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RESEARCH ARTICLE

Predicting adoption of agri-environmental schemes by farmers in the European Union

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Abstract

Much of the land across the European Union (EU) is threatened by unsustainable land-use through intensive farming. To help combat this, Agri-Environmental Schemes (AESs) are provided by the EU to encourage farmers to use a portion of their land to aid with environmental goals such as sustainable farming, bio-diversity or landscape recovery. Farmers in the EU are given the opportunity to take on an AES for a monetary payment that is based on the choice of scheme and the amount of land dedicated to it. If we know or can accurately predict which farmers adopt which AES, we can then predict if the intended benefits to the environment according to the given scheme are likely to be achieved. As a preliminary step, we develop a generalised linear model coupled with a microsimulation that is fed with data from the Farm Accountancy Data Network to predict AES uptake. We find the model is able to accurately predict approximately 70% of farmers' decisions on whether to adopt an AES across 27 countries in the EU. In the future, this model can be used to predict, for example, if the chosen schemes adopted will lead to their intended benefits, and if changes in the offered AES payment may affect AES adoption.

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Author summary

The intensity of farming practices differs greatly across the European Union (EU) and post-Brexit United Kingdom. More intensive farming (e.g. high use of fertilisers, pesticides and herbicides) has a negative effect on wildlife populations, air quality and natural flood management. Since 1992, the EU has offered Agri-Environmental Schemes (AES) which encourage farmers to adopt practices that reduce their farming intensity in environmentally sensitive areas in exchange for monetary compensation for the subsequent loss of income. This system has come under scrutiny amid widespread European farmer protests in 2024, with demonstrators demanding more flexibility in environmental rules

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and better compensation for green farming practices. Meanwhile, the UK has replaced EU policies with its Environmental Land Management Scheme (ELMS). It is important to be able to predict if farmers are likely to use these environmental schemes so the potential benefits can be understood. This paper develops a model predicting AES adoption using data on farm characteristics across the EU (e.g. economic size, crop/livestock types) and subsidy receipt history. The model achieves high accuracy and will help forecast how policy changes might affect scheme participation and subsequent environmental outcomes, while also evaluating if increasing advisory support for farmers could boost uptake.

1. Introduction

Agri-environmental schemes (AESs) are initiatives within the European Union (EU) that incentivise farmers to adopt environmentally friendly practices (and to continue to maintain these practices where it may not be economically viable without subsidies) in exchange for monetary compensation. Such practices include crop rotation or diversification, establishing buffer strips along rivers and lakes, or minimising soil cover in winter. The objectives of AESs are wide, including preserving bio-diversity, reducing pesticide use and improving water quality.

These schemes are a significant investment for governments. Countries across the EU allocate 14.8-32.4% of their EU agricultural funding to Agri-Environment and Climate schemes [1]. It is therefore crucial to ensure the effectiveness and efficiency of these schemes. A key factor in achieving this is understanding the motivations that drive farmers to participate in AESs. This insight can guide the design of schemes that successfully promote sustainable farming and environmental preservation.

Fig 1 shows the proportion of farmers that adopted an AES in the EU in 2016 ordered by adoption rates. The figure shows that uptake of AES differs greatly between different countries. For example, typically those in northern Europe are more likely to adopt than those in southern Europe [2]. There has been research investigating the impact of farm attributes such as size, profitability, and crop and livestock types on the likelihood of AES adoption. For example, larger farms are found more likely to participate in an AES because they are more likely to have suitable land for conservation practices, the labour needed to process the paperwork, and higher financial incentives to participate in an AES (as payments are usually per hectare [3]) [2,4,5]. Farm system archetypes have also often been found to have an effect. Studies have found that farms with grassland and permanent crops are more likely to adopt a scheme than those with arable farms [2,6]. In addition, farms with livestock are more likely to adopt than those without [7]. However, these findings (and others) are not always consistent as different studies do not always find the same variables to have the same significant effects [8].

Personal and social factors are also known to affect uptake. For example, uptake is increased if a farmer knows another farmer who has an AES, if the farmer has knowledge and awareness of sustainable practices and the AESs, or if the farmer has taken on an AES in the past [9–11]. The presence of a successor also increases uptake [12] and farms with low soil quality are also more likely to participate [13].

Simulation methods such as microsimulations and agent-based modelling have been used to study individual farmer behaviour and decision-making for their flexibility and adaptability. Large-scale simulation frameworks have been developed to study the impact of Common

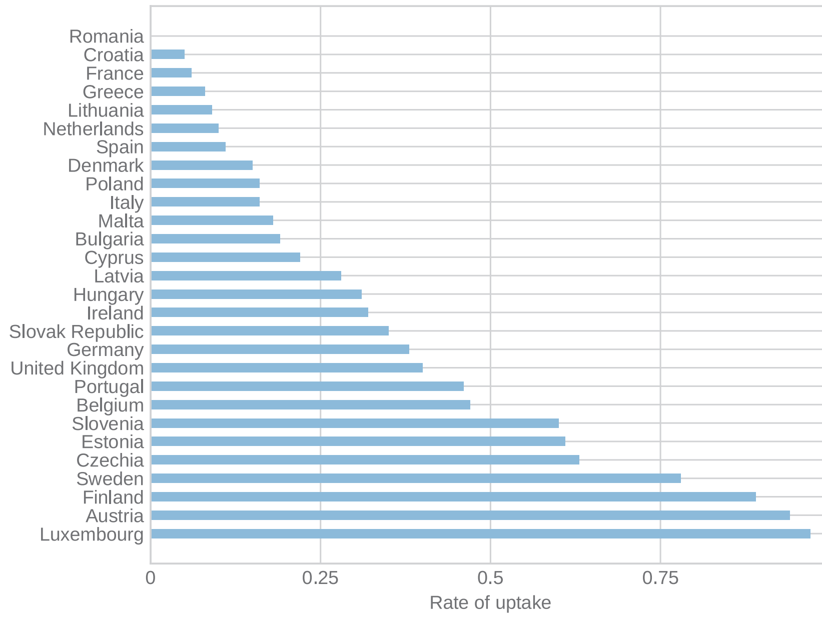

Fig 1. Proportion of sampled farms that take on an AES in each country given by the FADN data in 2016.

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Agricultural Policies (CAP) in European countries, of which two prominent ones are AgriPolis [14] and IFM-CAP [15]. AgriPolis is an agent-based agricultural policy simulator that simulates the impact of agricultural policy reform on farmers' land use decisions. IFM-CAP is an EU-wide individual-based model that assesses the impacts of CAP on European farms. In both models, farmers' land-use decisions are driven by profit maximisation and economic considerations using dynamic programming. AgriPolis shows potential in predicting changes in farm size and farmers choosing to close farms as a result of changing agricultural policies [16]. Although very useful, the existing simulation frameworks cannot fully capture the complex variables influencing farmer decision making and AES adoption, especially farmers' values, emotions and interactions [17].

In this paper, we present a two-staged approach to modelling farmer adoption of AES, combining a logistic regression and a microsimulation. This model can be used to predict how changes in the offered payment and availability of advisory support is likely to affect AES uptake. In addition, in future work, results will be used to predict the environmental outcomes of AES adoption [18]. We will first use a generalised linear model (GLM) to estimate the likelihood of individual farmers adopting AESs. We will then input these estimates into the microsimulation, which can accommodate more flexible behaviours beyond pure economic considerations, such as whether the farmers are open to AES, or if they have access to an advisory service. By doing so, we take advantage of both methods: the data-driven GLM generates predictions of adoption likelihood of farmers based on a diverse range of data, and the flexible microsimulation allows us to investigate rich behaviours and the impact of policies and scenarios.

2. Data

For this project we use data from the Farm Accountancy Data Network (FADN) database. The FADN is an EU dataset that collects standardised farm-level accounting data annually from a representative sample of agricultural holdings across EU member states. The data captures detailed financial, operational, and structural information including farm income, production costs, subsidies received, labour inputs, land use, livestock numbers and crop yields. For our model, we use the data for all EU countries in the year range 2014-2015 for training and 2016 for testing. Within the FADN database, each farm in each country is described by 350 variables that detail, for example, economic information and information detailing the use of the land. 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. Fig 1 shows the rate of farms sampled in each country that adopt a scheme according to this variable, ordered by adoption rates.

Fig 2 provides some contextual information for each country (ordered by AES adoption rates), including the total number of farms (in the sampled data), the percentage of land used

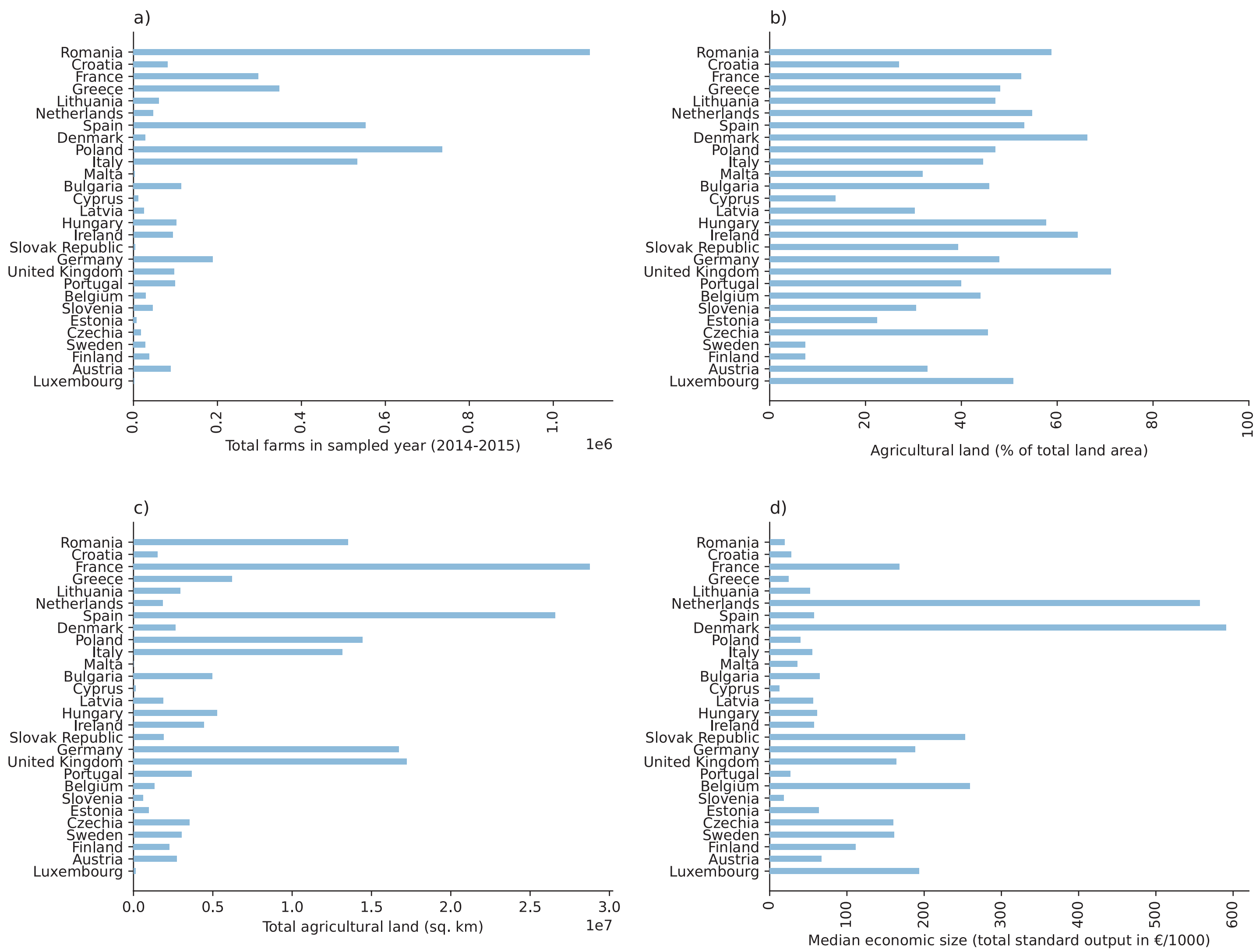

Fig 2. a) Total farms; b) Percentage of total land used for agriculture; c) Total area of agricultural land; d) Median economic size (of total farm standard output in €/1000) of each country in the sampled year in 2014-2015.

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for agriculture, the total land area used for agriculture, and the median economic size of the farms. Countries differ significantly within these four measures, and there is no clear correlation between any of these categories, or between these measures and rates of AES adoption.

3. Method

We model AES adoption in the EU as 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 rates in the data differ widely across different countries (see Fig 1) and, as a result, we have found that a single model is not effective for predicting all countries. More details on the methods and results of the GLM can be found in Sect 4.

Next, the GLM results are used as inputs for a microsimulation (MS). 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 MS 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 MS can also be altered. More details on the methods and results of the MS can be found in Sect 5.

4. Logistic Regression model

We first train a GLM to produce initial predictions on which farms within the FADN data will take on an AES. This work is in the same vein as that described by Paulus et al. [19] but differs in that we use a much larger set of data across multiple countries. The results of this will be interpreted as either a yes/no prediction that farmers will adopt an AES, or as a sorted rank order of farmers' likelihood of adoption. These results will then be fed as inputs for the MS.

4.1. Methods

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. Each variable has both an ID and a short description. For example, as given earlier, our independent variable has the ID *SAEAWSUB_V* and the description *Agri-environment and animal welfare payments value*. Before using regression to find which variables explain our independent variable, we must first clear the data of those that are obviously of no use. First, we remove any variables that have the string *subsidy*, *subsidies* or *payment* in the description as our independent variable is a subset of the information in other subsidy and payment related variables. There are also multiple (sometimes different) variables across the countries where the data are the same for all farms, or where data is missing. These are also excluded from consideration in the model. S1 Table lists all of the variables that were removed. Most relate to subsidies or payments and have a high correlation with our independent variable. The country and year are removed because we are sampling the data into groups of the same country and year. Altitude is also removed because this data is often missing for many of the farms. In total, 98 variables were removed, leaving 252 variables—this is the same across all countries.

Of the remaining variables, not all of them will be useful for predicting AES adoption. In fact, most are non-significant at $p < 0.1$. To find the variables that are useful and significant, we perform stepwise regression. This involves starting with a model that has no variables, gradually adding one significant variable at a time and removing any variables previously added that have become non-significant.

We first run a GLM containing only a single variable for each of our remaining 252 variables (therefore running 252 models). Of all the models where the variable was found to be statistically significant ($p < 0.1$) we choose the variable that reduced the total sum of squares the most (i.e. that provided the best fit between the predicted and actual AES adoption rates). This variable is now included in the model. We then test including two variables in the model (the one just added and one of the remaining 251 variables). As in the previous iteration, we test each variable separately, therefore testing 251 GLMs containing two variables. As before, we select the variable that has a significant p-value ($p < 0.1$) and reduces the sum of squares the most. We repeat this process, adding an extra variable each time, until none of the newly tested variables have a significant effect.

In addition, each time a new variable is added to the GLM, we check if any previously added variables have become non-significant ($p > 0.2$). We use a higher alpha-criterion for this to ensure we do not accidentally remove a variable that has a significant impact in explaining the model.

We run the above process separately for each country. As a result of considering only one significant variable that explains the data at a time, the final set of variables in the model do not have any issues with multicollinearity for any country. For each country, the variables that were found to predict AES uptake the best differed, as did the total variables selected. S2 Table lists each variable selected for each country and its coefficient.

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 rates in the data are under-predicted by the model.

4.2. Results

S2 Table lists the variables that were selected by the stepwise regression process for each country. The results show that some variables had a much stronger effect on predicting uptake over others, and a variable that has a positive effect for one country may have a negative effect for a different country. Variables that had an impact range from relating to crops, livestock and the financial status of the farm. For example, crop costs usually have a negative impact (Austria, France and Italy) and the specific choice of crops may also have a negative impact (Poland, Slovenia). Sometimes the values of crops had a positive effect (Lithuania, Luxembourg and Malta), but the accuracy of predictions in these countries was poor. Permanent crops on the farm always had a positive effect (where found to be significant). The use of livestock was sometimes found to have a positive effect on AES adoption (Czechia, Hungary, Slovakia and Sweden). Livestock was only found to have a negative effect in Croatia, but the model performs poorly in this case, suggesting that factors not described within the FADN data (e.g. social factors) may be better at explaining uptake within Croatia. The financial status of a farm often had the largest effect for a given country. For example, a farm having loans increased uptake (Belgium and Bulgaria). The effect of total owned cash differed, sometimes having a positive effect (Greece and Romania) but sometimes negative (Latvia). Finally, total output of the farm had a large negative effect for Spain (suggesting farms that value high output do not wish to forfeit production as a result of an AES), and the total utilised agricultural area had a large positive impact on uptake for the United Kingdom.

Fig 3 shows the adoption rates predicted by the GLMs. The percentage of adoption in the data is represented in blue, whilst the model predictions are in orange. Note that this figure shows how many farms were predicted to take on AES but it does not show if individual farms were correctly predicted. To see this, Fig 4a shows the total percentage of farms that have (or haven't) taken on an AES in the data and were correctly predicted to adopt (or not adopt) an AES by the GLM. These results are also summarised in S3 Table.

Fig 4b shows the accuracy of the GLM against the total agricultural land within a country. In this, there is some correlation showing that the more agricultural land a country has the better the GLM usually predicts AES uptake. It is most likely the case that the model performs poorly at predicting AES uptake in countries with little agricultural land because there is less data in these cases to train the model. It is also sometimes the case that in small countries all farms take on a scheme (e.g. Luxembourg) or that no farms adopt an AES (e.g. Romania). In these cases, there is either not enough data to confidently explain why a small proportion

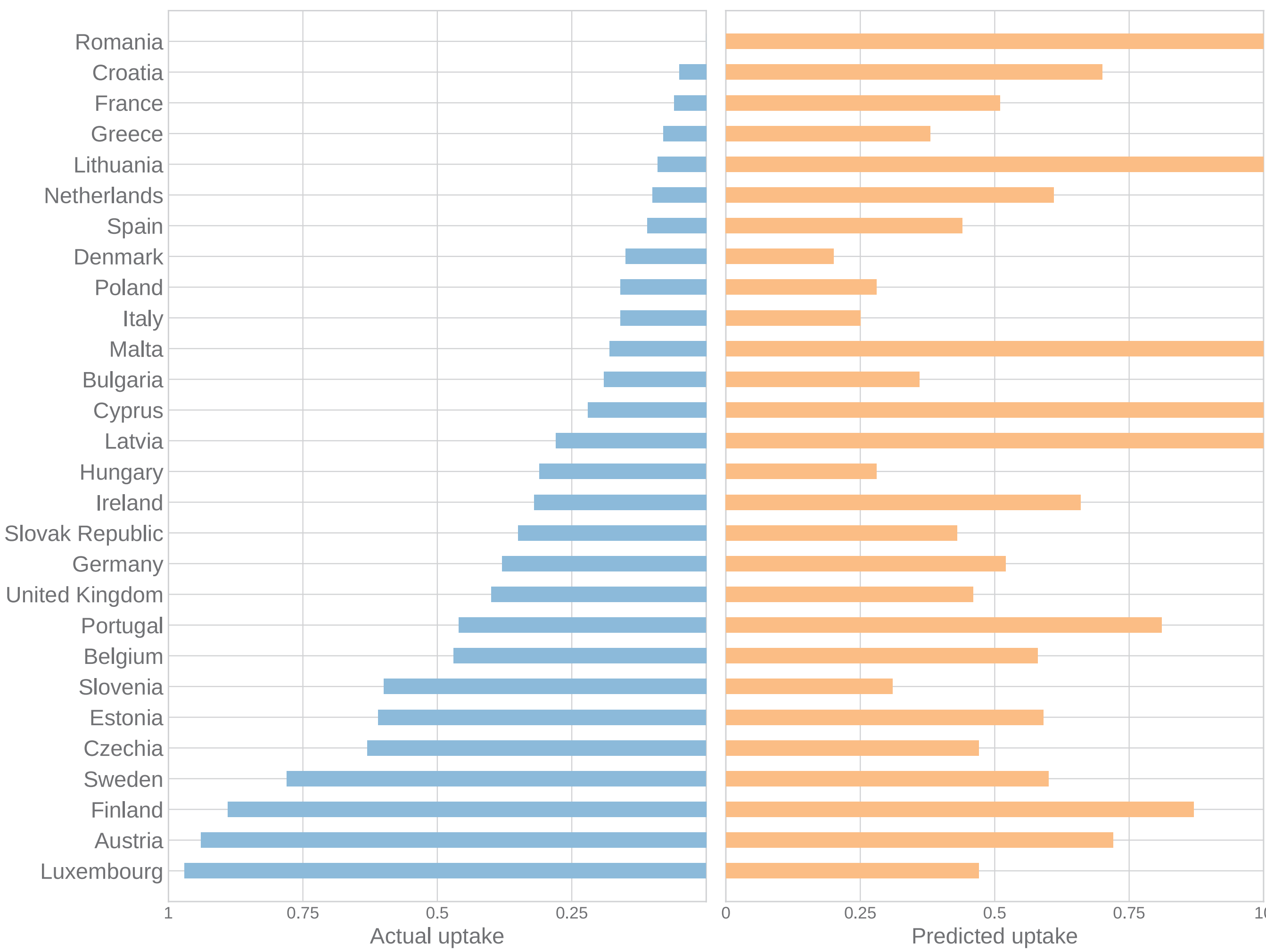

Fig 3. Total farms that take on an AES in the data (blue) and the GLM (orange).

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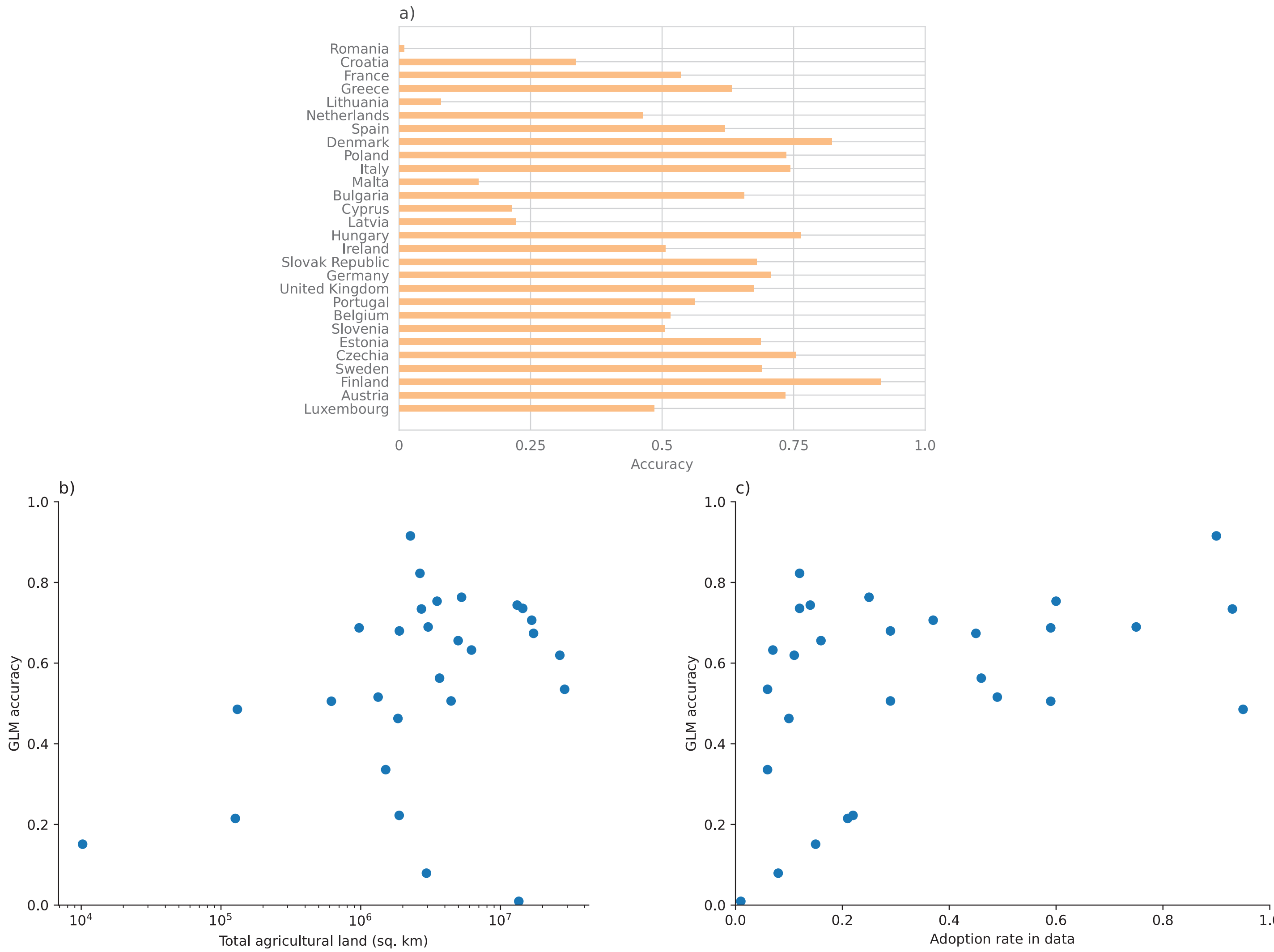

Fig 4. a) Accuracy of the GLM (i.e. the proportion of farms correctly predicted to adopt or not adopt by the GLM); b) Accuracy of the GLM against total agricultural land for each country; c) Accuracy of the GLM against adoption rates in the data.

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of farms are exceptions, or it may be that these cases are better explained with social and/or environmental information (which is not part of the FADN data). For countries with a large amount of agricultural land the model performs better, but there is still a trend of predicting higher rates of adoption than in the data for countries with little AES uptake, and predicting lower rates for countries with high uptake.

Fig 4c shows the accuracy of the GLM against AES adoption rates in the data. This shows there is little correlation between actual AES uptake and the GLM's ability to make accurate predictions.

5. Microsimulation

The MS used to predict uptake of AES in the EU is based on agent based models developed to predict uptake in five case studies (South Moravia, Czech Republic; Mulde Region, Germany; Catalonia, Spain; Bačka Region, Serbia; and Humber Region, United Kingdom) [20].

This model uses predictions from the GLM as input, as well as data on the proportion of farmers who have historically taken on an AES, and user defined inputs detailing the likelihood farmers will be open to adopting an AES and the likelihood they will have influence from an advisor. The payment offered for an AES may also be altered to differ from past data.

5.1. Methods

5.1.1. Clustering the data. Based on the literature, we expect the type of farming (e.g. livestock or crops) and the economic size of the farm will have an impact on AES uptake [2,6]. Therefore, we group the farms into clusters describing their Farm System Archetype (FSA). Using the FADN variable *TF8* (type of farming divided into eight categories) we regroup the farms into five FSA groups. The new categories 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. This grouping helps reduce the complexity of the model and ensure that there are no groups with only a small number of farms. Further details on these categories can be found in the BESTMAP project Deliverable 3.5 [21].

We also group farms according to their economic sizes (FADN variable *SE005*). Fig 5 shows a histogram of the total farms across all countries with a given economic size. Through this observation, we group farms into three clusters: those with an economic size of less than €7,000,000 (small), between €7,000,000 and €30,000,000 (medium) and greater than €30,000,000 (large). These thresholds are used across all countries.

5.1.2. Model process The model first decides if a farmer is open to the idea of adopting an AES. If the farmer decides they are open to the idea, they then decide whether to adopt based on the offered payment. Fig 6 shows a flowchart of the steps taken by the MS. First, the probability that a farmer is open to having an AES is based on having had previous experience. This is a parameter that can be chosen by the model user. If after this step the farmer is still not open to adoption then the likelihood of a farmer being open is related to the proportion of farms in their country, FSA type group and economic size group that have adopted in recent

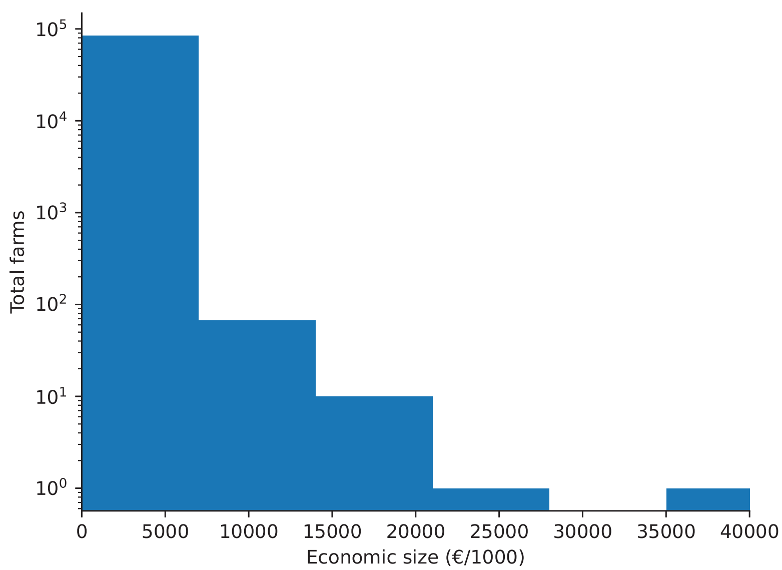

Fig 5. Histogram showing the total farms across all countries with a given economic size (total standard output in €/1000).

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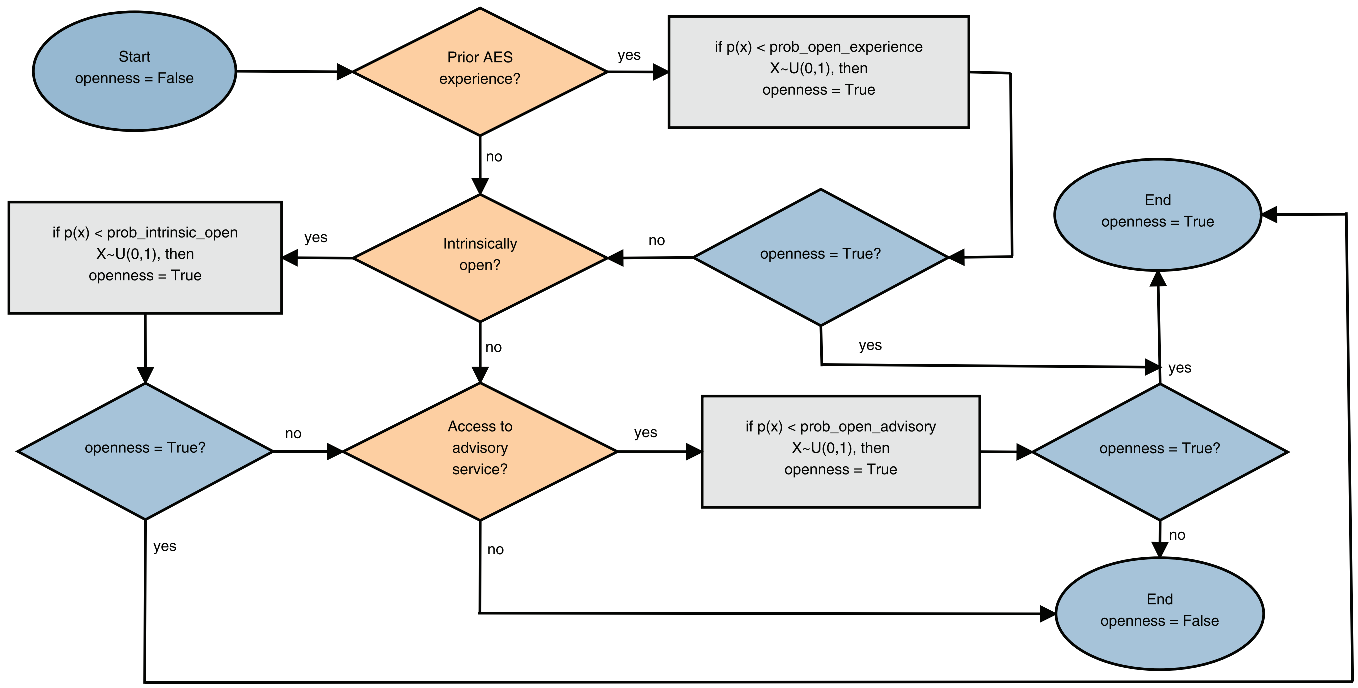

Fig 6. A flowchart of the process taken by the MS.

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years (i.e. the year chosen for the test data). Finally, if the farmer is still not open to adoption, their likelihood of adopting is affected by two parameters given by the user that describe a farmer's access to an advisory. These are the probability that a farmer will have access to an advisory, and the probability that having an advisory will result in a farmer becoming open to adoption. At the end of this process, a farmer is either open or not open to adopting an AES. Whether they then go on to adopt depends on if the payment they are offered is at least as great as the payment they are willing to accept as described next.

5.1.3. Selecting a farmer's accepted payment from the GLM results. The output of the GLM is a prediction of whether each farm will adopt an AES. This prediction can be used by the MS to decide the minimum payment a farmer is willing to accept for an AES. There are two methods by which the GLM prediction can be used. The first method is the *YES/NO* method. With this, if the prediction that a farmer will adopt according to the GLM 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 value greater than the offered payment. The payments are selected from a normal distribution (derived by [21]), with a mean based on the payment received and proportion of farms that have accepted the payment in the data, and a standard deviation of 0.1 (relative to the mean). A meta-analysis found farmers' mean willingness to accept (WTA) for sustainable farming practices ranges from $567/ha/year to $709/ha/year [22]. Applying a normal distribution with a 95% interval at the minimum and maximum values above, the figures translates roughly into 0.1 standard deviation relative to the mean value. Although the figures will vary by geographic location, farming practices and across farms and farmers, 0.1 is the best estimate we can obtain currently, which we will use throughout the study. Fig 7 shows an example.

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 of adopting (according

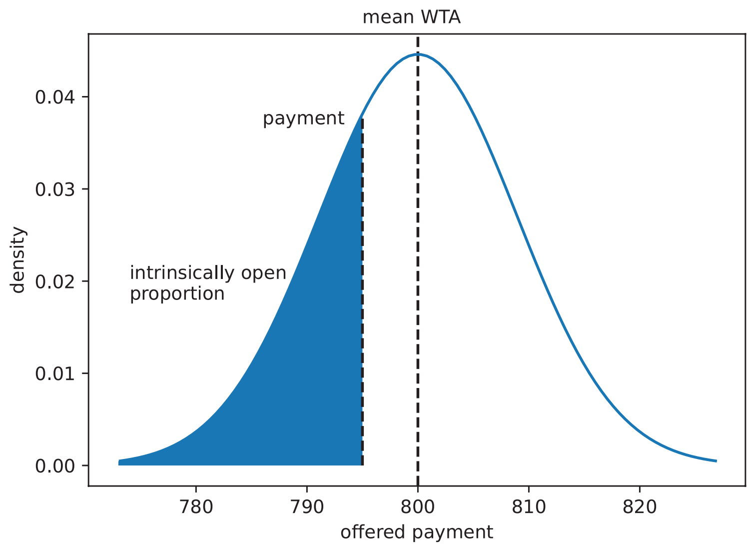

Fig 7. Exemplary distribution of expected payment levels for a scheme where the offered payment is 795€/ha, and the mean payment that farmers expected to receive (WTA: willingness to accept) is 800€/ha. The proportion of farmers expected to adopt an AES is highlighted in blue.

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to the GLM) 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 according to historical data. This cut off is defined as the proportion of farmers to have an AES contract in the data multiplied by a constant (denoted λ) that is tuned as part of the model calibration process. We find through calibration that $\lambda = 1.35$ produces the most accurate results against the training data.

Finally, we can choose to not use the GLM results in the MS model. This method is called *NONE* and farmers are given a random accepted payment within the normal distribution that was described for the method *YES/NO* and Fig 7.

5.2. Results

5.2.1. Model choices. Fig 8 shows the average adoption rate for each country using the three different model choices compared against the data. Fig 9 shows the accuracy of the MS for the different model choices (the proportion of farms correctly predicted to adopt or not adopt), and S3 Table lists the accuracy for each country.

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 it is using prior information on the total number of farmers who have adopted in each FSA and economic size group in the past. As a result, over half of the farmers in each country are predicted correctly.

When the model choice is *YES/NO*, the likelihood of a farmer adopting an AES in the GLM directly affects the likelihood of adoption according to the MS. Therefore, 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 Fig 8b) the accuracy of *which* farmers adopt an AES is fairly good (see Fig 9b) with some exceptions (Slovenia and Luxembourg). Correctly

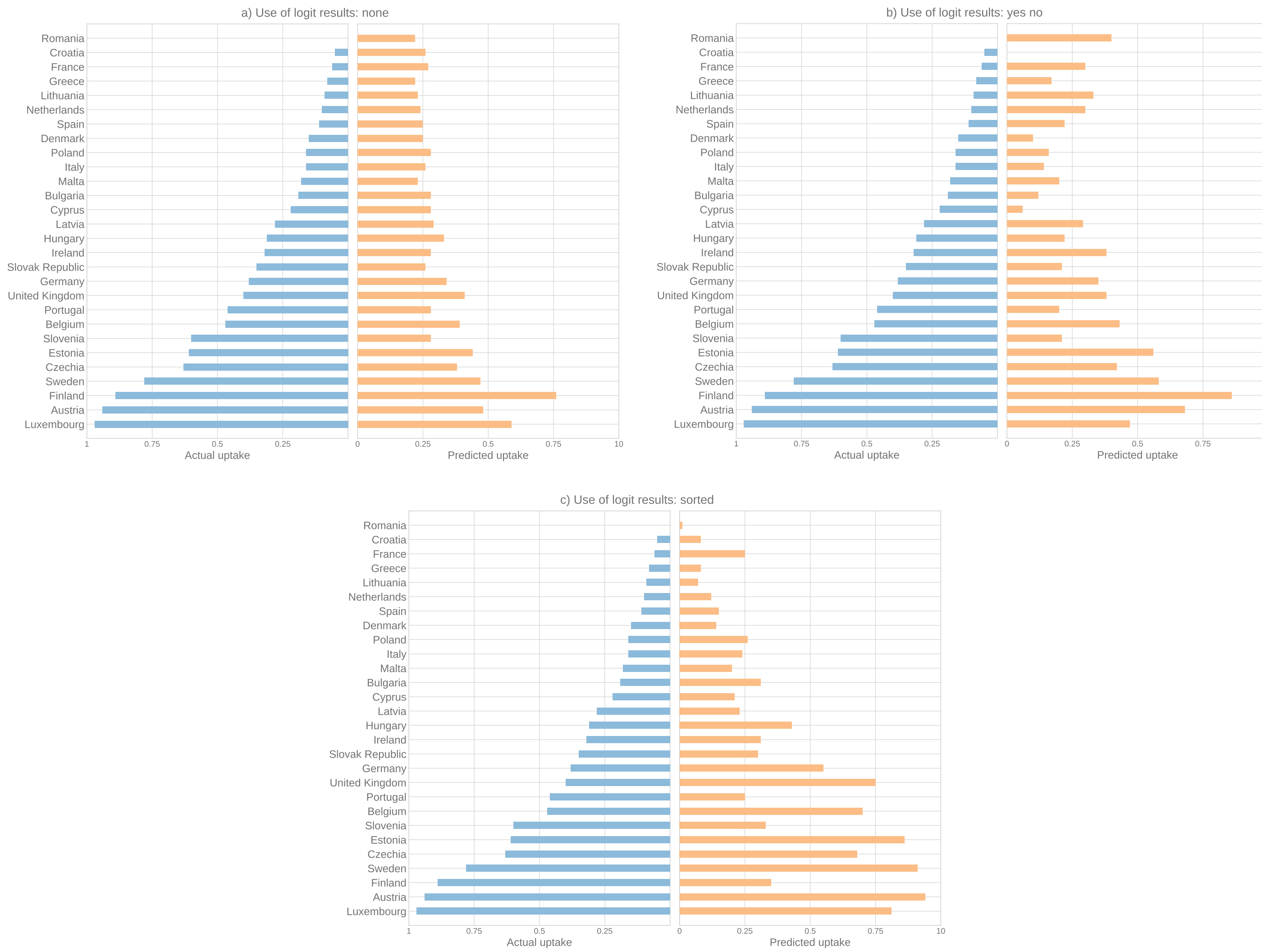

Fig 8. Total farms that take on an AES in the data (blue) and MS (orange) using the three different model choices a) none, b) yes/no and c) sorted.

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predicting which farms take on an AES rather than just how many is useful because the type of AES that a farm can take on depends on the type of land. For example, a scheme devoted to the protection of wetlands can only be applied to farms that contain wetlands. If we can correctly predict which farms will have an AES then we have a better chance at predicting which schemes are likely to be adopted in the future.

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 MS. This model performs the best in predicting how many farms take on a scheme. This is because historical data is used to decide the cut-off rate on how many farmers adopt an AES in the MS. The accuracy of predicting which farms adopt is more mixed, however. Generally this model produces poorer results where approximately half of the farms in the data adopt an AES.

Fig 10 shows the accuracy of the MS for each model choice against the total agricultural land of the country. We can see the results are better than those from the GLM (see Fig 4b)

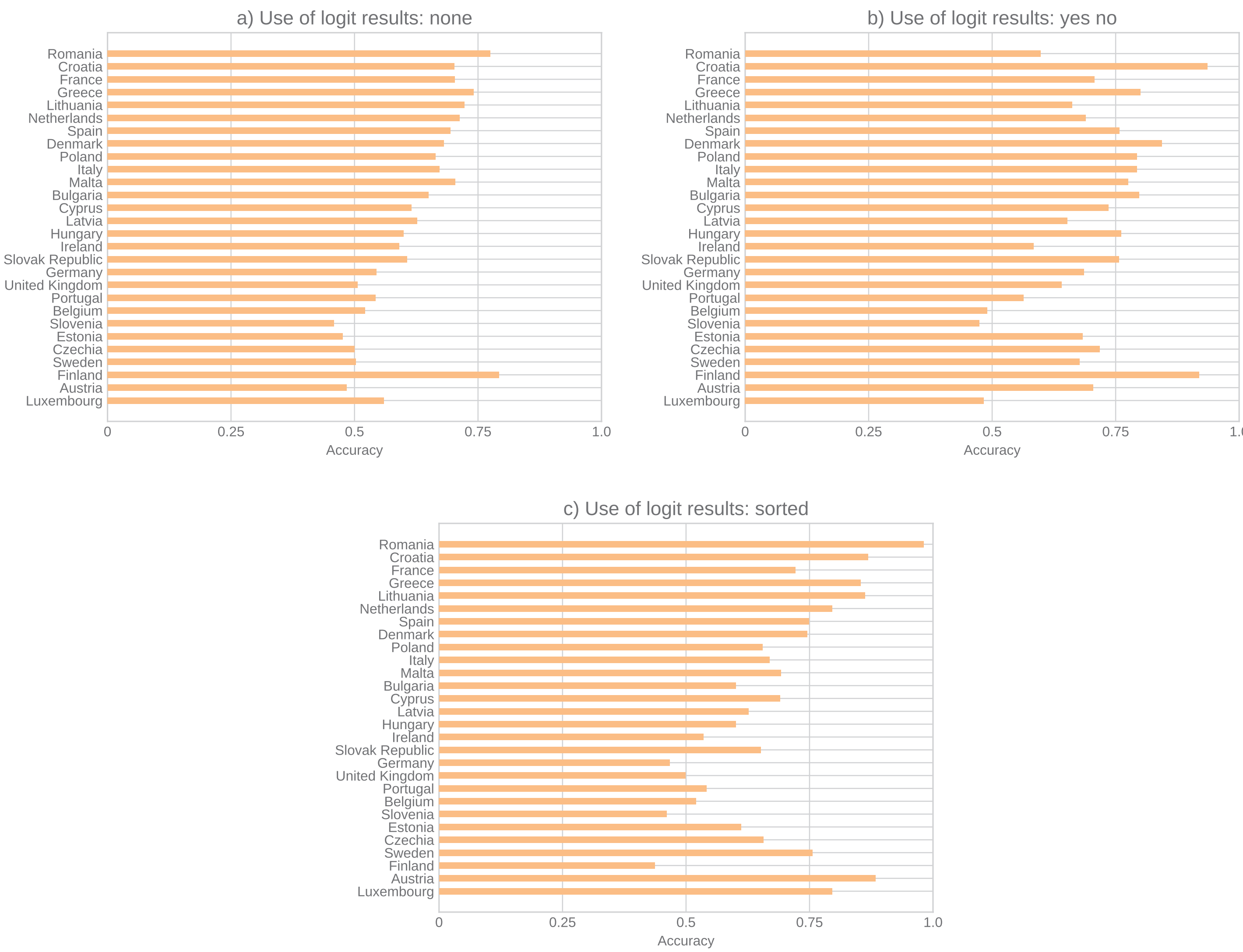

Fig 9. Proportion of farms correctly predicted by the MS using the three different model choices a) none, b) yes/no and c) sorted.

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where countries with little agricultural land were predicted poorly. The MS has performed better because we use historical adoption rates to help inform the model.

Fig 11 shows the model variance in the proportion of farmers adopting an AES from the average adoption rate across all countries within 50 runs using each of the three model choices. Variance comes from the user-defined probabilities of farmers being intrinsically open to an AES, and becoming open based on possible access to advisory support. The figure shows there is considerably more variance between different model choices compared to within a single model choice.

5.2.2. Levels of advisory support. As highlighted in the model flow diagram (see Fig 6), farmers' decision making is affected by the probability they have access to an advisory service, and the probability that the advisor will result in them deciding to adopt an AES when they had previously decided against adoption. These two probabilities are chosen by the user and

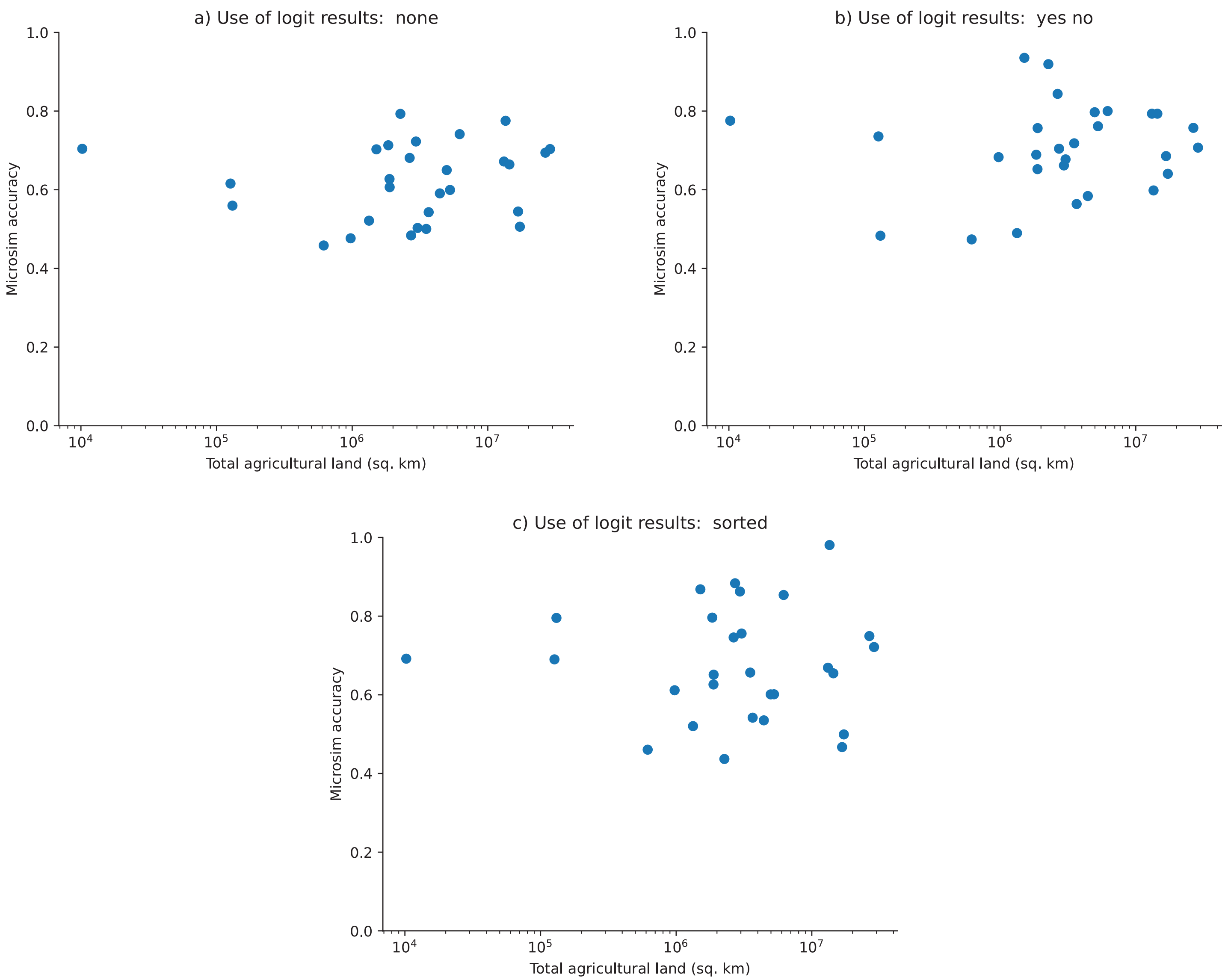

Fig 10. Accuracy of the MS against total agricultural land for each country using the three different model choices a) none, b) yes/no and c) sorted.

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are fixed across all countries. By default, all results in this paper use the probability of having access to an advisor as 0.5, and the probability of it having a positive impact as 0.8 (these values are chosen based on calibration results on UK Humberside data by Li et al. [20]).

To see the effects of the advisor within the model, Fig 12 shows uptake of AESs when farmers have no support (red) or full support with a probability of 1 that an advisor will convince a farmer to adopt (green).

Using the *NONE* model choice, we can see that the MS does not do well without prior information from the GLM. When advisory support is strong, it over-estimates countries with low rates of adoption in the data while still under-estimating countries that have high rates of adoption in the data.

Using the *YES/NO* model choice, for several countries (e.g. Romania and Lithuania) having full advisory support results in much higher adoption rates than those seen in the data

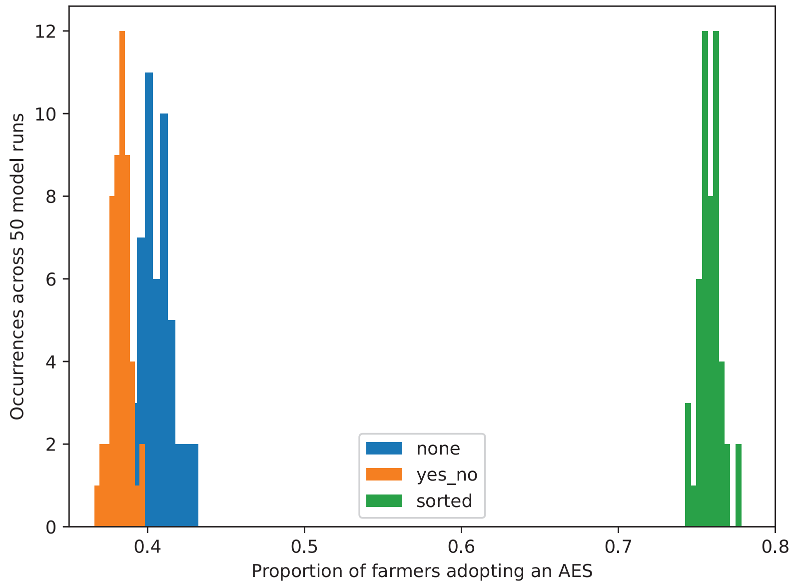

Fig 11. Variance in the proportion of farmers adopting an AES within an ensemble of 50 model runs for each of the three model choices.

https://doi.org/10.1371/journal.pstr.0000162.g011

(see Fig 1). In addition, removing all advisory support has caused some countries to have adoption rates lower than that in the data (e.g. Portugal and Slovenia). Finally, for those countries with high rates of adoption (Czechia, Sweden, Finland and Austria), receiving advisory support has caused little change in the results, suggesting this is not an important factor for choosing to take on an AES in these countries.

Using the *SORTED* model choice, we see similar results to the *YES/NO* method in high adopting countries where advisory support has little effect in the rate of AES uptake. In countries where adoption is typically less than 50% the model results suggest that advisory support may have the potential to increase adoption.

6. Discussion

This paper presents a two-staged approach to modelling farmer adoption of AES, combining a GLM and an MS. Using the results from the GLM as inputs for the MS provides better results than using the GLM alone or the MS model alone (when the chosen method is *NONE*).

The results show that the GLM is at least 50% accurate in predicting which farms adopt, except for small countries where the model performs poorly. This is useful because if we can predict which farms will take on an AES we can better predict which AESs will be adopted. However, the model is mixed at being able to predict the total farms that adopt an AES within a given country. The variables and the strengths of the effects that were found to explain AES uptake by the GLM differed between countries. In some cases, these results match those found in the literature. For example, we find that the presence of permanent crops increases uptake in all countries where this was found to be a significant factor [2,6], as does the presence of livestock [7], and having a large utilised agricultural area [2,4,5].

Using the *SORTED* and *YES/NO* methods of incorporating the GLM results into the MS produces improved results. However, the *SORTED* method of incorporating the GLM results into the MS may result in an over-fitted model as the percentage of farmers who adopt a

Fig 12. Proportion of farms correctly predicted using the different model choices when (red) no access to advisory support is given, and (green) full access is given with a positive influence in AES uptake.

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scheme is heavily influenced by past data with this method. Therefore, it may not be effective for understanding how adoption rates could change as a result of new policies. The *YES/NO* method, therefore, may be the best at predicting which farms are likely to adopt an AES.

Comparing the farms for which AES uptake was predicted correctly against those that weren't (for each model), we find no clear differences between the two groups. This suggests that the behaviours behind those that were predicted poorly are better explained by data that is not available in the FADN dataset. While the FADN data provides a comprehensive overview of each farm, it does not provide insight into social factors affecting the farmer. However, personal and social factors are known to affect uptake. For example, if a farmer knows someone who has an AES then they are more likely to adopt a scheme, and increasing farmers' knowledge of sustainable practices can increase AES uptake [9,10]. Including this information in the MS may help to improve predictions.

The model is limited in that it can only predict a binary outcome of whether a farmer chooses to have an AES on their farm. However, there are many types of AESs to choose from that are intended to have different environmental benefits (e.g. to increase biodiversity or improve water quality). Unfortunately, the FADN data does not provide an indication of which schemes a farmer has adopted. However, in future work the chosen scheme could be predicted based on the type of farming; for example, a farm cannot take on an AES intended to preserve woodland if it has no woodland.

Our methods and results provide scope for future research in predicting how policy changes may improve adoption rates of AESs and in predicting the outcomes of the AESs. We have begun by predicting if a farmer will adopt any type of AES but there are many different schemes that can be chosen. Therefore, in future work we will predict which specific AES is likely to be taken and therefore predict if the intended environmental benefit of the scheme is likely to be achieved given the location of the land [18]. Further to this, in future research the model can be expanded to include exploring additional factors that may improve adoption rates, such as changing the length of the AES's contract and social factors (e.g. the likelihood that a farmer with an AES will influence nearby neighbours).

The code associated with this project is available at https://git.ufz.de/bestmap/bestmap-aes-eu under the GNU General Public License. However, the FADN data contains confidential information and therefore cannot be made publicly available.

Supporting information

S1 Table. Variables removed. 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).
(PDF)

S2 Table. Variables retained. 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.
(PDF)

S3 Table. Prediction accuracy. The proportion of farms that were accuracy predicted for each country with each model.
(PDF)

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Author contributions

Formal analysis: Josie McCulloch.

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Software: Josie McCulloch.

Supervision: Jiaqi Ge.

Validation: Josie McCulloch.

Visualization: Josie McCulloch.

Writing – original draft: Josie McCulloch.

Writing – review & editing: Jiaqi Ge.

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