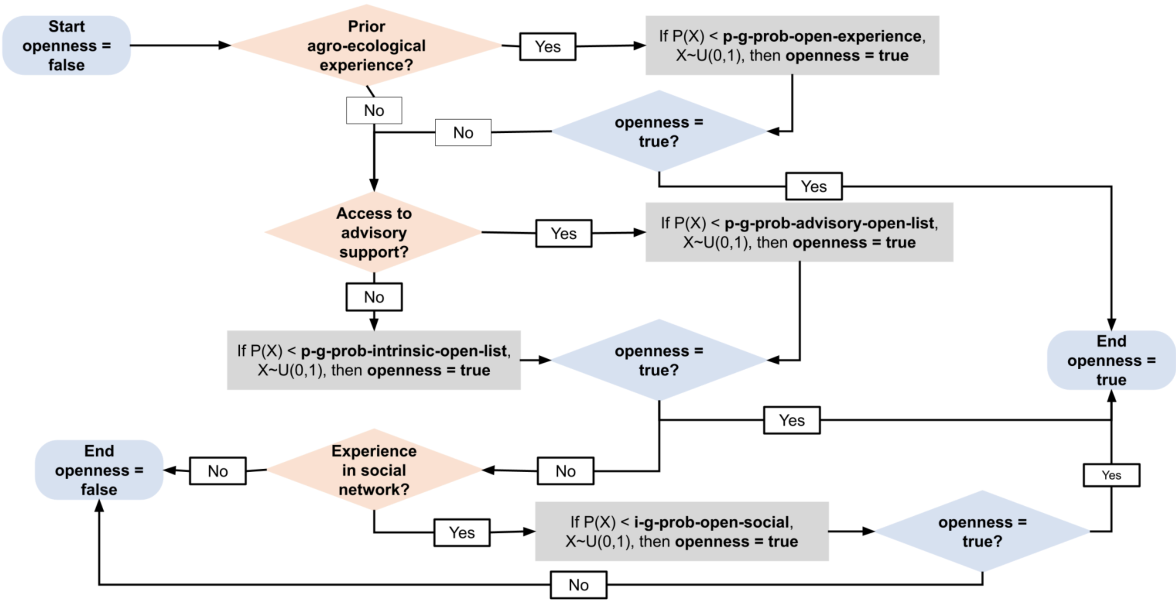

Figure 2: Schematic representation of the hierarchical design of Step 1 in the decision making framework for a selected AES. In the first time step, ‘Prior agro-ecological experience’ refers only to experience in organic farming, while in the t+1 time step, ‘Prior agro-ecological experience’ can be either organic farming or participation in specific AES.

Decision Making Step 2: Farmers compare field characteristics with AES requirements and select those as suitable that fulfill the requirements.

Decision Making Step 3: Farmers compare their individual expected payment level with the offered payment level. If their expected payment level exceeds the offered payment level for a specific AES, farmers select fields on which to adopt the specific AES. If several AES are accepted, the order in which the fields are selected is based on the highest difference between offered and accepted payment (i.e., farmers first select fields for AES with the highest difference between offered and accepted payment). If the difference between offered and accepted payment is equal for several schemes, one of them is selected randomly to be applied first. The envisioned area of adoption given as percentage of the total suitable area is determined by input data. Farmers select fields on which to adopt the specific AES based on fields’ size and soil quality.

Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?

A farmer’s openness towards a specific AES is influenced by their own prior experience, i.e., prior adoption of this AES or being an organic farmer, and by their social network, i.e., prior experience in agro-ecological practices (organic farming) at the first time step and adoption in the t+1 time steps of other farmers (endogenous state variable). Farmers’ openness and their accepted payment level are influenced by the availability of advisory support (exogenous state variables). Farmers' expected payment level depends on contract characteristics such as duration and administrative effort (exogenous state variables).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Do social norms or cultural values play a role in the decision making process?

Social aspects are included through the influence of farmers with prior experience in the social network. In the first simulation step, when farmers are introduced to AES for the first time, organic farmers could influence others to adopt AES. In contrast, in later time steps, farmers who have prior experience with a specific AES could influence others.

Do spatial aspects play a role in the decision process?

Spatial aspects at field level are included in the decision of where to apply a selected AES (i.e., based on soil quality and field size).
The social network is based on spatial aspects if it is defined by neighborhood (i.e. the social network consists of all farms with fields inside of a certain radius around a farmer's fields) or by belonging to the same village.

Do temporal aspects play a role in the decision process?

Previous experience as well as adoption in the social network influences the openness towards the adoption of AES (Decision Making Step 1).

To which extent and how is uncertainty included in the agents' decision rules?

Farmers do not know how other farmers will decide in the current period, they only know their adoption from previous periods.

2.3. Learning

Farmers who have adopted AES in previous time steps during the model simulation have a high probability of being open to consider AES in subsequent decisions.

Is collective learning implemented in the model?

Collective learning is not considered in the model.

2.4. Individual Sensing

What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Farmers can sense the state of all their fields, i.e. they know the properties of their land. Furthermore, farmers know the contract characteristics of all AES that they need to consider when deciding whether or not to adopt a scheme. Farmers remember their own previous AES adoption and the adoption of farmers in their social network. Social networks can be determined based on spatial characteristics (including farmers with fields in a specified radius around a farmer's fields or including farmers belonging to the same village). Sensing is not erroneous.

What is the spatial scale of sensing?

Farmers are aware of their own fields and the farmers who have fields next to theirs (i.e., the neighbourhood and villages social networks).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?

Individuals are assumed to know these variables without any explicit mechanisms.

Are the costs for cognition and the costs for gathering information explicitly included in the model?

Costs for cognition or gathering information are not explicitly included in the model. Implicitly, it is assumed that missing knowledge about a specific AES can be a barrier for farmers to not be open towards the adoption of AES in general (Decision Making Step 1).

2.5. Individual Prediction

Farmers do not predict future conditions.

2.6. Interactions

Interactions between farmers are indirect. Farmers perceive the actions of others only through the state of having experience in organic farming (time steps t=1 and t+1) or AES adoption (time step t+1) on fields of farmers in their social network which can influence their openness towards specific AES (Decision Making Step 1). Communication between farmers is not explicitly modeled. The network structure is imposed and based on the spatial distance between farmers (i.e., social network can be defined by neighborhood or by belonging to the same village).

2.7. Collectives

Collectives are not explicitly represented in the model. Farmers belonging to a social network that is based on neighborhood or a village can influence the openness towards specific AES.

2.8. Heterogeneity

Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

All farmers, fields, and AES contracts have the same set of state variables and processes, respectively. A fixed number of farmers have access to advisory support. Fields differ in area, land use, soil quality, and ownership. Farms differ in farm size, social network, FSA, available land, advisory support, and agro-ecological practices (conventional and organic farming).

For the calculation of the expected payment level (WTA) in Decision Making Step 3, we assume a gradual increase of complexity (see section 3.5.4).

1. We assume that the mean willingness to accept is the same for all farmers. Differences between farmers are only reflected in a normal distribution around the calculated mean. In this case, farmers randomly select the envisioned area from the consolidated file for all farmers from the DCE.
2. We assume heterogeneities between farmer types depending on the FSA farm

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

specialization (categorized in five distinct groups according to the land use) as derived in other steps of the BESTMAP project. In this case, the extracted envisioned area from the DCE and survey is differentiated per FSA farm specialization categories, and each farmer randomly chooses his envisioned area according to his category.

Are the agents heterogeneous in their decision making? If yes, which decision models or decision objects differ between the agents?

Only farmers who have passed the first step of decision making (general openness to AES) make decisions in the following two steps (selection of suitable fields, deliberation, and site selection).

2.9. Stochasticity

Stochasticity is included in the following processes:

1. ***General openness**:* Based on probability impacted by prior experience, advisory support, intrinsic openness, and social influence, general openness (Decision Making Step 1) is determined (for more information, see *Calculate openness (decision making step 1)* in section 3.4).
2. ***Expected payment level**:* The mean expected payment level for a specific AES is calculated based on empirical input data for the specific policy design and farmer characteristics (extracted from the DCE and literature, see section 3.5.4 for details). To take into account aspects not considered in the factors to derive the expected payment level (contract duration, administrative effort, availability of advisory support) but also include additional differences in attitudes between farmers, the individual expected payment level for each farmer is drawn from a normal distribution around the calculated mean with a standard deviation (for more information, see *Deliberation (decision making step 3)* in section 3.4).
3. ***Envisioned area**:* The percentages of envisioned areas for AES adoption are extracted from the DCE and survey by using farmers' reported values on farm area percentages where a particular scheme would be applied. Based on the FSA farm specialization type (if it's included in the model), farmers randomly choose one of the reported values for each AES (for more details on data extraction, see section 3.5.3).
4. ***Order of site selection**:* The order in which the fields for accepted AES are selected is based on the difference between offered and accepted payments. The AES with the highest difference is applied first, followed by the second, and so on. If the difference value is equal for several accepted schemes, one of them is selected randomly to be applied first (see *Deliberation (decision making step 3)* in section 3.4).

2.10. Observation

Observations can include effects of policy design, i.e. specifications of AES contracts, the availability of advisory support and its importance as well as the importance of social networks or the importance of land-use intensity (i.e the fraction of organic/conventional farms) on AES adoption rates.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Data can be collected at the level of *individual farms* as well as *aggregated across all farms*. Furthermore, the spatial adoption patterns can be collected. Data can be collected at *each time step* or *aggregated over all simulation steps*.
State variables for these observations include for each AES the total area under AES (*v-contract-area-list*) or the number of AES contracts (*v-nr-aes-fields-list*) at farm level and the AES currently applied (*v-aes-list*) or the AES previously applied (*v-aes-hist-list*) at field level.

3. Details

3.1. Implementation Details

How has the model been implemented? Is the model accessible, and if so where?

The model has been implemented in NetLogo 6.3.0. The model source code is publicly available at https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-SRB.

3.2. Initialization

What is the initial state of the model world, i.e. at time t=0 of a simulation run?

- AES contract characteristics are defined based on selected policy design.
- The landscape is imported from the GIS vector file including ownership, soil quality and land use. Field agents are created based on the input data.
- Farmers are initialized with their characteristics imported from empirical data. Access to advisory is randomly assigned.
- Data for the calculation of expected payment levels is imported. The expected payment level for each AES is calculated depending on contract details (contract duration, administrative effort) and explicit farmer (access to advisory) as well as implicit (translated in random distribution around mean) farmer characteristics.
- Probabilities of being open due to previous experience in agro-ecological practices, being intrinsically or due to advisory support open are imported into the model and assigned to farmers.
- The model imports the possible percentages of the envisioned area (in percentage of the total suitable area, i.e., arable land or grassland depending on AES) and randomly assigns them to farmers. Based on the assigned percentages and FSA farm specialization types (if included), farmers calculate the envisioned area per AES.
- The social network is defined based on the selected type (none, neighborhood, village).

Is initialization always the same, or is it allowed to vary among simulations?

The landscape and farmer characteristics are the same in all scenarios, but access to advisory services, the design of the social network, and the level of farmer heterogeneity differ. The individual accepted payment levels are imported from one of the three created data sets (see section 3.5.4). The envisioned areas for AES adoption are derived from empirical input data, but the actual file that will be imported depends on the chosen degree of heterogeneity, see section 2.8. AES contract characteristics (duration, administrative effort, offered payment level) are varied between scenarios representing different policy designs. The social network can be defined as "none", "villages", and "neighbors". If the social network is not "none", the importance of influence from the social network can differ. Furthermore, if the social network based on neighbors is selected, variation includes the network radius as well. The probabilities of having an advisory, being open due to previous experience, having advisory support, and being intrinsically open are imported from data, but nevertheless could be varied.

Are the initial values chosen arbitrarily or based on data?

Landscape and farmer characteristics are extracted from the AgroSense database. The values for percentage of envisioned area and percentage of farmers who have access to advisory support, as well as the probabilities of being open due to previous experience, being intrinsically open, and being open due to advisory support, are based on the responses from the survey. Values for expected payment levels could be either completely derived from the DCE results or in combination of DCE results and literature (see section 3.5.4). AES contract designs are composed within ranges assumed to be suitable for the case study. Importance of social influence and network radius are assumed.

3.3. Input Data

The model does not use any external input files to represent processes that change over time.

3.4. Submodels

<u>Setup functions</u>

Function name: setup

Field setup

Function name: create-landscape

Field agents are created from the imported GIS vector data set and the relevant attributes from the data set are assigned to agents, such as *p-owner-id*, *p-field-id*, *p-land-use*, *p-area*, and *p-soil-quality*. The list indicating AES history on the fields (*v-aes-hist-list*) is set to 0 since there is no AES in Serbia. The number of currently applied AES on the fields is also set to 0 (*v-aes-list*).

WTA setup

Function name: setup-aes-constants

The AES contract characteristics are defined by contract duration (1, 5, and 10 years), administrative effort (low, medium, and high), and offered payment per hectare. All those values are set using the interface. This function stores those values in the lists, where each list is dedicated to one variable type, while position indicates the specific AES to which a value is referring.

Function name: setup-wta-specifics

The AES contract characteristics can differ in the contract duration, administrative effort, and offered payment per hectare. Also, a farmer can have access to free advisory support.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

The mean expected payment level and its standard deviation for the baseline version of an AES contract (5 years duration, medium administrative effort, no advisory support) are loaded into the model for each AES and farmer type (if FSA specialization farmer types are differentiated in the model), together with the variation in the accepted payment level when contract duration is 5 years longer or shorter, when an administrative effort is low or high instead of medium, and when an advisory is available to a farmer. Moreover, the envisioned area percentages are imported into the model for each AES and farmer type (if FSA specialization farmer types are differentiated in the model). If FSA specialization farm types are distinguished in the model there is a separate file (different values) for each farmer type, while if they are not, there is only one file with unified values that refers to all farmers.

Farmers setup

Function name: setup-farmers

This function calls the *load-farmers*, *set-farmer-attributes*, and *setup-social-network* functions.

Function name: load-farmers

The CSV file that contains a list of farmers with their attributes (*p-farmer_id*, *p-farm_spec*, *p-farm_size*, and *p-farm_eco*) is loaded into the model and used for the creation of farmers agentset. Using farmers' ID values, each farmer gets his fields agents and stores in the *p-property-set* variable.

Function name: set-farmer-attributes

Files that contain probabilities of farmers being open due to previous experience in agro-ecological practices, availability of advisory support, and being intrinsically open are imported, and the values are assigned to farmers. The total farm area (p-farm-area) is calculated by adding the areas of farmer's individual parcels. A subset of farmers gets the access to advisory based on the random number drawn from uniform distribution and probability of having access to advisory which is defined in the interface. Lists needed for calculation of AES adoption (*p-accepted-payment-lis*t, *v-contract-area-list*, *v-nr-aes-fields-list*, *v-open-to-aes-list*) are initialized to starting values. Each farmer chooses at random a percentage of the imported envisioned area and calculates his envisioned area in hectares per AES.

Function name: setup_social_network

Two types of social networks are implemented in the model and can be defined via an interface variable (*i-g-social-network-type*). If the social network is defined as 'neighbors', then a model user also needs to define the radius of the social network in km (*i-g-social-network-radius*). In this model setup, owners of the fields that are in the *i-g-social-network-radius* distance circle from a farmer get into the farmer's social network (*p-social-network*) and can potentially influence the farmer. If the social network is defined as 'villages', all the farmers who have parcels in the same village are in the social network and can influence each other. Farmers that belong to a farmer's social network are stored in a *p-social-network* variable. The third option is 'none', when the social network is neither created, nor considered in the model. In this case, *p-social-network* is an empty agent set.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Go functions

Function name: go

Updating the current state

Function name: update-world

This function calls the *update-prior-knowledge* and *update-aes* functions.

Function name: update-aes

It updates the number of years of AES being applied in the fields (every tick, one year). Furthermore, it deletes AES if the contract finishes (i.e., if the contract duration exceeds the number of AES contract years).

Function name: update-prior-knowledge

If a farmer applied a certain AES, his previous experience is set to one/true (*v-prior-experience-list*).

Calculate openness (decision making step 1)

Function name: check-openness-to-aes

The calculation of openness is divided into 4 steps:

1. Positive prior experience: A farmer who has prior experience in agro-ecological practices (organic farming) or the particular AES is open towards adoption of that AES with the probability *p-g-prob-open-experience*
2. Advisory support: If a farmer has not had previous experience, but he has advisory support, he is open to the particular AES with the probability *p-g-prob-advisory-open-list*
3. Intrinsic openness: If a farmer has not had previous experience, nor advisory support, he is open to the particular AES with the probability *p-g-prob-intrinsic-open-list*
4. Social influence: If a farmer hasn't been open yet, he can be influenced by the social network with the probability *i-g-prob-open-social*. In order to be influenced by a social network, a farmer needs to have someone in the network with positive prior experience (*t-social-influence-list*). In the first year of model simulation (i.e., the first tick), if someone from the social network has experience in agro-ecological practices, *t-social-influence-list* is set to one/true for every AES. Later (tick + 1), if some members of the social network adopt a specific AES, the *t-social-influence-list* is updated for that AES.

Selection of suitable fields (decision making step 2)

Function name: select-suitable-fields

In the function, at first, fields are extracted from the agent set of fields that an agent possesses (*p-property-set*) and stored in the variable *v-suitable-fields-list*. Next, the fields are filtered based on land use and AES. As a result, the variable is updated so that the agent set in the first position presents fields suitable for AES buffer strips, a second for catch-cover crops, a third for grassland maintaining, and fourth for the conversion AES, based on land use. Further, fields are filtered based on the minimum field size on which AES should be applied (*i-g-area-min*). As a result, the variable is updated so that the agent set in the first position presents fields suitable for AES buffer strips, a second for catch-cover crops, a third for grassland maintaining, and a fourth for the conversion AES based on minimum field size.

Deliberation (decision making step 3)

Function name: deliberate-aes-decision

This function, first, calls the function *calculate-farmer-wta* to calculate farmers' expected payment levels for each AES. Then it compares the expected payment (calculated WTA) with the offered payment for each AES and stores the information in the *p-accepted-aes-list* list. Then it excludes the AES for which a farmer is not open to and stores the information in *t-accepted-open-list*. Based on the AES a farmer accepts, fields from the variable *v-suitable-fields-list* are erased or kept in the variable. Based on the envisioned area a farmer is willing to apply to each AES, fields from the variable *v-suitable-fields-list* are erased or kept in the variable. That means, for each AES where farmers' envisioned area is smaller than a contract area that is already under an AES (*v-contract-area-list*), fields from *v-suitable-fields-list* variable are removed for that AES, otherwise they are kept. Now, when the accepted AES list (*t-accepted-open-list*) and suitable fields (*v-suitable-fields-list*) are derived, the function *choose-suitable-contract* is called.

Function name: calculate-farmer-wta

For each open farmer and AES, expected payment (WTA), for the baseline contract scenario (5 years duration of contract, medium administrative effort, and no advisory), is drawn from the normal distribution based on the read mean WTA and its standard deviation from the input files. This can be done per FSA farm specialization category if a farmer type is differentiated in the model. For farmers that are not open to specific AES, expected payments are set to 99,999 (a number that is unrealistically high).

In the case that an offered contract is different from the contract specified by the baseline scenario (e.g., a farmer has advisory support, the length of the contract duration is longer or shorter, or the administrative effort is low or high), the corresponding change in expected payment value from the file is added to the calculated expected payment for the baseline scenario. The added value can either increase the calculated expected payment for the baseline scenario (e.g., if an administrative effort is high, the farmer would want a bigger payment) or decrease the expected payment for the baseline scenario (e.g., if a farmer has access to advisory support, the farmer would want a smaller payment, since he has help).

Function name: choose-suitable-contract

Farmers calculate their profit from accepted contracts by comparing the offered and expected payment.

$$profit = offered.payment - expected.payment$$

The AES with the highest gain is applied first. Farmers exclude the fields on which AES is already applied and choose fields in the *select-aes-fields* function. After a farmer applies an AES, the AES with the second highest gain is applied if there is available land, and so on.

Function name: select-aes-fields function

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Farmers choose fields with the poorest soil quality for AES application. If two fields have the same soil quality, a smaller field is chosen. Farmers iterate through fields and apply the AES to the fields, until the envisioned area becomes smaller or equal to the field size on which the AES is applied. If the available field size is smaller or equal to the envisioned area, the AES is applied to all available fields. When a field is selected, an AES agent is created, and its variables are instantiated in the setup-aes function. Fields where AES is already applied are not taken into account.

Function name: setup-aes
The AES variables such as AES type, contract year, AES area (field size), field ID and owner ID are initialized, as well as their appearance in the model canvas.

Model parameters

Parameter	NetLogo variable	Possible values	Baseline value	Unit
Simulated time period	i-g-years	1-20	1	years
Minimum required field size for each AES	i-g-area-min	>= 0	0	ha
Contract duration for specific AES	i-g-duration-buffer-strips i-g-duration-catch-crops i-g-duration-grassland i-g-duration-conversion	1, 5, 10	5	years
Bureaucratic effort for specific AES	i-g-bureaucracy-buffer-strips i-g-bureaucracy-catch-crops i-g-bureaucracy-grassland i-g-bureaucracy-conversion	“low”, “medium”, “high”	“medium”	-
Offered payment level for specific AES	i-g-payment-buffer-strips i-g-payment-catch-crops i-g-payment-grassland i-g-payment-conversion	Depending on policy scenario	662 287 136 551	EUR/ha
Probability that a farmer has access to advisory	i-g-access-to-advisory	[0-1]	0.53	-
Type of social network	i-g-social-network-type	“none”, “neighbors”, “village”	“none”	-
Radius around fields in which other field owners are	i-g-social-network-radius	5, 10	-	km

considered as belonging to social network ("neighbors")				
Probability that a farmer with prior agro-ecological experience or knowledge of a specific AES is open towards considering its application	p-g-prob-open-experience	[0,1] (4 items)	[0.86, 0.79, 0.43, 0.21]	-
Probability that a farmer with access to advisory is open towards considering application of a specific AES	p-g-prob-open-advisory	[0,1] (4 items)	[0.61, 0.83, 0.42, 0.22]	-
Probability that a farmer with positive social influence is open towards considering application of a specific AES	i-g-prob-open-social	[0,1]	0.1	-
Probability of being intrinsically open towards considering application of specific AES	p-g-prob-intrinsic-open-l——ist	[0,1] (4 items)	[0.6, 0.71, 0.25, 0.27]	-

Convention for NetLogo names: g - global variables, i - variables defined via interface, p - variables set via input files (exogenous), v - variables changed in the model procedures (endogenous)

3.5. Input Data Processing

3.5.1. AgroSens Data

The AgroSens database is a free digital agriculture platform in Serbia that was introduced in October 2017 (https://agrosens.rs/#/app-h/welcome). It combines processed Sentinel images with meteorological data (historical data and forecasts), on-the-ground information obtained through various measurements, and farmer inputs to enable farmers to use and monitor their crops. It is free of charge. The data we used, which ranges from 2018 to 2021, cover approximately 15% of the territory in the CS. A little over 14K parcels and 1K+ users are included in the data set. Figure 1 shows the distribution of field sizes.

The preprocessing implied the removal of duplicated users (i.e., users that were registered more than once with all the same parcels), merging users with their parcels across years if

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

they have overlapping parcels, removal of unexisting parcels that were drawn in residential areas (parcels were compared with Corine Land Use data), and removal of unrealistically large parcels (every parcel that has a line between any two points inside a polygon longer than 4 km was removed).

After the data was cleaned, the farm specialization per farm was assessed. Farms were mapped to one of 5 categories (Figure 3):

- P1 category: if ⅔ of the area is covered by field crops
- P2 category: if ⅔ of the area is covered by horticulture plants
- P3 category: if ⅔ of the area is covered by permanent crops
- P4 category: if ⅔ of the area is covered by plants for grazing livestock
- P5 (mixed) category: the other

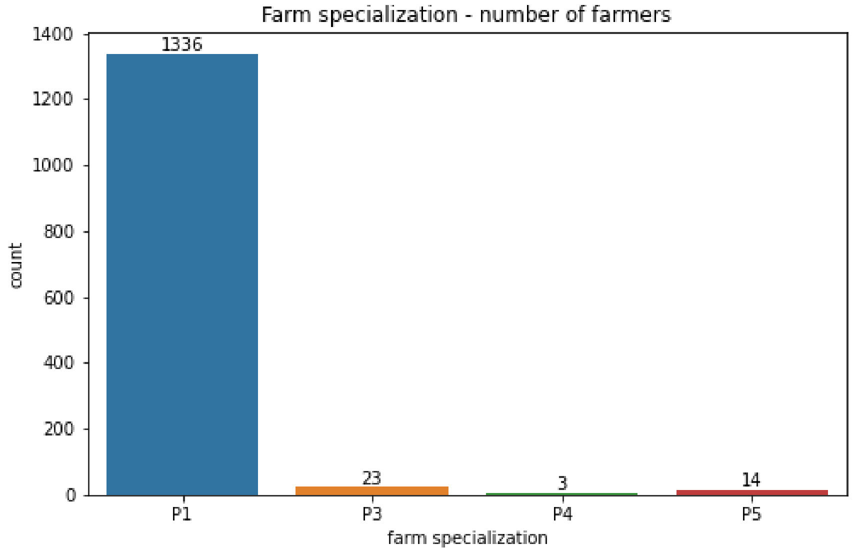

Figure 3: Number of farmers per farm specialization

Despite the fact that P1 farmers make up the majority of AgroSens data, we included the differentiation of FSA farm specialization types in the model as the number of additional farmers could easily rise as a result of an increase in registered users, which can be accounted for in the model.

Next, the economic size was calculated by summing the total market price for yields on a farm. Using a combination of farm specialization and economic size, the FSA type was derived following the rules in Table 1. For further information, please refer to Langerwisch 2021 et al.

Table 1: Definition of the FSA using farm specialization and economic farm size. The table was imported from Langerwisch et al. 2021.

	General cropping (P1)	Horticulture (P2)	Permanent crops (P3)	Grazing livestock and forage (P4)	Mixed
<2000	P1 <2000	P2 <2000	P3 <2000	P4 <2000	Mixed <2000
small	P1 small	P2 small	P3 small	P4 small	Mixed small
medium	P1 medium	P2 medium	P3 medium	P4 medium	Mixed medium
large	P1 large	P2 large	P3 large	P4 large	Mixed large

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

3.5.2. Soil Map

A soil map was created using Sentinel-2 satellite imagery data and laboratory values for organic matter measured at approximately 16,000 locations in the Vojvodina region. Using a Random Forest regressor, the Sentinel-2 image was transformed into an organic particulate matter map that was used as a proxy for soil quality. The average soil quality was calculated per field and imported into the model with a field file. Since satellite images from optical sensors are sensitive to atmospheric conditions, some parts of the map were covered with clouds; hence, those pixels did not have filled values. We filled those pixel values with the village region's average soil quality value.

3.5.3. Survey data

Survey data is used to parametrize some of the model input parameters:

- ***p-prob-open-experience*** The probability for each AES is calculated as a fraction of the number of organic farmers who answered that they are open to adopting a specific AES divided by the total number of organic farmers (Figure 4).

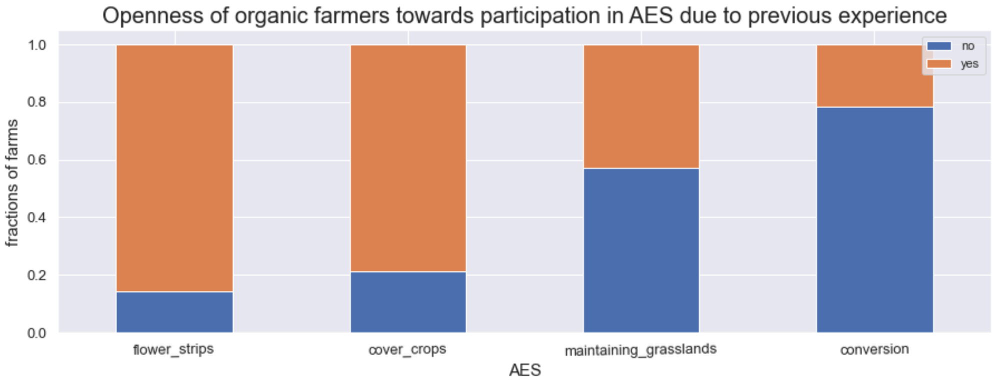

Figure 4: Openness of organic farmers towards participation in AES due to previous experience

- ***p-g-prob-advisory-open-list*** The probability of being intrinsically open when advisory support is available is calculated as a fraction of farmers who consult with their advisory at least 1-2 times a year and are open to specific AES divided by the total number of farmers who receive advisory support at least 1-2 times a year (Figure 5).

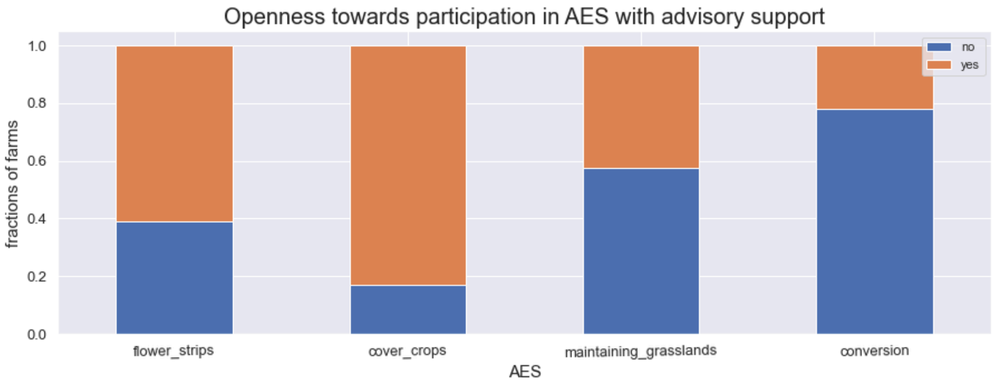

Figure 5: Openness of farmers towards participation in AES with available advisory support

- ***p-g-prob-intrinsic-open-list*** The probability of being intrinsically open is calculated as a fraction of farmers who don't have advisory support but are open to the adoption of specific AES, divided by the total number of farmers who do not have advisory support (Figure 6).

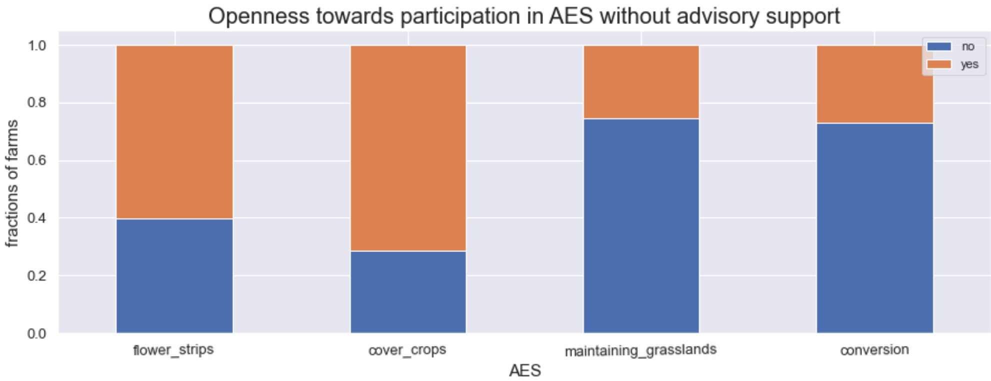

Figure 6: Intrinsically openness of farmers towards participation in AES (without available advisory support)

- ***i-g-access-to-advisory*** The percentage of farmers who have access to advisory support in the model is calculated as a fraction of farmers who consult advisory at least 1-2 a year divided by the total number of farmers (Figure 7).

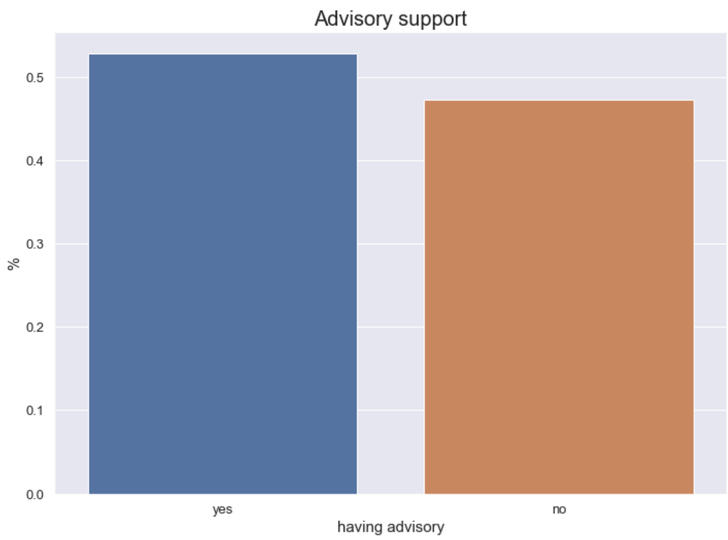

Figure 7: Fractions of farmers with and without advisory support

- ***p-g-area-list*** In the DCE part of the survey, when a farmer chooses a specific AES, he would also report the fraction of the total farm on which he would apply that AES. However, some farmers, even if they adopted the AES in the DCE section, put zero percent of the envisioned area. We consider reported zeros to be errors because it is contradictory to apply for AES and then not place them on the fields. Every reported

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

zero is replaced with the AES's average envisioned area. The model uses those reported values for a farm's envisioned area. Each farmer would randomly select one of the reported values per AES. FSA specialization farm type can be used to differentiate reported values.

Besides this, the survey data is used for the FSA specialization farm type differentiation, when calculating expected payment from the DCE part.

3.5.4. DCE data

DCE data were collected from farmers, and DCE was part of the survey in the BestMap project. Every farmer who went through the survey got six different choices, which included four cards of hypothetically designed contracts for four AES and a fifth card that indicated none of the choices offered. In each shown option, the contracts differ in offered payment, contract duration, administrative effort, and availability of advisory services. In each of the six choices, a farmer would select a preferable choice (one of the four designed AES or none option). The main purpose of the DCE was to inform the model on how the expected payment level (or "willingness to accept", WTA) of different farmer types changes with contract characteristics (contract duration, administrative effort, access to advisory). However, due to the low sample size and heterogeneity in answers, after the cleaning of outliers in the data set, we could only obtain statistically significant results for all farmers together using the Mixed Logit Algorithm (Hensher et al. 2003). Those results indicated that farmers preferred to have medium and high administrative effort over low administrative effort, which is not in line with the literature (Hasler et al. 2019, Latacz-Lohmann et al. 2019, Christensen et al. 2011, Ruto et al. 2009, Espinosa-Goded et al. 2010, Santos et al. 2015). However, an interview campaign (Bartkowski et al., under review) that was conducted at the beginning of the BestMap project revealed that farmers in Serbia miss transparency when the government is giving subsidies to farmers. In order to include additional differences in attitudes among farmers, in their mean expected payments for the baseline contract, we include standard deviations from obtained results and draw WTA from the normal distribution using those values (see Deliberation (decision making step 3) in section 3.4).

In order to differentiate the farmer types, we augmented the data set using the Synthetic Minority Over-Sampling Technique (SMOTE) algorithm (Chawla et al. 2002) which performs data augmentation by creating synthetic data points based on the original data points. It is usually used when there is an unbalanced class in the Machine Learning classification problem. Since we wanted to augment all classes, we created an arbitrary class with 1000 of records and augmented every real class (4 AES and None option) to that number. After the augmentation, the arbitrary class was deleted. The data set was augmented using the smote-variants Python library, which contains 85 variants of SMOTE algorithms compared in Kovács (2019). For every SMOTE algorithm that was applicable to the multi classification problem, we produced the results. We compared the results between the original and augmented data sets for every SMOTE algorithm run and selected six that best depicted the distribution of the original data set. The distribution similarity is assessed via visual inspection, using the descriptive statistics, as well as t-tests (Snedecor et al. 1989), Levene-tests (Levene 1960), and ks-tests (Chakravarti et al., 1967). The comparison

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

between the distribution of the original data set and the results for the SVM balance variation of the SMOTE algorithm can be seen in Figures 8 and 9.

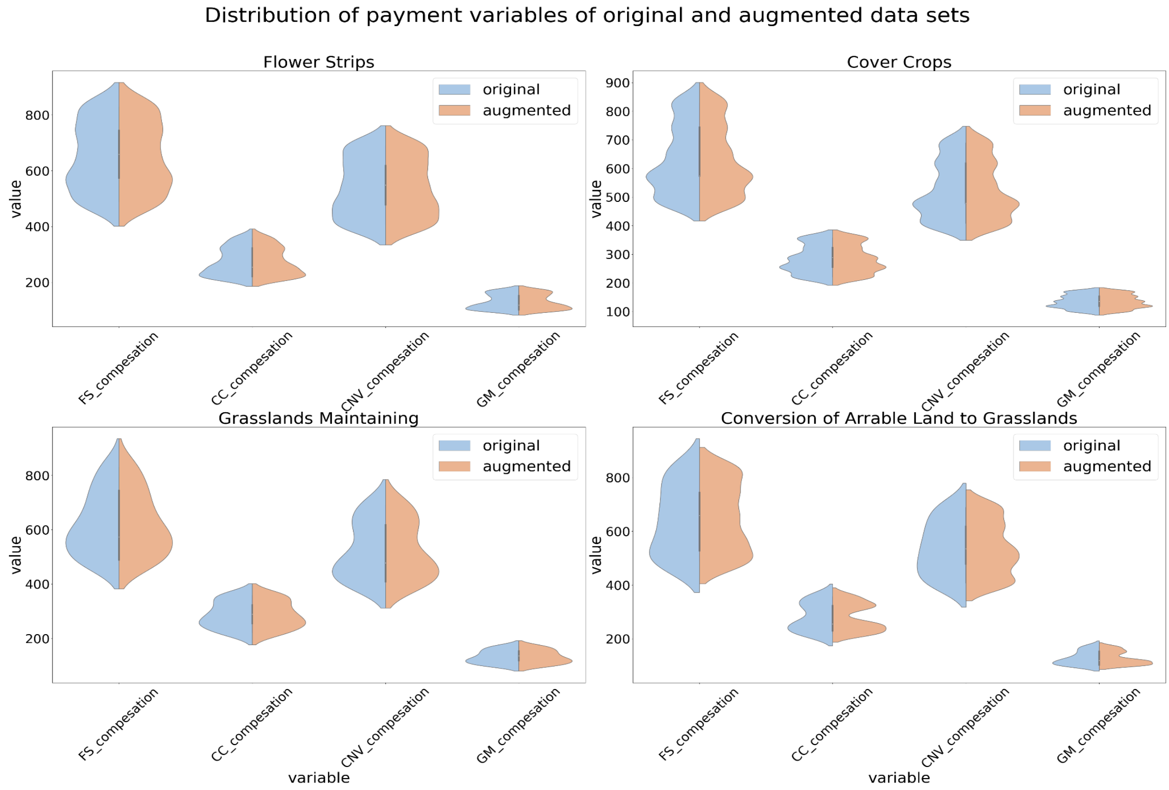

Figure 8: Distribution of payment variables original data set and augmented data set using SVM balance variation of the SMOTE algorithm

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

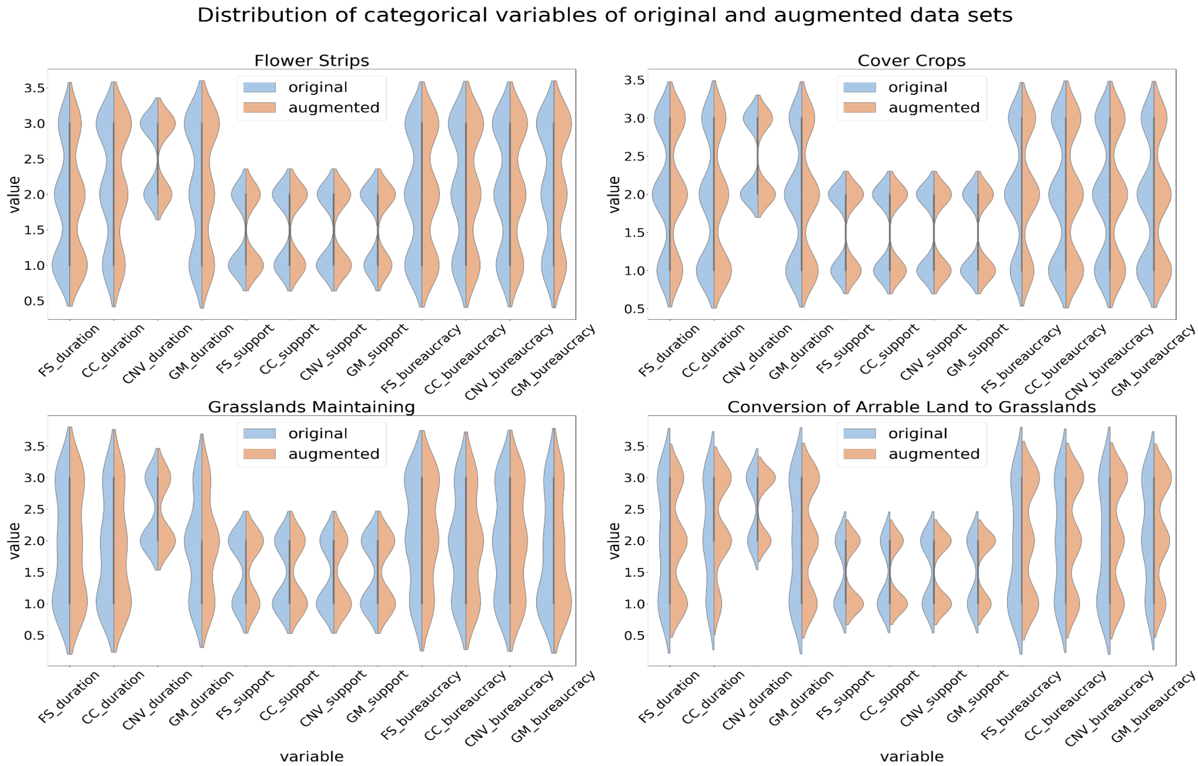

Figure 9: Distribution of categorical variables of original data set and augmented data set using SVM balance variation of the SMOTE algorithm

After getting the augmented data set, the Mixed Logit Model was run for each farmer category and the results were compared. In the survey, we could only distinguish P1, P3, and P5 farm categories of FSA farm specialization. Since both the SMOTE algorithms and the Mixed Logit Model are statistical algorithms and depend on the random seed used during the model's run, we run both of them a bunch of times. For statistically significant results, the expected payment for the baseline scenario differed by as much as 300 euros. Since AES is not yet available in Serbia and hence there was no possibility to validate results with other reliable data and research findings (e.g., WTA extracted from historical adoption or another research with similar topic in Serbia), we selected the results that were the most logical and expected to us and to some extent that is in accordance with the previously acquired results that do not distinguish the farmer types (i.e., we chose the results in which the values for baseline scenario have not deviated much (< 150€) from the previously acquired results of dominant categories presented in the survey (P1 and P5 categories)). In the model setup, we differentiated 5 categories of farmers, hence we equalized the mixed P5 category with the P4 and P2 categories. This has had no effect on the model because there is no P2 in the AgroSens data, and P4 farmers represent less than 0.02% of the total sample. Even though P1 farmers are the dominant category in AgroSens data (Figure 3), the number of other farmers could easily grow, as AgroSens records an increase in registered users, and hence can be incorporated into the model. By calculating WTA per FSA specialization farmer category, we included some sort of heterogeneity in the model, and when better results on farmers' preferences are obtained, they can be simply included in the model. Since the obtained standard deviations are not statistically significant for all results, we adopted the

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

average value from the previous data set, which is 15% of the base payment for each AES in all subsequent WTA data sets. However, this value can be varied.

As WTA differences that are results of contract changes (i.e., differences in the expected payment from the baseline contract when the contract duration and/or administrative effort is smaller or bigger, as well as when advisory support is available) are significantly different from the results reported in the literature (e.g., Serbian farmers want a smaller amount of payment for bigger administrative effort) (Hasler et al. 2019, Latacz-Lohmann et al. 2019, Christensen et al. 2011, Ruto et al. 2009, Espinosa-Goded et al. 2010, Santos et al. 2015), a third data set is created that relies both on the DCE results and the literature. For every data set produced in the previous steps (the WTA data set that does not distinguish the farmer types and WTA files for every farm type), a new one is created by keeping the values for the mean expected payment and its standard deviation for the baseline contract and replacing the WTA differences that are aligned to the ones reported in the literature (Hasler et al. 2019, Latacz-Lohmann et al. 2019, Christensen et al. 2011, Ruto et al. 2009, Espinosa-Goded et al. 2010, Santos et al. 2015). Changes in WTA are extracted independently of AES types. The respective changes adopted from the literature are the following:

- Availability of advisory: -5% (i.e., farmers would expect a 5% smaller payment if the advisory is available) (based on studies Hasler et al. 2019 and Espinosa-Goded et al. 2010)
- Administrative effort: +5% high effort, -5% low effort (based on study: Ruto & Garrod 2009)
- Contract duration: 1 year -10%, 10 years +40% (based on studies: Hasler et al. 2019, Latacz-Lohmann & Breustedt 2019, Christensen et al. 2011, Ruto & Garrod 2009, and Santos et al. 2015)

As we do not have a good data source for inferring the expected payments of Serbian farmers, in this way we experiment with various options and explore "what-if" model scenarios.

References

Bartkowski, B., Bartke, S., 2018. Leverage Points for Governing Agricultural Soils: A Review of Empirical Studies of European Farmers' Decision-Making. Sustainability 10, 3179.

Bartkowski, B., Beckmann, M., Bednář, M., Biffi, S., Domingo-Marimon, C., Mesaroš, M., Schüßler, C., Šarapatka, B., Tarčak, S., Václavík, T., Ziv, G., Wittstock, F. Adoption and potential of agri-environmental schemes in Europe: Cross-regional evidence from interviews with farmers. Under review.

Brown, C., Kovács, E., Herzon, I., Villamayor-Tomas, S., Albizua, A., Galanaki, A., Grammatikopoulou, I., McCracken, D., Olsson, J.A., Zinngrebe, Y., 2020. Simplistic understandings of farmer motivations could undermine the environmental potential of the common agricultural policy. Land Use Policy 105136.

Chakravarti, Laha, and Roy, (1967). *Handbook of Methods of Applied Statistics, Volume I*, John Wiley and Sons, pp. 392-394.

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, *16*, 321-357.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Christensen, T.; Pedersen, A. B.; Nielsen, H. O.; Mørkbak, M. R.; Hasler, B. & Denver, S. Determinants of farmers' willingness to participate in subsidy schemes for pesticide-free buffer zones — A choice experiment study. *Ecological Economics,* 2011, 70, 1558-1564

Dessart, F.J., Barreiro-Hurlé, J., Bavel, R. van, 2019. Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. European Review of Agricultural Economics 46, 417–471.

Espinosa-Goded, M.; Barreiro-Hurlé, J. & Ruto, E. What Do Farmers Want From Agri-Environmental Scheme Design? A Choice Experiment Approach. *Journal of Agricultural Economics,* 2010, 61, 259-273

Hasler, B.; Czajkowski, M.; Elofsson, K.; Hansen, L. B.; Konrad, M. T.; Nielsen, H. Ø.; Niskanen, O.; Nõmmann, T.; Pedersen, A. B.; Peterson, K.; Poltimäe, H.; Svensson, T. H.; Zagórska, K. Farmers' preferences for nutrient and climate-related agri-environmental schemes: A cross-country comparison. *Ambio,* 2019, 48, 1290-1303

Hensher, David A., and William H. Greene. "The mixed logit model: the state of practice." Transportation 30.2 (2003): 133-176.

Kovács, G. (2019). Smote-variants: A python implementation of 85 minority oversampling techniques. *Neurocomputing*, *366*, 352-354.

Lastra-Bravo, X.B., Hubbard, C., Garrod, G., Tolón-Becerra, A., 2015. What drives farmers' participation in EU agri-environmental schemes?: Results from a qualitative meta-analysis. Environmental Science & Policy 54, 1–9.

Latacz-Lohmann, U. & Breustedt, G. Using choice experiments to improve the design of agri-environmental schemes. *European Review of Agricultural Economics,* 2019, 46, 495-528

Langerwisch, F., Václavík, T., Ziv, G., Gunning, J., Gosal, A., Paulus, A., Brdar, S., Lugonja, P., Stojković, S., Bednář, M., Roilo, S. & Cord, A. (2021). Farming System Archetypes for each CS. Deliverable D3.5 EU Horizon 2020 BESTMAP Project, Grant agreement No. 817501

Levene, H. (1960). In *Contributions to Probability and Statistics: Essays in Honor of Harold Hotelling*, I. Olkin et al. eds., Stanford University Press, pp. 278-292.

Ruto, E. & Garrod, G. Investigating farmers' preferences for the design of agri-environment schemes: a choice experiment approach *Journal of Environmental Planning and Management,* 2009, 52, 631-647

Santos, R.; Clemente, P.; Brouwer, R.; Antunes, P. & Pinto, R. Landowner preferences for agri-environmental agreements to conserve the montado ecosystem in Portugal. *Ecological Economics,* 2015, 118, 159-167

Snedecor, George W. and Cochran, William G. (1989), Statistical Methods, Eighth Edition, Iowa State University Press.

Wittstock, F., Paulus, A., Beckmann, M., Hagemann, N., Baaken, M.C., 2022. Understanding farmers' decision-making on agri-environmental schemes: A case study from Saxony, Germany. Land Use Policy 122, 106371

Ziv, G., Beckmann, M., Bullock, J., Cord, A., Delzeit, R., Domingo, C., Dreßler, G., Hagemann, N., Masó, J., Müller, B., Neteler, M., Sapundzhieva, A., Stoev, P., Stenning, J., Trajkovic, M., Václavík, T., 2020. BESTMAP: behavioural, Ecological and Socio-economic Tools for Modelling Agricultural Policy. Research Ideas and Outcomes 6, e52052.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

ODD+D for Humber region (UK)

Corresponding author: Chunhui Li, University of Leeds

1. Overview

1.1. Purpose

What is the purpose of the study?

The BESTMAP-ABM-UK model is a member of the BESTMAP-ABM model suite focusing on the case study area of Humber, UK. The purpose of the BESTMAP-ABM is to determine the adoption and spatial allocation of four selected agri-environmental schemes (AES) by individual farmers in five countries across the EU (Ziv et al., 2020). The selected AES are flower strips, cover crops, maintaining permanent grassland, conversion of arable land to permanent grassland. In particular, the model investigates the effect of different scenarios of policy design on patterns of adoption. 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.
The four types of AES in the BESTMAP-ABM-UK are chosen from Countryside Stewardship Schemes (CSS) that were rolled out in England since 2015. Because CSS offers hundreds of scheme options, we group relevant scheme options into the four selected types according to the characteristics of the scheme designs, shown in the table below. More details of the AES options can be found on the UK government website[11] by the option codes.

AES typologies in BESTMAP-ABM-UK

AES types	CSS option codes
Buffer strips	SW1, SW2, SW3, SW4, SW11, AB1, AB3, AB8, WT2
Cover crops	SW6
Grassland management	GS2, GS5, GS6, GS7, GS9
Arable land conversion to grassland	SW7

For whom is the model designed?

The model is designed for policymakers and stakeholders responsible for agricultural policies to assess the impact of future policy designs. In addition, the model can be used by scientists to build upon the existing model structure and address further research questions in the context of farmer behaviour.

[11] https://www.gov.uk/countryside-stewardship-grants

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

1.2. Entities, state variables, and scales

What kinds of entities are in the model?

The model consists of these entities:

- Farmer agents representing individual farmers;
- Field agents representing the spatial environment. Each farmer agent manages a fixed set of fields;
- AES contracts agents representing the contracts when farmer agents decide to adopt an AES and apply it on one of their fields. A farmer agent can have multiple AES contracts for the same AES type. A proportion of the field area is put under AES, ranging from minimum required area (depending on AES designs) to 100% of a field.
- Social networks of farmer agents representing farmer groups that farmer agents can influence each other on the openness towards the available AES

By what attributes (i.e. state variables and parameters) are these entities characterised?

The table below lists the attributes of the agents, i.e., farmers, fields, AES contracts and the social networks. The naming conventions of the NetLogo variable are designed as follows: *g* for global variables; *i* for variables defined via interface; *p* for exogenous variables; *v* for endogenous variables.

Constant farmer state variables

	NetLogo variable	Possible values	Unit
Farmer ID	*p-farmer-id*	A string	-
Fields a farmer owns	*p-property-set*	-	NetLogo agentset
Size of farm (sum of field sizes)	*p-farm-area*	>0	ha
Farm specialisation*	*p-fsa-spec*	P1, P2, P3, P4, mixed	-
Economic farm size	*p-fsa-size*	<2000, small, medium, large	-
Probability for intrinsic openness towards each AES	*p-intrinsic-open-prob-list*	A list of 4 ‘0/1’ values, derived from *p-g-prob-intrinsic-open-list* see model parameters in 3.4	-
Access to advisory support	*p-advisory*	0/1	-
Accepted payment levels for all AES (list)	*p-accepted-payment-list*	A list of 4 items	EUR
Accepted AES list	*p-accepted-aes-list*	A list of 4 ‘0/1’ values	

Area percentages of the total farm area that a farmer is willing to use for each AES	*p-envisioned-area-list*	A list of 4 items	%
Farmers in social network	*v-social-network*	Depending on social network type	NetLogo agentset
The GIS feature list of a farmers' fields	*p-gis-feature-list*	Input spatial data	GIS shapefil e
Farmers' CSS adoption status in 2019	*p-baseline*	0/1	-
Regression model prediction of farmers' adoptions	*p-prob-uptake*	0/1	-
The rank of a farmer's score in the prediction by the regression model	*p-prob-uptake-rank*	0-3551	-
The list of a farmer's envisioned area (in ha) for the four AES	*p-envisioned-area-ha-lis t*	A list of 4 items	ha
The list of a farmer's farming area, and breakdown in land uses (i.e., total farm area, arable area, grassland area and horticulture area)	*p-stats-farm-area-list*	A list of 4 items	ha

*Farming system archetypes (FSA): General cropping (P1), Horticulture (P2), Permanent crops (P3), Grazing livestock and forage (P4), mixed. Full details of FSA are available in the BESTMAP Deliverable 3.5 Farming System Archetypes for each CS at https://bestmap.eu/about.php?storyid=2732.

Farmer state variables varying over time

	NetLogo variable	Possible values	Unit
Openness towards each AES	*v-open-to-aes-list*	A list of 4 '0/1' values	-
Prior experience with each AES	*v-prior-experience-list*	A list of 4 '0/1' values	-
Fields suitable for each AES	*v-suitable-fields-list*	A list of 4 items	NetLogo agentset
Total area under AES for each AES	*v-contract-area-list*	A list of 4 items	ha

Number of AES contracts for each AES	*v-nr-aes-fields-list*	A list of 4 items	-
The gaps between envisioned area and realised area	*v-gap*	A list of 4 items	ha
Whether a farmer enters into a decision-making phase	*v-time-decide?*	yes/no	-

Constant field state variables

	NetLogo variable	Possible values	Unit
Owner ID (farmer)	*p-owner-id*	-	-
Parcel ID	*p-field-id*	-	-
Land use	*p-land-use*	Arable land, grassland, horticulture, other	-
Size	*p-area*	>0	ha
Environmental stewardship scheme (ESS) status	*p-ess*	0/1	-
Soil quality	*p-soil-quality*	[40,110]	-

Field state variables varying over time

	NetLogo variable	Possible values	Unit
AES currently applied	*v-aes-list*	A list of 4 '0/1' values	-
Number of AES contracts previously applied	*v-aes-hist-list*	A list of 4 items	-
AES area currently applied on the field	*v-aes-area-list*	A list of 4 items	ha
Available area for implementing other AES on the field	*v-avail-area*	Calculated by p-area minus sum v-aes-area-list	ha

Constant AES contract state variables

	NetLogo variable	Possible values	Unit
AES type	*v-aes-name*	buffer strip, catch crops, grassland, conversion	-

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Duration since AES adoption	*v-aes-contract-year*	[1,10]	years
Field on which AES is applied	*v-aes-field*	-	NetLogo agentset
Farmer who owns the field	*v-aes-owner*	-	NetLogo agentset
Size of AES contract (field size)	*v-aes-size*	> 0	ha
AES contract ID	*v-aes-id*	"pre-x(year)" or "after-y(year)"	-

Constant state variables of farmer social networks

	NetLogo variable	Possible values	Unit
Social network types	*i-g-social-network-type*	"None", "neighbours", "FSA"	-
The radius of neighbourhood	*i-g-social-network-radius*	≥1	-

What are the exogenous factors / drivers of the model?

The AES contract design, in particular the payment level, contract duration and bureaucratic effort, is exogenously given. In addition, the eligible field land use types for the four AES are exogenously defined and fixed in the model. In the BESTMAP-ABM-UK, buffer strips can be applied on both arable lands and grasslands, grassland management can be applied on grasslands, and cover crops and arable land conversion to grassland can be applied on arable lands.
Farms are spatially represented by individual fields derived from IACS/LPIS data and also categorised into different FSAs (according to their farming system characteristics) and economic sizes. Farms' fields are characterised by land use types, field sizes and soil conditions. Soil organic carbon is used as the soil quality measure in the model.
Farmers' prior AES experiences are initialised based on the adoption data of CSS and ESS. Whether a farmer has access to advisory support is randomly assigned. Farmers' intrinsic openness towards an AES is assigned based on the historic adoption rate of the same type of farmers. The influences from prior AES experiences, intrinsic openness, advisory services and the social network on a farmer's openness are probability-based and randomly assigned.
A farmer's expected payment for an AES is influenced by the normal distribution of farmers' willingness to accept (WTA) for the AES and the impact on WTA by offered AES designs.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

What are the temporal and spatial resolutions and extents of the model?

Space is explicitly represented at field level with each farm consisting of several fields. The UK model includes 56,709 agricultural fields of the Humber region, covering around 350,000 ha agricultural area that belongs to 3,525 farmers.
Time is represented as discrete yearly time steps with AES adoption decisions made once a year. The model is capable of simulating multiple-year experiments, however, due to lack of data simulating the dynamics of the farms' and environmental changes, the BESTMAP-ABM-UK has been used for 1-tick simulations representing "alternative now". The temporal extent can be updated when we have multi-years of input data, for example, field or farm ownership changes and field land use changes over multiple years.
The model could be extended to support the scenario that a simulation starts with existing AES contracts, representing a starting year after 2016 when some farmers in Humber had already signed up with AES at the starting year of the simulation. When a simulation with pre-existing AES contracts is set up, the pre-existing AES contract agents' IDs are named with the prefix "pre". This is kept as a testing module in the model.

1.3. Process overview and scheduling

The following processes occur in each time step:

- Update prior knowledge based on own experience;
- Remove AES contracts that exceed contract duration and update state variables of farmers and fields related to AES adoption;
- Update farmers' status of whether to enter into a decision-making phase.
- **Decision Making Step 1** - Check openness to specific AES: Decide for each AES separately if a farmer can in general (independent of specific contract details) imagine applying the scheme;
- **Decision Making Step 2** - Select suitable fields: Compile a set of fields suitable for AES adoption by excluding fields with ongoing AES contracts, fields already signed up with ESS or fields which do not meet the requirements of minimum size or the eligible land use type;
- **Decision Making Step 3** - Deliberation and site selection: Check for each farmer and AES whether the offered payment equals to or exceeds the accepted payment and select fields where AES should be adopted.

2. Design concepts

2.1. Theoretical and Empirical Background

Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?

The underlying assumption is that farmers' adoption decisions are affected by the agricultural policy conditions, i.e. farmers are more or less willing to adopt AES depending on what they have to comply with and what is offered. The model can be used to examine the effects of different policy design scenarios on adoption patterns. Furthermore, it is assumed that adoption of AES or not is not a purely economic decision. Some farmers are

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

open to AES adoptions due to identity-driven barriers, personal situations (e.g., near retirement age) and so on.

On what assumptions is/are the agents' decision model(s) based?

Farmers accept an AES if they are open to consider the adoption. This is an identity-driven decision based on own prior experience, intrinsic openness, influence from advisory and/or social network.
In addition, they need to have suitable lands available. In the UK model, these assumptions are made when farmers choose suitable lands for AES:

1) Grassland management AES is applicable on grasslands, cover crops and conversion of arable lands to grasslands AES are applicable on arable lands and buffer strips AES is applicable on both arable lands and grasslands.
2) If a farmer agent has participated in the Environmental Stewardship Scheme (ESS)[12] on a field, this field will not be suitable for any CSS AES that we model. This is because ESS was launched in 2005 and co-exists with CSS that was launched in 2015.

Furthermore, agents only decide to adopt a scheme if the offered payment level (as defined in the policy regulations) equals to or exceeds their individual accepted payment level (economically and value driven decision, different depending on farm characteristics and external influences).

Why is a/are certain decision model(s) chosen?

The decision model is based on empirical observations from an interview campaign that was conducted in all case studies of the BESTMAP project at the beginning of 2020 (Wittstock et al., 2022, Bartkowski et al., under review). Themes and questions addressed in the interviews were derived from the literature including reviews that specifically focus on AES (Lastra-Bravo et al. 2015, Brown et al. 2020) and others that give a general overview on factors affecting the adoption of sustainable farming practices (Dessart et al. 2019) and agricultural soil management (Bartkowski and Bartke 2018).
A key observation from the interviews was that farmers face a sequence of decision making elements for AES participation. To account for this sequential process in the ABM, we follow the heuristic framework for interpreting farmers' decision making developed in Wittstock et al. (2022). Due to missing data, we could not, however, include all aspects considered relevant in that framework (e.g. we had to exclude aspects on tenant-owner relationship and the duration of tenure contracts since we did not have access to tenure data).

If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from? At which level of aggregation were the data available?

- The decision model is based on empirical data from an interview campaign that was conducted in all case studies of the BESTMAP project at the beginning of 2020. The interviews were conducted with individual farmers.
- The field-level spatial information for the UK model comes from Rural Payments Agency 2019 data.

[12] Environmental Stewardship: https://www.gov.uk/guidance/environmental-stewardship

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

- The soil data is sourced from the soil map produced by UK Center for Ecology and Hydrology and Natural England[13].
- CSS adoption data from Natural England[14] is used to inform the model baseline of AES adoption and parameterise farmers' intrinsic openness assuming farmers' intrinsic openness towards one AES is proportional to the historic adoption rate of the specific farmer group based on FSA and economic size.
- ESS adoption data from Natural England[15] is used to inform the farmers' prior AES experiences and the suitability of a field for CSS adoptions
- The Eurostat data of Agri-environmental indicator - farmers' training and environmental farm advisory services[16], in particular, the Measure 114 - the use of environmental advisory services, is used to parameterise the probability that a farmer with access to advisory is open towards considering application of a specific AES. 48% of UK farmers in 2010 used environmental advisory services out of the total farmers advisory service applications supported. Farmers are supported with the information and advice on how to apply production processes compatible with the enhancement of landscape or the wider protection of the environment.

2.2. Individual Decision Making

What are the subjects and objects of decision making? On which level of aggregation is decision making modelled? Are multiple levels of decision making included?

Individual farmers are the *subject* of decision making. Farmers decide whether and where to adopt AES, i.e. the adoption of AES contracts at field level is the *object* of decision making. There are *three levels of decision making* included, (1) the determination of general openness towards the adoption of specific AES, (2) the selection of suitable fields for each AES, and (3) the deliberation and site selection for each AES.

What is the basic rationality behind agents' decision making in the model? Do agents pursue an explicit objective or have other success criteria?

- **Decision Making Step 1:** Some farmers have general aversions against some AES due to lacking prior experience, lacking advisory or lacking experience in social network and never consider applying for those.
- **Decision Making Step 2:** Not all fields are available for AES adoption due to limitations in the contractual requirements or because they are already occupied by other AES or used as Ecological Focus Area.
- **Decision Making Step 3:** Farmers only apply AES if they consider it profitable for

[13] https://eip.ceh.ac.uk/naturalengland-ncmaps/reportsData

[14] https://naturalengland-defra.opendata.arcgis.com/datasets/Defra::countryside-stewardship-scheme-agreements-england/about

[15] https://naturalengland-defra.opendata.arcgis.com/datasets/Defra::environmental-stewardship-scheme-agreements-england/about

[16] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:Agri-environmental_indicator_-_farmers%E2%80%99_training_and_environmental_farm_advisory_services&oldid=227049

them, the individual threshold for profitability depends on farm and farmer characteristics as well as external circumstances. Farmers prioritise fields with lower soil quality and smaller size for AES contracts.

How do agents make their decisions?

Decision Making Step 1: Farmers are open to specific AES with a probability calculated based on their own prior experience with this AES, their intrinsic openness towards the specific AES as well as potential influence from advisory support independent of the specific AES and/or influence through their social network with respect to this specific AES (see also Figure 1).

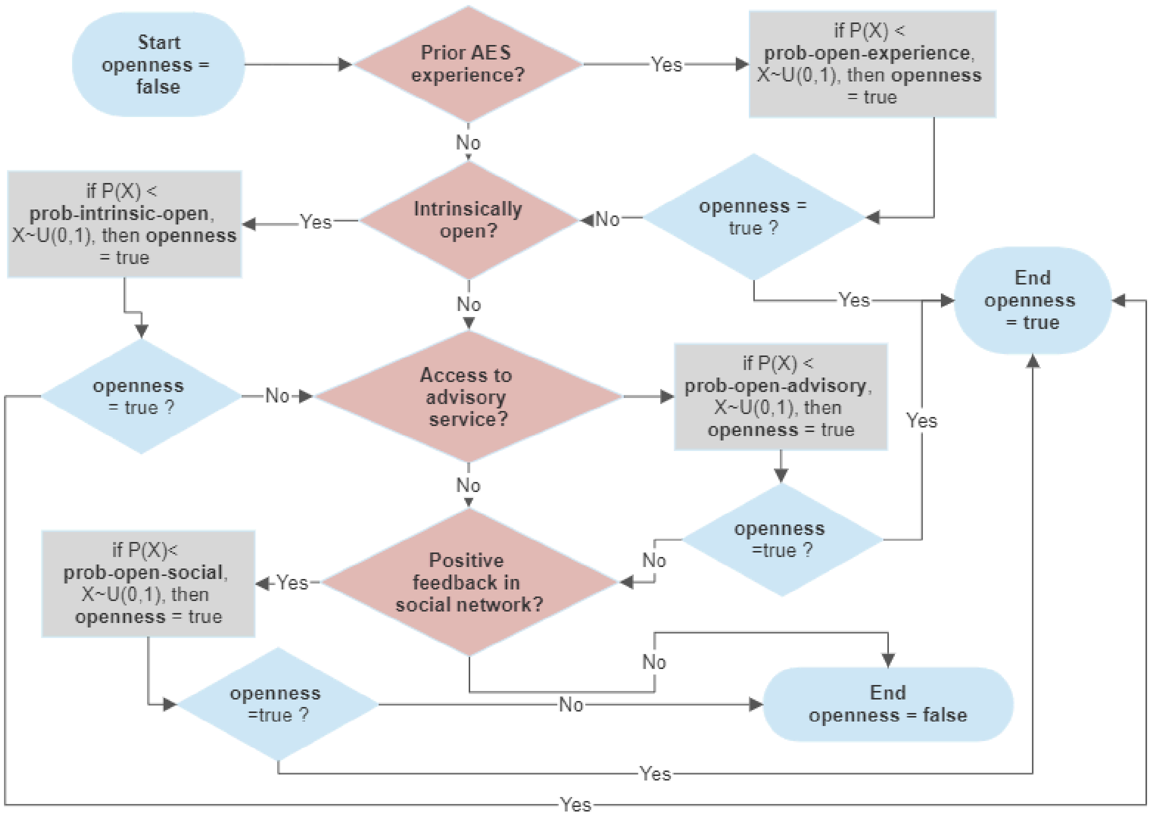

Figure 1: The flowchart of Step 1 in the decision making framework for a selected AES. Farmers' openness status (true or false) is decided by four factors – whether a farmer agent has prior experience, whether it is intrinsically open to the four types of AES, whether it has access to advisory service, whether other farmer agents in its social network have positive experience. The impact of the four factors are set to be four probabilities: "prob-open-experience", "prob-intrinsic-open", "prob-open-advisory" and "prob-open-social", subject to standard uniform distribution U(0,1). At the end of this process, the farmer agent either goes into the next step (if openness is true) or exits the decision-making process (if openness is false).

Decision Making Step 2: Farmers compare field characteristics with AES requirements and select those as suitable which fulfill the requirements.

Decision Making Step 3: Farmers compare their individual accepted payment level with the offered payment level. If their accepted payment level exceeds the offered payment level for a specific AES, farmers select fields on which to adopt the specific AES.
For the order in which the fields for accepted AES are selected, several options are

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

implemented. Farmers could first decide on where to apply schemes with the highest offered payment, the highest difference between offered and accepted payment, the highest ratio between offered and accepted payment or the largest envisioned area. If this selection condition is equal for several accepted schemes, i.e. if for example the offered payment is equal for several schemes, one of them is selected randomly to be applied first. Since we don't have data to support which option is the Humber farmers' favoured choice in their deliberation process, we keep all options in the model for other model users to explore. In our simulation experiments of UK case study, we use "the highest ratio between offered" as the default setting.
The envisioned area of adoption given as % of total suitable area is determined by input data depending on farm and farmer characteristics. Farmers prefer to put fields with lower soil quality and smaller sizes under AES.

Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes, how?

A farmer's openness towards specific AES is influenced by their own prior experience, i.e. prior adoption of this AES, and by their social network, i.e. the prior adoption of other farmers (endogenous state variable). Therefore, the average openness of farmers population is improving due to the increase of farmers' adoption in the region in a multi-year simulation. Farmers' openness and their accepted payment levels are influenced by the availability of advisory support (exogenous state variables). Farmers' accepted payment level depends on the contract characteristics such as duration and bureaucratic effort (exogenous state variables).

Do social norms or cultural values play a role in the decision making process?

Social norms or cultural values are included inexplicitly in the openness step (i.e. Decision Making Step 1) in the model: 1) Farmers' intrinsic openness is partially influenced by the social norms and values they believe in. 2) Farmers' openness is influenced by other farmers in their social network.

Do spatial aspects play a role in the decision process?

Spatial aspects at field-level are included in the decision where to apply a selected AES based on soil quality and field size.
The social network is spatially based if it is defined by neighbourhood (i.e. the social network consists of all farms with fields inside of a certain radius around a farmer's fields). If the social network is based on similar farming types (e.g. according to economic farm size or specialisation), spatial aspects do not play a role.

Do temporal aspects play a role in the decision process?

Previous experiences with AES (own adoption and adoption in the social network) influence the openness towards the adoption of AES (Decision Making Step 1).

To which extent and how is uncertainty included in the agents' decision rules?

Farmers do not know how other farmers will decide in the current period, they only know their adoption from previous periods.

2.3. Learning

Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?

Farmers who have adopted AES in previous time steps (or in the year reflected in the data used for initialization) have a high probability of being open to consider AES in subsequent decisions.

Is collective learning implemented in the model?

Collective learning is not considered in the model.

2.4. Individual Sensing

What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Farmers have the full knowledge of all their fields, i.e. they know the properties of their land. Furthermore, farmers are aware of the contract characteristics of all AES that they need to consider when deciding whether or not to adopt a scheme. Farmers remember their own previous AES adoption. Sensing is not erroneous.

What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?

Farmers know the adoption of other farmers in their social network. Social networks can be determined based on spatial characteristics (including farmers with fields in a specified radius around a farmer’s fields) or based on similar farming types (e.g. according to economic farm size or specialisation). The sensing process is not erroneous.

What is the spatial scale of sensing?

Farmers are aware of their own fields and the farmers who have fields next to theirs (i.e., the neighbourhood social network).

Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?

Individuals are assumed to know these variables without any explicit mechanisms.

Are the costs for cognition and the costs for gathering information explicitly included in the model?

Costs for cognition or gathering information are not explicitly included in the model. Implicitly, it is assumed that missing knowledge about a specific AES can be a barrier for farmers to not be open towards the adoption of AES in general (Decision Making Step 1).

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

2.5. Individual Prediction

Which data do the agents use to predict future conditions? What internal models are agents assumed to use to estimate future conditions or consequences of their decisions? Might agents be erroneous in the prediction process, and how is it implemented?

Farmer agents don't predict future condition changes. In reality, the environment conditions (e.g., climate, ownership of lands, economy, markets etc.) that farmers operate in are changing over time, however, due to lack of data we do not model these changes.

2.6. Interactions

Are interactions among agents and entities assumed as direct or indirect? On what do the interactions depend?

Interactions between farmers are indirect. Farmers perceive the actions of others only through the state of AES adoption on fields of farmers in their social network which can influence their openness towards specific AES (Decision Making Step 1).

If the interactions involve communication, how are such communications represented? If a coordination network exists, how does it affect the agent's behaviour? Is the structure of the network imposed or emergent?

Communication between farmers is not explicitly modelled. The network structure is imposed and based on the spatial distance between farmers (if the social network is defined by neighbourhood) or on similar farming types, i.e., farm economic size and farm specialisation.

2.7. Collectives

Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation? How are collectives represented?

Collectives are not explicitly represented in the model. Farmers belong to a social network which is based on neighbourhood or similar farming types and can influence each other's openness towards specific AES.

2.8. Heterogeneity

Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

The agents in the model are heterogeneous. The farmer agents differ in the farm size, FSA, the managed fields, the access to advisory support, the prior AES experiences, the intrinsic openness, their expected payment level for the four AES and their social network. The field agents differ in their location, the land use type, the size, the owner, the soil condition and the AES implementation situation. The AES contract agents differ in the owners, the location, the size of the AES area and the type of AES.
All farmers, fields and AES contracts have the same set of state variables and processes, respectively.

Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?

The farmer agents are heterogeneous in their decision-making. Even though the farmer agents share the same decision models, their decisions are made based on the state variables that are varied across the population, which leads to different decision results.

2.9. Stochasticity

What processes (including initialisation) are modelled by assuming they are random or partly random?

Stochasticity is included in the following processes:

1. *General openness:*
    a. Farmers with their own *prior experience* have a higher chance of being open towards the adoption of AES.
    b. Farmers are *intrinsically open* to consider the adoption of each AES with different probabilities depending on farm characteristics.
    c. A randomly chosen fraction of farmers has *access to advisory support*. Farmers with influence from advisory support have a higher chance of being open to consider the adoption of AES.
    d. Farmers with influence through their *social network* have a higher chance of being open to consider the adoption of AES.
2. *Willingness to accept:* The mean willingness to accept for a specific AES is calculated based on the input data for the specific policy design and farmer characteristics. We assume farmers' WTA is subject to a normal distribution with the mean value differed in different AES policy designs of contract duration, bureaucratic effort and availability of advisory support.
3. *Order of AES selection:* Farmers sign up AES in an order according to their preferences of the accepted AES when they accept more than one type of AES. Several preference options are implemented to generate the order: the highest offered payment, the highest difference between offered and accepted payment, the highest ratio between offered or accepted payment or the largest envisioned area. Farmers endeavour to achieve the envisioned area for the accepted AES. The more favoured AES get field allocation first. Therefore, the order of AES selection influences the AES field-level pattern.

2.10. Observation

What data are collected from the ABM for testing, understanding and analysing it, and how and when are they collected?

Farmers' and AES contracts' state variables are collected from the ABM for testing, understanding and analysing purposes at every tick of a simulation. The data is saved in csv files in the output folder by the NetLogo functions *write-farm-record* and *write-aes-record*, when the functions are turned on by '*i-save-csv?*' in the interface before a simulation run.
In addition, these measures at marco-level - all farmers and different types of farmers' average openness and average accepted payment levels, the total AES areas, the number

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

of fields under AES, the ABM's prediction errors against the baseline (i.e., the farmers' adoption in 2019) of the status-quo scenario and farm-level adoption rates, can be observed via the model statistics variables listed in the table below.

Model statistics variables (global)

	NetLogo variable	Possible values	Unit
A list of the proportions of FSA farmers (P1-P5) being open towards the four AES	*v-g-stats-openness-fsa*	A list of five lists containing double numbers between 0-100(%)	-
A list of the proportions of farmers being open towards the four AES	*v-g-stats-openness*	A list of four double numbers between 0-100 (%)	-
A list of the total AES area of the four AES	*v-g-stats-aes-area*	A list of four double numbers	ha
A list of the total number of fields under the four AES	*v-g-stats-aes-fields*	A list of four integer numbers	-
A list of FSA farmers' average WTA towards the four AES	*v-g-stats-accepted-payment-fsa*	A list of five lists containing double numbers	-
A list of the model's prediction errors on the four AES adoptions comparing to the baseline	*v-g-stats-farm-error-list*	A list of four float numbers between 0-1	
A list of the farmer adoption rates on the four AES and the total adoption rate	*v-g-stats-adoption-rate-list*	A list of five double numbers	-

What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)

Observations can include effects of policy design, i.e. specifications of AES contracts, the availability of advisory support and its importance as well as the importance of social networks or the importance of land-use intensity (i.e the fraction of organic/conventional farms) on AES adoption rates.

3. Details

3.1. Implementation Details

How has the model been implemented? Is the model accessible, and if so where?

The model has been implemented in NetLogo 6.2.1. The model source code is publicly available at https://git.ufz.de/bestmap/bestmap-abm/-/tree/main/BESTMAP-ABM-UK.

3.2. Initialization

What is the initial state of the model world, i.e. at time t=0 of a simulation run?

- AES contract characteristics are defined based on selected policy design.
- The landscape and soil characteristics are imported from GIS vector files including ownership, land use, and AES adoption. Field agents are created based on the input data.
- Farmers are initialised with the input data containing their characteristics, including FSA, economic sizes, farm areas, and prior AES experience (i.e., CSS and ESS experiences by 2016). A farmer's openness due to prior AES experience, intrinsic openness, the influence from advisory services or the influence from the social network is randomly assigned. In addition, the probability of a farmer being intrinsically open is assumed to be proportional to the historical adoption rate of the same FSA - economic type of farmers.
- Farmers' envisioned area for AES is initialised with the historic CSS adoption data, which is the average of the proportion of AES area in a farm.
- Data for the calculation of accepted payment levels is imported. The accepted payment level and for each AES is calculated depending on contract details (contract duration, bureaucratic effort) and explicit farmer (access to advisory) as well as implicit (translated in random distribution around mean) farmer characteristics. Details of the calculation are described in Section 3.4.
- The social network is defined based on the selected type (no social network, neighbourhood or FSA).
- Farmers' reasoning on the order of preferred AES is defined according to the selection of the options implemented in the model (*i-g-site-selection*)

Is initialization always the same, or is it allowed to vary among simulations?

Farmer characteristics are the same, however, the probabilities of farmers being open to AES adoption due to prior AES experiences, advisory services and intrinsic openness, the probability of having access to advisory and the design of the social network and farmers' reasoning preferences can be varied between scenarios.
The individual accepted payment levels and envisioned areas for AES adoption are derived from input data. The actual calculation depends on the chosen method of the integration of the regression model (see section 3.4 for more details). Three modelling choices for the integration can be chosen at the initialization stage: (1) without integration of the farm-level regression analysis, (2) with integration of the farm-level adoption prediction from the regression analysis and (3) with integration of the farm-level adoption probability from the regression analysis.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

AES contract characteristics (duration, bureaucratic effort, offered payment level) are varied between scenarios representing different policy designs.
Different landscapes can be set up: (1) The whole Humber dataset including all farms and fields (2) a sample of all Humber farms and fields representing the proportion of FSA farms in Humber farms (shown in Figure 2). The purpose of having a sampled input data is for the efficiency of running a large number of simulations. Using the sample landscape the model runs faster and produces representative results of the region.

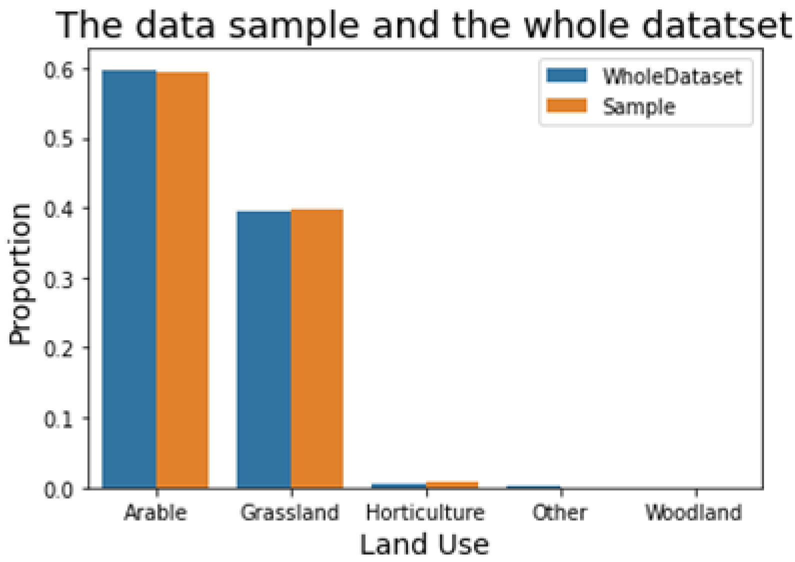

Figure 2: The comparison of the sampled data and the whole Humber dataset. In Humber, arable fields, grass-land fields and horticultural fields account for 59.8%, 39.6% and 0.6% respectively among all agriculture fields. In the sampled data, arable fields and grassland fields account for 59.4%, 39.8% and 0.8%.

Are the initial values chosen arbitrarily or based on data?

Initial values for landscape, farmer characteristics and envisioned area are based on IACS/LPIS data and the ESS and CSS adoption data from Natural England. Initial values for accepted payment level are set through calibration based on the model baseline, which is the CSS adoption in 2019. AES designs are composed within ranges assumed to be suitable for the UK. In particular, for the baseline the values for AES designs are set according to the current CSS designs.
These initial values are chosen arbitrarily because we don't have reliable data for them: A farmer's openness due to prior AES experience, intrinsic openness, the influence from advisory services or the influence from the social network is randomly assigned. In addition, the probability of a farmer being intrinsically open is assumed to be proportional to the historical adoption rate of the same FSA - economic type of farmers.

3.3. Input Data

Does the model use input from external sources such as data files or other models to represent processes that change over time?

The model does not use any external input files to represent processes that change over time.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

3.4. Submodels

What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'? What are the model parameters, their dimensions, and reference values? How were submodels designed or chosen, and how were they parameterized and then tested?

Model Initialisation

Model initialization sets up the model parameters using data in the input files (csv-format) and the input values from the NetLogo model interface. Below is the table of model parameters and their reference values. These parameters are set in the initialisation.

Model parameters in initialisation

Parameter	NetLogo variable	Baseline values	Possible values	Unit
Simulated time period	*i-g-years*	1	1-20	years
Minimum required field size for specific AES	*i-g-area-min-buffer-strips* *i-g-area-min-catch-crops* *i-g-area-min-grassland* *i-g-area-min-conversion*	0 0 0 0	Any value depending on policy designs	ha
Contract duration for specific AES	*i-g-duration-buffer-strips* *i-g-duration-catch-crops* *i-g-duration-grassland* *i-g-duration-conversion*	5 5 5 5	1, 5, 10	years
Bureaucratic effort for specific AES	*i-g-bureaucracy-buffer-strips* *i-g-bureaucracy-catch-crops* *i-g-bureaucracy-grassland* *i-g-bureaucracy-conversion*	"medium" "medium" "medium" "medium"	"low", "medium", "high"	-
Offered payment level for specific AES	*i-g-payment-buffer-strips* *i-g-payment-catch-crops* *i-g-payment-grassland* *i-g-payment-conversion*	£524 £124 £183 £321	Any value depending on policy designs	EUR/ ha
Offered free advisory services for specific AES	*i-g-advisory-BS?* *i-g-advisory-CC?* *i-g-advisory-MG?* *i-g-advisory-CVN?*	false fasle false false	true/false	-
Order of site selection for accepted AES	*i-g-site-selection*	"highest-payment-ratio"	"highest-payment", "highest-payment-diff", "highest-payment-ratio", "largest-area"	-

Probability that a farmer has access to advisory	*i-g-access-to-advisory*	80%	20% - 80%	-
Type of social network	*i-g-social-network-type*	"none"	"none", "neighbours", "FSA"	-
Radius around fields in which other field owners are considered as belonging to social network ("neighbours")	*i-g-social-network-radius*	-	5, 10	km
Probability that a farmer with prior knowledge of a specific AES is open towards considering its application	*i-g-prob-open-experience*	0 (The model simulates the year 2015 when the CSS started to roll out, therefore no prior experience)	80%	-
Probability that a farmer with access to advisory is open towards considering application of a specific AES	*i-g-prob-open-advisory*	50%	10%-90%	-
Probability that a farmer with positive social influence is open towards considering application of a specific AES	*i-g-prob-open-social*	10%	10%-90%	-
Probability of being intrinsically open towards considering application of specific AES	*p-g-prob-intrinsic-open-list*	*i-lambda-openness* * Adoption rate of FSA-economic farms	0-1	-

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

The proportion of intrinsic openness to the historic adoption rates	*i-lambda-openness*	24	1.0-30.0	-

These submodels are initialised In the initialisation stage: Farmers' social network and farmers' WTA calculation.

Farmers' social network

The social network type of a farmer is defined by *i-g-social-network-type* which can be either "none", "neighbours" or "FSA". The social network (*v-social-network*) is set to an empty turtle agentset if "none" is chosen. The owners of fields in a radius *i-g-social-network-radius* around each field of a farmer are added to the social network of a farmer, If the "neighbours" option is chosen; The farmers with the same FSA and economic size are added to the social network of a farmer If the "FSA" option is chosen.

Farmers' WTA calculation

The farmers' WTA calculation is implemented in the NetLogo function *r-calculate-farmer-DCE*. This process calculates WTA mean value of an AES for the farmer population based on the contract length *c* (1, 5 or 10 years), the bureaucratic effort *b* (low, medium or high) and the availability of advisory support *a* (yes or no) of the AES as specified in the policy design of the respective simulation run. The calculation is based on the reference value for a five years contract with medium bureaucratic effort and without advisory support *WTA (5, medium, no)* (status quo) and the differences for a different contract length, bureaucratic effort or availability of advisory Δ*WTA(c,b,a).*

In total, the calculation is composed as follows:

$$WTA(c,b,a) = WTA(5,\text{medium},\text{no}) + \begin{cases} \Delta WTA(1,\text{medium},\text{no}) & \text{if } c = 1 \\ \Delta WTA(10,\text{medium},\text{no}) & \text{if } c = 10 \end{cases} + \begin{cases} \Delta WTA(5,\text{low},\text{no}) & \text{if } b = \text{low} \\ \Delta WTA(5,\text{high},\text{no}) & \text{if } b = \text{high} \end{cases} + \begin{cases} \Delta WTA(5,\text{medium},\text{yes}) & \text{if } a = \text{yes} \\ 0 & \text{if } a = \text{no} \end{cases} \quad (1)$$

In farmer agent initialisation *setup-farmers*, the WTA for a type of AES of an individual farmer *i*, noted as WTA_i, is drawn randomly based on the normal distribution and stored in the NetLogo parameter *p-accepted-payment-list*:

$$WTA_i \sim N(\mu, \sigma^2) \quad (2)$$

Where $\mu = WTA(c,b,a)$ and $\sigma^2 = 0.1 * \mu$.

In the model, we implement multiple ways of WTA setups. When the interface chooser "*i-how-integrate-regression*" is set to be "no", the process in the model will carry out as

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

described above. Further, there are two other ways of integrating a regression analysis, which plays a vital role on setting WTA_i is in the model, when “regression-yes-no-adoption” or “regression-sorted-score” is chosen.

Farm-level regression model and its integration to ABM

We build a farm-level logistic generalised linear regression model (GLM) that predicts the probability p of the Humber farmers’ participation of AES using the method presented in the paper by Paulus et. al. (Paulus et al., 2022). The regression model is based on farm attributes x_i, with coefficients β_j, $j = 0, 1,..., m$ derived in :

$$p = (1 + exp(-(\beta_0 + \sum_{i=1}^{m} \beta_i x_i)))^{-1} \tag{3}$$

As a result, a farmer i is predicted to participate if $p_i > 0.5$, and he/she doesn’t participate if $p_i \leq 0.5$. The prediction of farmers’ participation (yes or no) is implemented in the ABM as the farmer agents’ parameter *p-prob-uptake.* Furthermore, p_i values of all farmers are sorted in an ascending order and the ranking is stored in the ABM parameter *p-prob-uptake-rank.*
If the parameter ‘*i-how-integrate-regression*’ is set to be ‘regression-yes-no-adoption’, we deliberately assign a WTA value that is lower than the mean WTA to a farmer agent with *p-prob-uptake=1* and a WTA value that is higher than the mean WTA to a farmer agent with *p-prob-uptake=1*. These WTA values are randomly drawn and subject to the normal distribution (equation (3)). This process of assigning WTA values is implemented in the NetLogo functions *report-random-normal-controlled* and *setup-farmers*.
If the parameter ‘*i-how-integrate-regression*’ is set to be ‘regression-sorted-score’, in addition to making sure the farmers’ WTA above or below the mean WTA according to their *p-prob-uptake*, farmers with higher *p-prob-uptake-rank* are assigned with lower WTA values. In summary, the WTA values of the farmers are sorted based on the probability of farmers’ participation. This process of assigning WTA values is implemented in the NetLogo functions *set-up-WTA-pool* and *setup-farmers*.

Update prior knowledge based on own experience

In this process, the model updates farmers’ prior AES experience (*v-prior-experience-list*) based on the AES adoption history (*v-aes-hist-list*) in the NetLogo function *update-prior-knowledge*. The AES adoption history is updated when a farmer signs up for an AES in the Decision Making Step 3.

Remove AES contracts that exceed contract duration and update state variables of farmers and fields related to AES adoption

AES contracts are updated in the NetLogo function *update-aes*. As the simulation progresses, the contract year of an AES contract (*v-aes-contract-year*) is increased by one. If the contract year is larger than the AES contract duration (*i-g-duration-xxx,* whose value is stored in *p-g-duration-list*), the model removes the AES contract and updates the field and farmer agents’ status. Field agents’ variables - the list of AES on a field (*v-aes-list*), the available area in the field for other possible AES implementations (*v-avail-area*) and the

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

current different AES area on the field (*v-aes-area-list*) are updated, and farmer agents' variable - the AES contract area (*v-contract-area-list*) is updated in this process.

Update farmers' decision-making status - whether to enter into decision-making phase

In this process, the model updates farmers' status of whether to enter into decision-making phase (*v-time-decide?*) in the NetLogo function *update-time-decide*. This step is implemented to accommodate the UK case study situation that while farmers have live AES contracts on their farm lands, they do not actively apply for more AES each year according to the adoption data. Therefore, in a multiple-year simulation farmers enter into decision-making phase when they don't have any live AES contracts on their lands.
In future the model can be extended to simulate farmers entering into the decision-making phase under other different conditions, by modifying this step. It is worth pointing out that this step is not necessary when AES contract durations are set to be 1 year or when in a scenario where farmers are willing to actively check out AES and apply for new contracts every year.

Openness (Decision Making Step 1)

Calculate openness for each AES individually (see also Figure 1):

- Check prior experience: For farmers with prior knowledge set openness to this AES to 1 with probability *i-g-prob-open-knowledge*
- Check intrinsic openness: For farmers without prior experience set openness to 1 with probability *p-g-prob-intrinsic-open-list*
- Check advisory support: For farmers not intrinsically open but with access to advisory support set openness to 1 with probability *i-g-prob-open-advisory*
- Check social network: For farmers not open after advisory support or farmers without access to advisory support check social network. If at least one member of the social network has previously applied the AES, set openness to 1 with probability *i-g-prob-open-social.*

Selection of fields (Decision Making Step 2)

Farmers select suitable fields for the AES that they are open to in the NetLogo function *select-suitable-fields*. Only fields that are the eligible types of land use, larger than the minimum required area and not having ESS on are selected (stored in *v-suitable-fields-list*) and passed to the Decision Making Step 3 for further consideration.

Deliberation (Decision Making Step 3)

In the deliberation process (the NetLogo function *deliberate-aes-decision*), farmers update their knowledge base about whether there are gaps (*v-gap*) between the envisioned areas for their favoured AES and the realised AES areas. If it is a proper time for them to enter decision-making (*v-time-decide? = true*), they compare WTAs with the offered payments in the NetLogo function *r-compare-payment* and get the profitable AES list (*p-accepted-aes-list*). Then farmers select fields for the AES that they are open to and update *v-suitable-fields-list*. Farmers also produce an order of their favoured AES according to the model setting of *i-g-site-selection*, which is implemented in the NetLogo function *get-aes-decision-order*.

ARPHA Preprints Author-formatted document posted on 11/12/2024. DOI: https://doi.org/10.3897/arphapreprints.e144085

Farmers then select fields based on the soil quality and the size of the field to realise the AES contracts (the NetLogo function *select-aes-fields-uk*). In the UK case study area, buffer strips are put on field margins and can be implemented with grassland management can be implemented on the same field. Therefore we introduce a global variable *p-g-aes-in-field-max-list* to define the maximum proportion of the AES area in a field for each AES. According to the adoption data, the proportions vary in different fields for an AES. The farmers always put the maximum proportion of a field for their selected AES in the model and also can sign multiple fields up for AES to achieve the envisioned area.

4. Additional information

The model is built in with some processes for testing and analysis purposes.

Multiple runs in one go

The process (the NetLogo function *go-x-times*) is built to run the model for multiple times with the same setting and analyse the results at the end of the simulation. This way is easier than running an experiment in BehaviourSpace and then analysing the result afterwards. To use this function, *i-g-times* needs to be set to the number of runs, *i-multi-run-AES* decides how the simulation output data is collected and analysed. If "All AES in list" is chosen, the result will include the average adoption rates of buffer strips, cover crops, grassland management, arable land conversion to grassland and the total farm adoption rates; if individual AES is chosen, i.e., "Buffer Strips", "Cover Crops", "Grassland Management" or "Land Conversion" is chosen, the result will only include the average adoption rate of the selected AES. The results will be displayed in the Command Centre by clicking the "*Display adoption rates*" button after the simulation finishes.

Testing WTA distribution

The below lists the NetLogo interface variables that are created for users to explore WTA distribution's impact on the model. To run this test, *i-test-WTA-mode?* needs to be set to "true".

Interface parameters for exploring WTA distribution

Parameter	NetLogo variable	Unit
The switch for a testing mode	*i-test-WTA-mode?*	-
The mean WTA for buffer strips of the reference scenario	*base-WTA-bs*	£
The mean WTA for cover crops of the reference scenario	*base-WTA-cc*	£
The mean WTA for grassland management of the reference scenario	*base-WTA-gm*	£
The mean WTA for arable land conversion to grassland of the reference scenario	*base-WTA-cvn*	£

The fraction of standard deviation over the mean WTA	*i-sd-fraction*	-

Running the model via R nlrx package

The switch *i-nlrx-run?* is used to decide how the seeds are set up and changes the stats-output file names when i-save-stats? is true.
The switch *i-go-x-times?* is used to record seeds when the model is run for multiple times by the NetLogo function *go-x-times* via R.
The interface variable *nlrx_id* is usually left blank, because the R nlrx package will generate an ID for each run automatically and record it in the results.

Interface parameters for running simulations through R nlrx package

Parameter	NetLogo variable	Unit
The switch for indicating a nlrx run	*i-nlrx-run?*	-
The switch for informing the model using function go-x-times in nlrx runs	*i-go-x-times?*	-
The id of nlrx runs	*nlrx_id*	-

References

Bartkowski, B., Bartke, S., 2018. Leverage Points for Governing Agricultural Soils: A Review of Empirical Studies of European Farmers' Decision-Making. Sustainability 10, 3179.
Bartkowski, B., Beckmann, M., Bednář, M., Biffi, S., Domingo-Marimon, C., Mesaroš, M., Schüßler, C., Šarapatka, B., Tarčak, S., Václavík, T., Ziv, G., Wittstock, F. Adoption and potential of agri-environmental schemes in Europe: Cross-regional evidence from interviews with farmers. Under review.
Paulus, A., Hagemann, N., Baaken, M.C., Roilo, S., Alarcón-Segura, V., Cord, A.F., Beckmann, M., 2022. Landscape context and farm characteristics are key to farmers' adoption of agri-environmental schemes. Land Use Policy 121, 106320.
Wittstock, F., Paulus, A., Beckmann, M., Hagemann, N., Baaken, M.C., 2022. Understanding farmers' decision-making on agri-environmental schemes: A case study from Saxony, Germany. Land Use Policy 122, 106371.
Ziv, G., Beckmann, M., Bullock, J., Cord, A., Delzeit, R., Domingo, C., Dreßler, G., Hagemann, N., Masó, J., Müller, B., Neteler, M., Sapundzhieva, A., Stoev, P., Stenning, J., Trajkovic, M., Václavík, T., 2020. BESTMAP: behavioural, Ecological and Socio-economic Tools for Modelling Agricultural Policy. Research Ideas and Outcomes 6, e52052.