Will, M., B. Bartkowski, N. Schwarz, F. Wittstock, N. Grujić, C. Li, J. Ge, G. Ziv, and B. Müller. 2024. From primary data to formalized decision-making: open challenges and ways forward to inform representations of farmers' behavior in agent-based models. Ecology and Society 29(4):31. https://doi.org/10.5751/ES-15400-290431

Synthesis

From primary data to formalized decision-making: open challenges and ways forward to inform representations of farmers' behavior in agent-based models

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ABSTRACT. Model-based analyses can effectively contribute to investigating leverage points for sustainability transformations in agriculture. They allow for a systematic evaluation of policies under changing environmental, economic, or institutional conditions, and can be used to assess the effectiveness and efficiency of different policy designs. For analyzing agricultural systems, agent-based modeling is particularly useful because it can represent individual farmers—the crucial actors in land use systems—their interactions and emerging patterns at the landscape level. In order to provide policy-makers with relevant and accurate information, an adequate representation of farmers' decision-making is essential. However, formalizing empirically observed farmers' behavior into model rules is challenging, in particular when the observations are qualitative. With this article, we aim to guide modelers through the process of formalizing farmers' decision-making based on empirical findings. First, we discuss which primary data collection designs are appropriate for inferring particular aspects of farmers' behavior, focusing in particular on when a theory-driven design is helpful and when inductive approaches are needed. Second, we compile aspects that need to be covered in empirical data to best inform agent-based models. Finally, we present approaches for translating empirical findings into formalized decision rules. We underpin our discussion with model examples from the literature and our own model developed to represent farmers' decision-making on the adoption of agri-environmental schemes in Europe. With this methodological contribution, we aim to help make agent-based models less stylized, thereby providing greater potential to support policy-makers in identifying leverage points for a sustainable transformation of agriculture.

Key Words: *agent-based modelling; agriculture, farmer behavior; formalization; primary data; policy support*

INTRODUCTION

The sustainable transformation of the agricultural sector is incentivized by a wide range of environmental policy instruments aimed at reducing ecologically harmful practices and preserving multifunctional landscapes (van Zanten et al. 2014, Hasler et al. 2022). To ensure that agricultural policies are designed in line with these objectives, they must be critically evaluated. Especially for ex-ante policy evaluation, model-based analyses are well suited. They allow for a systematic assessment of policies under changing environmental, economic, or institutional conditions (Baumgärtner et al. 2008, Grimm et al. 2020). In particular, models can consider direct and indirect drivers of a system, such as future climate and market conditions, as well as different policy regimes and management options (Bruch and Atwell 2015, Holtz et al. 2015). By providing socioeconomic and environmental outputs for different future scenarios, models can help evaluate the effectiveness of different policy designs in achieving sustainable and economically viable outcomes under changing conditions.

Because agricultural policies usually target the farm level (Langrell et al. 2013, Kremmydas et al. 2018), it is particularly valuable to use models for policy analysis that allow a representation of individual farmers—the crucial actors in land use systems (Nolan et al. 2009, Reidsma et al. 2018). Agent-based models (ABMs) are particularly suitable to serve this purpose. They can capture heterogeneity in terms of decision-making, available resources, and environmental conditions (Parker et al. 2003, Matthews et al. 2007), and make it possible to distinguish farmer types (Arneth et al. 2014) as well as to explore the role of interactions among farmers. Thus, for example, the conditions under which farmers decide to adopt sustainable practices can be explicitly represented. Moreover, when biophysical aspects are taken into account, feedbacks between the behavior of individual farmers and impacts on the environment can be disentangled (An 2012, Schlüter et al. 2012, Robinson et al. 2018).

Yet, although the explicit representation of human behavior is one of the strengths of agent-based models, it is also one of its greatest challenges (Elsawah et al. 2020, An et al. 2021). Part of the criticism of land use ABMs is that simulated decision-making is often based on ad hoc assumptions that are not supported by empirical evidence or grounded in behavioral theories (Crooks et al. 2008, Groeneveld et al. 2017). Furthermore, some ABMs in the land use context have been criticized for omitting elements that may be crucial for farm management decisions, such as heterogeneity among farmers and social interactions (Huber et al. 2018). However, in order for ABMs to provide policy makers with the information necessary to achieve the desired policy design, an adequate representation of farmers' decision-making is crucial.

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Although recently several approaches to formalize theories of human decision-making for ABMs of social-ecological systems have been developed (Schlüter et al. 2017, Schwarz et al. 2020, Constantino et al. 2021), most social science theories only consider certain aspects of decision-making and fall short when it comes to accounting for the multiple influences that farmers face (Meyfroidt 2013). Therefore, even well-formalized theories might not represent farmers' decision-making processes in their entirety. In addition, in order to be applied to real-world situations, theory-driven models need an empirical reference, which requires that primary data collection be specifically designed to cover all aspects relevant to a theory. It can also be difficult to formalize into behavioral model rules empirical observations derived without a well-formalized underlying theory. Here, a broad range of complex interplaying factors need to be captured in a limited number of survey questions, which later have to be simplified into clear cause-effect relationships.

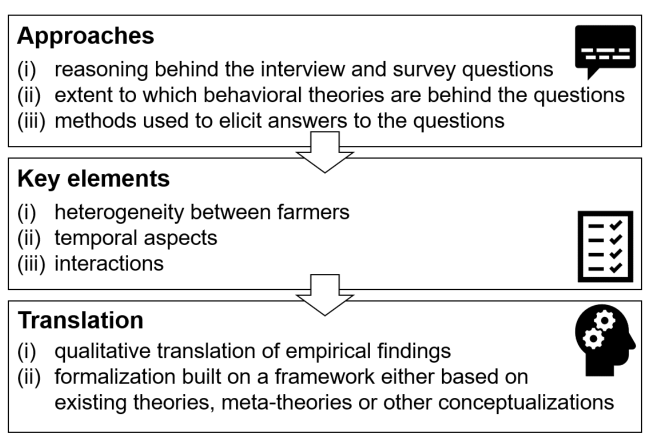
Depending on the scope of application, both explicitly data-driven and theory-driven ABMs are relevant (Taghikhah et al. 2021). However, all applications that aim to inform ABMs with empirical information about agents' behavior require a structured process of translating these data into model rules. There is a wide range of approaches to empirically support ABMs for land use research, including surveys, unstructured or semi-structured interviews, ethnographic methods (such as participant observation), focus groups, field and laboratory experiments, participatory modeling, GIS and remote sensing, or even the use of mobile phone and social media data (Janssen and Ostrom 2006, Robinson et al. 2007, Bell 2017, Smith and Rand 2018). Here, we focus on qualitative and quantitative primary data collected in interviews and surveys that explicitly address farmers' behavior and the reasons farmers provide for their behavior. Moreover, we narrow our scope to how empirical data can be used to determine the model rules related to human decision-making in an ABM. We thus omit a number of different purposes for using empirical data, such as validation or stakeholder discussions (Boero and Squazzoni 2005, Polhill et al. 2010, Smajgl et al. 2011, Smajgl and Barreteau 2017). All of these approaches have their justification. In particular, participatory modeling has proven to be effective in the context of modeling land management (see examples in Voinov et al. 2016). However, these methods also have their individual challenges, some of which vary widely (see, e.g., Voinov and Bousquet 2010, Voinov et al. 2016, Gray et al. 2018, or Sterling et al. 2019 for experiences related to participatory modeling), and thus require separate treatments. With interviews and surveys to inform farmer decision-making, we only focus on a small part of the field of empirically supported ABMs, but throughout the paper we provide perspectives on where this approach reaches its limits and how these can be overcome by alternative methods.

Although existing frameworks mainly deal with guiding the parameterization of human behavior (Smajgl et al. 2011) and describing the formalization (e.g., ODD+D, Müller et al. 2013), there are few guidelines on how to translate primary data into behavioral model rules. To contribute to a better representation of farmers' behavior in land use models, the main objective of this article is to structure the process of using primary data to inform the representation of human decision-making in ABMs. We believe this can help realize the full potential of ABMs and, ultimately, assist policy makers in identifying appropriate interventions for transformation of agriculture toward sustainability. We divide the process in three steps:

1. Selecting approach: We discuss which primary data collection options are appropriate for inferring specific aspects of farmers' behavior. Specifically, we distinguish the potential of inductive and deductive approaches and show which approach is best suited to obtain which type of information. In this context, we also distinguish the extent to which an approach is based on behavioral theories and how the data are obtained and analyzed.
2. Choosing key elements: We summarize aspects that need to be captured in empirical data to inform behavioral model rules in an ABM. In particular, we discuss how heterogeneity, temporal processes, and interactions can be captured with primary data.
3. Translating findings: We compile approaches for translating empirical findings into formalized decision rules. Here, we observe that it is often unclear how empirical evidence is accounted for in the model and highlight how to increase the transparency of the formalization.

The remainder of the paper is organized along these three guiding steps. For all three steps, we discuss challenges and trade-offs arising in the use of various approaches. We underpin each formalization step with model examples from the literature. A summary of the guiding steps and the aspects they cover is provided in Figure 1. In addition, we draw on our own experience in developing an empirically grounded ABM that includes a decision-making framework for the adoption of agri-environmental schemes in Europe. We present how we addressed the guiding steps and highlight challenges we faced during the formalization process. We conclude with a discussion on the potential of using primary data for ABMs in the context of farmers' behavior, its limitations, and how these can be overcome by applying other approaches to include empirical knowledge into ABMs.

Fig. 1. Conceptual diagram of the three guiding steps and the aspects they cover.



FORMALIZING HUMAN BEHAVIOR IN ABMS USING PRIMARY DATA

Formalizing human behavior in ABMs using primary data spans multiple steps from designing data collection to translating empirical observations into behavioral model rules. In order to structure this process, we loosely follow a framework developed by Schwarz et al. 2020 on formalizing theories, which summarizes key steps to consider when including theories of human decision-making in ABMs. The main focus of this framework is on selecting and formalizing a theory. Furthermore, it deals with the translation of formalization into code and the documentation of the model development. For models based on primary data, we focus on the first two aspects because we perceive parallels with the translation to code and the model documentation when using primary data to inform an ABM. Adapted to the empirical context, we end up with three main topics that are crucial for using primary data in ABMs: (1) how to select an appropriate empirical method to collect primary data?, (2) which elements to cover in primary data collection to inform an ABM?, and (3) how to formalize decision rules in ABMs based on empirical data? For each of the three aspects, we provide a general conceptual overview of the ways in which the problem can be addressed. In addition, we present literature examples to show the wide range of possible realizations of empirically based behavioral model rules in ABMs and highlight strengths and limitations of the different approaches. To identify suitable examples from the ABM literature, we performed a Web of Science Core Collection TOPIC search using the search string (agricult* OR farm*) AND "agent-based model*" AND (interview* OR survey*). All articles indexed by 7 August 2023 were included, which resulted in a total of 73 publications. We selected those studies in which (a) it was made clear how the decision rules were derived from interview or survey data, and which (b) provided sufficient information on how the data were collected and translated into behavioral model rules. This resulted in 13 articles. In addition, we screened the literature included in a recent review of the representation of decision-making in European agricultural ABMs (Huber et al. 2018) and added three studies that fulfill the selection criteria but were not found through the database search (Millington et al. 2008, Valbuena et al. 2010a, Acosta et al. 2014).

Approaches for primary data collection to inform farmers' behavior in an ABM

To be able to draw the desired information from empirical observations, it is crucial to design data collection among farmers, stakeholders, or other relevant informants in an appropriate way. We structure the process behind the selection of a suitable strategy for the design of empirical data collection into three dimensions: (1) the reasoning behind the interview and survey questions that are posed, (2) the extent to which behavioral theories are behind the questions, and (3) the methods used to elicit answers to the questions.

For the first dimension, we differentiate between inductive and deductive approaches. In inductive data collection, no prior assumptions about farmers' behavior are included in the formulation of the questions but determinants for behavior or specific behavioral rules are derived from primary data. A common approach for formalizing logical relationships on the basis of empirical observations is the "grounded theory" (Strauss and Corbin 1997) that involves constructing hypotheses and theories through a systematic analysis of qualitative data. It is particularly suitable when targeting a new field of research, addressing a region where no data collection on a specific topic has been conducted yet, or when it is unclear if existing theories or assumptions fit to the specific case and therefore should not dominate data collection. In deductive data collection, interview or survey questions are based on prior information, usually from empirical or theoretical literature. In this case, the behavioral factors of interest are known, and data collection is used to quantify the importance of these factors or to better understand their relationships with each other.

A priori insights about farmers' behavior may be derived from previous surveys or discussions with stakeholders, a literature review, or behavioral theories. This leads to our second dimension where we distinguish the extent to which interview or survey questions are driven by theory. In particular, we distinguish two stylized categories that reflect the origin of the prior information: theory-driven and data-driven. By data-driven we mean the absence of an explicit reference to an established and recognized theory, although even in this case a behavioral theory may implicitly influence the selection of factors that are considered relevant. In fact, it is fair to assume that every researcher working on human behavior has implicit theories/models of how people behave. However, as long as they remain implicit, it is effectively not existent for the outside observer (e.g., reader of a scientific publication). We apply this differentiation only to deductive approaches, because data collection with inductive approaches is by definition free of prior assumptions and therefore always falls into the "data-driven" category. With theory-driven data collection, we refer to studies that explicitly assume that existing behavioral concepts and theories, such as expected utility theory (von Neumann and Morgenstern 1947, as applied by Bocquého et al. 2013), theory of planned behavior (Ajzen 1991, as applied by Borges and Oude Lansink 2016, Despotović et al. 2019, and Bonke and Mussof 2020), or prospect theory (Kahneman and Tversky 1979, as applied by Coelho et al. 2012), provide an appropriate description of farmers' decision behavior. However, it can be difficult to capture all components relevant to a specific situation from empirical data with one specific theory. Depending on the decision context, different influence factors may be of importance (Dessart et al. 2019, Epanchin-Niell et al. 2022). Uncertainty and risk play a role, for example, when an outcome of a decision cannot be entirely influenced (e.g., when a result-based payment scheme is evaluated before subsidies are granted). Societal influences are particularly relevant in observable actions, such as spraying pesticides or planting flower strips. Thus, a data-driven approach based on empirical observations or literature might be more appropriate to guide the development of suitable survey questions. Alternatively, structured frameworks combining elements from different theories (e.g., Klöckner 2013, Epanchin-Niell et al. 2022) can be useful in such situations.

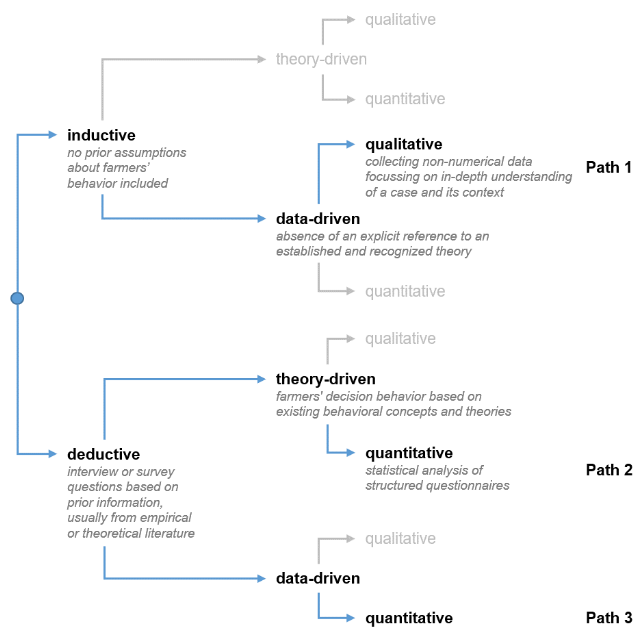
The last decision that has to be made with regard to data collection is that of the method with which the questions are asked. Here, we distinguish between qualitative and quantitative approaches. In principle, data from open-ended questions can also be analyzed by means of quantitative methods, such as natural language processing or topic modeling. However, in most cases, quantitative methods are used to analyze more structured data (from questionnaires, etc.), so we simplify by distinguishing "qualitative" and "quantitative data collection." Qualitative data collection refers to many forms of collecting non-numerical (text, audio, video) data focusing on in-depth understanding of a case and its context. This allows for generating hypotheses, building new theories and concepts, or reconstructing social action. One method popular in the context of empirical ABMs are unstructured or semi-structured interviews (Kruse 2014, Przyborski and Wohlrab-Sahr 2014). These are mostly conducted in direct contact between interviewer and respondent (either face-to-face or via phone/virtually). This approach is often used to get general insights into specific decisions without limiting the range of relevant factors a priori. In the context of farmers' behavior, this can, for example, include reasons for application of specific environmentally friendly practices.

Quantitative data collection involves structured questionnaires with mostly closed-ended questions that allow a statistical analysis (in some cases open-ended questions are coded to be translated to quantitative values). Often, this includes data collection on independent (e.g., socio-demographic data, attitudes) and dependent variables (e.g., adoption of specific practices). With sufficiently large sample sizes, this can be used to statistically determine behavioral rules (e.g., via regression analysis). Alternatively, it is possible to ask respondents to rate the importance of specific reasonings for a certain action. One could ask about the role of certain influencing factors, such as the economy or the environment, or preformulate possible behaviors and analyze farmers' preferences. This could include specific rules such as "If insect x is spotted in my region, I apply insecticide y" or "I always use insecticide z." In combination with the collection of socio-demographic data, these data can be analyzed to derive different types of agents, e.g., farmer types (Bartkowski et al. 2022). Again, the differentiation of qualitative and quantitative data collection is only relevant for deductive approaches. Inductive collection of primary data is always qualitative because without any prior knowledge predefined questions to obtain quantitative data are not reasonable. (However, administrative data in quantitative format not collected by researchers themselves might theoretically be used for inductive explorations of behavior.)

To provide an overview of possible approaches to data collection, we summarize the three dimensions in a decision tree (Fig. 2). Before discussing the resulting paths of possible combinations, we want to point out that the classification into binary categories is a simplification that does not cover the entire spectrum of data collection approaches. We acknowledge that some methods cannot be clearly assigned to either the qualitative or quantitative category (e.g., Q methodology explicitly combines both approaches with participants having to rank statements and explain their ordering, and the results being evaluated in a factor analysis), but we believe that even the simple classification can be helpful in distinguishing different ways of data collection and their strengths and limitations.

Out of the possible eight combinations of the three binary dimensions, we highlight three paths for data collection for ABMs. As argued before, we omit theory-driven and quantitative approaches for inductive study approaches because these do not fit with the general definition of inductive data collection. In addition, we did not find studies that combine deductive

Fig. 2. Possible combinations of the three dimensions of data collection design with three paths highlighted that appear most relevant for data collection for ABMs. We omit theory-driven and quantitative approaches for inductive study approaches since these do not fit with the general definition of inductive data collection. We did not find studies that combine deductive reasoning for survey design with qualitative data collection when the study is meant to inform an ABM. See Table 1 for literature examples for the selected paths.



reasoning for survey design with qualitative data collection when the study is meant to inform an ABM. The few studies we are aware of that use the approach deductive–theory-driven–qualitative (e.g., Riley 2016 using Bourdieu's notion of hysteresis to investigate farmers' agri-environmental actions and identities) are not conducted in context of ABMs. For the combination deductive–data-driven–qualitative we have not found any examples. When empirical data are collected for ABMs, a possible reason why these combinations of approaches are not used could be that quantitative information is needed to parameterize the behavioral model rules. Qualitative approaches might therefore rather be applied in inductive settings where no prior information about driving factors for behavior is available.

The remaining three paths are (1) inductive–data-driven–qualitative, (2) deductive–theory-driven–quantitative, and (3) deductive–data-driven–quantitative. To underline the potential of these different approaches, we summarize their strengths and limitations and their importance in the modeling cycle (Schmolke et al. 2010). We add literature examples from studies where farmers' decision-making in ABMs is based on empirical data (Table 1). We do not claim to provide an exhaustive overview of all existing studies. Rather, we aim to highlight the diverse range of how empirical information is used to derive respective model rules and parameterize farmers' behavior. Among the selected

Table 1. Data collection design and formalization of behavioral rules in selected agricultural ABMs.

Reference	Path	Type of interview	Type of questions	Interview administration	Respondents	Formalization of behavioral rules
Millington et al. (2008)	1	Semi-structured[†]	Open-ended	Face-to-face	5 local stakeholders	Qualitative formalization of empirical observations
Acosta et al. (2014)	1	Semi-structured	Closed & open-ended	Face-to-face	28 farmers	Decision tree based on CONSUMAT approach
Mertens et al. (2018)	1	Semi-structured	Open-ended	Face-to-face	14 experts and stakeholders	CONSUMAT approach
Pacilly et al. (2019)	1	Semi-structured	Open-ended	Face-to-face	25 farmers	CONSUMAT approach
Zagaria et al. (2021)	1	Semi-structured Semi-structured	Open-ended Open-ended	Face-to-face Face-to-face	14 key informants 53 farmers	Qualitative content analysis of interviews with coding frame following MoHuB framework, structured empirical findings on decision process linked to behavioral theories (protection motivation theory, theory of basic values)
Kaufmann et al. (2009)	2	Structured	Closed	Face-to-face	357 farmers (two case studies: 170 + 187 farmers)	Parameterization of weights of attributes of theory of planned behavior
Pouladi et al. (2019)	2	Semi-structured Structured	Open-ended Closed	Face-to-face Questionnaire	274 farmers	Structural equation model to determine relationship among structural parameters of theory of planned behavior
Liu et al. (2021)	2	Structured	Closed	Questionnaire	364 farmers	Parameterization of belief-desire-intention theory for decision-making
Noeldeke et al. (2022)	2	Structured	Closed	Tablet-based	145 farmers	Structural equation model to determine relationship among structural parameters of theory of planned behavior
Valbuena et al. (2010a)	3	Structured	Closed	Postal	495 farmers	Parameterization of an existing conceptual framework adapted to the specific decision-making process using farmer types
Valbuena et al. (2010b)	3	Semi-structured	Closed & open-ended	Face-to-face	30 farmers	Parameterization of an existing conceptual framework adapted to the specific decision-making process using farmer types
Sun and Müller (2013)	3	Structured	Closed	Face-to-face	509 farmers	Decision-making process captured with Bayesian belief networks further modulated by opinion dynamics models
Pouladi et al. (2020)	3	Semi-structured Structured	Open-ended Closed	Face-to-face Questionnaire	274 farmers	Machine learning (association rule) to derive patterns of farmer behavior
Tieskens et al. (2017)	1 & 3	1: semi-structured 3: structured	Open-ended Closed & open-ended	Face-to-face Face-to-face	20 experts 75 farmers	Qualitative formalization of empirical observations; parameterization with results from structured survey
Yao et al. (2018)	1 & 3	1: semi-structured 3: structured	Open-ended	Face-to-face	55 farmers	Qualitative formalization of four key rules into stepwise decision rule; model parameterization with results from structured survey
Burg et al. (2021)	1 & 3	1: semi-structured 3: structured	Open-ended Closed & discrete choice experiment	Face-to-face Online & paper version	10 farmers 186 farmers	Qualitative formalization of stepwise decision process; parametrization with results from structured survey and discrete choice experiment

[†] Other terms for semi-structured used in our literature sample are "open" and "explorative."

studies, we find five studies that follow path 1, four path 2, and four path 3. The remaining three studies pursue a combined approach of path 1 and path 3.

The main strength of the first path (inductive–data-driven–qualitative) compared to the other two is its potential to uncover unexpected reasons or determinants for certain behavior. The approach is often characterized by small sample sizes because interviews conducted face-to-face require far more time compared to online or postal surveys (or even structured surveys conducted face-to-face). For studies in our literature sample, the number of respondents ranged from five local stakeholders (Millington et al. 2008) to interviews with 53 farmers and 14 key informants (Zagaria et al. 2021). Acosta et al. 2014 conducted face-to-face interviews with 28 farmers, which represent more than 90% of the total farmers in the region and therefore provide a good overview of the case study. Although small sample sizes are often sufficient in qualitative social science once a saturation of knowledge and a general understanding of the system is achieved (Roller and Lavrakas 2015), it is also possible to instead use participatory modeling with focus group discussions or workshops that involve not only farmers but also experts, such as agricultural policy makers, administrators, or advisors. This approach has been widely used in the context of land use management (e.g., Gaube et al. 2009 or Bakker et al. 2015). However, one should also keep in mind that farmers' (and in particular other actors' beliefs about farmers') behavior may be biased or even plainly wrong (see Brown et al. 2021, Gütschow et al. 2021). In addition, parameterizing the model is difficult when quantitative data are lacking. Data collected through the first path can therefore mainly contribute to a general system understanding and model conceptualization (Yang and Gilbert 2008).

The scopes of the second (deductive–theory-driven–quantitative) and third (deductive–data-driven–quantitative) paths both mainly serve model parameterization. With those approaches, researchers have the opportunity to reach many respondents and to provide a broader and potentially representative picture of the surveyed population. Valbuena et al. 2010a, for example, based their behavioral model rules on a postal survey with 495 Dutch farmers (Jongeneel et al. 2008). Kaufmann et al. 2009 included their question block on farmers' behavior in a larger survey with farm managers and were therefore able to interview 170 farmers in Latvia and 187 farmers in Estonia. However, to conduct such a deductive study, additional information must be available in advance. For data-driven approaches (path 3) this can, for example, be a general understanding of agronomic and economic processes or an existing conceptual framework of farmers' behavior refined to the specific case study (Valbuena et al. 2010a, 2010b). If the approach is theory-driven (path 2), the empirical information must in addition fit into a theoretical framework that forms the basis for the questionnaire and the formalization into behavioral model rules. Kaufmann et al. 2009 argue that they have chosen the theory of planned behavior to model conversion to organic farming because of its conceptual parsimony and successful empirical applications. Liu et al. 2021 formalized their behavioral model rules on the belief-desire-intention theory to include agents' knowledge about the farm and the environment, their farming goals as well as their actual technology adoption. Although this approach provides the possibility to parameterize predefined behavioral rules or the importance of different behavioral options, there is limited potential to detect unexpected behavior (e.g., by giving the possibility to indicate "other reasons" in an open-ended way to otherwise fixed response options or by providing a feedback format at the end of the survey).

In order to precisely tailor the empirical basis to one's own case study and collecting quantitative information to parameterize the empirical observations, a combination of an inductive approach (path 1) and a deductive approach (path 3) is possible. In our literature sample, this approach was performed through a combination of semi-structured expert interviews to identify issues regarding hedgerow management (Tieskens et al. 2017), cultivation patterns (Yao et al. 2018), or participation in biogas production (Burg et al. 2021), and a survey to parameterize action rules for farmers in the model. Although such a combined approach can provide detailed insights for one's research question, it also comes with challenges that must be considered when planning a project. First, it can be challenging to translate the interpreted findings from the qualitative part into meaningful quantitative questions. Moreover, observations from the inductive data collection do not necessarily need to be supported by the quantitative survey, which makes it difficult to justify the underlying model concept. Apart from that, the combination of approaches requires a lot of expertise, as the team needs to be familiar with qualitative social research and quantitative methods from economics or psychology in addition to ABM expertise (with additional knowledge on ecological aspects required in the land use context). Combining this experience and conducting the two-step approach takes a considerable amount of time, which is hardly available in typical projects with a duration of a few years.

Key elements of primary data needed to inform an ABM

To adequately inform the representation of farmers' decision-making in an ABM with primary data, certain aspects of farm and farmer characteristics have to be addressed when collecting empirical information. Inspired by the elements considered in the MoHuB framework, which was developed for mapping behavioral theories in models of social-ecological systems (Schlüter et al. 2017), we distinguish three main categories: (1) heterogeneity between farmers, (2) temporal aspects, and (3) interactions (for a list of examples of survey components that fall into the different categories see Table 2).

Heterogeneity between farmers

It cannot be assumed that all farmers behave in the same way; on the contrary, a high degree of heterogeneity must be taken into account (Malek and Verburg 2020, Bartkowski et al. 2022). In fact, heterogeneity of actors is one of the main reasons for applying ABM (Railsback and Grimm 2012) rather than, e.g., conventional bioeconomic models based on a representative agent approach. During empirical data collection for ABMs, this heterogeneity among respondents needs to be addressed. On the one hand, in many empirical studies heterogeneity is primarily derived from farm and farmer characteristics. In this case, socio-demographic variables, such as age, gender, education, or the availability of a successor, and farm properties, such as location, area, or specialization, can be sampled. On the other hand, heterogeneity may also be characterized by strictly behavioral attributes. These can include attitudes toward past changes in land use, expected impacts of climate change, or the importance of landscape functions or environmentally friendly farming practices. Similarly, perceptions of current or previous situations as well as aspirational thresholds can be used to distinguish among farmer groups. Existing studies cover, among others, questions on barriers or enablers of future adaptation strategies as well as past drivers of change in the agricultural sector. Heterogeneity in attitudes and perceptions can be assessed in quantitative studies by using Likert scales, where farmers are asked to rate their agreement with particular statements or the importance of certain measures. To ease comparability between studies, we suggest using standardized frameworks, especially when sampling attitudes and perceptions instead of inventing new questions for each study. Attitudes can, for example, be classified according to the Environmental Attitudes Inventory (Milfont and Duckitt 2010) or the New Ecological Paradigm (Dunlap et al. 2000). Risk preferences should ideally be investigated by different elicitation methods, such as lottery decisions (e.g., following the initial setup by Holt and Laury 2002) or domain-specific self-assessment (see Finger et al. 2022 for an example on Swiss fruit producers). To analyze the heterogeneity among farmers, deriving farmer typologies is a promising approach (see Bartkowski et al. 2022 for a summary of existing studies on farmer typologies and methods that are used to synthesize empirical data). In ABMs, such typologies can be used to represent diversity between farmers while keeping a meaningful number of different behavioral types (Arneth et al. 2014).

Temporal processes

Decision-making processes often do not consist of single choices but represent a series of consecutive choices. In addition, behavior may change over time, especially in response to evolving biophysical and socioeconomic conditions. To model the decision-making of farmers in ABMs, it is therefore necessary to

Table 2. Summary of components addressed in existing studies that cover the three main elements of primary data needed to inform an ABM on farmers' behavior.

Main elements	Components
Heterogeneity	
Socio-demographic data	Age, gender, education, time spent on farm (i.e. full- or part-time), farming experience, availability of a successor
Farm characteristics	Farm area, specialization, management intensity (organic/integrated production), land use, land ownership, employment of agricultural workers, subsidies, off-farm activities
Biophysical characteristics	Farm location, parcel characteristics, accessibility of parcels, availability of specific land types (arable land, grassland)
Values, preferences and attitudes	Toward recent land use change, toward risk, regarding environmentally friendly farming practices (e.g. agri-environmental schemes, hedgerows), toward off-farm labor, toward extensive land use, perspective on future of local agricultural sector, influence of declining profits, expected future impacts of climate change on agriculture, importance of landscape functions, farmer's trust in the government, farmer's identity
Perceptions/beliefs, expectations and cognitions	Factors that facilitate or impede adoption of organic farming, past drivers of change in agricultural sector, causes of land use change, barriers or enablers of future implementation of (transformational) adaptations, determinants of drought adaptation
Temporal processes	
Past strategies (habitual behavior)	Past drought adaptations, past adaptation investments targeting water scarcity, past changes to farming system
Future strategies (intentions)	Farming objectives, intentions regarding future farming strategies, adaptive strategies in response to global environmental change/drought, investment decisions/ decisions on new agricultural practices, actions after retirement, intention to convert to organic farming
Interactions	
Peer orientation	Influence of significant others
Organizations	Membership in farming cooperative/conservation organization, access to advisory support/advisory support received, contact with authorities/political decision-makers
Society	Perceived perception by the society, social norms

have knowledge about the temporal processes behind the behavior. With respect to data that are meant to inform an ABM, we reflect this in three main aspects: (1) development over time, (2) the sequential aspect of decision-making, and (3) scheduling of the behavior of several agents.

First, we argue that it is important to have a dynamic view on a system and not assume that decisions remain fixed over time. Especially if behavior is conditioned by previous experiences or other developments such as extreme events, it needs to be considered that agents might learn or adapt and actions might change. This has to be reflected in interviews and surveys, for example, by asking for past actions in response to exceptional situations and the likelihood for future implementation of adaptations given a potential increase of extreme events (Zagaria et al. 2021). In these questions, however, it is difficult to distinguish sudden from gradual changes in behavior. Such different rationale may be easier to uncover in unstructured or semi-structured interviews with inductive reasoning (path 1), as farmers may inherently distinguish long-term from short-term responses. In addition, it is worth investigating if there are specific triggers for some behavior. Possible questions in this regard can be targeted at behavior in an exceptionally warm, dry, or wet year and reasons for this behavior. In the context of pesticide use in vineyards, Chen et al. 2022 asked, for example, for the amount and number of sprayings in average years compared to years with exceptionally high and low use of pesticides as well as for a description of the climatic conditions of those exceptional years. However, dynamic responses are highly dependent on the farmer's perceptions of the social and biophysical environment as well as the evaluation of the perceived state of the system that make it difficult to elucidate specific moments when someone actually reconsiders his or her behavior (Sutherland et al. 2012). Alternatively (though very resource-intensively), one could use a longitudinal approach, such as, e.g., Riley 2016 who interviewed farmers twice across multiple years to see changes in their attitudes.

Second, the sequential aspect of decision-making has to be considered, i.e., that a decision is a stepwise process ranging from problem detection to implementation (Öhlmér et al. 1998). Here, the crucial aspects that need to be derived from empirical data are the phases of the specific process and the importance of each element. Existing theories, such as theory of planned behavior, inherently include some kind of scheduling of processes. Although this theory has been included into a more general concept of farmers' action space (Gütschow et al. 2021) that allows the formalization of opportunities and constraints at specific steps in the decision-making process, for some processes it might not be possible to be formalized in such frameworks. In that case, unstructured or semi-structured interviews could be particularly helpful to get an understanding of the sequential manner behind how actions are performed. In addition, it needs to be taken into account that farmers take several related but disconnected decisions (e.g., investment decision, decision what to crop, where to allocate which crop, etc.), i.e., the sequential aspects might need to be disentangled for several actions relevant for the specific context.

The last aspect concerning temporal processes refers to the multitude of actors in a system. This is particularly important when actions may be constrained by previous actions of other actors because of the limited availability of resources, such as when making decisions about using common property or applying for subsidies with limited resources (see, e.g., Johnson and Salemi 2022 for a discussion on conception of time to capture resource competition in an agent-based model on firewood harvesting). Here, empirical data collection should clarify whether there are hierarchies among actors that might influence the order of decision-making, or whether resource allocation follows a first-come, first-served basis. Hierarchies can be revealed indirectly in interviews or surveys by asking about preconditions that must be met before an action can be performed. Beyond interviews or surveys, such constraints can also be exposed in role-playing games, where the order of actions can be inferred directly from observing the behavior of the players.

Interactions
A third crucial aspect of ABMs is interaction among agents (Railsback and Grimm 2012). Although farms may be influenced by other farms via the environment (e.g., pesticide usage in one field affects organic farming in other fields) or agricultural trade (Dou et al. 2019), with respect to social interaction we here primarily focus on the effect of perceptions of what others do, as well as on the impact of perceived societal expectations on one's own behavior (Burton et al. 2004, Dessart et al. 2019). Although social contracts through membership in farming cooperatives and access to advisory services can be relatively easily accessed through interviews and surveys, peer orientation can be difficult to derive (Bartkowski and Bartke 2018). One approach to eliciting these influences in interviews is to ask directly whether farmers consult other farmers (Mathijs 2003) or to have farmers assess the importance of friends' or neighbors' behavior on their own behavior (Caffaro et al. 2019). However, it is unclear how reliable responses to such specific questions are. Farmers may not want to admit (or may not even be aware) that they are influenced by the actions of others because they want to present themselves as an independent company. Additionally, there may be collaborations that are not consciously perceived as such because they have always been established, for example, when farmers share equipment and automatically engage in exchanges about land use strategies. Such tacit social influences might not surface through explicit questions in questionnaires or surveys and other ways of obtaining the information may be required. Kreft et al. 2021 applied a touchscreen-based data collection where farmers were asked to draw lines between persons with whom they regularly exchange about specific agricultural issues and rank the influence of others. Furthermore, in terms of social influence, secondary data may be suited to infer imitation or cooperation. Here, administrative data including location or remote sensing data could be helpful to infer similar behavior of proximate farms. Vroege et al. 2020 show, for example, that there are spatial spillover effects with respect to diversification using census data of farms in the Netherlands (see there also for an overview of literature regarding spillover effects in agricultural decision-making). Cooperative farming strategies can also be analyzed through serious games (see Janssen et al. 2023 for an overview on collective action games). Ryschawy et al. 2022, for example, applied a participatory approach to generate scenarios in the context of crop-livestock integration among farms. Rommel et al. 2022 evaluated the willingness to cooperate using a public goods game.

Translation of primary data into decision rules
In the following, we compile approaches to translating empirical findings into formalized decision rules based on our selection of literature. Although this overview does not provide exhaustive guidelines of how behavioral model rules can be derived from primary data, it can nevertheless provide illustrations of how empirical data can be used in the process of formalization.

In the literature examples we collected, we find two main approaches of how primary data are used to derive behavioral model rules: qualitative translations of empirical findings and formalizations built on a framework based on existing theories, meta-theories, or other conceptualizations. For the first approach, behavioral model rules are derived ad hoc on the basis of empirical findings, i.e., empirical findings are formulated into a heuristic framework that is qualitatively translated into behavioral model rules, yet without providing explicit reasons for the interpretation beyond own observations and a general understanding of agronomic and economic processes. As this approach is based on qualitative input data, it is closely linked to the approach taken in path 1 (i.e., inductive reasoning to collect qualitative data without reference to a specific theory anchored in the literature). This also reflects that in our literature sample, all examples that derive behavioral model rules in this way follow path 1 to collect empirical data (Millington et al. 2008, Tieskens et al. 2017, Yao et al. 2018, Burg et al. 2021). For models that base the derivation of behavioral model rules on a conceptual framework, we observe different approaches related to the paths that were used for data collection. For models where empirical data are obtained through deductive reasoning with quantitative approaches (paths 2 and 3), behavioral model rules are based on the framework that was used to structure the questionnaire for data collection. For example, in our sample that is based on a theoretical framework (path 2), farmers' behavior is formalized in a way to match the theory of planned behavior (Kaufmann et al. 2009, Pouladi et al. 2019, Noeldeke et al. 2022) or the belief-desire-intention model (Liu et al. 2021). Kaufmann et al. 2009, for example, calculate the intention to switch between conventional and organic farming as a weighted sum of attitude, subjective norm, and perceived behavioral control. Pouladi et al. 2019 and Noeldeke et al. 2022 perform a statistical analysis using a structural equation model to derive the relationship among structural parameters of the theory of planned behavior. Liu et al. 2021 weighted agents' belief, desire and intention according to the statistical analysis of farmer characteristics, risk attitude, and environmental awareness. For the four example models following path 3 (i.e., quantitative data collection based on deductive reasoning without an explicit theory behind), behavioral model rules are the translation of a conceptual framework based on a systematic review of empirical literature (Valbuena et al. 2010a, 2010b) or a statistical analysis of the collected data using Bayesian belief networks (Sun and Müller 2013) or the association rule (Pouladi et al. 2020) to derive patterns of farmer behavior. In cases where data collection was not based on assumptions for behavior (path 1; i.e., no theory or framework was used to develop the interview questions), we find that four of the five models were afterwards tested for compatibility with an existing framework that comprises the basis for the behavioral model rules. Zagaria et al. 2021 apply an extensive qualitative content analysis of the transcribed interview data and structure their empirical data using the MoHuB framework (Schlüter et al. 2017). This approach helps them to link their findings on the decision process to different behavioral theories, which then build the basis for the formalized model rules. Acosta et al. 2014, Mertens et al. 2018, and Pacilly et al. 2019 argue that the elements found in the analysis of their empirical data (i.e., repetition, deliberation, imitation, social comparison) are well aligned with the concept of CONSUMAT approach (Jager 2000, Jager and Janssen 2012), which is based on different psychological theories and incorporates components such as uncertainty, satisfaction behavior, habits, and influence of others. Therefore, they base their behavioral model rules on this meta-theoretical framework.

We also find that primary data are often used to derive farmer typologies. For different farmer types, either different behavioral rules or different parameterizations are assumed (Rounsevell et al. 2012, Huber et al. 2018). If agents vary in their decision rules, behavioral paths that farmers can follow are defined by their characteristics. In our sample, this approach was taken by two studies that collected primary data in a qualitative way (path 1). Millington et al. 2008, for example, derived two types of farmers (commercial and traditional), who have different options for land management. Acosta et al. 2014 formalize farmers' behavior in a decision tree where farmer characteristics, such as farm size, education, or income, determine which type of land management is performed. In models where farmer types follow the same behavioral rules but are parameterized differently, only their probabilities for certain behaviors differ. For such probabilistic approaches, quantitative data need to be collected. Valbuena et al. 2010a used this to determine decisions on expansion and diversification. Farmer types in Tieskens et al. 2017 differ in their likelihood to expand or reduce their farm area as well as the probability to participate in agri-environmental schemes at the beginning or during the course of the simulation and to continue participation in agri-environmental schemes. Kaufmann et al. 2009 clustered farmers by their attitude, subjective norm, perceived behavioral control, and the respective levels of uncertainty as derived from the empirical data. For each farmer type, the mean value of these characteristics was used to parameterize the behavioral model rules in the ABM.

For the derivation of farmer types, lack of transparency in reporting methods and data has been criticized (Bartkowski et al. 2022). In our sample, we found that formalization of behavioral model rules was described in a particularly non-transparent manner. Especially for models that are not built on a predefined framework (path 1), it often remains unclear how empirical evidence is accounted for in the model. In models where the decision rules are based on theories or conceptual frameworks, the formalization of the behavioral model rules is often clearer because the basic assumptions are known. Here, it is particularly necessary to argue why certain assumptions are supported by the (subsequently collected) empirical data. Especially if a rather abstract theory is used as a basis, an explanation is needed of how the theory is interpreted and how the empirical observations are linked to the underlying theoretical framework (Muelder and Filatova 2018). This involves documenting the model formalization following a protocol such as the ODD+D (Müller et al. 2013) or a documentation with a particular focus on data use such as ODD+2D (Laatabi et al. 2018) or the RAT-RS reporting standard (Achter et al. 2022). However, these protocols mostly only include the description of the final model version but seldomly an explanation how this version was reached. For a fully transparent description of model development, it is necessary to explain how the formalization was derived, especially if there is no existing (theoretical) framework underlying the chosen representation of human behavior, and being realistic about what empirical data can provide and what their limitations are (Edmonds 2015). If assumptions are made ad hoc and are not based on empirical data (e.g., because relevant data are difficult to obtain), this does not necessarily reduce the quality of the model. In particular, models that are not based on empirical data may even be more flexible in terms of including possible influences than empirically driven models and might therefore show a larger range of (potential) outcomes. In addition, care must be taken to ensure that the consideration of all available data does not lead to the model becoming too complex, which can lead to a lack of understanding, especially if the model is used for policy advice (Sun et al. 2016, Zellner et al. 2022). In any case, when including both empirical input and assumptions, it must be made clear which behavioral model rules are based on empirical data and which are not. Furthermore, sensitivity analysis is particularly important for the ad hoc parts of the model to illustrate the implications of certain choices (for suitable sensitivity analyses for ABMs see Ligmann-Zielinska et al. 2014, ten Broeke et al. 2016, or Troost et al. 2023). A thorough sensitivity analysis can provide a deep understanding of the potential solution space resulting from different input parameters. Policy analyses can benefit from these detailed results as they can reveal unexpected outcomes (e.g., extreme cases) that may not be contained in empirical data. In addition, a documentation of alternative model variants that were considered but not chosen for the final model version is helpful to follow the complete process of model development. By documenting all steps, the iterative character of model development becomes clear. No model is built all at once, but it always includes step-by-step development of system understanding, which is influenced by empirical observations and (theoretical) assumptions (more details on the gradual model development are included in the concept of the modeling cycle, see e.g., Augusiak et al. 2014 for ecological models). This documentation can be included in a modeling notebook such as TRACE (Schmolke et al. 2010, Grimm et al. 2014, Ayllón et al. 2021). Finally, we strongly advocate that the questionnaire or semi-structured guiding questions used to collect the empirical data are made public. This is the only way to explicitly understand which questions provided which model-relevant information.

EXEMPLARY FORMALIZATION OF FARMERS' BEHAVIOR ON THE ADOPTION OF AGRI-ENVIRONMENTAL SCHEMES

To illustrate the process of model formalization based on primary data and outline possible difficulties, we draw on our own experience in the BESTMAP project (Ziv et al. 2020) where we developed an empirically grounded ABM that includes a decision-making framework for the adoption of agri-environmental schemes (AES) in Europe. AES are voluntary programs offered as part of the European Union's Common Agricultural Policy to provide incentives for environmentally friendly farming practices (European Union 2013a). To systematically test the impact of different policy designs on the adoption rate among farmers and the resulting spatial allocation of AES, we designed an ABM where decisions of individual farmers on four selected schemes are explicitly included. In the following, we describe our approach of data collection, key elements included in the model, model formalization, and parameterization, and highlight the lessons we learned from our approach. Our own experiences are not intended to serve as a particular example of best practice. Rather, we would like to show one potential approach but also highlight shortcomings and difficulties we have encountered. At best, this will help to ensure that certain aspects are taken into account from the outset in future projects, which could lead to behavioral model rules being based on empirical data to an even greater extent than in our case.

Approach: semi-structured interviews and follow-up survey

To formalize and parameterize behavioral model rules, we applied a two-step approach. First, we conducted semi-structured interviews (path 1) that we used to derive behavioral model rules. In a second step, we performed an online survey to parameterize the model (path 3). When designing the interview campaign, we applied an inductive approach with no prior assumptions on the adoption of agri-environmental schemes. Nevertheless, any study (even if semi-structured) needs a starting point to guide the interview into the desired direction. In our case, we first collected possible influence factors in an extensive literature search to capture the most important processes of the decision-making on AES. We considered reviews that specifically focus on AES (Lastra-Bravo et al. 2015, Brown et al. 2021) 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). Based on the literature search, we derived themes and questions that provided the basis for an interview campaign with farmers in five case study (CS) regions across Europe (Czech Republic, Germany, Serbia, Spain, and the United Kingdom). We chose semi-structured face-to-face interviews as a method to identify potential key factors that influence the decision-making process. Data collection consisted of two parts: (1) a qualitative interview, based on an interview protocol, covering open questions on the farmer's background, attitudes toward farming, reflection on ecological aspects, and especially the motivation to apply, or not apply, for AES; and (2) a standardized questionnaire, focusing on background information on the farm, information on environmentally sustainable practices, concrete experiences with two selected AES most common in the respective CS, motivation to apply for AES, and opinions on the EU's Common Agricultural Policy in general. Whereas the interviews enabled an in-depth dialogue about farmers' decisions on AES and their practical experiences and needs, the focus of the questionnaire was on closed questions, mostly using quantitative scales and answer categories. Across all case studies, a total of 124 interviews were conducted. The identification of overarching and more CS-specific factors was based on qualitative content analysis of transcripts (Schreier 2012) by using a coding frame informed both by our literature search and a first set of interviews, CS summary reports provided by the interview teams, as well as statistical exploration of the questionnaire data (see Wittstock et al. 2022 for an analysis of the results of the German case study and Bartkowski et al. 2023 for a case study comparison). In order to be able to evaluate the relative importance of all factors, local case study experts with necessary context knowledge about the local circumstances of farmers' decision-making on AES were consulted (see Table 3 for a summary of the importance of all factors). A key observation from the interviews was that farmers face a sequence of decision-making elements for AES participation. Based on the empirical findings, Wittstock et al. 2022 derived a heuristic framework in which the decision-making process is divided into three elements: (1) a farm-specific decision-making context, (2) a leeway in decision-making that is restricted by AES administration in a given funding period, and (3) more specific decision-influencing factors that influence if and how a particular plot is devoted to a particular scheme.

Table 3. Factors influencing farmers' decision-making as denoted in the interviews and their consideration in the ABM.

Element	Factors	Importance in interviews	Included in ABM
Heterogeneity	Economic benefit from AES	High	Included
Heterogeneity	Fit with established farm practices	High	Included
Heterogeneity	Soil productivity	High	Included
Heterogeneity	Farm size	Medium	Included
Heterogeneity	Administrative burden	Medium	Included
Heterogeneity	Lack of knowledge about AES	Medium	Included[†]
Heterogeneity	Inflexibility of AES	Medium	Excluded[‡]
Heterogeneity	Computer-based AES management system	Medium	Excluded[§]
Heterogeneity	Perceived corruption	Low	Excluded
Heterogeneity	Perceptions about the environment	No clear rating possible	Included[|]
Temporal processes	Past experience with AES	Medium	Included
Temporal processes	Duration of AES	Medium	Included
Temporal processes	Duration of tenure contracts	Low	Excluded[§]
Interaction	Tenant-owner relationship	Medium	Excluded[§]
Interaction	External influence on AES outcome	Medium	Excluded[¶]
Interaction	Influence of other farmers	Low	Included[#]

[†] Due to the diverting importance in the interviews (ranging from hardly important to very important), we decided to include this factor and test its implications.
[‡] Excluded in the sense of the interview analysis ("a decision to adopt AES is perceived as a decision to give up independent decision-making"); however, included as part of fit with established farm practices and administrative burden.
[§] Excluded due to missing data availability.
[|] Possible to consider for farmer types using organic/conventional land use as proxy, but because of limitations for combination of AES with organic farming not analyzed in detail.
[¶] More relevant for result-based schemes that are not covered with the ABM.
[#] Farmers might not report social influence as much as it actually affects their behavior as the literature shows that considerable influence is exerted by the social network (Brown et al. 2020). Currently we consider social influence through information of farmers about AES; potentially it will also be included with respect to societal reputation or as social capital with influence on pro-environmental value.

Despite the quantitative component, our interview campaign provided limited information to parameterize model rules and infer differences in behavior between farmer types. Therefore, we decided to conduct a follow-up online survey consisting of mostly closed-ended questions and a discrete choice experiment (DCE) (see Appendix 1 for the complete questionnaire). With the survey, we covered in particular farm characteristics (including questions on the specialization of the farm), personal values (covering questions on attitudes toward the environment, societal influence, and exchange with other farmers), and socio-demographic questions. In addition, we included experience with existing AES and asked for reasons why farmers did or did not participate in specific schemes. In the DCE, respondents had to choose between four alternative AES and a "no scheme" option where farmers would not get any funding for agri-environmental practices. In addition to the offered payment level, we chose contract length, bureaucratic effort, and advisory support as key attributes to be varied between the schemes, i.e., those aspects mentioned as most important with respect to contract design in the interviews (cf. Table 3). By using a combination of the results of the DCE and the survey questions, our aim was to derive the expected payment level ("willingness to accept") for each AES and farmer type.

Key elements: decision factors included in the ABM

For a description of the main aspects included in the ABM, we follow the key elements of primary data for informing ABMs, namely (1) heterogeneity between farmers with a focus on farmer types; (2) temporal aspects, in particular the sequential decision-making; and (3) interaction between farmers, in our case specifically social influence. Because of missing data that could also not be collected in the survey, we could not, however, include all aspects considered relevant in the framework developed in Wittstock et al. 2022 that forms the basis for our formalization (the third column in Table 3 indicates if the aspects were included; see footnotes for justifications).

Heterogeneity: farm types

From the interviews, we learned that a good fit with established farm practices is one of the key factors in whether or not a farm participates in AES. Within the project, a generalized typology of farming systems (farming system archetypes) that are assumed to have similar responses to policy change has been developed (Langerwisch et al. 2021). With respect to farm practices, farming system archetypes are distinguished by their farm specialization (general cropping, horticulture, permanent crops, and grazing livestock, or "mixed" if not at least 2/3 of the total farm area is dedicated to one of the corresponding land use types). Farm size was found to mainly positively influence the adoption of AES (Paulus et al. 2022, Wittstock et al. 2022). The farming system archetypes are therefore further divided by economic size, i.e., the economic output calculated using crop specific standard output coefficients (EUROSTAT 2017) multiplied by the field size (four groups: < 2000 EUR, small, medium, and large). We also leave the possibility to differentiate between organic and conventional farms to account for perceptions about the environment. However, because some AES cannot be combined with funding for organic farming, organic farming sometimes reduces the participation in AES. We therefore did not include the effect of organic farming on AES adoption in the farm types so far.

Temporal processes: sequential decision-making

We account for the sequential process of decision-making as described in the heuristic framework developed in Wittstock et al. 2022 as key concept for the decision-making process. Additional aspects with a temporal component were found to be past experience with AES as well as the duration of AES contracts. Both are included in the behavioral model rules. The duration of tenure contracts as further temporal aspect would, however, need to be available on a field-specific basis to accurately account for which fields are suitable for AES and which not. This factor is not captured in the data because of privacy issues.

Interaction: social influence

In the interviews, interaction was mentioned with respect to three instances. First, tenant-owner relationship was highlighted as a limiting factor because tenants might not be in accordance with adoption of AES on their fields. However, information on tenure would need to be available for all farmers and could not be extrapolated from a limited sample. Secondly, farmers indirectly interact with others in ways that might externally influence AES outcomes, such as dog walkers who do not respect the presence of the schemes (Wittstock et al. 2022). However, because this interaction is mostly relevant for results-based schemes that are not covered with the ABM, it is not included. Finally, although social influence was not reported as being important for the decision on AES, we decided to include the factor given our skepticism about the explanatory power of the interviews in that context.

Translation into decision rules: formalization of farmers' behavior

With respect to the specific conceptualization of the model, we found that no behavioral theory or framework (such as CONSUMAT) includes all factors that were considered important for the decision to adopt AES in the heuristic framework concluded from our interviews. Therefore, we decided to derive our own formalization based on the heuristic framework that can be adapted to peculiarities in the different case studies, e.g., by allowing us to switch on or off some components that are more or less important in some case studies (Table 4 for an overview of the resulting decision-making framework).

In their framework, Wittstock et al. 2022 first account for the decision-making context in which farmers consider AES. This first step does not focus on economic considerations but rather includes preceding considerations and restrictions before taking the actual decision on AES adoption. Wittstock et al. 2022 argue that farmers have legal and contractual land use commitments, make non-AES related land use decisions, and are restricted by workflows corresponding to their farm type and size. Because our model focuses on the decision of AES adoption and therefore does not cover the entire farm management, we do not explicitly model these decisions. Instead, we decided to summarize this into an identity-driven decision at farm level on whether the farmer is open to considering the adoption of a specific AES. In order to nevertheless take into account the diversity of influencing factors, we consider openness to be composed of several aspects. First, we assume that farmers have an intrinsic motivation to participate in AES. Second, we consider that farmers' perceptions about the relevance of AES might change over time depending on their own experience and external circumstances. Although perceptions about the environment and related changing climatic conditions were not found to influence the decision-making with respect to the adoption of AES, in the interviews it was observed that farmers who previously adopted a scheme are likely to continue with that practice in subsequent funding periods. However, some also reported negative experiences that caused them to refrain from participating. We account for these observations in a probability with higher chances of being open for participation with previous participation. The last aspect that was reported to decrease the general willingness to adopt AES was missing knowledge, e.g., regarding administrative issues or implementation. With regard to this, we assume that farmers with higher knowledge are more likely to consider AES. Although perceived corruption may also discourage farmers from participating, this factor was mentioned in only a few case studies and therefore was not considered in the overall decision framework. We assume that knowledge can be generated through advisory support or by exchange in social networks. We summarized these aspects in a stepwise process to derive openness based on probabilities for being open due to the different influencing factors (intrinsic openness, prior experience, advisory support, experience in social network). Using a probabilistic approach, we accounted for unexpected behavior not captured in the model rules. Especially because we could not explicitly include the decision-making steps expressed in the interviews, this provides the required flexibility.

Table 4. Summary of three step decision-making framework based on the heuristic framework with level of decision-making and decision process based on factors influencing farmers' decision-making as denoted in the interviews (see Table 3).

Heuristic element	Step in ABM	Decision level in ABM	Decision process in ABM
Decision-making context	Openness to specific AES	Farm level	Influenced by prior experience, intrinsic openness, influence from advisory support and/or influence through social network
Leeway in decision-making	Subset of suitable fields	Field level	Selection of fields available for AES adoption
Decision-influencing factors	Economic decision and spatial selection	Field level	Comparison of expected payment with offered payment Selection of fields on which to adopt the specific AES based on biophysical characteristics

According to Wittstock et al. 2022, more practical aspects like availability of funding for specific AES or the eligibility of certain areas for specific AES in the computer-based AES management system further restrict the participation in AES (referred to as "leeway in decision-making" in the heuristic framework). Although we do not have precise data on the availability of schemes in the application software, we nevertheless included that farmers consider if they have suitable land for the respective schemes. This comprises checking if they have the required land type for a specific scheme (e.g., arable or grassland) and land that is not occupied by other funding schemes, such as ecological focus areas that are not compatible with AES. We also leave the possibility open of restricting the selection of suitable fields according to a minimum field size, which is sometimes given as a contract detail. In this decision step, we closely adhere to the heuristic framework in terms of restricting the decision-making to external constraints.

For the final step, Wittstock et al. 2022 conclude that a range of factors influence the actual decision of participating in AES (namely they distinguish economic, routine-related, biophysical, geographic, legal, ownership-related, policy-related, and administrative factors). Again, we were not able to explicitly include all of these aspects. Instead, we focus on the particularly high importance of economic factors for the decision on AES adoption (Bartkowski et al. 2023). For the ABM, we therefore base the last decision step on an economic decision. To account for individual circumstances on a farm, we assume an individual expected payment for each AES and farm type. Specifically, we assume that farmers might be willing to accept a lower compensation if the circumstances for a scheme better fit their expectations (for example, with respect to the administrative effort for applying and maintaining a scheme). We assume that a scheme is adopted if the payment offered as defined in the policy design is at least as high as the amount expected. With respect to the final decision on where to implement a scheme, we assume that biophysical characteristics such as soil quality or distance from the farm are the primary factors, given the importance of biophysical factors in the interviews.

Challenges

Although in principle the two-step approach has shown to be a valuable combination of inductive data collection to get a general model understanding and formalize behavioral model rules (path 1) and a deductive approach with which the developed decision framework can be further specified and parameterized (path 3), we have encountered difficulties in particular with representing farmer heterogeneity. First, the empirically derived heuristic framework (Wittstock et al. 2022) included a broad range of factors influencing the behavior on AES adoption. Many of these were related to available funding for AES on particular plots, but data for the underlying computer-based management system are not publicly available and could therefore not be included in the ABM. Similarly, tenure-related aspects and legal constraints were mentioned as critical to AES participation, but information on tenure agreements is not made public and could also not be asked for in the survey because this information needs to be available for all fields. Here we had to make a reasonable decision on which factors to omit. We solved the problem by keeping the general structure of the heuristic framework, i.e. a three-stage decision process, and including only those factors for which data were available or could in principle be collected in the follow-up survey. Because we omitted a number of factors with this approach, we applied a probabilistic decision rule to allow for behaviors not explicitly covered in the model rules.

With respect to the follow-up survey, we decided to design the questionnaire as an online survey to reach as many farmers as possible and distributed the link through farmer associations and contacting farmers directly. In addition, we incentivized participation in the survey with the opportunity to take part in a raffle. However, with 381 completed responses across case studies (sample sizes ranging from 69 for the Czech Republic to 131 for Serbia; for Spain we received only 22 completed responses, which we decided not to evaluate because of lack of representativeness), we still had to deal with a low sample size. With between 50% and 77% of respondents quitting the survey before reaching the end, we furthermore had a rather large drop-out rate. Many farmers reported that the survey was too long and some participants perceived the DCE as too stylized, which might have led to some not finishing the survey and in particular the DCE. Because a statistically sound analysis of a DCE requires a substantial number of responses (especially if more detailed analyses, such as latent class analysis, are to be conducted to uncover hidden clusters among farmers), this limits the practical use of the DCE for parameterization. Furthermore, there are no alternative statistical approaches to meaningfully analyze the DCE part of the survey. These difficulties prevented us from realizing the full potential of a combined interview and follow-up survey approach. Accounting for these difficulties would have meant repeating the survey in a different way (e.g., collecting data that provide reliable results with smaller sample sizes) or involving stakeholders in a way that was not originally planned. Unfortunately, given the tight time frame and limited financial resources of scientific projects, we were unable to apply these steps to our own research. As a result, we had to resort to alternative approaches, such as pattern-oriented modeling (Grimm et al.

2005) and sensitivity analyses especially with respect to parameterizing the expected payment level in the third step of the decision-making framework. This leads to analyses that are less empirically based and therefore have less potential to support policy. We are still able to show a range of possible outcomes, but the results are subject to a greater uncertainty than those which are parameterized with more robust quantitative empirical data.

DISCUSSION

Underpinning farmers' behavior in agent-based models with empirical knowledge is increasingly important especially when these models are used for assessing agricultural policies (Kremmydas et al. 2018). However, although substantial amounts of empirical data are collected among farmers, it is often unclear how the data can be used in models. Based on insights from literature examples, we presented three pathways of how primary data can be collected among farmers and three main types of information that need to be covered to derive behavioral rules for an ABM. Below, we discuss the specific challenges related to these aspects with a particular focus on problems we faced in developing a model for farmers' decision-making in the adoption of agri-environmental measures.

In terms of the three paths, we conclude that there is not one path that works best in every situation. Depending on the problem and the specific context, each approach has its advantages but also comes with a number of challenges. Path 1 (i.e., a qualitative approach not based on an established theory) is adaptable to the specific needs of a research question and therefore well suited to exploring unfamiliar contexts, but it requires a lot of assumptions in the formalization process. Nevertheless, such an approach has the potential to well represent hidden processes that might get lost in other approaches. With respect to model-based assessment of agricultural policies, it may therefore be able to capture a wide range of mechanisms and thus highlight diverse policy implications. In many cases, however, models that are solely based on primary data collected following path 1 are parameterized by assumptions or their parameters are varied in sensitivity analyses. In both cases, this increases the uncertainty of the results compared to a parameterization with quantitative data. Models following this path can therefore mainly show the possible space of outcomes after the introduction of a policy. A theory-driven approach where quantitative data are collected (path 2) is the least ad hoc and most transparent approach, but, because of the framework of the theory, it is also the least flexible approach. Yet, the immediate transparency that one expects in a theory-guided study only occurs if the theoretical concept is adequately considered in data collection (see Sok et al. 2020 for an overview of the use of the theory of planned behavior in empirical studies in agriculture and the difficulties that arise when the theory is only loosely followed). Moreover, when using theory-based approaches for policy evaluation, it might be more difficult to convince stakeholders of the potential of such a formalized approach, which may appear overly scientific (in the sense of being detached from reality), particularly in the context of farmer behavior. A quantitative approach that is not based on theory (path 3) can provide insightful contributions as a stand-alone approach if a rich literature on (related) contexts is available from which factors and relationships (i.e., implicitly an underlying framework) can be derived. In the absence of such literature, formalization assumptions drawn from this approach can quickly appear ad hoc. In such cases, transparency about the choices made in the design of both the data collection and, ultimately, the model is particularly important. This also needs to be considered when applying this approach for policy assessment. Here, in particular, a combination of path 1 and path 3 can help overcome the challenges of the individual approaches and provide a solid basis for evaluating agricultural policies.

With respect to the main elements that need to be collected with primary data to support ABM construction, we find that heterogeneity between farmers can be derived rather easily because many approaches are available to obtain socio-demographic data, farm characteristics, as well as characteristics such as values or perceptions that might differ between farmers. Especially for the latter two types of data, we argue that the use of standardized survey instruments and constructs can help make different studies comparable. Information about the social environment and interactions among farmers might be more difficult to identify using primary data and complementary indirect analyses may be required. Even more difficult is the collection of information about temporal processes and their translation to a dynamic ABM. In real life, many processes are not as clear-cut as they need to be for a questionnaire. Here, concepts such as the consumer journey mapping (Rosenbaum et al. 2017) where stages of decision-making are disentangled might help to structure the process. However, this would add additional layers of complexity to an already extensive amount of data required.

For our own implementation, we decided to use a combination of an inductive qualitative interview campaign and a follow-up survey. Although this allowed us to tailor the questionnaire specifically to our needs, we also encountered difficulties. In particular, we had to deal with an aspect that is often problematic in surveys among farmers: small sample sizes and moderate representativeness. Acquiring sufficient participants and covering a representative share is particularly problematic in surveys for ABMs, which are usually designed for spatially limited case studies where the total population of farmers is not too large. In addition, we faced high drop-out rates in the survey. To avoid this, a trade-off between the high level of detail needed for parameterizing the ABM and cognitively demanding surveys (such as in our case the DCE where farmers repeatedly had to decide on similar situations) with high risk of drop out or unreliable responses must be found. Since farmers are short on time (especially in certain seasons) and filling out extensive questionnaires can take a long time, this might cause them not participating in the survey, abandoning it before it is completed or, which may be the worst possibility, filling it quickly in an inconsistent and unreflected manner. Therefore, it is important to prioritize the importance of getting specific information and to consider alternative data sources. To limit the number of farmer surveys, surveys can be supplemented with expert knowledge gained through focus group discussions or workshops. Such participatory modeling approaches comprise their own field of research and have been successfully applied to a range of case studies (see, e.g., Voinov et al. 2018 for an overview of methods). For relationships that are assumed to be less decisive, it might also be appropriate to assume ad hoc rules rather than include additional questions in a questionnaire (and thus making it longer). This does not need to affect the validity of the model as long as it is explained explicitly and the influence of the model rule is tested (e.g., in a sensitivity analysis).

With an increasing amount of studies targeting farmers and given that many questions in surveys are similar (especially regarding farm characteristics and socio-demographic properties), it should be considered whether results from previous surveys can be used or surveys on different topics can be combined. To achieve this goal, it is important to make the survey results publicly available to enable sharing of existing data across research groups (ensuring the necessary data protection). Similar to re-using survey data, also applying the same model concepts to several case studies reduces the effort for collecting empirical data. Although data would still be needed to parameterize the model, it would be assumed that the behavioral model rules remain structurally the same as, for instance, done by Chen et al. 2022 for European viticultural practices. In a similar vein, Murray-Rust et al. 2014 developed the agent-based modeling framework Aporia with the aim to reduce the difficulty with creating land use models. Going even further, Huber et al. 2021 developed the FARMIND framework that allows integrating different bioeconomic farm models in the same generic behavioral ABM (drawing upon the CONSUMAT framework). ABMs that cover the entire farm sector instead of focusing on specific decisions (such as the adoption of AES) can be more easily adapted to address different research questions. Examples in this regard are the AgriPoliS model, which has been calibrated with empirical data for different regions (Brady et al. 2009, Hristov et al. 2020) or the ALUAM-AB model that was developed to map land use changes influenced by market and policy dynamics and has, for example, been applied in the context of payment for environmental services (Huber et al. 2013), land abandonment and reforestation (Brändle et al. 2015), and resilience of social-ecological systems to global change (Grêt-Regamey et al. 2019). However, to develop such a comprehensive ABM, a large team with dedicated long-term funding is needed. Current funding schemes often do not offer such opportunities in a structured way.

In addition, secondary data (i.e., data processed from primary data) can serve as a valuable source of information, complementing primary data collection. Examples of potential secondary data sources for agricultural ABMs are the European Union's farm accountancy data network (FADN) (European Union 2013b) (to be extended to a farm sustainability data network, FSDN) or the Integrated Administration and Control System (IACS) (European Union 2013c). Whereas the former records agricultural income and farm activity in a representative but aggregated manner, the latter contains farm types, received subsidies, livestock and spatial information on parcels such as size and agricultural use in anonymized form. Zimmermann et al. 2015, for example, used FADN data to parameterize farmers in an ABM of the Swiss agricultural sector. Paulus et al. 2022 analyzed the influence of farm structure and landscape characteristics on the adoption of agri-environmental schemes using spatially explicit LPIS data of the Mulde region in Germany. The identified regression models describe farmers' behavior in terms of the likelihood of a farm adopting AES, the selection of fields to which these schemes are applied, and the area that farmers consider to put under AES, and can be translated into behavioral model rules of an ABM. However, limitations for using secondary data are that reasons for behavior are not explicitly covered and representativeness is not given with respect to all relevant determinants (e.g., FADN data are representative with respect to FADN region, economic size and type of farming but not necessarily with respect to other dimensions [Neuenfeldt and Gocht 2014]).

CONCLUSION

To effectively use agent-based modeling to support agricultural policy, the appropriate incorporation of farmer behavior is crucial. Although it is generally acknowledged that model assumptions must be empirically supported to adequately represent realistic relationships, how empirical observations are translated into behavioral model rules is often not explicitly described. To structure the process of formalizing farmers' behavior in ABMs using primary data, we divided it into three main steps, for each of which we discussed different approaches using literature examples. In particular, we focused on the selection of an appropriate empirical method, the design of the study to best inform an ABM, and the actual formalization of the empirical data into behavioral model rules. We highlighted the strengths and weaknesses of different strategies for collecting empirical data, particularly for use in ABMs. In addition, we elaborated that empirical data must at least cover heterogeneity among farmers, temporal aspects, and interaction in order to adequately formalize farmers' decision-making in an ABM with primary data. Although it would be desirable to formulate exhaustive guidelines for translating empirical findings into decision rules in order to make the formalization of behavioral model rules more systematic, we see no way to do so at present given the wide variety of empirical contexts. Nevertheless, we take a first step in this direction by highlighting both successful examples and shortcomings in communicating formalization. In this way, we provide an overview from which readers can learn and draw inspirations from own efforts. If future formalizations of human behavior take into account the elements we consider important, they could also form the basis for guidelines that we have not yet been able to derive from the current state of the literature. By incorporating our own experience with a model on agri-environmental schemes in Europe, we were also able to point out particular difficulties that can arise on the way to formalizing a model based on empirical observations. We hope that our methodological contribution will help to strengthen the empirical embedding of farmers' behavior into ABMs. This is ultimately critical to using ABMs as a reliable tool for effective policy advice in the agricultural sector.

Acknowledgments:

This work was supported by the European Union's Horizon 2020 research and innovation programme under grant agreement No 817501 (BESTMAP). BB acknowledges funding by the German Ministry of Education and Research within the junior research group AgriScape (grant 01UU2203). NS received funding by the Netherlands Organisation for Scientific Research (NWO), grant E10004, within the research project SECBIVIT funded through the 2017–2018 Belmont Forum and BiodivERsA joint call for research proposals. BM was supported by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) in the project

InsuranceGrass - 460738920 and by the German Federal Ministry of Education and Research (BMBF) in the project NamTip (FKZ 01LC2321D).

Data Availability:

Data/code sharing is not applicable to this article because no data/code were analyzed in this study.

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Appendix 1. Questionnaire of the online survey conducted in the BESTMAP project

The following questions were part of the questionnaire in all case studies of the BESTMAP project (Czech Republic, Germany, Serbia, Spain, United Kingdom). In addition to these common questions, the UK version of the survey included questions on the post-Brexit situation. For Serbia, specific questions on organic farming were added.

Consent

Thank you for your interest in this survey. The following questionnaire is part of research carried out by the *[please insert your institute]* as part of the European Union funded research project BESTMAP. The project aims at shedding light on the differences in farmers' motivation and decision making to allow policy makers to better include expected behaviour into the design of new regulations and subsidies for agriculture.

This questionnaire focuses on the opinion of farmers on various issues regarding agri-environmental schemes and is conducted across BESTMAP Case Studies in the Czech Republic, Germany, Serbia, Spain and the United Kingdom *[please reorder, your case study first]*. It is carried out exclusively for academic purposes and it has no commercial intentions.

It will take you approximately 15 minutes to complete the questionnaire.

Confidentiality Data use and Anonymity

You will not be asked any personally-identifying information, only general information about your activity and views. All information and data will be kept on password protected computer systems in line with University of Leeds protocols and the UK Data Protection Act *[check what needs to be inserted here for your CS]*, and will not be shared outside the research team. Results of the survey will be used for academic and other relevant publications. Results will only be published at the aggregated level and it will not be possible to identify answers from any individual participant.

If you have any questions about this questionnaire or the research, you can do so by contacting *[please insert CS contact person]* at the *[please insert your institute]* (*[please insert your email address]*).

Withdrawal of consent

You may request that your answers are withdrawn up to 30 days after your interview by contacting the email address above. We will then destroy and not use your responses. If you contact us after the 30 days have passed, we will not be able to delete all your responses.

This research is funded by the European Union's Horizon 2020 research and innovation programme (grant agreement: No. 817501) and it has been approved by the Ethics Committee of the *[please insert your institute]*.

By clicking "Next" you confirm that you have understood the above information and that you consent to taking part in this survey.

Background information on the farm

Q1.1 What is the first half of your farm's postcode (if your farm is extensive across a large area, what is the postcode for the largest share of fields)?

____

Q1.2 What kind of farm do you manage?

- ☐ Full-time individual/family-run farm (1)
- ☐ Part-time individual/family-run farm (2)
- ☐ Cooperative of farms (3)
- ☐ Company owned (4)
- ☐ Other: ________________ (5)

Q1.3 Is your farm organic?

- ☐ No (1)
- ☐ Yes, certified organic (2)
- ☐ In transition to fully organic (3)
- ☐ Mixed, organic/non-organic (4)

Q1.4 Do you participate in quality / voluntary certification schemes?

- ☐ Yes - which? ________________ (1)
- ☐ No (2)

Q1.5 What types of agricultural land did your farm manage last year (owned and rented)?

- ☐ Arable land (area in ha) ________________ (1)
- ☐ Permanent grassland (area in ha) ________________ (2)
- ☐ Permanent crops (area in ha) ________________ (3)
- ☐ Vineyards (area in ha) ________________ (4)
- ☐ Orchards (area in ha) ________________ (5)
- ☐ Woodland or forestry (area in ha) ________________ (6)
- ☐ Fallow, not in use (area in ha) ________________ (7)
- ☐ Other use (area in ha) ________________ (8)

Q1.6 How much of the agricultural land have you rented (in ha)?

____

Q1.7 How good is the average fertility of your soil compared to the average soil fertility in your district?

- ☐ Much worse (1)
- ☐ Somewhat worse (2)
- ☐ About the same (3)
- ☐ Somewhat better (4)
- ☐ Much better (5)

Q1.8 What share of land is more than 3km away from your farmstead?

- ☐ <10% (1)
- ☐ 10-30% (2)
- ☐ 31-50% (3)
- ☐ 51-70% (4)
- ☐ 71-90% (5)
- ☐ >90% (6)

Display This Question:

If What types of agricultural land did your farm manage last year (owned and rented)? = Arable land (area in ha)

Q1.9 What were your economically most important crops on arable land in the last year?

- ☐ 1: ________________ (1)
- ☐ 2: ________________ (2)
- ☐ 3: ________________ (3)
- ☐ 4: ________________ (4)
- ☐ 5: ________________ (5)

Display This Question:

If What types of agricultural land did your farm manage last year (owned and rented)? = Arable land (area in ha)

Or What types of agricultural land did your farm manage last year (owned and rented)? = Improved grassland (area in ha)

Or What types of agricultural land did your farm manage last year (owned and rented)? = Permanent grassland (area in ha)

Q1.10 Do you have livestock on your farm?

- ☐ Yes (1)
- ☐ No (2)

Display This Question:

If Do you have livestock on your farm? = Yes

Q1.11 What are the most important livestock animals you have on your farm? Please indicate the number of animals for the last year if you remember.

livestock (1)	heads/individuals (2)	
		(1)
		(2)
		(3)
		(4)
		(5)

Q1.12 How often …

	Weekly (1)	Monthly (2)	3-4 times a year (3)	1-2 times a year (4)	Never (5)
do you get consultation by an agricultural advisory or extension service in general? (1)	☐	☐	☐	☐	☐
do you get consultation related to nature conservation? (2)	☐	☐	☐	☐	☐
do you get consultation specific to agri-environmental schemes? (3)	☐	☐	☐	☐	☐

DCE Intro

[Please choose the introduction suitable for your CS:]

UK: Following the exit of the UK from the European Union, discussions are taking place regarding new ways for farming subsidies, the details of which have not yet been fully developed. These schemes (such as Sustainable Farming Incentive and Local Nature Recovery) will subsidise farming practices comparable to those offered in the Countryside Stewardship, with the broad aim of enhancing the delivery of public goods on farmland. This part of the survey is aimed at getting your opinion on possible designs of agri-environmental schemes. **We are interested in your decision-making process concerning a particular group of farming practices.** You should fill this section of the survey imagining that your farm is receiving the 2019-2020 level of Basic Payments. Please consider what choices you would make for the **hypothetical agri-environmental options** presented below as offers in the Countryside Stewardship. These schemes would have different characteristics and we are going to ask you in repeated choices to select the option you prefer. Note that these schemes are designed for research purposes only. However, we will be sending the results of our research to DEFRA to feed into their ongoing discussions. Therefore, we kindly ask you to respond as if these choices were real, so we can provide accurate information on the true opinions of farmers.

RS: In Serbia, the possibilities of financing environmentally friendly agricultural practices are currently being considered. The purpose of the survey is to examine the **attitude and interest of the farmer in applying such a practice**. For this purpose, 4 agro-ecological practices will be presented to you. After that, we will ask you to choose the option you would prefer.

EU: The European Union is discussing future options for **funding environmentally friendly agricultural practices** within its Common Agricultural Policy. This part of the survey is aimed at getting your opinion on possible designs of agri-environmental schemes. We are going to present you with a series of **hypothetical schemes**. These schemes would have different characteristics and we are going to ask you in repeated choices to select the option you prefer. Please note that these schemes are hypothetical and have been entirely designed for research purposes only. However, we will be sending the condensed results of our research to the policy makers responsible for agricultural policies in *[please insert your case study]* to feed into their ongoing discussions. Therefore, we kindly ask you to respond as if these choices were real, so we can provide policy makers with accurate information on the true opinion of farmers.

The choices are characterised as follows:

Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland
• Sowing of a **specific seed mixture** required • Use of **fertilizers and plant protection products not permitted**, with the exception of those allowed in organic farming • **Cutting** only allowed to **prevent grasses smothering** the flowering species • Applicable on **arable land** • Minimum plot size **0.1 ha** (whole parcels) or minimum width **6m** (strips at the border of a parcel)	• Cultivation of cover crops **after harvesting the main crop** • Cover crop **cannot be used as the main crop** in the following year • Cover crop must be removed no more than **6 weeks** before establishing the following spring crop • Applicable on **arable land** • Minimum plot size **0.3 ha**	• **Mowing** not allowed before a specific date announced by local authorities every year depending on the **phenological conditions** • Use of **fertilizers and plant protection products is limited** • **Ploughing** is prohibited • Applicable on **permanent grassland** • Minimum plot size **0.1 ha**	• **Mowing** not allowed before a specific date announced by local authorities every year depending on the **phenological conditions** • Use of **fertilizers and plant protection products is limited** • Area has **permanent grassland status** at the end of the contract • Applicable on **arable land** • Minimum plot size **0.1 ha**

In addition, the four different schemes differ in a **range of characteristics** you will have to comply with in order to receive payment. In the table below, you can see a summary of these characteristics.

Attributes		Your options		
Duration of contract	• **Duration** for which the respective practice would need to be implemented • The scheme has to be maintained on the **same plots** for the duration of the contract	1 year	5 years	10 years
In-person advisory support	• **Availability of free in-person advisory support** specific to agri-environmental schemes • Support with **administrative work** and with **implementation**	Yes, free of charge	No	
Administrative effort	• Effort for **non-operational aspects of the scheme** such as information gathering, applying for and monitoring the scheme	Low	Medium	High

Each option will also include the **yearly payment** that you would receive for each hectare enrolled in the particular scheme.

We ask you to choose which of the schemes you would like to apply in each case and decide how much land (in % of your area of the respective land type) you would be willing to place under the chosen contract. Only consider schemes that are applicable to land types you have. If none of the schemes suits your preferences, you can choose the no scheme option. This means that you would prefer not to receive funding related to agri-environmental schemes on your farm.

An **example** of the types of contracts you will be asked to choose from is shown below:

	Flower areas/strips	**Cover crops**	**Maintaining permanent grassland**	**Converting arable land to permanent grassland**	**No scheme**
Duration of contract	1 year	10 years	5 years	10 years	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.
In-person advisory support	Yes, free of charge	Yes, free of charge	No	Yes, free of charge	
Administrative effort	Low	High	Medium	Medium	
Yearly payment	£825 per hectare	£90 per hectare	£140 per hectare	£1,100 per hectare	

In the following, we will show you **six different scenarios** for agri-environmental schemes and ask you to select your preferred scheme for each combination.

[each respondent is randomly assigned to DCE group 1 or 2]

DCE (group 1)

Q2.1 Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland	No scheme
Duration of contract	10 years	1 year	10 years	5 years	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.
In-person advisory support	Yes, free of charge	No	Yes, free of charge	No	
Administrative effort	Low	Low	High	High	
Yearly payment	£620 per hectare	£180 per hectare	£190 per hectare	£1,100 per hectare	

- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)
- ☐ No scheme (5)

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q2.2 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q2.3 I would apply the chosen scheme on ________ % of my permanent grassland.

Q2.4 Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland	No scheme
Duration of contract	10 years	1 year	5 years	10 years	You will not **receive funding for any agri-environmental practices** you may carry out on your farm.
In-person advisory support	No	No	Yes, free of charge	No	
Administrative effort	Medium	Medium	High	Low	
Yearly payment	£690 per hectare	£135 per hectare	£190 per hectare	£800 per hectare	

- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)
- ☐ No scheme (5)

Display This Question:

If Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q2.5 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q2.6 I would apply the chosen scheme on ________ % of my permanent grassland.

Q2.7 Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland	No scheme
Duration of contract	10 years	1 year	5 years	10 years	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.
In-person advisory support	No	No	No	Yes, free of charge	
Administrative effort	Low	Low	Low	Medium	
Yearly payment	£410 per hectare	£135 per hectare	£285 per hectare	£1,250 per hectare	

- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)
- ☐ No scheme (5)

Display This Question:

If Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q2.8 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q2.9 I would apply the chosen scheme on ________ % of my permanent grassland.

Q2.10 Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland	No scheme
Duration of contract	1 year	5 years	10 years	10 years	You will not receive funding for any agri-environmental practices you may carry out on your farm.
In-person advisory support	No	Yes, free of charge	No	Yes, free of charge	
Administrative effort	Medium	Medium	Medium	Low	
Yearly payment	£410 per hectare	£120 per hectare	£285 per hectare	£1,100 per hectare	

- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)
- ☐ No scheme (5)

Display This Question:

If Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q2.11 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q2.12 I would apply the chosen scheme on ________ % of my permanent grassland.

Q2.13 Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland	No scheme
Duration of contract	1 year	5 years	10 years	5 years	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.
In-person advisory support	Yes, free of charge	No	Yes, free of charge	No	
Administrative effort	Medium	Medium	Low	Low	
Yearly payment	£825 per hectare	£150 per hectare	£240 per hectare	£800 per hectare	

- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)
- ☐ No scheme (5)

Display This Question:

If Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q2.14 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q2.15 I would apply the chosen scheme on ________ % of my permanent grassland.

Q2.16 Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland	No scheme
Duration of contract	5 years	10 years	10 years	5 years	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.
In-person advisory support	Yes, free of charge	Yes, free of charge	Yes, free of charge	No	
Administrative effort	High	High	High	Medium	
Yearly payment	£550 per hectare	£90 per hectare	£190 per hectare	£1,665 per hectare	

- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)
- ☐ No scheme (5)

Display This Question:

If Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q2.17 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q2.18 I would apply the chosen scheme on ________ % of my permanent grassland.

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Q2.19 In the previous questions you chose the "cover crops" option at least once. Which main crop would you cultivate after the cover crops?

____

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

Q2.21 In the previous questions you never chose the option "Converting arable land to permanent grassland". Can you indicate why? (several answers possible)

- ☐ I do not want to lose arable land. (1)
- ☐ I do not think this scheme will improve the environment. (2)
- ☐ Participation requires knowledge/skills which I do not have. (3)
- ☐ Participation requires technical equipment which I do not have. (4)
- ☐ Converting arable land to permanent grassland would be a bad financial decision for me. (5)
- ☐ Other reason, please specify: ________________ (6)

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

Q2.20 In the previous questions you chose the "no-scheme" option every time. Can you indicate why? (several answers possible)

- ☐ I am generally not willing to enrol in agri-environmental schemes. (1)
- ☐ I did not find the options suitable for my land or current situation. (2)
- ☐ Enrolling in such schemes would be a bad financial decision for me. (3)
- ☐ There is no need for actions to protect the environment in my farm. (4)
- ☐ Other reason, please specify: ________________ (5)

DCE (group 2)

Q3.1 Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	No scheme	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland
Duration of contract	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.	5 years	1 year	1 year	10 years
In-person advisory support		Yes, free of charge	Yes, free of charge	Yes, free of charge	No
Administrative effort		Low	High	Medium	High
Yearly payment		£620 per hectare	£120 per hectare	£215 per hectare	£1,400 per hectare

- ☐ No scheme (5)
- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q3.2 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q3.3 I would apply the chosen scheme on ________ % of my permanent grassland.

Q3.4 Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	No scheme	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland
Duration of contract	You will not **receive funding for any agri-environmental practices** you may carry out on your farm.	5 years	10 years	1 year	5 years
In-person advisory support		No	No	No	Yes, free of charge
Administrative effort		High	Low	Low	High
Yearly payment		£550 per hectare	£180 per hectare	£140 per hectare	£1,250 per hectare

- ☐ No scheme (5)
- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)

Display This Question:

If Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q3.5 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q3.6 I would apply the chosen scheme on ________ % of my permanent grassland.

Q3.7 Scenario 3/6: Please choose your preferred scheme. Click [here]() to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	No scheme	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland
Duration of contract	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.	1 year	10 years	5 years	10 years
In-person advisory support		Yes, free of charge	Yes, free of charge	No	Yes, free of charge
Administrative effort		Low	High	Medium	Medium
Yearly payment		£825 per hectare	£90 per hectare	£140 per hectare	£1,100 per hectare

- ☐ No scheme (5)
- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)

Display This Question:

If Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q3.8 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q3.9 I would apply the chosen scheme on ________ % of my permanent grassland.

Q3.10 Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	No scheme	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland
Duration of contract	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.	10 years	5 years	1 year	5 years
In-person advisory support		No	No	No	Yes, free of charge
Administrative effort		High	Low	Low	Low
Yearly payment		£550 per hectare	£150 per hectare	£140 per hectare	£800 per hectare

- ☐ No scheme (5)
- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)

Display This Question:

If Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q3.11 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q3.12 I would apply the chosen scheme on ________ % of my permanent grassland.

Q3.13 Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	No scheme	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland
Duration of contract	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.	5 years	10 years	1 year	5 years
In-person advisory support		Yes, free of charge	Yes, free of charge	Yes, free of charge	Yes, free of charge
Administrative effort		Medium	Medium	High	High
Yearly payment		£410 per hectare	£120 per hectare	£215 per hectare	£1,665 per hectare

- ☐ No scheme (5)
- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)

Display This Question:

If Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q3.14 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q3.15 I would apply the chosen scheme on ________ % of my permanent grassland.

Q3.16 Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme characteristics. If you do not have permanent grassland, please do not consider the option "Maintaining permanent grassland".

	No scheme	Flower areas/strips	Cover crops	Maintaining permanent grassland	Converting arable land to permanent grassland
Duration of contract	You will **not receive funding for any agri-environmental practices** you may carry out on your farm.	1 year	5 years	5 years	10 years
In-person advisory support		No	Yes, free of charge	No	No
Administrative effort		High	High	Medium	Medium
Yearly payment		£690 per hectare	£90 per hectare	£240 per hectare	£1,400 per hectare

- ☐ No scheme (5)
- ☐ Flower areas/strips (1)
- ☐ Cover crops (2)
- ☐ Maintaining permanent grassland (3)
- ☐ Converting arable land to permanent grassland (4)

Display This Question:

If Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Flower areas/strips

Or Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Converting arable land to permanent grassland

Q3.17 I would apply the chosen scheme on ________ % of my arable land.

Display This Question:

If Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Maintaining permanent grassland

Q3.18 I would apply the chosen scheme on ________ % of my permanent grassland.

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Or Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = Cover crops

Q3.19 In the previous questions you chose the "cover crops" option at least once. Which main crop would you cultivate after the cover crops?

____

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

And Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... != Converting arable land to permanent grassland

Q3.21 In the previous questions you never chose the option "Converting arable land to permanent grassland”. Can you indicate why? (several answers possible)

- ☐ I do not want to lose arable land. (1)
- ☐ I do not think this scheme will improve the environment. (2)
- ☐ Participation requires knowledge/skills which I do not have. (3)
- ☐ Participation requires technical equipment which I do not have. (4)
- ☐ Converting arable land to permanent grassland would be a bad financial decision for me. (5)
- ☐ Other reason, please specify: ________________ (6)

Display This Question:

If Scenario 1/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 2/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 3/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 4/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 5/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

And Scenario 6/6: Please choose your preferred scheme. Click here to reopen the summary of the scheme... = No scheme

Q3.20 In the previous questions you chose the "no-scheme" option every time. Can you indicate why? (several answers possible)

- ☐ I am generally not willing to enrol in agri-environmental schemes. (1)
- ☐ I did not find the options suitable for my land or current situation. (2)
- ☐ Enrolling in such schemes would be a bad financial decision for me. (3)
- ☐ There is no need for actions to protect the environment in my farm. (4)
- ☐ Other reason, please specify: ________________ (5)

Experience with AES

[Please choose the introduction suitable for your CS:]

EU + UK: After having shown you different design options, we would now like to know more about your current and previous participation in **specific agri-environmental schemes that already exist**.

RS: After we showed you the different options for agri-environmental subsidies, we would like to know more about your opinion about them. In addition, we would like to know about your views and your previous experience, if you have any, with organic production.

[Present max. four CS-specific schemes which are the ones closest to our four selected schemes in the DCE. For RS: Present four schemes and additional scheme on moving livestock to state land for grazing.]

AES1 Is your farm engaged in the agri-environmental scheme *"xyz"*?

- ☐ Yes - on ________________ ha. (1)
- ☐ No, currently not but I have participated in that scheme in the past. (2)
- ☐ No, I have never participated. (3)

Display This Question:

If Is your farm engaged in the agri-environmental scheme "xyz"? = Yes - on ... ha.

AES2 I apply *"xyz"* because... (several answers possible)

- ☐ of the monetary compensation (1)
- ☐ of the ecological effects (2)
- ☐ many of my neighbouring farmers apply this scheme (3)
- ☐ I think it improves my image as a farmer in the society (4)
- ☐ it fits fit with what we do on our farm (5)
- ☐ it contributes to climate resilience and/or carbon sequestration (7)
- ☐ Other reasons, please specify: ________________ (6)

Display This Question:

If Is your farm engaged in the agri-environmental scheme "xyz"? = Yes - on ... ha.

AES3 What are the main criteria for selecting fields on which you apply *"xyz"*? I select fields that… (several answers possible)

- ☐ have a difficult to manage soil (1)
- ☐ are of low productivity (2)
- ☐ are of high elevation/steep slope (3)
- ☐ are further away of farmstead/farm yard (4)
- ☐ have higher expected ecological benefit (5)
- ☐ Other, please specify: ________________ (6)

Display This Question:

If Is your farm engaged in the agri-environmental scheme "xyz"? = No, currently not but I have participated in that scheme in the past.

AES4 Why are you currently not participating in *"xyz"*? (several answers possible)

- ☐ Demand for extra time or labour for installing and maintaining the scheme is too high (1)
- ☐ Demand for extra time or labour for bureaucratic tasks is too high (2)
- ☐ I have had negative experiences with the monitoring of the schemes (3)
- ☐ The scheme does not fit with what we do on the farm (4)
- ☐ The financial support does not cover the costs (5)
- ☐ The contract duration is too long (6)
- ☐ The scheme contains too many rules and constraints (7)
- ☐ I do not think this scheme will improve the environment (8)
- ☐ The risk of sanctions is too high (9)
- ☐ None of the farmers in my social network participates (10)
- ☐ Lack of support from advisory services (11)
- ☐ Other reasons, please specify: ________________ (12)

Display This Question:

If Is your farm engaged in the agri-environmental scheme "xyz"? = No, I have never participated.

AES5 Do you know that the agri-environmental scheme *"xyz"* exists?

- ☐ Yes (1)
- ☐ No (2)

Display This Question:

If Do you know that the agri-environmental scheme "xyz" exists? = Yes

AES6 Could you in general imagine participating in *"xyz"*?

- ☐ Yes (1)
- ☐ No (2)

Display This Question:

If Could you in general imagine participating in "xyz"? = Yes

AES7 Why did you not participate in *"xyz"* so far? (several answers possible)

- ☐ Demand for extra time or labour for installing and maintaining the scheme is too high (1)
- ☐ Demand for extra time or labour for bureaucratic tasks is too high (2)
- ☐ The scheme does not fit with what we do on the farm (3)
- ☐ The financial support does not cover the costs (4)
- ☐ The contract duration is too long (5)
- ☐ The scheme contains too many rules and constraints (6)
- ☐ I do not think this scheme will improve the environment (7)
- ☐ The risk of sanctions is too high (8)
- ☐ None of the farmers in my social network participates (9)
- ☐ Lack of support from advisory services (10)
- ☐ Other reasons, please specify: ________________ (11)

Display This Question:

If Could you in general imagine participating in "xyz"? = No

AES8 Why can you not imagine participating in *"xyz"*? (several answers possible)

- ☐ Participation requires knowledge/skills which I do not have (1)
- ☐ Participation requires technical equipment which I do not have (2)
- ☐ Demand for extra time or labour for installing and maintaining the scheme is too high (3)
- ☐ Demand for extra time or labour for bureaucratic tasks is too high (4)
- ☐ The scheme does not fit with what we do on the farm (5)
- ☐ The financial support does not cover the costs (6)
- ☐ The contract duration is too long (7)
- ☐ The scheme contains too many rules and constraints (8)
- ☐ I do not think this scheme will improve the environment (9)
- ☐ The risk of sanctions is too high (10)
- ☐ None of the farmers in my social network participates (11)
- ☐ Lack of support from advisory services (12)
- ☐ Other reasons, please specify: ________________ (13)

[Additional questions for cover crops]

Display This Question:

If Is your farm engaged in the agri-environmental scheme "xyz"? = Yes - on ... ha.

CC4 Which main crop would you cultivate after the cover crops?

____

Display This Question:

If Is your farm engaged in the agri-environmental scheme "xyz"? = No, currently not but I have participated in that scheme in the past.

CC6 Which main crop did you cultivate after the cover crops?

____

Other AES

Q7.1 Has your farm ever been engaged in other agri-environmental schemes (in addition to the ones asked for in the previous questions)?

- ☐ Yes (1)
- ☐ No, I have not participated in other schemes. (2)
- ☐ No, I have never participated in agri-environmental schemes before. (3)

Display This Question:

If Has your farm ever been engaged in other agri-environmental schemes (in addition to the ones aske... = Yes

Q7.2 The following other agri-environmental schemes are currently executed or have been executed in the last five years (please separate the individual entries with a comma):

____

Personal views

Q8.1 Please rate your level of agreement to the following statements:

	Strongly agree (1)	Somewhat agree (2)	Neither agree nor disagree (3)	Somewhat disagree (4)	Strongly disagree (5)
Producing food is the single objective of farming (1)	☐	☐	☐	☐	☐
Safeguarding of the environment is an important task of farmers. (2)	☐	☐	☐	☐	☐
Maximizing profit is the single objective of my management (3)	☐	☐	☐	☐	☐
It is important to be perceived as environmentally friendly by society (4)	☐	☐	☐	☐	☐
I always make time to socialise with other farmers (5)	☐	☐	☐	☐	☐
I am keen to apply new technology on my holdings as it becomes available (6)	☐	☐	☐	☐	☐

Sociodemographic background

Q9.1 How many total years have you been working in agriculture?

____

Q9.2 What is the highest level of farming education you have completed? If currently enrolled, the highest certification already received.

- ☐ No training (1)
- ☐ Vocational/professional training (2)
- ☐ Bachelor's degree (3)
- ☐ Master's degree (4)
- ☐ Professional degree (5)
- ☐ Doctorate degree (6)
- ☐ Prefer not to say (7)

Display This Question:

If What kind of farm do you manage? = Full-time individual/family-run farm

Or What kind of farm do you manage? = Part-time individual/family-run farm

Q9.3 Is there already a designated successor for your farm?

- ☐ Yes, a successor is designated (1)
- ☐ Not yet designated (2)
- ☐ No (3)
- ☐ Other (4)

Display This Question:

If What kind of farm do you manage? = Full-time individual/family-run farm

Or What kind of farm do you manage? = Part-time individual/family-run farm

Q9.4 Is your household generating further income, besides agricultural production, on your farm (e.g. tourism/hospitality, lending storage space, food processing,…)?

- ☐ Yes (1)
- ☐ No (2)

Display This Question:

If Is your household generating further income, besides agricultural production, on your farm (e.g.... = Yes

Q9.5 Which share of your household income is generated by activities other than farming?

- ☐ <10% (1)
- ☐ 10-30% (2)
- ☐ 31-50% (3)
- ☐ 51-70% (4)
- ☐ 71-90% (5)
- ☐ >90% (6)

Q9.6 How much of your produce is marketing directly to consumers (e.g. vegetable boxes)?

- ☐ <10% (1)
- ☐ 10-30% (2)
- ☐ 31-50% (3)
- ☐ 51-70% (4)
- ☐ 71-90% (5)
- ☐ >90% (6)

Q9.7 What is your gender?

- ☐ Male (1)
- ☐ Female (2)
- ☐ Other (3)
- ☐ Prefer not to say (4)

Q9.8 How old are you?

- ☐ Under 18 (1)
- ☐ 18-24 (2)
- ☐ 25-34 (3)
- ☐ 35-44 (4)
- ☐ 45-54 (5)
- ☐ 55-64 (6)
- ☐ 65-74 (7)
- ☐ 75-84 (8)
- ☐ 85 or older (9)
- ☐ Prefer not to say (10)