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D5.3 Agent-based model at the European scale

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Agent-based model at the European scale

Deliverable D5.3

24 August 2023

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

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Preface

This deliverable provides a report on the generalised linear model and agent-based model for the European Union developed in the Work Package 5 (WP5) – Upscaling to national, EU and global level. In particular, it includes a description of how the models can be accessed and which input data are needed. This document is accompanied by a description of the ABM in a structured form (see Appendix) which follows the ODD+D protocol (Müller et al., 2013).

Summary

This document presents the generalised linear model (GLM) and agent-based model (ABM) that were developed in the H2020 project BESTMAP to model and predict the uptake of Agri-Environmental Schemes (AES) in the European Union. The deliverable is based on the work done in Work Package 4.1 (WP4.1) – Agent-Based Modelling and Analysis of BESTMAP. This deliverable comprises a description of the particular implementation of the ABM including a discussion of how and why the European Union model differs from the case study-specific models described in Deliverable 4.1. The link to the model's code on GitLab is provided. Furthermore, data requirements and potential limitations with respect to data accessibility are outlined. The ABM 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 and how the GLM and ABM are linked. As an outlook, research questions that can be answered with the models, model limitations and potential further extensions are discussed. Additionally, it is briefly discussed how the ABM outputs will enhance the biophysical modelling upscaling, which is the other part of Task 5.2.

1. Introduction

1.1. Data

For this project we use data from the Farm Accountancy Data Network (FADN) database (in the year range 2014-2016), which includes information on the 28 countries within the European Union. We have access to 350 variables that describe each farm in each country. The data within these variables contains economic information (e.g. the value of the agricultural land, costs of equipment, and subsidies received for buffer strips) and information detailing the use of the land (e.g. total poultry and total economic value of cereals). We wish to understand which farms decide to adopt an AES. For this we use the FADN variable SAEAWSUB_V (Agri-environment and animal welfare payments value). Although this gives the monetary amount received by the farmer, we use it as a binary indicator of whether or not a farmer has taken on an AES. Figure 1 shows the rate of farms sampled in each country that adopt a scheme according to this variable, ordered by adoption rates.

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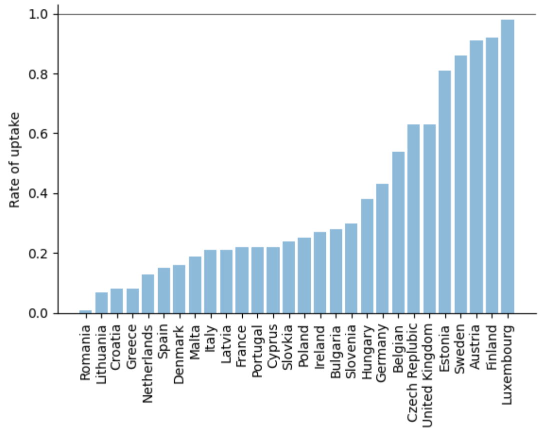

Figure 1. Proportion of sampled farms that uptake an AES in each country.

1.1. Process

Modelling AES adoption in the EU is a two-stage process. First we use a GLM to predict the likelihood of AES adoption for each farmer. To achieve this, stepwise regression is used to find which independent variables can help predict adoption, where adoption is defined by the variable SAEAWSUB_V. Once significant variables and their coefficients have been determined, the model is used to predict AES uptake. This is performed separately for each country as adoption differs widely across different countries (see figure 1) and, as a result, we have found that a single model is not effective for predicting all countries. More details and results from the GLM can be found in Section 2.

Next, the GLM results are used as inputs for an ABM. This model uses the probability of AES uptake according to the GLM, along with user-provided probabilities of farms having access to and influence from advisory support. The ABM is intended to provide a more accurate prediction than the GLM, and enables the model user to assess the influence of changing variables, such as those describing advisory support or the payment offered to farms for adopting an AES. How the GLM results are incorporated into the ABM can also be altered. More details and results from the ABM can be found in Section 3.

2. Logistic Regression Model

We first train a GLM as described by Paulus et al. (2022) to predict which farms within the FADN data will take on an AES.

2.1 Methods

Before using the ABM to generate predictions, we first train a GLM to obtain a rank order of probabilities that each farmer will adopt an AES. These ranks will then be used as an input to the ABM in determining the likelihood that each farmer will adopt an AES.

Although each farm in each country is described by 350 variables within the data, not all of these are useful for predicting AES adoption and therefore have to be removed. Specifically, we removed variables where all values are the same (e.g. year), variables with missing data (e.g. altitude), and variables that are of no use (e.g. farm ID). In addition, all variables relating to subsidies and payments a farm received were removed as these are closely related to the variable we are trying to predict (SAEAWSUB_V). In total, 98 variables were removed (listed in the appendix in section 8.1), leaving 252 variables.

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Of the remaining variables, not all of them will be useful for predicting AES adoption. In fact, most are statistically insignificant. To find the variables that are useful and significant, we perform stepwise regression. This involves starting with a model that has no variables and gradually adding one significant variable at a time and removing any variable previously added has become non-significant. Specifically, the process is as follows:

0. Initial state: No variables are included in the model.
1. For each variable not included in the model, test adding them to the model (separately). If any of the variables were found to be statistically significant ($p<0.1$), add the variable to the model that reduced the total sum of squares the most. If no variables were found to be significant, the process ends.
2. For all previous variables previously added to the model, check if any are no longer statistically significant ($p>0.2$). For each variable that is found to be non-significant, test removing them from the model (separately), and remove the variable from the model that reduced the total sum of squares the least.
3. Go to step 1.

Note that in step 2 we use a higher alpha-criterion of 0.2 to ensure we do not accidentally remove a variable that has a significant impact in explaining the model.

When running the stepwise regression process, we find that using a subset of the data is more effective than using the full data set for each country. Specifically, we take a sample such that half of the sample contains farms that choose to adopt an AES, while the other half contains farms that do not adopt. Without sampling the data in this way, we find the predictions become heavily skewed by the data. Specifically, countries with low levels of adoption are generally over-predicted (i.e. predicted to have a higher adoption rate than seen in the data), and countries with high levels in the data are under-predicted by the model.

We run the above process separately for each country. The appendix in section 8.2 lists the variables that were selected for each country for the regression model.

2.2 Results

The variables that are selected through stepwise regression to predict AES uptake differ for each country. A full list of the variables chosen is given in the appendix in section 8.2. Figure 2 shows the adoption rates predicted by the GLMs. The rate of adoption in the data is represented in blue, whilst the model predictions are in orange. Note that this figure does not show if a farm was correctly predicted. Figure 3, however, shows the accuracy of the GLM; i.e. the total rate of farms that were correctly predicted to adopt or not adopt an AES. A numerical list of the accuracy of each country is provided in the Appendix in section 8.3. While the GLM is able to predict most countries with reasonable accuracy, several countries have been modelled poorly. The GLM particularly struggles to predict adoption in countries where under 10% of farms adopt an AES. In these cases, the model incorrectly predicts that most farmers do take on AES. Similarly, the model is poor where over 95% of farms adopt (i.e. Luxembourg), predicting that most farmers do not take on an AES. This suggests that the available macro-economic data cannot explain these few cases. However, they may be explainable with social and/or environmental information.

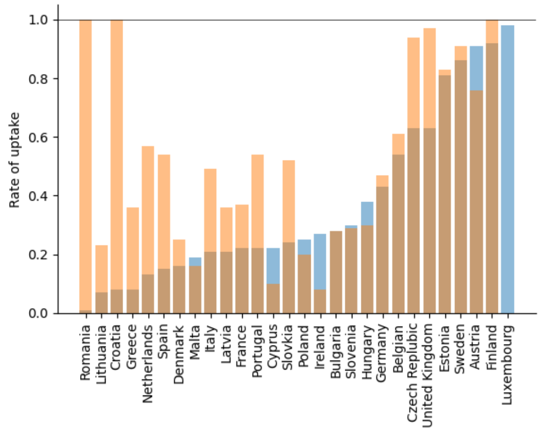

Figure 2. Proportion of farms that take on an AES in the data (blue) and the logistic regression model (orange).

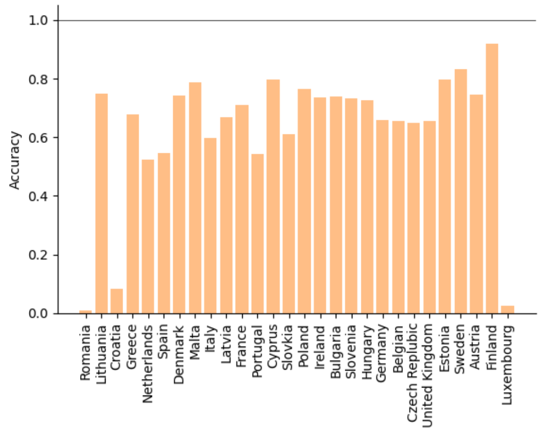

Figure 3. Proportion of farms correctly predicted by the logistic regression model.

3. Agent-Based Model

The ABM used to predict uptake of AES in the EU is based on the ABM used to predict uptake in the five case studies (South Moravia, CZ; Mulde Region, DE; Catalonia, ES; Bačka Region, RS; and Humber Region, UK) that have been developed in Work Package 4 (a detailed description is provided in Deliverable 4.1).

3.1 Methods

3.1.1 Grouping the data

We group data into clusters of Farm System Archetype (FSA), details of which can be found in the BESTMAP Deliverable 3.5 Farming System Archetypes for each CS at https://bestmap.eu/about.php?storyid=2732. We use five FSA groups that cluster farms according to whether the land is used for 1) general cropping; 2) horticulture; 3) permanent crops; 4) livestock; or 5) a mixture of the previous four groups.

We also group farms into groups of different economic size. We create three clusters, grouping small, medium and large farms. Note that the ABM used for the case studies uses a fourth group: farms with an economic size of less than €2000. However, the FADN

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database does not include information about such small farms, and so we do not have any farms that fall into this category. Figure 4 shows histograms of the economic sizes of farms across four countries: Lithuania, Czech Republic, Netherlands and Italy. In most other cases, countries have a distribution of farm sizes that are similar to that of Lithuania or Czech Republic. Most farms have an economic size of less than €70,000, we find a small number of farms between €70,000 and €300,000, and an even smaller number of farms with a size greater than €300,000. Therefore, we use these limits as clusters for small, medium and large farms. Specifically,

- A *small* farm has an economic size of at least €2000 and less than €70,000
- A *medium* size farm is from €70,000 to less than €300,000.
- A *large* farm has an economic size of €300,000 or greater.

Considering both the five FSA groups and the three economic size groups, each farm is clustered into one of 15 groups.

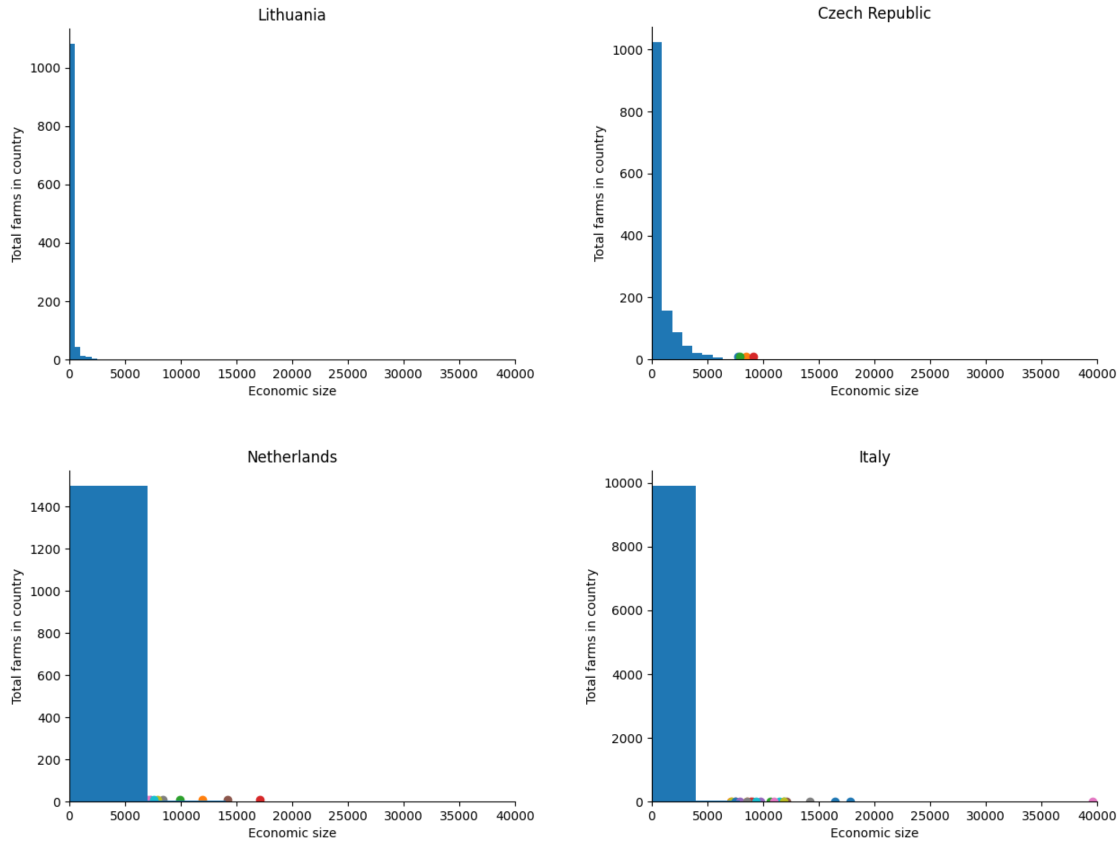

Figure 4. Histograms showing examples of the distributions of the economic size (in multiples of €1000) of farms in different countries. A dot along the x-axis indicates there is only one farm in the data of that size.

3.1.2 Model inputs

The output of the GLM is a prediction of whether each farm will adopt an AES. There are two methods by which the logit prediction is used to decide the minimum payment a farmer is willing to accept for an AES. The first method is the *YES/NO* method. With this, if the farmer's prediction is greater than 0.5, then their accepted payment will be a pseudo-randomly chosen value that is less than the offered payment. Otherwise, it will be a

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value greater than the offered payment. The payments are selected from a normal distribution, with a mean based on the payment received and proportion of farms that have accepted the payment in the data, and a coefficient of variation of 0.1. Figure 5 shows an example.

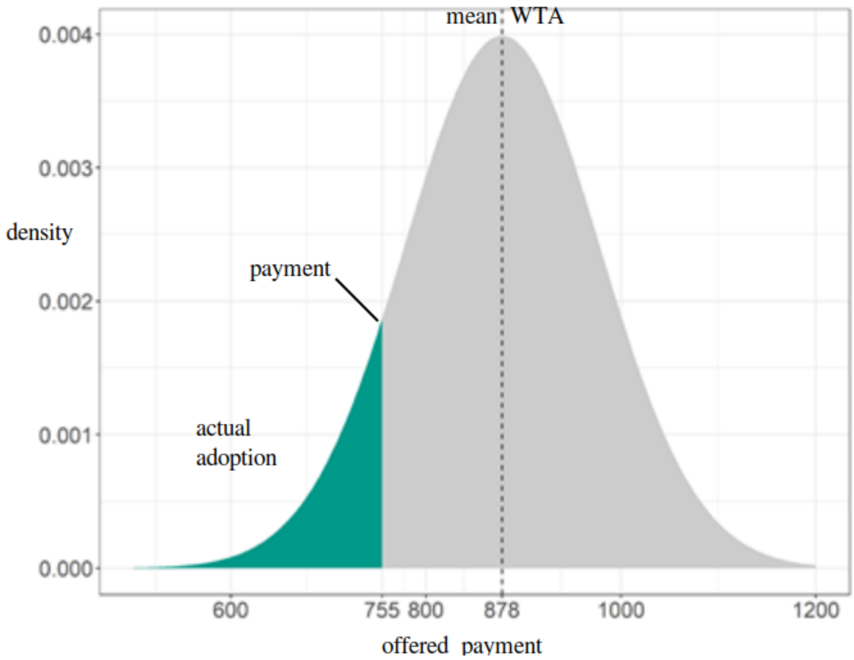

Figure 5. Exemplary distribution of expected payment levels for a scheme with adoption rate 10.9% (highlighted in green), offered payment level 755€/ha and standard deviation of 100€/ha. The resulting mean expected payment level is 878€/ha.

The second method is called the *SORTED* method. For this, once the farms have been clustered into their relevant FSA/economic-size group, their probabilities (from the GLM prediction) are transformed into a rank order (where the rank order is only relevant to the given group). The ranks are used to decide which farmers (with a high rank) will be assigned an accepted payment that is lower than the offered payment, and which (with a low rank) are assigned a higher accepted payment. The cut off is based on the proportion of farmers that are expected to be intrinsically open to adopting an AES (given in the ODD has openness). This cut off is defined as the proportion of farmers to have an AES contract in the data (those with prior experience) multiplied by a constant (denoted lambda) that is tuned as part of the model calibration process. We find through calibration that lambda=1.35 produces the best results.

A third method may instead be used in the model that does not use the GLM results. The method is called *NONE* and the farmers are given a random accepted payment within the normal distribution described in the method *YES/NO*.

3.2. Results

3.2.1 Choosing different model choices

Figure 6 shows the average adoption rate for each country using the three different model choices. Figure 7 shows the accuracy of the ABM for the different model choices. A

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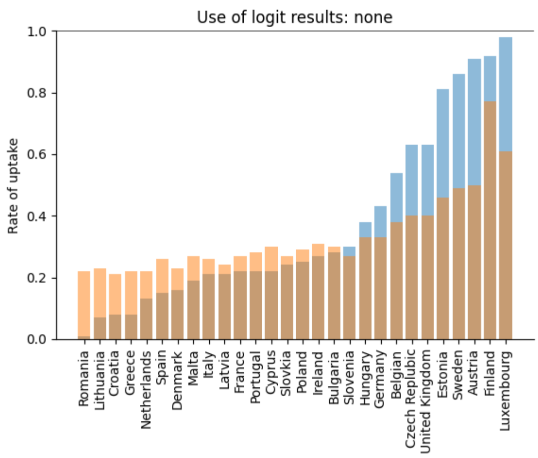
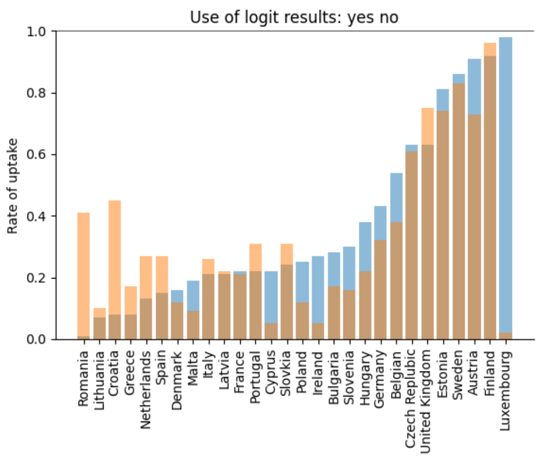
numerical list of the accuracy of each country for each model choice is provided in the Appendix in section 8.3.

When the model choice is *NONE*, a farmer's accepted payment is randomly chosen and unlikely to accurately reflect the data. Despite this, the model performs better than by entirely random chance as we are still using prior information on the total number of farmers who have adopted in each FSA an economic size group in the past.

When the model choice is *YES/NO*, the probability of AES uptake according to the GLM determines if the farmer will accept the offered payment after deliberation (based on past experience and access to an advisory). This method is expected to predict poorly where the GLM performed poorly. Although the accuracy on how many farmers take on an AES is mixed (see Figure 6) the accuracy of which farmers uptake an AES is fairly good (see Figure 7).

When the model choice is *SORTED*, the ranked probabilities of the GLM are used, but the actual probabilities are unimportant. That is, a farmer who has a less than 0.5 chance of adopting an AES according to the GLM may end up adopting in the ABM. This model performs the best in predicting how many farms take on a scheme. The accuracy of predicting which farms adopt is more mixed, however. Generally this model produces poorer results where approximately half of the farms have an AES.





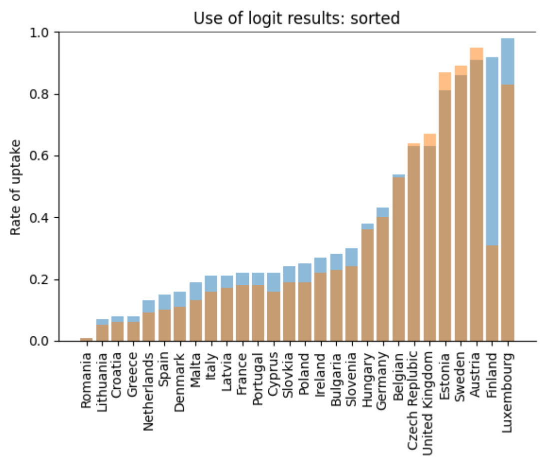


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Figure 6. Proportion of farms that take on an AES in the data (blue) and ABM (orange) using the three different model choices (none, yes/no and sorted).

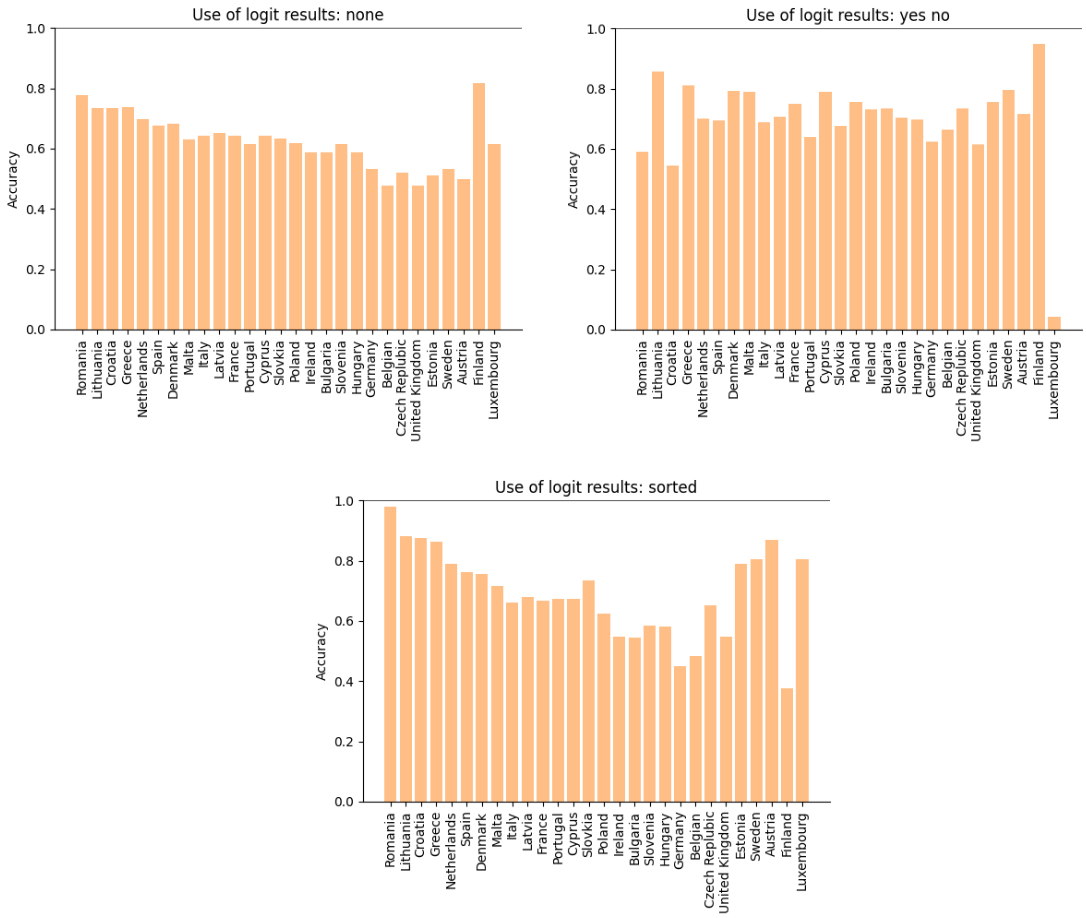

Figure 7. Proportion of farms correctly predicted by the ABM using the three different model choices (none, yes/no and sorted).

3.2.2 Choosing different levels of advisory support

The model may be used to assess how different levels of access to advisory support may affect AES uptake. For example, figure 8 shows the effects of having no (left) or full (right) advisory support.

When countries receive no advisory support (Figure 8 - left) there is a drop in adoption rate in countries that normally have high levels of adoption (compared with Figure 6 - where probability of access to an advisory is 0.8 and probability of the advisory influencing the farm is 0.5). Also Romania and Croatia (that were predicted to have higher adoption rates according to the model than in the data) are modelled more accurately when advisory support is excluded from the model.

When countries receive full advisory support (Figure 8 - right), the model shows much greater levels of adoption across countries that usually have little adoption. This suggests that increasing the influence of and access to advisory support will increase the adoption rate among farmers.

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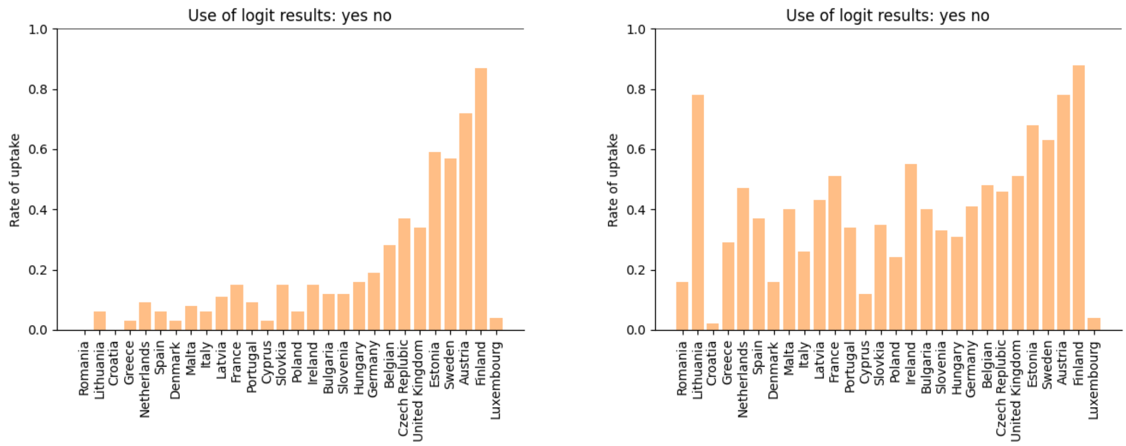

Figure 8. Proportion of farms that adopt an AES using the yes/no model choice when (left) no access to advisory support is given, and (right) full access is given and this access has only a positive influence in AES uptake.

3.2.2 Choosing different offered payments

The model can be used to predict changes in AES uptake when the price offered to farmers differs. For example, figure 9 shows the predictions in AES uptake if the offered payment is decreased (left) or increased (right) by 5%. When the price is increased, compared to no change in price (model predictions are shown in figure 6) the AES uptake in countries with less than 50% adoption is generally unchanged, whereas for countries that normally have more than 50% adoption, the rate of adoption with a price decrease drops dramatically. By contract, when the offered price is increased by 5%, as expected countries that normally have low adoption rates show an increased rate of adoption.

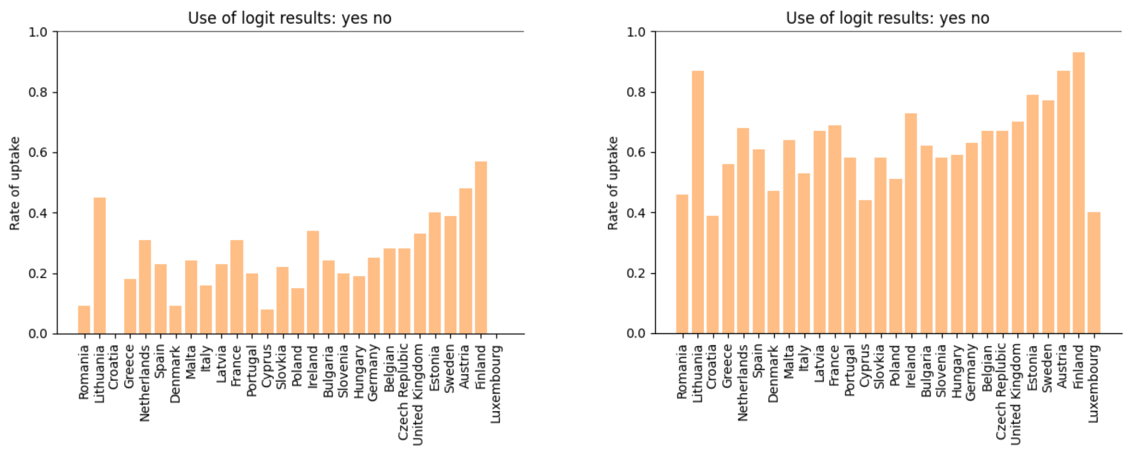

Figure 9. Results of ABM uptake predictions when the offered payment is decreased by 5% (left) or increased by 5% (right).

4. Model Accessibility and Data Requirements

The GLM and ABM are available online at https://git.ufz.de/bestmap/bestmap-aes-eu/. While the complete source code is publicly accessible, model usage is limited by data accessibility due to privacy issues. The FADN data contains confidential information and can thus not be made publicly available. Unfortunately, this means that the BESTMAP-ABM can only be operated by users that are part of the BESTMAP project, or that have permitted access to FADN data. However, the data can be requested from the respective agencies in the case studies for research purposes.

5. Outlook

In this deliverable, we have focused on the reasoning behind the formalisation of the decision-making ABM and its technical implementation. In the future, the model can be used to predict and understand how AES adoption changes…

… with higher or lower payment levels for AES.
… with reduced or increased administrative effort for farmers.
… if more farmers have access to advisory support.

The results from the upscaled ABM will also enable the results of the biophysical models (BPM) to be upscaled to farms within the EU and selected Associated Countries (Serbia and UK). In the BPM upscaling methodology, the adoption of AES is a binary variable which is often a significant predictor of different ecosystem services. Therefore, the ABM results predicting whether a farm is likely to adopt an AES will be used, with other bioclimatic data and region-averaged data, in the BPM upscaling to determine ecosystem services at a farm-level across Europe. This process will be detailed in Deliverables 5.1 and 5.2.

6. Acknowledgements

We thank the Agriculture and Rural Development of the European Commission for granting access to the FADN data.

7. References

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8. Appendix

8.1 Variables removed for logistic regression model

Below is a list of variables that were removed from the GLM because they are closely related to the independent variable *SAEAWSUB_V,* do not contribute to the model because every value is the same (e.g. *COUNTRY*), or have missing data (*ALTITUDE*).

Table 1: Variables removed before stepwise regression.

Variable name	Variable description
SAEAWSUB_V	Agri-environment and animal welfare payments Value
SE621	Environmental subsidies

SAEAWSUB_2_V	Agri-environment and animal welfare payments Value with fi 2
SAEAWSUB_3_V	Agri-environment and animal welfare payments Value with fi 3
SE624	Total support for rural development
COUNTRY	Country (3 digits FADN acronym)
YEAR	Year
countryyear	Country and year
ALTITUDE	Altitude Code
AASBIO_SUB	Biological assets - plants - Subsidy value
ALNDAGR_SUB	Agricultural land - Subsidy
ALNDFRSTST_SUB	Forest land including standing timber - Subsidy
ALNDIMP_SUB	Land improvements - Subsidy
AMCHQP_SUB	Machinery and equipment - Subsidy
QSPSXSPLOWQ_Q	Entitlements for payments under basic payment scheme. Owned
SAEAWSUB_2_V	Agri-environment and animal welfare payments Value with fi 2
SAEAWSUB_3_V	Agri-environment and animal welfare payments Value with fi 3
SAEAWSUB_V	Agri-environment and animal welfare payments Value
SAFR_N	Afforested areas greening subsidy. Number
SAGRFR_N	Hectares of agro-forestry greening subsidy. Number
SAGRPRCTCLIMENVSUBGR_T	Agricultural pract. beneficial for climate and environment greening subsidy. Type
SANC_1_V	Payment for areas with natural constraints subsidy. Value with fi1
SANC_2_V	Payment for areas with natural constraints subsidy. Value with fi2
SANC_V	Payment for areas with natural constraints subsidy. Value
SBFR_N	Buffer strips greening subsidy. Number
SBPS_1_1_N	BPS subsidy, EU financed Number of head
SBPS_1_2_N	BPS subsidy, EU financed per hectare
SBPS_1_3_N	BPS subsidy, EU financed per ton
SBPS_1_V	BPS (Basic payment scheme) subsidy. Value with fi1
SBPS_2_1_N	BPS subsidy, cofinanced Number of head
SBPS_2_2_N	BPS subsidy, cofinanced per hectare
SBPS_2_3_N	BPS subsidy, cofinanced per ton

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SBPS_2_V	BPS (Basic payment scheme) subsidy. Value with fi2
SBPS_3_1_N	BPS subsidy, non EU financed Number of head
SBPS_3_2_N	BPS subsidy, non EU financed per hectare
SBPS_3_3_N	BPS subsidy, non EU financed per ton
SBPS_3_V	BPS (Basic payment scheme) subsidy. Value with fi3
SBPS_V	BPS (Basic payment scheme) subsidy. Value
SCRPCATCH_N	Areas with catch crops greening subsidy. Number
SCRPDVRSUBGR_N	Crop diversification greening subsidy. Number
SCRPDVRSUBGR_T	Crop diversification greening subsidy. Type
SE605	Total subsidies - excluding on investments
SE610	Total subsidies on crops
SE611	Compensatory payments/area payments
SE613	Other crops subsidies
SE615	Total subsidies on livestock
SE616	Subsidies dairying
SE617	Subsidies other cattle
SE618	Subsidies sheep & goats
SE619	Other livestock subsidies
SE621	Environmental subsidies
SE622	LFA subsidies
SE623	Other rural development payments
SE625	Subsidies on intermediate consumption
SE626	Subsidies on external factors
SE630	Decoupled payments
SE631	Single Farm payment
SE632	Single Area payment
SE699	Other subsidies
SEFASUBGR_N	Ecological focus area greening subsidy. Number
SEFASUBGR_T	Ecological focus area greening subsidy. Type
SFLNDSUBGR_N	Land laying fallow greening subsidy. Number
SFRSUBIMP_2_V	Forestry subsidy: Investments in area development and improvement of the viabilit. Value with fi2
SFRSUBIMP_V	Forestry subsidy: Investments in area development and improvement of the viabilit. Value
SFRSUBN2000_2_V	Forestry subsidy: Natura 2000, environmental and climate services, conservation. Value with fi2
SFRSUBN2000_V	Forestry subsidy: Natura 2000, environmental and climate services, conservation support. Value

SFRSUB_2_V	Forestry incl. Natura 2000 payments for forestry Value with fi 2
SFRSUB_V	Forestry incl. Natura 2000 payments for forestry Value
SINVSUB_2_V	Investment subsidies Value with fi 2
SINVSUB_3_V	Investment subsidies Value with fi 3
SINVSUB_V	Investment subsidies Value
SLNDS_N	Landscape features greening subsidy. Number
SLNTL_N	Of which env. sens. perm. grassland outside Natura 2000 greening subsidy. Number
SN2000SUB_2_V	Natura 2000 payments excl. forestry Value with fi 2
SN2000SUB_V	Natura 2000 payments excl. forestry Value
SNFC_N	Areas with nitrogen-fixing crops greening subsidy. Number
SNHNDMNTSUB_2_V	Natural handicap payments mountain and other areas Value with fi 2
SNHNDMNTSUB_V	Natural handicap payments mountain and other areas Value
SORGSUB_2_V	Organic farming subsidy. Value with fi2
SORGSUB_3_V	Organic farming subsidy. Value with fi3
SORGSUB_V	Organic farming subsidy. Value
SPERMGRSN2000_T	Of which env. sensitive perm. grassland in Natura 2000 greening subsidy. Type
SPERMGRSNON2000_T	Of which env. sens. perm. grassland outside Natura 2000 greening subsidy. Type
SPERMGRSSUBGR_N	Permanent grassland greening subsidy. Number
SPERMGRSSUBGR_T	Permanent grassland greening subsidy. Type
SPRCTCLIMENV_1_V	Agricultural practices beneficial for the climate and the environment subsidy. Value with fi1
SPRCTCLIMENV_2_V	Agricultural practices beneficial for the climate and the environment subsidy. Value with fi2
SPRCTCLIMENV_V	Payment for agricultural practices beneficial for the climate and the environment subsidy. Value
SSAPS_1_V	SAPS (Single area payment scheme) Value with fi 1
SSAPS_2_V	SAPS - Subsidy per hectare
SSAPS_3_V	SAPS (Single area payment scheme) Value with fi 3
SSAPS_V	SAPS (Single area payment scheme) Value
SSHROT_N	Areas with short rotation coppice greening subsidy. Number
SSTRFR_N	Strips of eligible hectares along forest edges greening subsidy. Number
SYF_1_V	Payment for young farmers. Value with fi1

SYF_2_V	Payment for young farmers. Value with fi2
SYF_V	Payment for young farmers. Value

8.2 Variables selected through stepwise regression

Table 2 lists the variables used by the GLM for each country. Note that all variables selected were found to be statistically significant with an alpha-criterion of 0.1.

Table 2. Variables used by the GLM for each country

Variable name	Variable description	Coefficient
Romania		
SE437	Total assets, opening valuation	10.635474
Lithuania		
AASBIO_CV	Biological assets - plants Closing value	22.674618
Croatia		
SE100	Pigs	-14.193872
Greece		
ACSHEQ_CV	Cash and equivalents Closing value	37.009428
ORGNA	Sectors in organic farming Not applicable	-24.187149
AASBIO_CV	Biological assets - plants Closing value	3.766763
NUTS3_EL543	NUTS NUTS3: class EL543	-13.606015
Netherlands		
SE005	Economic size	-25.847924
SE025	(OGA) in total labour	27.574305
SE298	Fertiliser. Quantity of K2O in mineral fertilisers used	-13.507874
SIZC_14	Economic size class (cf. EU typology): class 14	11.862576
Spain		
SE165	Industrial crops	13.908154

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SE054	Permanent crops	10.857807
ACSHEQ_CV	Cash and equivalents Closing value	-11.13984
SE074	Total agricultural area out of production	15.295233
SE410	Gross Farm Income	288.87124
AASBIO_CV	Biological assets - plants Closing value	5.092934
SE136	Total crops output / ha	-45.241371
SE175	Fruit trees and berries grown in the open (including tropical fruit), excluding citrus fruit orchards and grapes.	45.269543
ORGANIC	Organic farming Code	17.766311
SE131	Total output	-512.318997
SE281	Total specific costs	240.466735
SE125	Milk yield	11.36649
SE750	Total specific costs for OGA	12.132709
SE011	Labour input	-40.348135
SE356	Other direct inputs	35.385069
SSPSN_1_V	SPS normal Value with fi 1	-50.836709
ICNTR_V	Contract work and machinery hire Value	22.38548
SSPSS_1_V	SPS special entitlement. Value with fi 1	-11.820478
AMCHQP_CV	Machinery and equipment Closing value	10.680191
UAAOWNED	UAA for owner farming Area	-5.879081

Denmark		
SE650	Support_Art68	33.876871
AGE	Age	-15.592034
SE074	Total agricultural area out of production	138.954392
SE072	Agricultural fallows	-119.637185

Malta		
AASBIO_CV	Biological assets - plants Closing value	11.240036

Italy		
SE120D	SE120 denominator	55.975325
SE132	Total output / Total input	-15.855088
SE054	Permanent crops	35.098501
SE050	Vineyards	15.300098

SE165	Industrial crops	12.09007
AGE	Age	-17.4963
SE206	Total output livestock & livestock products	-18.512054
AFRMBLD_CV	Farm buildings. Closing valuation	14.420215
SE041	Other field crops	6.691618
SE305	Other crop specific costs	-27.412069

Latvia		
SE120	Stocking density	-9.613763
SE005	Economic size	15.655252

France		
SE284	Specific crop costs / ha	-718.864574
NAT2000	Natura 2000 area Share	20.706225
NUTS3_FRA10	NUTS NUTS3: class FRA10	48.54365
SE305	Other crop specific costs	9.06644
SE441	Total fixed assets	18.494814
SE309N	SE309 numerator	-11.052391
OTRISM_SV	Tourism, accommodation, catering and other leisure activities Sales value	4.993765
NUTS3_FRA40	NUTS NUTS3: class FRA40	9.462961
NUTS3_FR432	NUTS NUTS3: class FR432	17.097531

Portugal		
cAASBIO_CV	Biological assets - plants Closing value	11.061012
SE046	Vegetables and flowers	-149.633989

Cyprus		
SE065	Other permanent crops	32.710826

Slovkia		
SE080	Total livestock units	18.193912
SE110	Yield of wheat	-14.476316

Poland		
SE041	Other field crops	87.771458
SE160	Oil-seed crops	-107.94097

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SE284	Specific crop costs / ha	-239.118728
SE115D	SE115 denominator	33.392014
SE025	(OGA) in total labour	232.871289
IWATR_V	Water Value	-17.609774
SE085	Dairy cows (incl. buffaloes)	-39.669836
SE140	Cereals. Value	-75.190993
SIZC_13	Economic size class (cf. EU typology): class 13	-21.289267
SE035	Cereals. Area	-81.064772
SE420	Farm Net Income	16.22381
SE132	Total output / Total input	-12.462641
SE356	Other direct inputs	21.684591
SE030	Rented U.A.A.	-30.63455

Ireland		
ACSHEQ_CV	Cash and equivalents Closing value	-16.158371
ANC	Areas facing natural and other specific constraints	12.489862

Bulgaria		
SE495	Short-term loans	24.419456
SYS02	Farms represented	-30.880123
SE425	Farm Net Value Added / AWU	27.825556
SE132	Total output / Total input	-20.308294
TF8_6	Type of Farming (8): class 6	9.257247
TF	Subd/Part TF (3 digits + 0)	10.829579
NUTS3_BG332	NUTS NUTS3: class BG332	-4.734726

Slovenia		
SE041	Other field crops	20.67478
ALNDAGR_CV	Agricultural land Closing value	-10.945392
SE284N	SE284 numerator	10.691036

Hungary		
AASBIO_CV	Biological assets - plants Closing value	41.596573
SE284	Specific crop costs / ha	-496.164942
SE010	Total labour input	100.851204
SE110N	SE110 numerator	-27.482311

SE430N	SE430 numerator	16.752627
SE054	Permanent crops	19.844932
IRNT_V	Rent paid, total Value	36.656299
SE035	Cereals. Area	-57.417502

Germany		
SE072	Agricultural fallows	-316.590451
ALNDFRSTST_CV	Forest land including standing timber Closing value	33.105751
SE170	Vegetables & flowers	-35.124094
WPROTH_P	Other Paid Number of persons	26.377094
SE095	Sheep and goats	12.818242
ORGANIC	Organic farming Code	370.741066
WPCCA_P	Casual Paid Number of persons	-335.253981
SE185	Wine and grapes	-24.786914
NUTS3_DE118	NUTS NUTS3: class DE118	35.111906
SE200	Other crop output	-9.229017
NUTS3_DE21	NUTS NUTS3: class DE21	-8.72853
NUTS3_DE937	NUTS NUTS3: class DE937	-25.369616
NUTS3_DE939	NUTS NUTS3: class DE939	-16.105018
NUTS3_DEB23	NUTS NUTS3: class DEB23	-16.328214

Belgium		
SE495	Short-term loans	24.510486
SE206	Total output livestock & livestock products	-13.10869
SE136	Total crops output / ha	-19.275744
SE055	Orchards	6.094285

Czech Republic		
SE460	Breeding livestock	52.863901
SE110	Yield of wheat	-15.030686
SE225	Pigmeat	-14.161729
AASBIO_CV	Biological assets - plants Closing value	10.731191
ACSHEQ_CV	Cash and equivalents Closing value	-7.993011

United Kingdom		
SE025	(OGA) in total labour	37.181896

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SE011	Labour input	-24.370596
STRUCTF	Structural Funds area Code	-17.477759

Estonia		
SE071	Forage crops (roots and brassicas, other fodder plants, temporary grass, meadows and permanent pastures, rough grazing.	48.676774

Sweden		
SE120	Stocking density	29.914838
SE132	Total output / Total input	-9.802423

Austria		
SE284	Specific crop costs / ha	-36.070672
ALNDAGR_CV	Agricultural land Closing value	17.628611
SE185	Wine and grapes	16.511112

Finland		
SE046	Vegetables and flowers	-53.080045
SE501	Net worth	7.116317

8.3 Results of GLM and ABM

Table 3. The proportion of farms that were accuracy predicted for each country with each model

Country	GLM	ABM Choice = None	ABM Choice = yes/no	ABM Choice = sorted
Romania	0.01	0.78	0.59	0.98
Lithuania	0.07	0.73	0.86	0.88
Croatia	0.35	0.73	0.55	0.87
Greece	0.75	0.74	0.81	0.86
Netherlands	0.63	0.7	0.7	0.79
Spain	0.72	0.67	0.69	0.76
Denmark	0.88	0.68	0.79	0.76
Malta	0.19	0.63	0.79	0.71
Italy	0.75	0.64	0.69	0.66

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Latvia	0.63	0.65	0.71	0.68
France	0.65	0.64	0.75	0.67
Portugal	0.37	0.61	0.64	0.67
Cyprus	0.22	0.64	0.79	0.67
Slovakia	0.65	0.63	0.68	0.73
Poland	0.74	0.62	0.76	0.63
Ireland	0.6	0.59	0.73	0.55
Bulgaria	0.71	0.59	0.74	0.54
Slovenia	0.67	0.61	0.71	0.59
Hungary	0.75	0.59	0.7	0.58
Germany	0.71	0.53	0.63	0.45
Belgian	0.72	0.48	0.67	0.48
Czech Republic	0.73	0.52	0.73	0.65
United Kingdom	0.68	0.48	0.62	0.55
Estonia	0.81	0.51	0.76	0.79
Sweden	0.74	0.53	0.8	0.81
Austria	0.71	0.5	0.72	0.87
Finland	0.94	0.82	0.95	0.38
Luxembourg	0	0.61	0.04	0.8

8.4 ODD+D for European Union ABM

The ABM for the EU is adapted from the ABM used in the case studies in Deliverable 4.1.

1. **Overview**

Purpose

What is the purpose of the study?

The BESTMAP-ABM-EU model is a member of the BESTMAP-ABM model suite focusing on the European Union. The purpose of the BESTMAP-ABM-EU model is to determine the adoption of any agri-environmental scheme (AES) by individual farmers in 28 countries across the EU (Ziv et al., 2020). 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.

For whom is the model designed?

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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.

Entities, state variables, and scales
What kinds of entities are in the model?
The model contains *farm* agents that represent individual farmers, who may own multiple fields and may or may not adopt an AES.

By what attributes (i.e. state variables and parameters) are these entities characterised?
The table below lists the attributes of the farmers.

Constant farmer state variables

Description	**Variable name**	**Class**	**Value restrictions**
Farmer ID	id	string	-
Size of farm in ha	area	float	>0
Farm specialisation*	fsa	integer	In the range [0-5] representing P1, P2, P3, P4 and mixed
Economic size of holding expressed in 1000 euro of standard output (on the basis of the Community typology).	eco_size	integer	In the range [0-2] representing small, medium and large
Probability for intrinsic openness towards each AES which is derived from the adoption rate in the data, multiplied by a constant *lambda* which may be tuned by the model user.	openness	float	In the range [0-1]
Whether or not a farmer has access to advisory support	p_advisory	binary	-
The minimum payment given for an AES in Euros that the farmer is willing to accept	accepted_payment	integer	>0
Whether the farmer accepts an AES	accepted_open	binary	-
The rank of a farmer's score in the prediction by the regression model, which is used to decide	subset_mod_rank	integer	>0

the order in which farmers consider an AES.

*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.

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. Farmers' prior AES experiences are initialised based on the adoption data of AES. 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 and advisory services 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.

Process overview and scheduling
The following processes occur in each time step:

- Update farmers' status of whether to enter into a decision-making phase.
- Decision Making Step 1 - Check openness to an AES.
- Decision Making Step 2 - Deliberation: Check for each farmer whether the offered payment equals to or exceeds the accepted payment.

Further details on each of these steps are given in the next section.

2. **Design concepts**

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.

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 and/or influence from advisory.
In addition, 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 data available?

- From the FADN data, the variable SAEAWSUB_V (Agri-environment and animal welfare payments value) provides the monetary amount received by the farmer for an AES. This is used as a binary indicator of whether or not a farmer has adopted an AES. Further, this variable is used to parameterise farmers' intrinsic openness towards an AES by assuming that openness towards an AES is proportional to the historic adoption rate.

- The Eurostat data of Agri-environmental indicators—farmers' training and environmental farm advisory services, 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. Using data describing the UK, 48% of 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.

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 to adopt an AES. There are two levels of decision making included, (1) the determination of general openness towards the adoption of specific AES, and (2) the deliberation 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 applying for an AES.

- Decision Making Step 2: 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 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 (see also Figure 10).

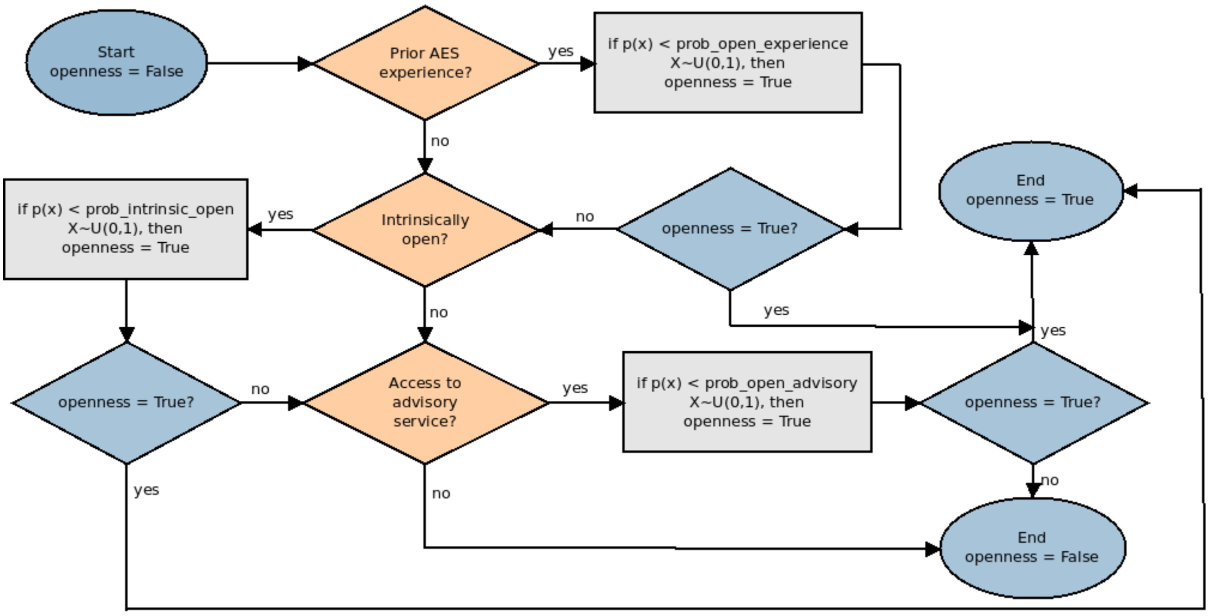

Figure 10: The flowchart of Step 1 in the decision making framework for a selected AES. Farmers' openness status (true or false) is decided by three factors – whether a farmer agent has prior experience, whether they are intrinsically open to an AES, and whether they have access to advisory service. The impact of these three factors are set by three probability-based parameters: "prob_open_experience", "prob_intrinsic_open" and "prob_open_advisory", 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 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.

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. 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).

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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 as farmers' intrinsic openness is partially influenced by the social norms and values they believe in.

Do spatial aspects play a role in the decision process?

Spatial aspects are not included in the model as the data does not include information on which fields and how much of a field is dedicated to an AES.

Do temporal aspects play a role in the decision process?

Previous adoption of an AES influences the openness towards the adoption of an 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.

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.

Is collective learning implemented in the model?

Collective learning is not considered in the model.

Individual Sensing
What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?
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 do not know the adoption of other farmers in their social network.

What is the spatial scale of sensing?
Farmers are not aware of spatial information.

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).

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.

Interactions
Are interactions among agents and entities assumed as direct or indirect? On what do the interactions depend?
Farms do not interact with other farmers.

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.

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 access to advisory support, the prior AES experiences, the intrinsic openness and their expected payment level for the four AES. All farmers have the same set of state variables and processes.

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.

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:

    1. Farmers with their own prior experience have a higher chance of being open towards the adoption of AES.

    2. Farmers are intrinsically open to consider the adoption of each AES with different probabilities depending on farm characteristics.

3. 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.

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 to 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.

Observation
What data are collected from the ABM for testing, understanding and analysing it, and how and when are they collected?
Farmers' identification number, decision to adopt an AES and their minimum accepted payment are collected from the ABM for testing, understanding and analysing purposes. The data is saved in csv files. Further analysis information can be obtained by linking a farm to the FADN data by its ID.

What key results, outputs or characteristics of the model are emerging from the individuals?
Observations can include effects of policy design, e.g. the availability of advisory support and its importance on AES adoption rates.

3. **Details**

Implementation Details
How has the model been implemented? Is the model accessible, and if so where?
The model has been implemented in Python 3.x. The model source code is publicly available at https://git.ufz.de/bestmap/bestmap-aes-eu/.

Initialization
What is the initial state of the model world, i.e. at time t=0 of a simulation run?
- Farmers are initialised with the input data containing their characteristics, including FSA, economic sizes, farm areas, and prior AES experience (from FADN data 2014-2017). A farmer's openness due to prior AES experience, intrinsic openness or the influence from advisory services 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.

- 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.

Is initialization always the same, or is it allowed to vary among simulations?
Farmer characteristics are the same, but the probabilities of farmers being open to AES adoption due to prior AES experiences, advisory services and intrinsic openness and the probability of having access to advisory support 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.
AES contract characteristics (duration, bureaucratic effort, offered payment level) are varied between scenarios representing different policy designs.

Are the initial values chosen arbitrarily or based on data?
Initial values for landscape, farmer characteristics and envisioned area are based on sampled FADN data in the period 2014-2017. Initial values for accepted payment level are set through calibration based on the model baseline.
A farmer's openness due to prior AES experience, or access to and the influence from advisory services is randomly assigned using the model parameters *prob_open_exp, access_adv and prob_open_adv*. 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.

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.

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 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. In addition, each farmers' WTA is calculated at the initialisation stage.

Model parameters in initialisation

Parameter	Variable name	Baseline values	Possible values
Offered payment level for an AES in Euros/ha	offered_payment	Based on JRC data	And value depending on policy designs

Probability that a farmer has access to advisory	access_adv	0.8	0.2-0.8
Probability that a farmer with prior knowledge of AES is open towards adopting an AES	prob_open_exp	0 (The model starts with the assumption that farmers have no prior experience)	0.0-0.8
Probability that a farmer with access to advisory is open towards adopting an AES	prob_open_adv	0.5	0.1-0.9
Probability of being intrinsically open towards considering adopting an AES	intrinsic_opennness	lambda_open * (adoption rate of FSA farms)	0.0-1.0
The proportion of intrinsic openness to the historic adoption rates	lambda_open	1.5	1.0-30.0

Farmers' WTA calculation
The farmers' WTA calculation is implemented in the function *set_wta* and assigned to each farm in the function *setup_farmers*. The WTA of each farmer is drawn randomly based on the normal distribution $N\,(\mu,\, v^2)$ where μ is the mean WTA of the FSA and v^2 = 0.1 where v is the coefficient of variation.. Figure 11 shows an example.

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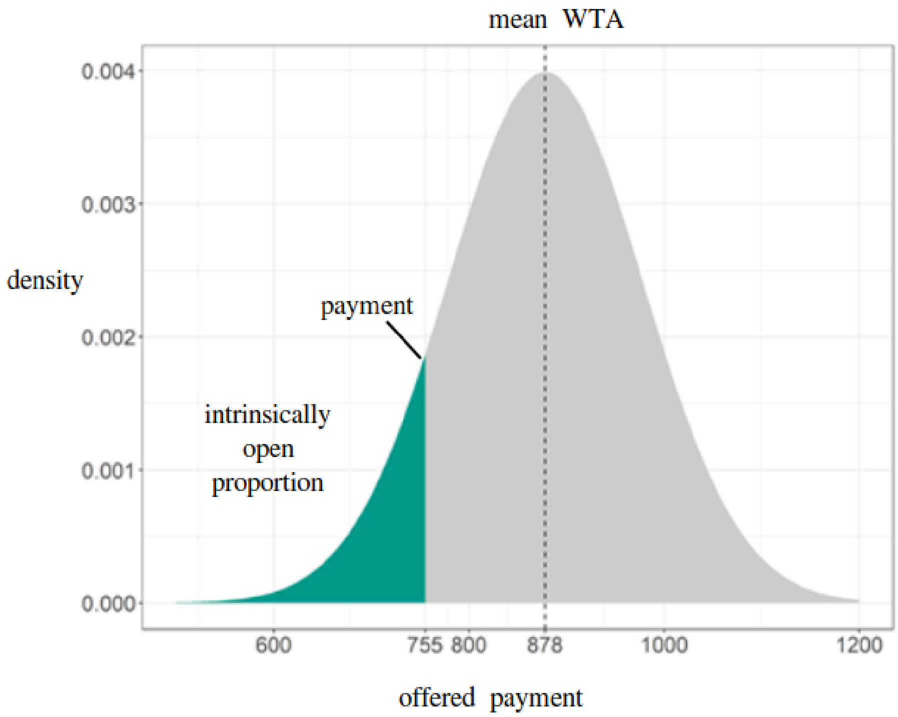

Figure 11. Exemplary distribution of expected payment levels for a scheme with adoption rate 10.9% (highlighted in green), offered payment level 755€/ha and standard deviation of 100€/ha. The resulting mean expected payment level is 878€/ha.

In the model, we implement multiple ways of WTA setups. If the attribute model_choices is selected as NONE, the process in the model will carry out as described above. Furthermore, if model_choices is selected as YES_NO or SORTED then the WTA is calculated by integrating the regression model results as described next.

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 each country's farmers' participation of AES using the method presented in the paper by Paulus et. al. (2022). The regression model is based on farm attributes x_i, with coefficients β_j, $j = 0, 1,..., m$ derived in :

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

As a result, a farmer is predicted to participate if $p_i > 0.5$, and he/she doesn't participate if $p_i \leq 0.5$. The pi values of all farmers are sorted in an ascending order and the ranking is stored in the ABM parameter *mod_subset_rank*.

If the parameter *model_choices* is set to *YES_NO*, 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 functions *random_normal_controlled* and setup_farmers.

If the parameter model_choices is set to be SORTED, 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 functions set_wta and setup_farmers.

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 prob_open_exp.

- Check intrinsic openness: For farmers without prior experience set openness to 1 with probability openness.

- Check advisory support: For farmers not intrinsically open but with access to advisory support set openness to 1 with probability prob_open_adv.

Deliberation (Decision Making Step 2)
In the deliberation process (the function deliberate_aes_decision), farmers compare their WTA with the offered payment, and if their WTA is less than or equal to the offered payment then they will choose to adopt an AES.

Additional information
The model is built in with some processes for testing and analysis purposes.

Running the model for each country
The file run_all_countries is built to run the model once for every country with the same settings.

Tuning parameters
The file tune_lambda is built to run the model for each country for different values of *lambda* (affecting WTA) to analyse the results and choose an appropriate value of *lambda*. *Lambda* must be a value greater than 1 to gain accurate results. In the current value, values from 1.0 to 1.9 are compared, and values in the range 1.4-1.6 produce good results. If *lambda* is lower than 1.4 the model consistently underestimates AES uptake across countries, and if *lambda* is greater than 1.6 the model consistently overestimates uptake. The average absolute error in uptake is used to measure model accuracy and determine an appropriate value of *lambda*.

Multiple runs in one go
The file run_ensembles is built to run the model multiple times with the same settings (including the same country) to analyse how stochasticity in the model affects the results. We find that stochasticity does not create noticeably large changes in results.

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