BESTMAP Conceptual Framework Design & Architecture (update)

Deliverable D2.5

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Guy Ziv, Arjan Gosal, Rosemary Wool, Jodi Gunning,
Tomáš Václavík, Fanny Langerwisch, Michael Beckmann, Anne Paulus,
Birgit Müller, Meike Will, Anna Cord, Stephanie Roilo,
James Bullock, Paul Evans, Cristina Domingo-Marimon, Joan Masó Pau

University of Leeds
Palacký University Olomouc
Helmholtz Centre for Environmental Research - UFZ
Technische Universität Dresden
UK Centre for Ecology & Hydrology
Centre for Ecology Research & Forestry Applications

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

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Summary

This deliverable provides an update of the General Framework for the BESTMAP Policy Impact Assessment Modelling (BESTMAP-PIAM) toolset. A previous version of this framework was described in Deliverable 2.2. The BESTMAP-PIAM (see figure) is based on the notion of (1) setting up a set of representative case study (CS) areas within regions of the Farm Accountancy Data Network (FADN); (2) defining (a) a typology of agricultural systems, later referred to as Farm System Archetype (FSA); (b) mapping all individual farms within the case study to FSAs, based on the data in the Integrated Administration and Control System (IACS); (c) model the adoption of agri-environmental schemes (AES) within the spatially-mapped FSA population using Agent Based Models (ABM), based on literature and a discrete-choice survey with sufficient representative sample in each FSA of each CS, to elucidate the non-monetary drivers underpinning AES adoption and the relative importance of financial and non-financial/social/identity drivers; (d) linking AES adoption to a set of biophysical, ecological and socio-economic impact models; these in turn are (3) developed into meta-models and linked to indicators developed for the post-2020 CAP output, result and impact and (4) upscaled to EU scale in FADN regions where CS developed meta-models are transferable to; finally (5) all outputs are visualized and a dashboard for policy makers is provided to explore a range of policy scenarios and ‘story maps’, focusing on cost-effectiveness of different AES. Each of these steps are detailed in a separate section below.

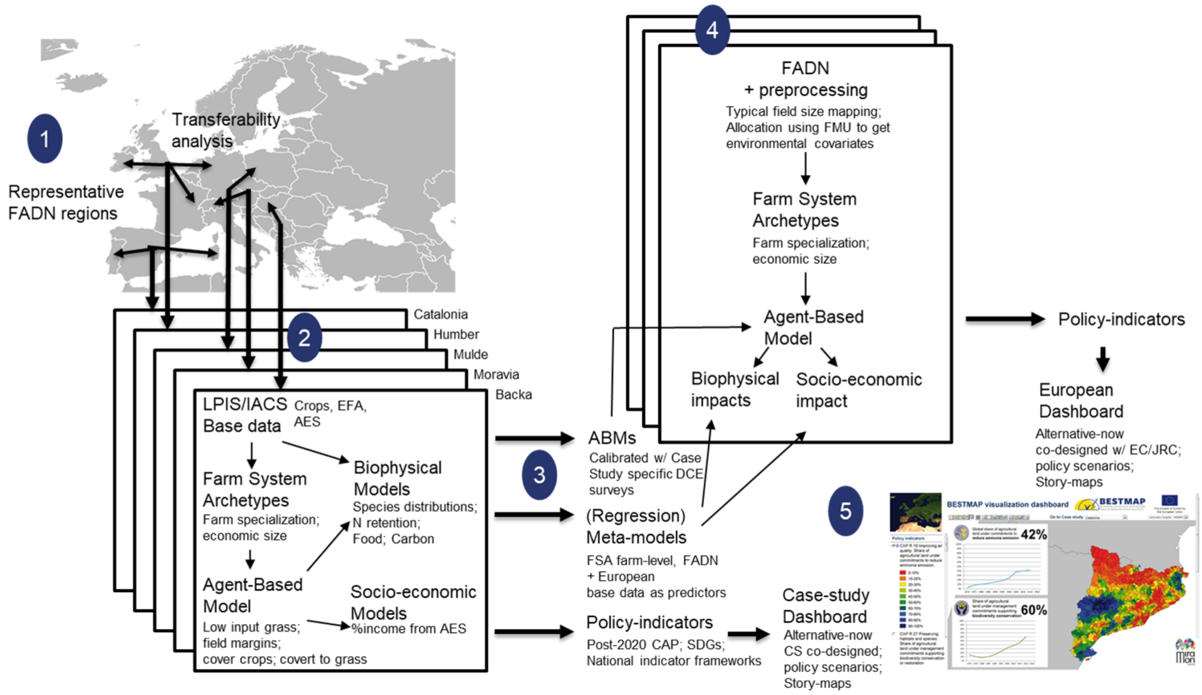


Figure 1: Overview of the BESTMAP-Policy Impact Assessment Model (BESTMAP-PIAM) framework

Before detailing each step, we list a number of assumptions made in the development of the Conceptual Framework:

- That decision factors are similar for farmers who belong to the same FSA (for extended discussion of FSAs in BESTMAP see Deliverable 1.3). Indeed that is how we define what an FSA is.

- That the decision factors of adoption of an AES in the CS region, for a specific FSA, is the same for all farmers within that FSA in other FADN regions belonging to the same strata of agricultural systems (see step 1).

- That ecosystem services/public goods and socio-economics impacts, which we derive per CS as regression meta-models linking impact to FSA and farm areas with and without each modeled AES scheme, can be applied in similar FADN regions using the FADN microdata record in other regions.

1. Farming System Archetypes

To allow linkages between CS and EU level to work and after revising our first approach we focused on a set of attributes to define FSAs which must.

- Be mappable for each individual farm in all CS based on spatial data from public or administration sources. In particular, these include IACS/LPIS data - providing for each farmer and year of data the individual fields they managed, the crops grown, ecological focus areas (EFA)[1], and ongoing AES contracts.
- Be mappable from FADN microdata, so we can use the FADN data to create a set of ‘farmer agents’ which individually “decide” if they adopt the set of AES, based on the same relationships found in the CS ABM.
- Use weighing coefficients based on Standard Output (economic size) and Farm Specialization (type of farm) which FADN already includes.
- Not exceed a reasonable number of different FSAs, allowing for surveying (step C) with reasonable resource requirements. Around 5-6 FSAs would be a limit for a survey, considering each FSA should have a sufficient sample of farmers surveyed.

We removed the following necessities of attributes

- Be based on attributes that farmers can easily and reliably answer in an online survey without the need for intensive search for that information, allowing farmers to fill the data and get classified into specific FSAs in consequent analyses
- Correspond to or be proxies of factors affecting farmers’ AES adoption decision. There is a wealth of literature on the subject (e.g. Lastra-Bravo SB, Hubbard C, Garrod G, Tolon-Becerra A, 2015), as well as BESTMAP interviews where we asked >120 farmers in the five CS about those (c.f. Deliverable 3.4).

[1] Post-Brexit the plan of UK DEFRA is to cancel ‘greening’ payments, hence field level information on implementation of EFAs may not be collected. We find that data extremely useful for modeling agricultural systems, so would advise policymakers to keep collecting such data even if regulations are simplified and monitoring EFA is not mandatory.

To develop and map the full classification of FSAs in our five CSs, we originally envisioned that FSAs would be characterized by (1) dominant environmental conditions (e.g. climate, soil), (2) land-use intensities and management practices (e.g. crop types, crop rotations, mechanization, fertilizer application), but also by (3) socio-economic factors (e.g. land tenure and ownership, size of the fields/agricultural holding) that would provide a link to farmers' behavioral characteristics. However, in order to meet the assumptions required to upscale our FSA classification from CS to EU level and after discussing possible attributes included in IACS/LPIS and FADN, BESTMAP made the decision to base our FSA classification on two primary dimensions, following the FADN approach of **(1) farm specialization** and **(2) economic size class**. The methodology below describes the data sources and procedures needed to identify and map the FSAs for **individual farms** in each of the CS areas.

Farm specialization as one main dimension of FSAs. To connect our classification to FADN data, we chose to use the farm typology classification 'Type of Farming' (TF8) of FADN (defined in Annex IV of EU regulation 2015/220), which represents the farm specialization. However, we reduced the eight TF8 to four types (for details see D3.5): general cropping (P1, TF8 = 1), horticulture (P2, TF8 = 2), permanent crops (P3, TF8 = 3 or 4), grazing livestock (P4, TF8 = 5 or 6). Additionally, we used a mixed class for farms with no dominance of one of the above mentioned types (as well as granivores, which is a small number of farms; TF8 = 7 or 8). Farms classified as P1, P2, P3 or P4 have to dedicate at least 2/3 (66.6%) of the total farm area to the corresponding land use type (area-based rules defined in EU regulation 2015/220). If this condition is not met, the farm is classified as mixed. The farm specialization can also be easily obtained by farmers in an online survey, which makes it possible to combine the FSA classification with the ABM related project work.

The **economic size** of the farm as the second attribute of FSAs relates to the income, which is a well-known factor affecting decision making in the agricultural sector. It is given as variable SE005 in Standard Result in FADN microdata and as a categorical variable SIZ6 based on ES6 classes. Here we adopt a simplified version of FADN ES6 (resulting in 3 classes - small, medium and large farms, see Deliverable 3.5 for details). Since economic size is not directly available from the LPIS data, we used Eurostat 2013 Standard Output (SO) Coefficients (in EUR per hectare, for ~90 crop types) to calculate it. SO represent the average monetary value of the agricultural output at farm-gate price, in Euro per hectare or per head of livestock. The Economic size of each farm was hence calculated by multiplying the area of each crop (extracted from the LPIS data) by the corresponding SO.

To map the **FSA** of individual farms we made use of the combination of both dimensions explained above. By overlaying the farm specialization (P1 to P4, and mixed) with the economic size of the farm (small to large, and <2000), we identify and map the FSA for each individual farm in all CSs (Table 1). This procedure gives an overall number of possible combinations of 20 FSAs, however not all will be present in each CS area.

Table 1: Definition of the FSA using farm specialization and economic farm size.

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

1.2 Other Farmers' Attributes

There are a number of other attributes we considered for FSA. None of these met all objectives (i.e. mappable from spatial data for all farms, mappable to FADN microdata, easy for farmers to answer in a survey). We describe some of these attributes below, as they may be used in some steps e.g. as attributes assigned to each farm from spatial data that are used in ABM. *Note that if used (and important) in CSs ABMs or biophysical models, one should find a FADN region/NUTS2 scale source for the same data, to be used for typology of agricultural systems.* Alternatively, we can use spatial data to find the distribution of parameters for an FSA and perhaps correlations to attributes common between spatial data and FADN microdata (for proportional allocation micro-simulation) and use a stochastic approach to set those attributes to the FADN microdata in the upscaling step.

<u>Past participation in AES</u> - this is also a known factor differentiating farmers. We do not have data to suggest *successful/positive* participation vs. *negative* experience. From IACS/LPIS data, we know which farmer had at least one field under AES contract within a period of several years (limited by the years provided by administrations). This is a binary variable - yes (had >1 field under AES contract between e.g. 2014-2018) / no (had no fields with AES contract in that time period). From FADN, we can check if SE621 'Environmental subsidies'[2] is larger than zero or not. However, we can't know in FADN anything except for the year of the data, as farm returns are not all the same year to year. FADN does have <u>some farms</u> repeat across multiple years, but it is not designed as a longitudinal study. Of course, asking the farmers is rather simple for this attribute.

[2] SE621 is defined as subsidies on environment (caution to avoid double-counting of DP under Art 69 of 1782/2003) + Subsidies on environmental restrictions. It is calculated (from FADN 2015 onwards) as the sum of agri-environment-climate and animal welfare payments + organic farming + Natura 2000 and Water Framework Directive payments (excluding forestry)

Average size of fields may be a proxy of level of mechanization / intensification. This is easy to derive from spatial data (again,using a method like IoU to link the same farm across data years), and likely okay for farmers to answer. However, this attribute cannot be deduced from any data in FADN. There are some maps of field size across Europe (e.g. Kuemmerle T, Hostert P, St-Louis V, Radeloff VC.) or GeoWiki campaigns (Van der Zanden, Emma H., et al.) - these can be used in defining agricultural systems (in Step A) if needed, or approximating field size for FADN regions we do not have IACS/LPIS for (in upscaling part).

Farming intensity which can be defined in Eurostat as inputs expenditure per hectare, a value that can be extracted from FADN. Note some projects like SEAMLESS used total output per hectare as an intensity measure. As IACS/LPIS provide no data on inputs, we cannot adopt the Eurostat metric. As for output per hectare, this is nearly identical to Standard Output coefficients we are taking as given from Eurostat to calculate Economic Size, hence are not useful as an additional dimension.

Average distance between groups of fields managed by the same famer as a proxy of mechanization and family vs. corporate farming. This is not available in FADN data, and hard for farmers to answer in an online survey.

Average period of crop rotation as indicator of pro-environmental attitudes, for example, is again unavailable in FADN data. Also, our IACS/LPIS data is currently only for 4 years in several CSs which is too short to identify rotations.

Soil quality/agricultural productivity per field is an important factor affecting farmers' adoption of AES on particular fields and not others. We only have farm level yields in FADN, not per field yield but this is difficult to get as spatial data.

Percent of UAA land under short lease / "field swapping" (Pflugtausch/ Flächentausch in German) may hinder farmers from adopting AES as they have little ‘ownership’ over the land. We can compare farms across years in IACS/LPIS and compare the area of ‘core’ fields (which they report on year-after-year) and fields reported only in some years. FADN include SE030 ‘Rented UAA’ which can be useful, albeit some farms rent their land for a very long time (especially in Eastern Europe) and therefore these may not compare well - in CZ over of land 70% is rented but IACS/LPIS shows nearly no change in managed area per farm over ~5 year period of data. There is no other FADN data that can help as a proxy for this.

Percent of Farm Area as landscape features which is an impact indicator post-2020, possibly can be assessed from the Small Woody Elements in High Resolution Layers of Copernicus and/or IACS/LPIS data for buffer strips, hedgerows etc. (if around arable land). FADN, however, does not include such information.

2. Step A – Defining representativeness of case studies

The initial set of 5 CSs used in BESTMAP were chosen for geographic spread, as well as organizational and institutional match to partners and previous connections (which are key for proper engagement with farmers). However, the Conceptual Framework and WP5 of BESTMAP will be upscaling those CSs to wider FADN regions across the EU. Generalization and transferability of findings from CSs is limited by their specific geographical context and characteristics unique to each study region. Upscaling of policy effects to EU level may be biased if based on selection of CS information that is not representative for a larger European region. Therefore, BESTMAP CSs will be evaluated for their representativeness within their countries and across the EU. This will allow identifying the locations and the number of extra CSs where further regional analyses might be needed to represent the EU as a whole.

BESTMAP-PIAM assumes the farmers' behavioural AES adoption characteristics and biophysical/socio-economic 'bundles' are transferable between regions within the same strata of agricultural systems. Several different typologies of agricultural systems have been proposed in the past, such as Agricultural landscapes (van der Zanden et al. 2016), Environmental stratification of Europe (Metzger et al. 2005), Rural typology for strategic European policies (van Eupen et al. 2012) or the Regional typology of farming systems contexts developed by the SEAMLESS project (Andersen et al. 2010). These typologies capture different aspects of agricultural landscapes, but they typically include climate, biophysical, socioeconomic and agricultural characteristics of farmlands. BESTMAP will assess the correspondence between the categorical maps of typologies by quantifying their spatial concordance. However, as these typologies were typically developed by expert-based or data-driven clustering of different agricultural systems variables, they do not necessarily account for the key dimensions of farming systems in the CSs.

Therefore, we apply the transferability analysis developed by Vaclavik et al. (2016), that centers clusters of agricultural systems around the CS and calculates the statistical distance between the centroid (average) of each CS study area with a selected list of European-level variables. The similarity of a region within Europe (e.g. FADN or NUTS2 region) with the CS study area is represented by absolute distance (D):

$$D = \frac{1}{e \times c \times v} \sum_{i=1}^{v} \sum_{n=1}^{c} \sum_{m=1}^{e} \left| x_{i,n} - x_{i,m} \right|$$

with x being the normalized (between 0 and 1) value of each variable i, e being the number of regions (e.g. FADN regions or NUTS2 region) within Europe, c being the number of regions within the CS and v being the number of considered variables.

As our upscaling strategy relies on FADN, the 'regions' we will consider hereafter are FADN regions. In a large portion of the EU, FADN regions are equivalent to NUTS2 but in places where they are too large, we will use NUTS2 or potentially even NUTS3 regions, using FADN microdata when accessible.

We will select a list of variables that represent important region attributes we argue control either adoption or impact of AES. Two groups of variables will be considered, representing either farm system (e.g. economic size, farm specialization, area of arable land, field size) or biophysical characteristics (climate, topography, soils). These data are collected from either FADN Standard Reports (already online in FADN regions), the *temporal trend* in some FADN indicators in the last years, European Social Survey/World Values Survey (coarsed to FADN region via weighted averaging)/Hofstede Culture Compass/Eurostat/FAOStat/Eurobarometers, and a number of gridded biophysical/climate/pedological[3] sources[4] (averaged over FADN polygons). See table 8 in section 6.2 for data sources available both at the CS level and the EU level. However, different subsets of variables will be used to assess the upscaling potential for the BESTMAP biophysical models of ecosystem services and the ABMs of farmers' adoption of AES.

The inverse distance will be taken as a 'transferability potential', and will be mapped spatially across the FADN/NUTS regions of the EU as a gradient of similarity. A spatial overlay of the areas with the highest transferability potential (e.g. a distance smaller than 0.25) will indicate the other regions for which the results of BESTMAP models developed for a particular CS are most representative. At the same time, this analysis will allow identifying the regions that are under-represented by the CSs of BESTMAP, and (in the future) prioritize new CSs.

3. Step B - Mapping from spatial datasets to FSAs

The mapping of individual farm data provided by IACS/LPIS to FSAs follows the procedure detailed above to calculate (1) the farm specialization, based on a rule-based procedure by crop area, in combination with (2) the economic size, calculated by weighing each farm field by SOC from Eurostat and by thresholding to small/medium/large categories. Combining farm specialization and economic size categories led to a farm specific FSA.

In mapping between LPIS/FADN/Eurost we identified a number of challenges and made several decisions with respect to:

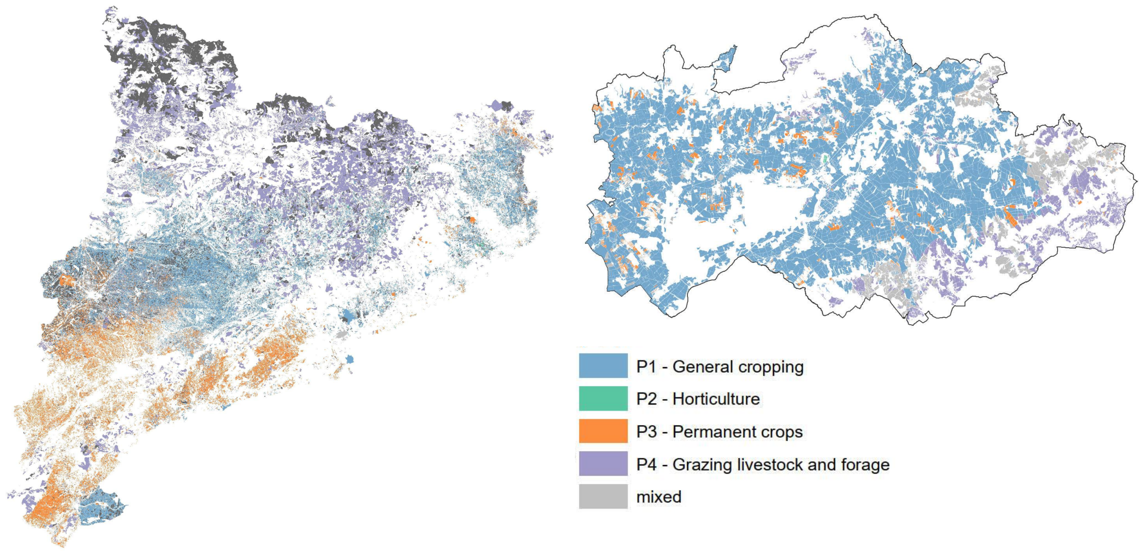
- Distinguishing market sale vs. direct sale and in/out of glasshouses (P1 vs. P2). It was hard to distinguish between different vegetable types, such as in glasshouses, in 'protected' space, for market sale vs. for direct sale (P1 vs. P2). We used a combination of OpenStreetMap and local experts and decided that glasshouses are negligible in our case studies, therefore we neglected them in our analysis

[3] See e.g. https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/soil-related-indicators-support-agro-environmental-policies

[4] Some consideration for gridded inputs relates to layers or auxiliary inputs used in biophysical models. For example, baseline N application rate is an input to nutrient delivery model.

- Distinguishing between general cropping and livestock farming (P1 vs. P4). To identify livestock farms we had to distinguish between permanent and temporal grasslands assuming that livestock farms need permanent grassland. However, we only had sparse and inconsistent information on livestock. Where we had no information we decided for each case separately how to deal with this inconsistency.
- Standard Output Coefficients. SO can generally be derived from a common database. However, assigning the correct/best values was hampered by several issues. For matching crops with SO it's sometimes not clear which value to choose, e.g. for the Humber all permanent grassland was designated to the SO "Permanent grassland and meadow - pasture and meadow", which has a value of €237.28 per/ha rather than the "Permanent grassland and meadow - rough grazings" variant which has a value of €1.25 per/ha. Additionally, there are no different economic values for organic farming, which would be expected.

Examples of spatial mapping of farm specialization, economic size and the final FSAs are given below.



a b

Figure 2: Farm specialization for Catalonia (a) and South Moravia (b).

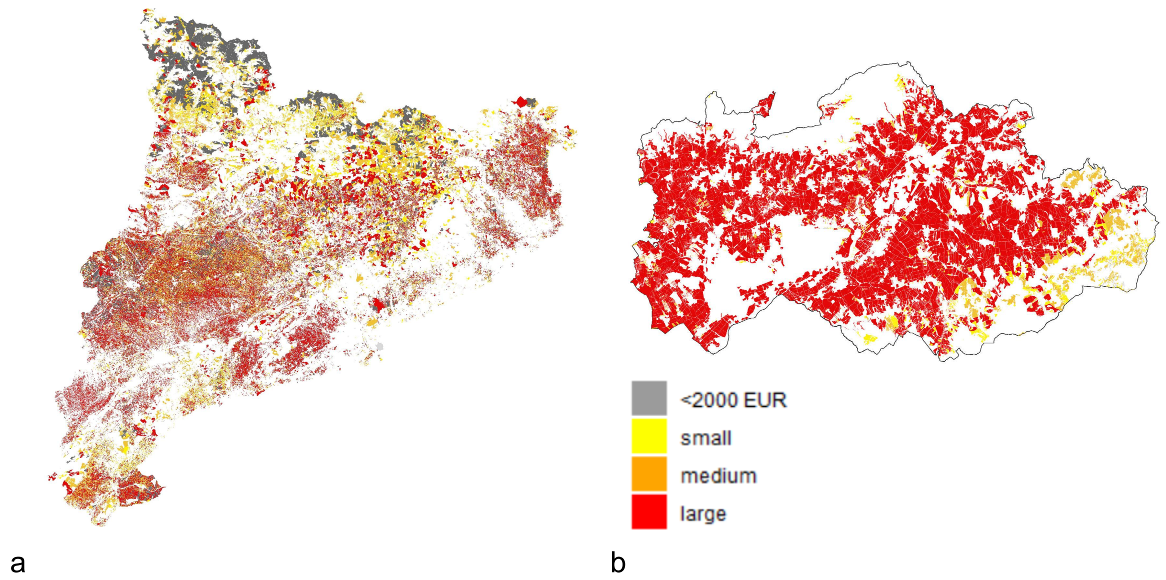


Figure 3: Economic size class for Catalonia (a) and South Moravia (b).

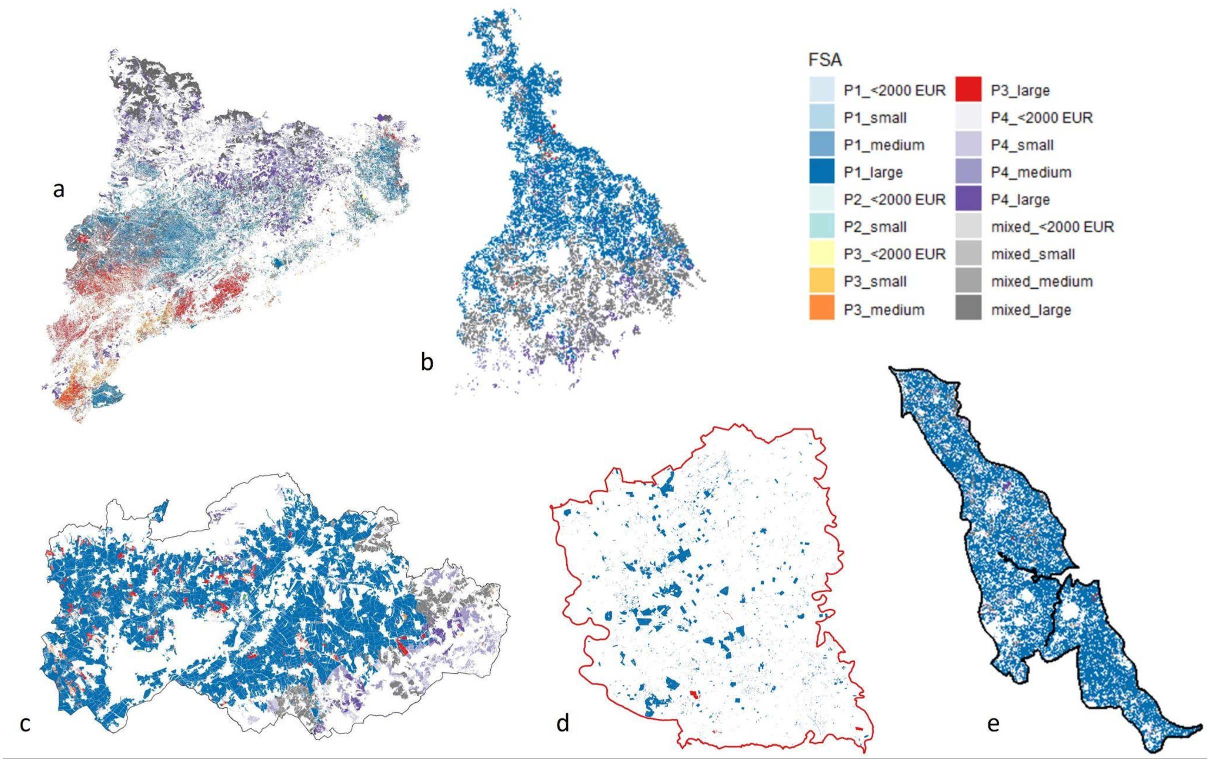


Figure 4: Farming system archetypes for all case study areas: a) Catalonia, b) Mulde, c) South Moravia, d) Bačka and e) Humber.

Full details on the construction of FSAs from IACS/LPIS see Deliverable 3.5.

4. Step C – model AES adoption using Agent-Based Modeling

To identify what determines the spatial allocation of AES adoption, BESTMAP-PIAM uses an agent-based modeling (ABM) approach. ABMs are process-based simulations that allow to represent decisions of individual farmers and their interactions with others as well as the environment. In BESTMAP, the ABM will be used to model land-use patterns that arise from the adoption of four selected agri-environmental schemes (flower strips, cover crops, maintaining permanent grassland, conversion of arable land to permanent grassland). In combination with the biophysical models, this allows to study the social-ecological consequences of agricultural policies at different spatial and temporal scales and to test the implications of different designs of the EU's Common Agricultural Policy. ABMs provide the opportunity to include farmer decision-making explicitly and consider influence factors that go beyond purely economic considerations (Groeneveld et al., 2017; Huber et al., 2018). The conceptual framework for the ABM includes the specification of spatial and temporal scales, the description of incorporated farm and farmer characteristics, relevant AES properties and the structure of the decision process of the farmers.

4.1 Entities, state variables and scales

BESTMAP considers the case study regions explicitly and assumes a spatial resolution at field level. The output of the ABM will be the pattern of implementation of the four AES at the field level.

We have incorporated two types of agents: individual farmers and fields, with each farmer managing a fixed set of fields (data on parcels managed per farm included in the Case Study Base Layer, see Deliverable D3.1). All farmer agents belong to a FSA based on their Economic Size and Farm Specialization (as described in Section 1). For simplification, we assume that farmers do not switch between FSAs which also implies that they do not change the size of their farms and their specialization. Additionally, farmers are described by state variables which are related to external conditions (availability of consultancy and social network) or to specific AES (previous experience and intrinsic openness). An overview of the included state variables and sources that are used for their parameterization are given in Table 2.

Table 2: Overview of farmer characteristics included in the model and sources for parameterization

	Parameter	**Source/Remarks**
Farmer specific	Farm economic size	FSA classification (cf. Step B)
	Farm specialization	FSA classification (cf. Step B)

	Set of fields	LPIS/IACS
	Access to consultancy	Follow-up survey on CS level (see Section 4.5), switched on or off to test importance for model outcomes
	Social network	Spatially proximate neighbors or other farmers in same FSA group, switched on or off to test importance for model outcomes
AES specific*	Prior experience with specific AES	Emerging property of the system; the initial state is derived from LPIS/IACS
	Intrinsic openness to specific AES	Follow-up survey on CS level (see Section 4.5) Reviews on AES adoption, e.g. Lastra-Bravo et al., 2015; Dessart et al., 2019; Brown et al., 2020

*All AES specific variables are composed of four values, i.e. one value per AES.

Fields are characterised by state variables such as size or soil conditions (see Table 3). Furthermore, we include the spatial distribution of the fields, i.e. their location as well as ownership (reflected also as the farmer characteristic 'set of fields'). The ABM has a realistic spatial representation (at farm with field levels) derived from IACS/LPIS data. For each field, land use (i.e. arable crops, permanent grassland etc.) and intensity (organic, conventional) will be assigned. Depending on the availability of geospatial data in the CS, further soil and terrain characteristics can be incorporated in the model if the survey (see Section 4.5) reveals that other geospatial characteristics determine the spatial selection of fields on which a farmer adopts AES.

Table 3: Overview of field characteristics included in the model and sources for parameterization (see Deliverable D3.1 for more information on data availability in the CSs).

	Parameter	**Source/Remarks**
Field specific	Ownership	LPIS/IACS
	Size	LPIS/IACS
	Location	LPIS/IACS
	Land use	LPIS/IACS
	Intensity (organic/conventional)	LPIS/IACS

	Soil conditions	data available at case study level

The four selected AES can differ in several attributes which determine farmers' decision on adopting a specific AES or not (Table 4). In addition to the specific requirements of the AES, these characteristics include spatial properties, i.e. the minimal field size required to implement a specific AES, temporal properties, i.e. the duration of an AES contract and the level of bureaucracy to apply for, implement and monitor the scheme (discretized in three classes low/medium/high). The minimal field size of the selected AES is based on existing regulations. The AES properties contract duration and level of bureaucracy will be varied between scenarios to compare the AES adoption rates for different policy designs.

Table 4: Overview of AES properties and sources for parameterization. Parameter values are different for different AES.

	Parameter	**Source/Remarks**
AES properties	Minimal field size	AES regulations (CS level)
	Contract duration	Varied between scenarios
	Level of bureaucracy (low/medium/high)	Varied between scenarios
	Offered payment level	Varied between scenarios

4.2 Elucidate influence factors for farmer decision-making

To elucidate important influence factors for the decision on adopting AES, an interview campaign with farmers was conducted within BESTMAP in all five case studies to identify potential key factors for farmers' decision-making on agri-environmental schemes. In brief, data was obtained via semi-structured face-to-face interviews that consisted of two parts: 1) a qualitative interview based on an interview protocol covering open questions on the farmer's background, attitudes towards farming, reflection on ecological aspects and especially the motivation to apply, or not apply, for AES and 2) a 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. Across all case studies, 124 interviews were conducted in the period January – May 2020. Sample sizes vary from 14 (DE) to 47 (ES) interviews. Due to national restrictions as reaction to the COVID-19 pandemic, the interview process had to be changed in all CS. A more detailed description of the design, execution, reaction to limitations that arise due to COVID-19 and an in-depth analysis and description of the results is provided in Deliverable 3.4. Here, we only provide a summary of the most important factors that were found to influence farmer decision-making and that were considered to be included in the decision-making process of the ABM. Overall, the survey revealed that decision-making factors relevant in all case studies include (a) economic benefit from AES, (b) fit with established farm practices, (c) soil quality and (d) inflexibility of AES, (e) farm size and (f) the administrative burden. In some case studies, a lack of knowledge about AES, past experience with AES, the tenant-owner relationship, external influence on AES outcome, automatization of AES placement on land, duration of AES / duration of lease contracts and corruption play a role.

In addition, we take important behavioral characteristics/elements mentioned in reviews on farmers' adoption in different case studies in Europe into consideration (e.g. Lastra-Bravo et al., 2015; Dessart et al., 2019; Brown et al., 2020). Besides economic factors, these reviews reveal influence of socio-demographic factors such as education or age of the farmer, farm structural properties such as farm size, tenure or consistency with farm activities, farmer beliefs and values including motivation behind farming, the design of the policies, i.e. the complexity of implementing, the flexibility or the coherence with other policies, various influence sources such as consultancy, farming organisations, governments or social networks and general attitudes towards AES framed e.g. by previous experience.

Based on these two main sources, we compiled possible influence factors to decide which aspects to include in the ABM (see Table 5). Some factors that were not mentioned as being important in our interviews are considered influential in the reviews. On the other hand, to allow for a reasonable analysis of the ABM, we decided to include only a limited number of aspects. Therefore, we had to omit some factors that were mentioned in the interviews. This explains the slight derivation between the interview results and the resulting decision on factors to include in the ABM. Factors for which the weighting differs between our interviews and what is summarized from existing literature are marked and explained separately. This selection builds the basis for the underlying conceptual framework of the ABM which will be identical for all case studies. Depending on data availability and the importance of specific influence factors in certain case studies, some aspects might, however, be less important in some of the case studies. The conceptual ABM framework will therefore be adapted to case study specific conditions.

Table 5: Factors influencing farmer decision-making as denoted in the interviews and their consideration in the ABM

Factors	*Importance in interviews*	*Included in ABM*
Economic benefit from AES	high	included
Fit with established farm	high	included

practices		
Soil productivity	high	included
Farm size	medium	included
Administrative burden	medium	included
Lack of knowledge about AES	medium	included*
Past experience with AES	medium	included
Duration of AES	medium	included
Inflexibility of AES	medium	excluded**
Tenant-owner relationship	medium	excluded#
External influence on AES outcome	medium	excluded##
Computer-based AES management system	medium	excluded#
Duration of lease contracts	low	excluded#
Perceived corruption	low	excluded
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
#Excluded due to missing data availability
##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.

4.3 Decision-making framework

With respect to the specific conceptualisation of the model, we were inspired by different behavioural concepts and theories such as expected utility theory, theory of planned behaviour or prospect theory (see examples for applications of these theories in the context of farmer decision-making in Despotović et al. 2019, Coelho et al. 2012). However, we decided not to follow one specific theory because none of the theories includes all factors that were considered as being important for the decision on AES adoption in our interviews or the literature. Therefore, we decided to rather choose components relevant for our context regarding the adoption of the four AES, such as the behavioral characteristic of loss aversion from prospect theory or the concept of opportunity costs from expected utility theory. In addition we were influenced by the CONSUMAT approach (Jager 2000; Janssen and Jager 2001; Jager and Janssen 2012) which was developed with the aim to formalise human behavior for ABMs. It is based on different psychological theories and incorporates components such as uncertainty, satisfaction behavior, habits and influence of others. However, we felt that some aspects of the CONSUMAT approach, such as social influence and uncertainty, were weighted too heavily for our context, which does not fit with the insights on farmers' behavior related to AES adoption that we obtained from the interview campaign. Therefore, we decided to derive our own formalization which 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.

Our decision-making framework is structured as a three step procedure where choices are made at different spatial levels. We propose this hierarchical decision-making in the context of AES because our own interview campaign and other empirical studies (e.g. Lienhoop and Brouwer, 2015) have shown that some farmers are not at all open to consider a specific AES and therefore do not enter into in-depth deliberations (Figure 5). The different processes to be run in one time step include:

1. **General openness to specific AES:** Decision-making at farm level on whether at all the farmer is open to consider adoption of a specific AES
2. **Subset suitable fields:** Selection at field level which locations are available for AES adoption
3. **Individual deliberation and site selection**: Deliberation on which AES to adopt on which field

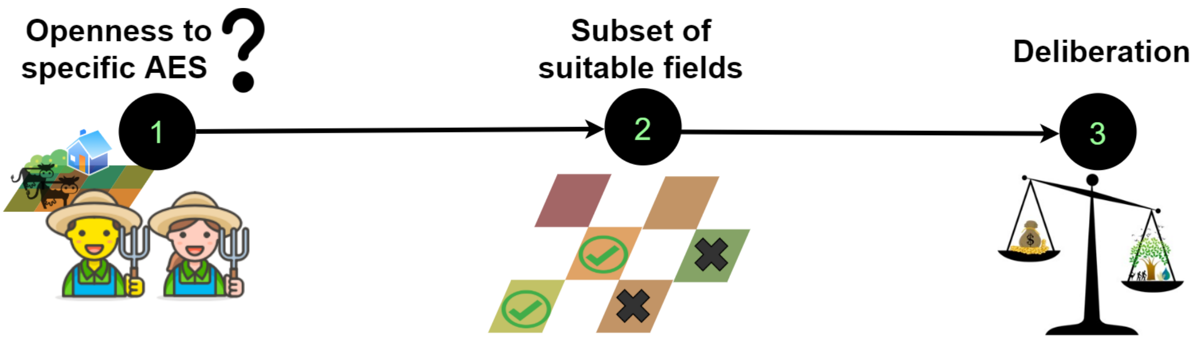


Figure 5: Schematic representation of the three steps of the decision-making process: (1) general openness to specific AES, (2) subsetting suitable fields and (3) individual deliberation and site selection.

The specific assumptions and calculations for the different decision-making steps are the following:

Step 1: In the first step, farmers individually decide whether they are at all open to think about applying a specific AES. This is a rather identity driven consideration, in contrast to the actual AES decision which is designed to be strongly based on economic profit. We decided to include this separate decision step as it was observed that some farmers have general aversions against some AES and never consider applying for those. This includes, for example, when farmers see themselves as farmers and not as foresters and therefore are not willing to convert their arable land to woodland (Lienhoop and Brouwer, 2015). Furthermore, as it was stated in the interviews, some farmers are reluctant because of their own negative experience or rumours about AES, e.g. including sanctions due to actions that were not the farmers' faults. Additionally, for some farmers their reluctance might simply be based on missing knowledge about specific AES, the long time frame that some AES impose and that might not be in accordance with the business plans of the farm or because they do not see the environmental benefits.

The first decision-making step is therefore designed in a hierarchical way (Figure 7). First, it is checked for each AES individually if a farmer previously adopted this specific AES. If a farmer has previously applied a specific scheme, we assume that he/she is open to applying that scheme again with a certain (high) probability. We include this probabilistic selection, since some farmers might have had negative experience with some schemes, which discourages them from applying for these measures again. Unsuccessful AES could, for example, include that farmers had to pay back money because others have unintentionally interfered with AES implementation such as dog walkers using buffer corridors as footpaths. In addition, some farmers may have had positive experiences but may no longer be willing to adopt AES due to other circumstances, such as retiring and not having a successor for their farm. Since we do not explicitly model these structural factors, a probabilistic approach allows us to implicitly capture such situations as well.

We assume that of the farmers who have no prior personal experience, a certain proportion are intrinsically open to the application of AES. This implicitly includes farmers who feel well-informed about a particular practice and can generally imagine adopting it, or farmers who have a high environmental value and are open to practices that serve to improve the environment. On the other hand, some farmers might have individual barriers against the application of particular schemes and therefore may not be open to applying them.

For farmers that are not intrinsically open, we assume that they have a certain chance of being convinced by advisory support (if they have access to advisory). Information from consultants can either fill knowledge gaps or clarify fundamental misconceptions that potentially lead to resistance to applying some measures. Similarly, farmers that do not have access to advisory or are not convinced by this support, have a small chance of turning open to AES if a scheme is applied in their social network. The social network is implemented in the model in different ways, allowing a comparison of its impact on the adoption of AES: Either the nearest neighbors (i.e. all other farmers whose fields are within a certain radius of the fields of a farmer) or other farmers of the same FSA type, i.e. farmers with similar farm sizes and specializations, influence the adoption of AES. In both cases, we assume that the social network has a positive influence on a farmer if at least one member of the influence group already applied the specific scheme in the past.

For testing purposes, we will run simulations with and without considering advisory support and social networks. From the results of the follow-up survey (see Section 4.5), we obtain information on the possible range of importance of the different aspects (own experience, intrinsic openness, access to advice, social networks). In the survey, we specifically distinguish between reasons for applying a scheme, reasons why farmers used to apply a scheme but no longer do, and reasons why farmers are not willing to use a scheme at all. In general, the probabilistic approach leaves room for rather unexpected or uncommon behavior that might arise from other influence factors not explicitly included.

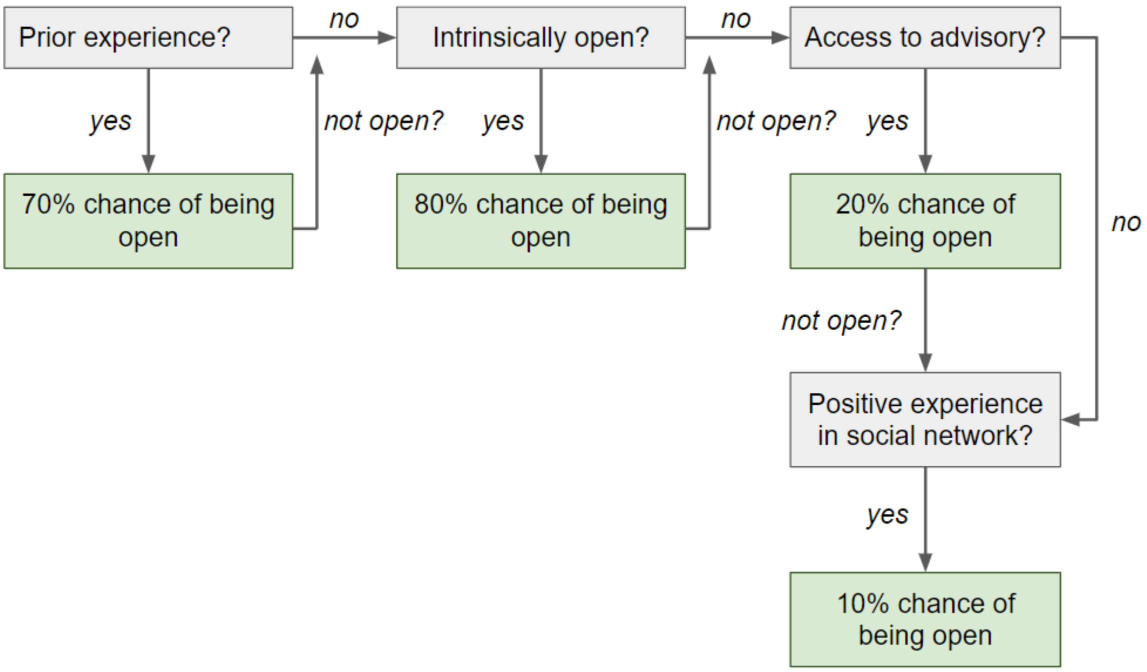


Figure 6: Schematic representation of the hierarchical design of Step 1 in the decision-making framework. For demonstration purposes, the percentages indicating the chance of being open are selected in a range assumed to be realistic. When analyzing the model, they will be varied in ranges that are in accordance with the results from the follow-up survey. Potentially, they also vary between AES.

Step 2: The second step is supposed to operate at field level and determines the fields that are in general available for specific AES applications. Therefore, farmers first exclude fields that still have ongoing AES contracts as those are not eligible for new schemes. Additionally, farmers decide on which fields they apply mandatory Ecological Focus Areas (EFAs) and exclude those as well. Here, the selection of the fields is based on the adoption of AES in 2019 to resemble the current situation as closely as possible. To comply with the rules for the minimum field size needed for application of specific AES, farmers furthermore exclude fields that are too small. After this step, farmers have for each AES a set of fields in their selection list, on which it can potentially be applied. Further restrictions on the available farm land for AES (e.g. due to the duration of lease contracts or specific administrative restrictions that inhibit the application of certain AES on some fields) are not considered in this version of the model.

Step 3: In the third step, farmers consider whether it is profitable for them to adopt AES. This calculation is done separately for each AES. The central element of the decision-making is the payment level that farmers require for a specific AES. Depending on their farm specialization, land properties and personal characteristics, farmers might consider different payment levels as suitable to cover their perceived financial costs of implementation. Crucial elements that farmers might include in their decision-making could cover:

- **Contract length:** Farmers might feel restricted in their choices on their land for AES with long contract durations. Therefore, lengthier contracts might require higher subsidies.
- **Bureaucracy:** Farmers might consider transaction costs for bureaucratic effort required to apply for and monitor an AES. The more time farmers have to spend on non-operational aspects of the program, such as paperwork, the higher the expected payment amount could be.
- **Advisory support:** Farmers might be willing to accept a lower payment level if they get support from advisory services with respect to administrative work with the contract and on how to implement and integrate the measures into their farming practices.

In addition to these contract specific attributes, individual farmer characteristics and conditions on the farm might influence the level of payment that is accepted as reasonable. In addition to pure economic considerations, farmers might also consider the environmental benefit of AES, e.g. the increase in soil quality due to cover crops or perceived contribution to biodiversity through flower strips. If these aspects are important to a farmer, it could be that his personal expectation of compensation is lower, especially for AES contracts that are expected to have a high impact on the environment. Implicitly, the expected payment level will also reflect the fitness with established farm practices if farmers compare their regular farming activities with what is required to implement the AES and deliberate the effort that is needed to fulfill the requirements of the schemes. Farm characteristics such as farm size or soil productivity might also influence the expected payment level. Large farms might experience less bureaucratic effort compared to small farms with fewer employees to deal with administrative tasks. Farms with difficult soil conditions and lower expected yields might accept a lower price which already overcompensates their forgone income.

To parameterize the accepted payment level given these various influence factors, a discrete choice experiment (DCE) where respondents are presented with choices between alternatives of concrete AES contracts is conducted (see Section 4.5). The results of the DCE can be summarized in a willingness to accept for each AES and can include differences between farmer types which might be based on individual farmer characteristics and conditions on the farm as outlined above. In the model, it is assumed that a farmer adopts a specific scheme if its individually accepted payment level is exceeded by the offered payment level denoted in the contract details. The individually accepted payment level can be derived from the empirical results for the willingness to accept obtained from the DCE. To investigate the effects of different policy designs, the offered payment level but also contract characteristics such as the contract length or the bureaucratic effort can be varied in the simulation.

When a farmer accepts the payment for multiple AES, there are several options of determining the order of adoption. For example, a farmer could first distribute the schemes for which he/she will receive the highest payments or start with those that best fit with established farm practices. We have implemented various options to account for this and will systematically analyze what effect the order of selection of the schemes has on the distribution of the AES.

The second decision farmers have to face in the third step of the decision framework is where and on how much area to apply a selected AES that fulfills the requirements, i.e. for which the offered payment level meets personal expectations. Conditions for the site selection can include factors that indicate a low expected yield, e.g. whether a field has difficult to manage soil, low productivity or high elevation/steep slope. Furthermore, fields that are more difficult to reach, e.g. because they are further away from the farmstead than other fields, might be more likely to be used for AES with less concrete applications on the field. To include the explicit conditions for site selection in the model, we rely on the outcome from the follow-up survey (see Section 4.5). We will also be able to derive the size of the area to which an AES with certain characteristics would be applied from the results of the survey. Technically, the selection of the fields to be used for AES is included by a modification of the Knapsack algorithm (see e.g. Kellerer et al. 2004) which allows to select fields with the required area that minimize specific constraints given by the selection characteristics named above.

4.4 Implementation

BESTMAP will build the ABMs based on an open-source modelling platform. As the InVEST modelling toolbox that is employed in BESTMAP to model the provision of ES (see Section 4.3) is implemented in Python, our first choice was to use an existing open-source Python-based ABM environment such as Mesa (https://mesa.readthedocs.io/en/master/index.html). However, during the implementation phase we realized that Mesa has limitations especially when running the model with many agents. Therefore, we decided to implement the model in the commonly used NetLogo ABM environment and a NetLogo extension that provides the ability to load GIS data in NetLogo models (https://ccl.northwestern.edu/netlogo/docs/gis.html). Although we first planned to use the pyNetLogo package (https://pynetlogo.readthedocs.io/en/latest/), a library that allows to access and run NetLogo from Python (Jaxa-Rozen and Kwakkel, 2018), to ensure a tight coupling with Python-based biophysical models, we now decided to run the models using the R package NLRX (https://docs.ropensci.org/nlrx/reference/nlrx-package.html) which is more flexible and provides more options for running sensitivity analyses. The input data for the biophysical models will be provided using text files.

4.5 Parameterization

The model rules are built upon several sources of input, including (1) the available literature on AES adoption, comprising several studies from CS across the EU, reviews summarizing these studies and reports or additional surveys in our CS; (2) the quantitative and qualitative results from first our interview campaign and (3) assessment of BESTMAP CS experts and farmer experts that validate our model assumptions. Next to the model rules, the model, however, includes several variables for farmer and field characteristics as well as AES classification that need to be parameterized. Field level variables (Table 3) and spatial farmer variables (farm size and specialization, managed fields) can be determined from LPIS/IACS data and AES variables are varied between the simulations to test the implications of different policy designs (Table 4).

To specify the remaining parameters that describe farmer agents, we are conducting a second online survey campaign framed as a DCE with an additional questionnaire on farm and farmer characteristics as well as experience with AES. The questionnaire expands the quantitative part of the first interview campaign on reasons for AES adoption and can be used to derive relationships between farmer characteristics, a broad range of influence factors and their decision-making. This information will be used to derive the distribution of certain farmer characteristics (such as intrinsic openness) across a CS and to specify the respective parameters. In addition, we included questions that will provide insight into the decision-making process for selecting specific sites for AES (e.g., soil quality, distance to farm, etc.).

With the DCE, we are able to test the influence of specific contract details on the willingness to adopt an AES. In the DCE, four different types of AES (flower strips, cover crops, maintaining permanent grassland and conversion of arable land to permanent grassland) are offered as alternative contracts. The descriptions of the schemes are based on the regulations for existing schemes. However, since the description of the measures in the DCE is the same for all CS, it may differ to some extent from the existing case study-specific regulations. Farmers have to make six repeated choices between the four schemes and a 'no scheme' option where they would not receive funding for any agri-environmental practices they may carry out on their farm. For each choice, the schemes differ in their characteristics on duration, bureaucratic effort, advisory support and payment level (see Figure 7 for an example of a resulting choice card). We ask farmers for each choice to select the option they prefer. In addition, farmers have to specify on how much of their suitable land (percent of arable land or grassland depending on the AES) they would apply the selected scheme.

	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	

Figure 7: Example of a choice card from the UK CS.

Based on the selection of schemes in the DCE, we will be able to calculate the *willingness to accept*, i.e. the minimum payment that farmers require to adopt a scheme with specific characteristics. This allows us to reveal and measure trade-offs between the different choices and the ranking of importance of the contract characteristics. The results from the DCE can directly be included in Step 3 of the model, where a farmer adopts a scheme if the offered payment level (varied in the between scenarios to represent different policy designs) exceeds its accepted payment, i.e. the willingness to accept derived from the DCE. The accepted payment level will be AES specific and might vary between the CS and farmer types (for example, there could be differences in willingness to accept between FSA groups, between arable and grassland farmers or due to other characteristics of the farms/farmers). Differences between farmer types might also be reflected in the area on which a specific scheme would be adopted (e.g., when farmers who manage grassland want to make the highest profit of their small arable land that they do not need for their daily farm practices by applying profitable AES).

Until the results of the survey campaign are available (approx. beginning of 2022), existing DCEs that derive the importance of various factors such as the availability of consultancy (Hasler et al., 2019; Espinosa et al., 2010) or bureaucracy (Ruto & Garrod, 2009) will be used as a first source to calculate the accepted payment level in Step 3 of the model. With respect to the area on which farmers are willing to apply AES, current adoption available in LPIS/IACS data as well as the results from Latacz-Lohmann & Breustedt 2019 will be used as preliminary input values.

4.6 Validation

After having tested the model's robustness by performing a parameter sensitivity analysis, we will compare the model outcomes with existing datasets on patterns of adoption of AES for validating the ABM. We will apply a pattern-oriented modeling (POM) approach, which is a method to design, test and validate complex computational models (Grimm et al. 2005). POM can be used to reduce uncertainties in model parameters by matching model results against multiple observed patterns, and rule out those model specifications that do not match the observed patterns in the data (on CS-level mainly LPIS/IACS data).

However, due to the stylized nature of the model, there are several challenges that must be considered when validating the model. First, we are modeling only four selected schemes, but in reality there are many more schemes offered in the CS, some of which have regulations that significantly differ from the hypothetical schemes in the DCE. One approach to overcome this issue and compare the actual adoption with the model outcomes, is to rely on the grouping of AES developed in BESTMAP (see Section 5.1). However, even within an AES group, actual payment levels can vary widely, making it difficult to average over several schemes. In addition, the specific requirements for applying a scheme vary within an AES group (e.g. flower strips are assumed to be only available on arable land in the ABM, but some types of buffer strips in the UK can be applied to arable land and grassland) which makes it difficult to compare model outcomes with patterns of actual adoption. For some schemes offered as hypothetical schemes in the DCE, it is even difficult to find a comparable existing scheme (e.g. there are currently no types of buffer areas offered in Spain). Finally, we cannot quantitatively validate the model for Serbia, as AES are not yet offered there. Here we have to rely on qualitative validation to assess the reasonability of the results.

5. Step D - model ecosystem services/public goods and socio-economic impacts at case study level

The framework proposed for BESTMAP-PIAM uses calibrated and validated biophysical models to estimate impacts of AES adoption. The biophysical models developed at the CS level have the specific goals of identifying trade-offs and synergies between biodiversity and ecosystem services in and across the five CSs, and to detect the effects of AES implementation on biodiversity and the selected ecosystem services. Building on such a basis, the models will also reflect and demonstrate differences in biodiversity and ecosystem services between the FSAs. The model outputs will be used to derive useful policy indicators at the CS level, which later be upscaled to the European level, and incorporated and visualized into an interactive dashboard where different policy scenarios and their effects will be explored.

The input data of the biophysical models at case study level consist of geospatial data compiled in the Case Study Base Layer and described in the Deliverable 3.1, as well as non-spatial data (e.g. soil carbon content in each land cover/land use type) needed for model parameterization and validation. Since the data compiled in the European Base Layer (see Deliverable 3.2) is significantly different in terms of spatial resolution and continuity than the Case Study Base Layer (Deliverable 3.1), the development of biodiversity, ES and socio-economic models at the European scale will consist of a separate modeling task (see Step E below) rather than an upscaling of the models developed at the CS level.

Model selection was based on previously selected AES (described in the next subchapter 5.1) and on data availability across the CSs. One of the challenges in the modeling task is in fact the compilation and harmonisation of input data across CS, and ensuring comparability of model outputs given the heterogeneity of input data from different sources and countries (e.g. structural differences in the IACS/LPIS data across countries; but see Deliverable 1.3 for the adopted guidelines and protocols harmonizing activities across CSs). Four different models are currently being developed for each CS: food and fodder, carbon sequestration, water quality, and biodiversity models.

The carbon model estimates the status of carbon in the soils and the sequestration of carbon. It uses the current land use patterns, derived from LPIS, in combination with the distribution of AES and EFA schemes. The model runs spatially explicit on the resolution of the available LPIS data (i.e. field level). The amount of carbon in the soil depends on the crop, the scheme as well as soil characteristics and climate. Here we use relationships based on the work of Zhong et al. (2018) and Cui et al. (2019), which show a positive relationship of clay content on soil organic carbon (Zhong et al. 2018) and positive relationship between mean annual precipitation and soil organic carbon (Cui et al. 2019). We also make use of work e.g., conducted by Quemada et al. (2020), who investigated the effect of cover crops on the sequestration of carbon. The output of the carbon sequestration model is a map showing the current and alternative state, as well as the sequestered/released carbon.

The water model uses the InVEST Nutrient Delivery Ration (NDR) model (Sharp et al. 2018). The approach the NDR model utilises is one of simple mass balance by the movement of nutrients (phosphorus and nitrogen) through space. Rather than use details of the nutrient cycle, the NDR model instead uses long-term, steady state flows through empirical relationships (Sharp et al., 2018). Nutrient loads are associated with different land (or crop) types with nutrient delivery ratios computed for nutrient transport by surface flow (with the option for subsurface flow in the model). Surface flow is calculated using a delivery factor, which represents ability to transport nutrients without retention for downstream pixels and a topographic index (Sharp et al., 2018). The model provides spatial outputs, including a raster tif file showing how much load from each pixel eventually reached the stream in kg/pixel. Validation has been carried out by Redhead et al. (2018) for the UK, and was found to perform well for relative magnitude of nutrient export (Redhead et al., 2018).

The food and fodder model uses aggregated predictions of the WOFOST (World FOod STudies, Diepen et al. 1989) simulation model as a main input. The data used here were previously generated in the JRC study Analysis of climate change impacts on EU agriculture by 2050 (Hristov et al. 2020). The data have a spatial resolution of approximately 11km and include annual yield predictions of the following six crops: maize, sugar beet, wheat, sunflower, winter rapeseed, spring barley. If necessary, these yield data can be amended by CS specific yield data for further relevant crops. The effects of AES on crop production and yield were estimated based on local legacy data from the case studies and findings from meta-analyses. For example, we used the SoilHealthDatabase to estimate yield effects of cover crop plantations depending on soil texture, crop type, cover crop species, and climate (Jian et al.

2020). The outputs of the food and fodder model is a map of crop yield with and without AES implementation.

The biodiversity model consists of ensemble species distribution models (SDMs, Araújo & New, 2007) for selected farmland bird species. SDMs allow us to estimate the effects of environmental characteristics like climatic, topographic, land-cover and land-use variables including the implementation of AES and EFAs, on habitat suitability for the modeled species (Morelli et al. 2014). The output of the model are habitat suitability maps for each farmland bird species. The SDMs are validated by means of cross-validation through selected evaluation metrics (Area Under the Curve of Receiver Characteristic Operator, True Skills Statistics, specificity and sensitivity) (Fletcher & Fortin 2018). Each model will be accompanied by a factsheet based on the Overview, Data, Model, Assessment and Prediction protocol (Zurell et al. 2020), including detailed information on inputs and outputs of the model, its objectives, assumptions and methodological descriptions. The factsheets are meant to make models and model results understandable and reproducible.

BESTMAP aims to model socio-economic impacts of adoption of the four AES, particularly on issues such as farm labour and income. The conceptualization of these models is still ongoing, but they would likely be regression based models using FADN microdata.

5.1 Selection of AES and EFA and their descriptions

The 5 AES to be modeled (buffer strips/areas, cover crops, land-use conversion, maintaining permanent grassland and organic farming) were originally selected according to the relative importance in terms of spatial coverage of AES across CSs as well as the findings of the interviews conducted with the farmers. To overcome inherent differences in the AES in different countries, selected AES were grouped into higher-level measures with similar management practices and purposes. To ensure that the groupings were consistent across CS, definitions were drafted for each measure's group and reviewed by all CS leads (Table 6).

Table 6: AES groups selected for modeling and their description.

AES group	Description
Buffer areas/strips	Strips or areas taken out of production, and either left as self-vegetated land or sown with specific seed mixtures.

Cover crops	Cultivation of cover/catch crops between the harvest of the cash crop and the sowing of the next main crop. Cover crops are planted to cover the soil rather than for being harvested, and help in limiting soil erosion, improve soil structure, minimise losses of mineral nitrogen during winter, maintain associated biodiversity, etc.
Land-use conversion to permanent grassland	Conversion of arable land to permanent grassland.
Land-use conversion to forest	Conversion of agricultural land to forest.
Maintaining permanent grassland	Preserve shrub-free, vegetated and potentially species-rich low input permanent grassland fields, by preventing/limiting/reducing mowing pressure, fertilizer and pesticide use. Ploughing is not allowed. The use of fertilizers and PPP is limited.
Organic Farming	Agricultural system that uses fertilizers of organic origin and avoids the use of synthetically produced chemicals for pesticides or growth regulators. Other conditions may apply depending on location.
Fallow land	Land lying fallow, areas taken out of production for one or multiple years, but not permanently, and which do not require any management. No tillage or sowing is allowed. Mowing is allowed under specific time intervals, but not for agricultural use (e.g. for fodder or biogas). The use of fertilizers and PPP is not permitted, with the exception of those allowed in organic farming.

This review process ensured that the AES definitions were broad enough to include similar schemes from all (or most) CS: for example, regulations on pesticide and fertilizer applications on low-intensity permanent grassland are more stringent in certain countries than in others; the definition of the “maintaining permanent grassland” measure was hence phrased in a way that was general enough (e.g. “The use of fertilizers and PPP is limited.”) to include schemes from all CS. The BESTMAP team agreed on 7 AES groups: buffer strips/areas, cover crops, land-use conversion to permanent grassland, land-use conversion to forest, maintaining permanent grassland, organic farming and fallow land. The latter was added to the original 4 AES groups to be included in the biodiversity models, as fallows are known to be of high importance for certain taxa (e.g. farmland birds). Land-use conversion was split into two subcategories, depending on the type of land cover, grassland or forest, that the land is converted to. In all CS (except for RS), certain EFA schemes exist, which have similar management and purpose to the selected AES, and are thus likely to elicit equivalent effects on biodiversity and ecosystem services. We therefore included EFA schemes into the AES groupings whenever they fit in one of the definitions agreed upon for the AES. For example, cover crops can be applied to a field as AES or as EFA in the UK and in Germany. The complete grouping of schemes for each CS can be found in the appendix.

5.2 Trade-offs and synergies between biodiversity and ecosystem services

The biophysical models developed at the CS level have the specific goals of identifying trade-offs and synergies between biodiversity and ecosystem services in and across the five CSs, and to detect the effects of AES implementation on biodiversity and the selected ecosystem services. To do this, one potential approach is to consider changes in AES adoption as drivers of trade-offs between biodiversity and ecosystem services/socio economic impacts, using farms as spatial units of analysis, thus allowing an easy linkage to the FSAs. This approach would allow us to describe how changes in AES adoption drive changes in ES/biodiversity provision levels (see Fig. 8).

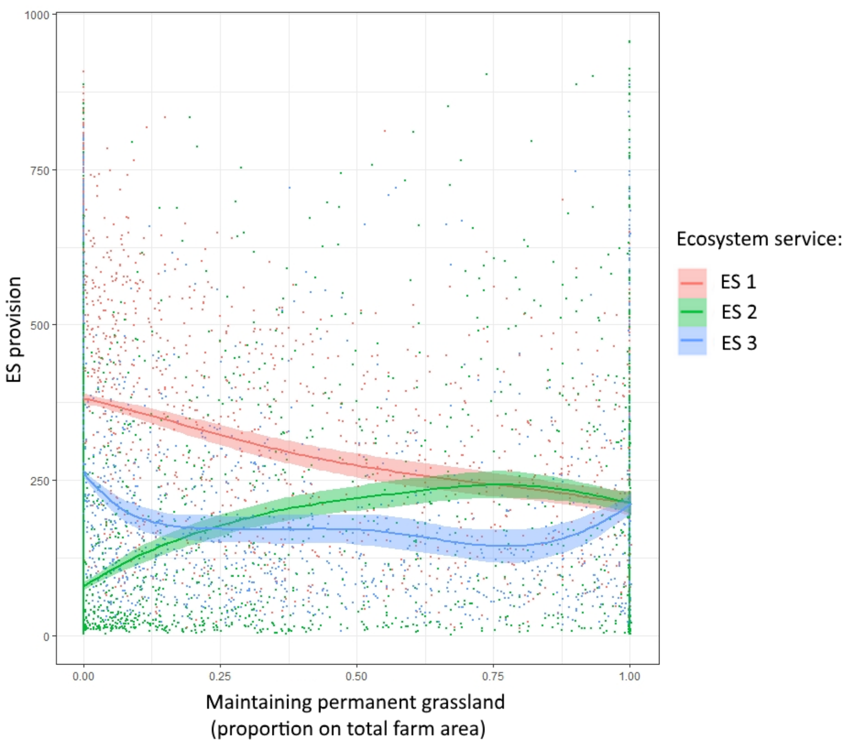


Fig. 8 Exemplary graph of multiple ecosystem services´ provision along a gradient of AES adoption levels. Dots correspond to farms.

Interesting trade-offs/synergies between pairs of ES/biodiversity could then be further investigated to assess how their relationship would change under different management strategies (see Fig. 9). Such analysis will be carried out within and across CS. As this task has only just started, this approach is subject to changes and expansions, e.g. including different AES scenarios, socio-economic characteristics at the farm level, etc.

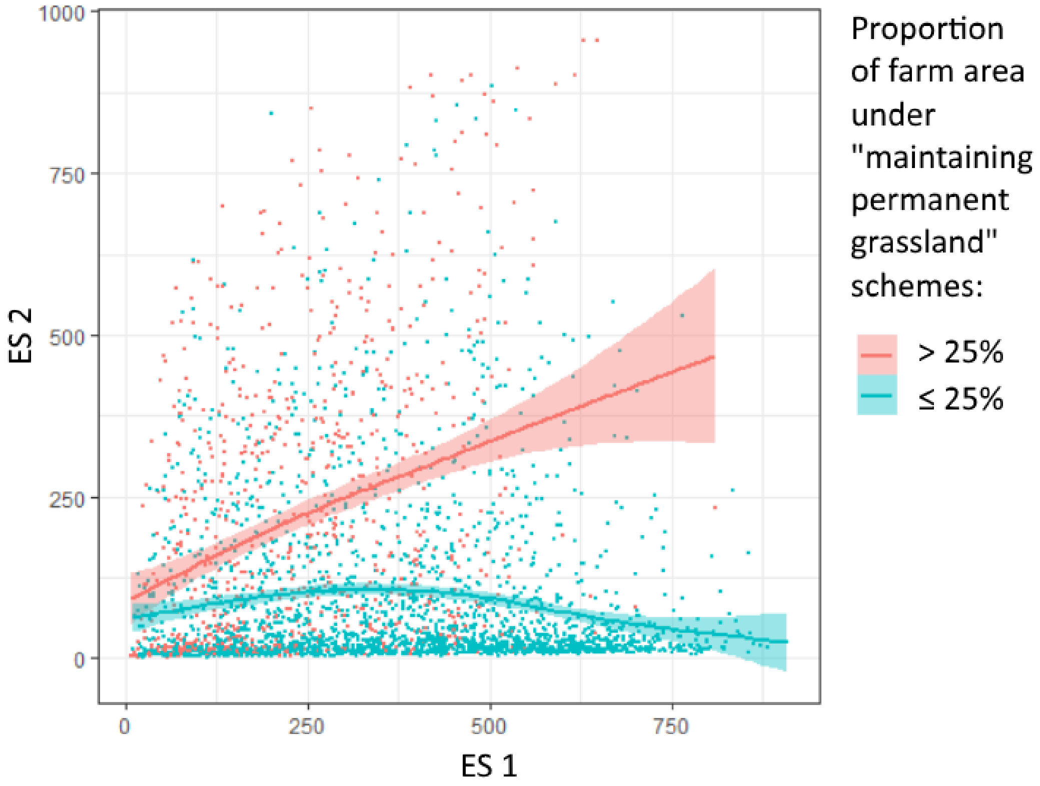


Fig.9 Exemplary graph of trade-off/synergies across two ecosystem services under varying proportions of a selected AES. Dots correspond to farms.

6. Step E - upscaling to a model operating on FADN regions

6.1 BPM Upscaling

The approach that will be used for upscaling biophysical models is a type of meta-model, a statistical emulation. Meta-models are used to retain numerical relationships between inputs and outputs of a model without having to run the initial model again. This method enables the user to change the scale of model, and to choose, via selection, only the important variable inputs. Due to simplified estimation of the underlying processes from the computer-simulated model (Figure 10), the process requires fewer computational resources and/or less time. Due to reduced resource requirement, meta-models enable simulated scenarios of change to be obtained in a manner that is much more time-efficient than the running the initial model they are based upon. This aspect is important for enabling informed decision-making, which is an integral part of BESTMAP plan. Additionally, other models (e.g. economics ones) can incorporate meta-models results, meaning the results can affect and feedback other outputs speedily. As an example, see Britz and Leip (2009) who integrated the results of CAPRI and a process-based environmental model, DNDC.

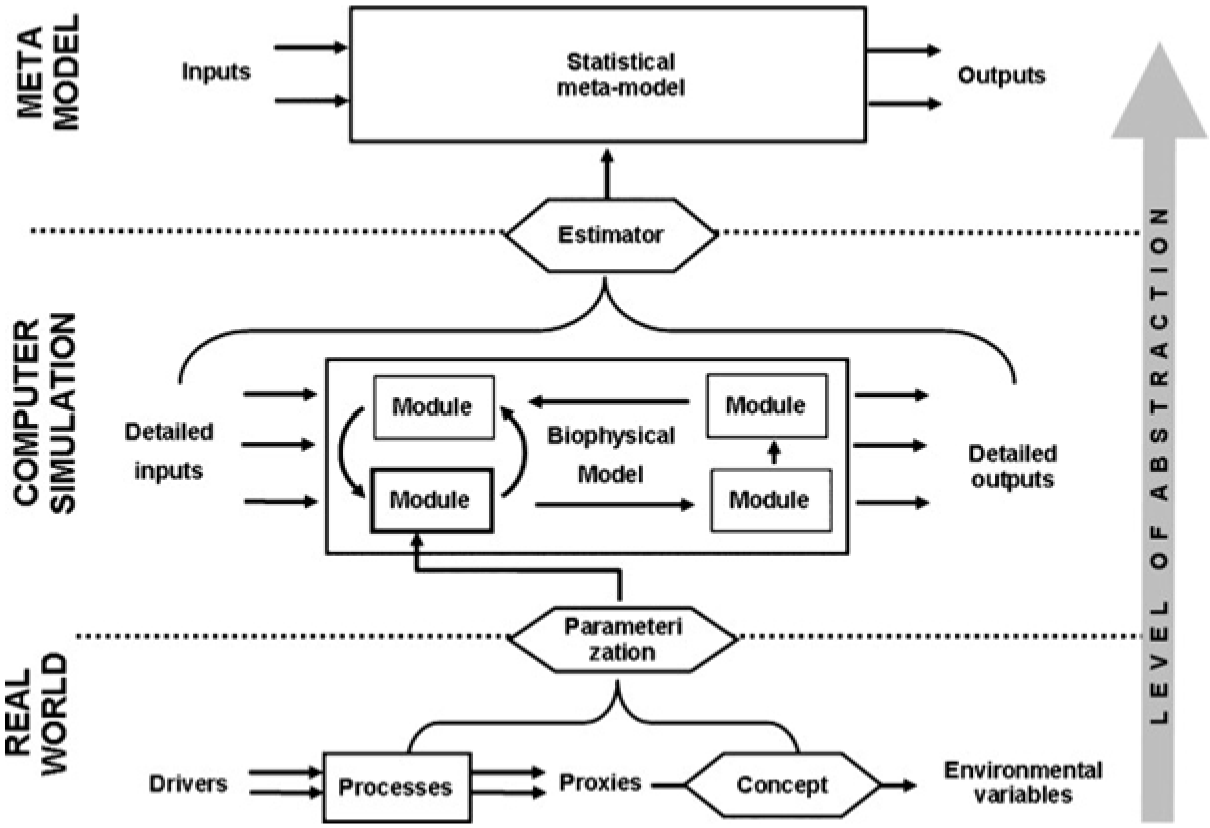


Figure 10: Conceptual representation of the increasing level of abstraction from real-world phenomena over biophysical models, meta-models up to the integrated modeling framework (Britz and Leip, 2009).

Specifically for BESTMAP, the aim of the meta-model is to expand results from the different CSs to predict what the ES intensity – ES results per unit (farm/ UAA) area – will be in other places within the EU. Initially, the results will be upscaled to the rest of the FADN regions that the CS lie within, and then, if the results are feasible, to the rest of the EU FADN regions. Inputs will be variables that have an effect at the farm scale, while the outputs will be ES intensity. A different meta-model will be used for each ES, CS, and FSA combination, meaning the transferability of each ES intensity will be different based on the initial CS the data were derived from. However, the meta-model methodology will be consistent for all combinations. The methodology is explained below.

Meta-model methodology

Data from CS ES models

Within each CS, farms are delineated in the LPIS/IACS datasets (with the exception of Serbia). As described above, each individual ES model will be run using these spatial data. However, sharing the polygons would breach data sharing contracts signed by BESTMAP partners with CS institutions. Therefore, data will be provided to the meta-modeling team in tabular form, where the farms would not be identifiable spatially. The data provided by the CS ES modelers would provide information on the CS region for which the model was simulated, and the ES intensity results disaggregated by FADN, and NUTS-2 regions, and by the individual FSAs within the CS. In addition, variables related to AES adoption on the farm, and the ES model parameter values will be provided.

European-level variables relevant to each ES

Meta-models require input variables that are analogous to those used in ES models to upscale CS results to the EU level, as the variables will be influential factors in the distribution of ES. Therefore, European-level data is required for the input variables, to ensure consistency of modeling across the EU when using the meta-model. The input variables for some individual ES models use country-specific data for the initial input variables, while others will use European-level data. Where country-specific data were initially used for the ES models, alternative European-level datasets are required. To meet this need, each ES modeler has listed the variables used as inputs for the specific ES model, in each CS, and also indicated which European-level datasets provide the same information. All the appropriate datasets are listed in the BESTMAP's GeoNetwork, and are therefore easily accessible.

The final European-level spatial gridded data (e.g. precipitation) will be averaged by sub-FADN regions known as farm mapping units (FMU), which were provided by Alexander Gocht of the Thünen Institute, Germany, and have been used as part of the CAPRI economic model (wherein called Homogeneous Spatial Units (HSUs)) in https://susfans.eu/system/files/public_files/Publications/Reports/SUSFANS-Deliverable-D4.6-UBO.pdf. FADN microdata are probabilistically assigned to regions of 1x1 km grid cells having similar conditions. The FMU dataset is a spatial dataset that consists of 0.1 ha (100 m^2) vectorised pixels containing information about the area of each NUTS2 region that a specific sub-FADN region composes. Information that connects the FMUs with more FADN region information will be obtainable in the near future. Once the European-level variable datasets have been averaged at the FMU-level, they will be able to be added to the tabular data provided by the ES modeling partners in part 1 of the methodology.

Meta-model variable selection and set-up

Regression functions will be used as the final part of the meta-model process, to enable the capturing of environmental and farm-level controls to estimate upscaled ES intensity. The parameters that will be used as explanatory variables used will initially consist of the European-level layers relevant to each individual ES that has been averaged across FMUs, and the AES variables, FSA type, and regional data provided by the ES modelers. These variables will be input in linear and transformed forms (e.g. logs, square roots), giving a wide range of possible predictors.

Sensitivity analysis and variable selection will determine which of the range of possible variables are appropriate to use in the upscaling meta-model. The (multi-dimensional) range of the initial set of variables included in the model will be compared to the full sample of farms in an FADN region (either of the CS, or another FADN region where we want to apply the meta-model). This will enable determination of whether (a) the model is sufficiently accurate within the CS, as determined by a multi-scale error analysis; (b) the 'target' FADN region farm-level-derived predictors have 'similar' (multi-dimensional) range to justify 'robust extrapolation'; and (c) factors varying at large scale e.g. ecoclimatic are the same for CS and 'target' FADN region as determined by Task 5.1 transferability analysis. In addition, the least significant regressors will be dropped if that causes the adjusted R^2 to increase.

Once the meta-model has been run, a FSA-specific prediction for 'ES intensity' will be obtained based on the explanatory variables relationship. These values will then be summed (multiplied by UAA of FADN farms) to get total ES values across a FADN region. These results will then be applied to i) the rest of the FADN region that the CS is in, and ii) the rest of the EU (assuming results in i were accurate).

Transferability of results

The transferability of BESTMAP models will be assessed by mapping the similarity of FADN regions across the EU to the study regions of BESTMAP CSs, using the approach described in Step A. Mapping the gradient of transferability for each of the CS will allow highlighting the regions for which the models from individual CS are most relevant. However, two aspects are crucial to define what constitutes an acceptable degree of transferability potential. First, a different set of EU-wide FADN region-scale variables needs to be defined for the transferability of (a) biophysical models of ecosystem services and of (b) the ABMs of farmers' adoption of AES. Second, a specific threshold for the transferability gradient needs to be selected to divide the potential into an acceptable and unacceptable level of transferability. Previous approaches used either equal intervals or a certain percentage of distance values (e.g. top 25% of the gradient) to select such a threshold. Here, we will compare the EU-wide variables with CS-specific data and validate the biophysical and ABM models in order to find the most appropriate threshold of transferability. Such analysis will subsequently serve as a basis for the actual upscaling of CS level results. The end result will be a model operating on all FADN regions across Europe. Results will be transferred for each CS, ES, and FSA combination to the entirety of the rest of the EU, accompanied by a level of how 'certain' we are that the results are transferable to that FADN.

Uncertainty and validation

Uncertainty is a fundamental characteristic of modeling, being caused by things such as incomplete data, model limitations, and lack of knowledge and/or incorporation of associated or underlying processes. One way that could be used to assess the uncertainty of results is through sensitivity testing of results over a range of scales, e.g. varying pixel size, or altering certain model parameters. This will allow the methods used to be tested in terms of robustness.

When the meta-models are being defined, 70% of the farm data will be used. The remaining 30% will be 'degraded' to the FADN level. This will allow comparison between the modeled results based on the 70% and the actual ES results from the 30%.

6.2 ABM Upscaling

ABM upscaling is aimed to develop a set of approaches that allow us to apply the case study level ABM in other EU regions. We will first demonstrate the robustness of our ABM by building a valid model that produces meaningful results for the five different case study areas using the designed decision-making framework (see Section 4.3). Then we will take different steps in the ABM setup, calibration and validation to tackle the challenges we encounter at the upscaling stage.

Data Sources for EU level ABM

The first challenge we face is the data availability at EU level. Table 6 lists the data sources for the ABM parameterisation at the case study level and EU level. The data sources for the two levels of ABM are different for most of the variables. One of the main data sources at case study level is LPIS/IACS data. LPIS/IACS data exists in each EU member state, however, it is not harmonized to the same schema/data structure. Besides, it is difficult and time consuming to access due to the confidentiality requirements of the responsible organization within each member state. Considering these disadvantages of using LIPS/IACs at EU level and our project timeline, we decided to use harmonized FADN microdata for the BESTMAP-PIAM. Another missing dataset at the EU level is farmers' behavioral data, i.e., farmers' willingness to accept (WTA) and the relationship between WTA and its influential factors. At the case study level, these values are derived by the DCE survey. However, such behavioural data is not widely available across the EU. In addition, we will not have field-level adoption data under different AES like at the case study level for calibration and validation. Instead, we have aggregated data about farms' income from AES subsidies recorded in the FADN data set and regional AES adoption areas (in ha) collected by JRC.

We propose to use statistical methods to overcome the data challenges.

- First, FADN data contains farm samples of a region. To set up ABM farmer agents, we will create a farm population based on the distribution of FSA types of FADN farms, UAA, the average number of fields and percentage of large fields (recorded in the EU Agriculture Field Parameters on NUTS-3 regions for Wind erosion research).
- Second, FADN data does not include the field level information that our ABM needs, for example, spatial information of farms, such as the location and land use of fields. We will create a synthetic farm spatial data layer based on FADN data using the method developed in the SEAMLESS project (Kempen et. al 2011). This approach will use the Homogeneous Spatial Mapping Units (HSMU) that are built from the datasets of soil, slope, land cover and administrative boundaries as the spatial data layer and allocate FADN farms to the HSMUs in two steps. The authors first construct Farm Mapping Units (FMUs) by grouping HSMUs to reduce the number of FMUs and the

complexity of allocation procedures. The similarity between FADN farms' characteristics and the corresponding FMUs are evaluated. Then the allocation gets optimised considering less favored area (LFA) and attitude zone, yield and land use information, under the constraints that the total percentages of one farm over all FMUs is 1 and total Utilizable Agriculture Area (UAA) of a FMU should be the same as the total UAA of farms that are allocated to it.

- Third, DCE data is missing in other EU regions. We will test the benefit transfer approach to estimate the WTA values of farmers in other regions using the available DCE data. The benefit transfer method refers to applying empirical estimates of one study in a location or context to another similar location or context. Generally there are two methods to carry out benefit transfer: one is transfering mean values; the other is transfering adjusted mean values based on a function that accounts for factors significantly affecting the WTA values (Brouwer 2000 and Brouwer & Bateman 2005).
- The last, we will derive the model baseline of AES adoption using FADN and JRC regional AES enrolment data (subject to availability of regions and AES types). If we model an EU region where JRC regional AES enrolment data of the selected AES is available, the adoption baseline will be the aggregated AES contract area of the region; For other EU regions that lack of AES adoption data, we will need further investigation.

Table 6 Data sources for ABM at case study level and EU level

Data variables	Case study level	EU level
Fields location, size, land use	IACS/LPIS data	FADN, CORINE Land Cover data, EU Agriculture Field Parameters on NUTS-3 regions for Wind erosion research
Farm location and farm's fields	IACS/LPIS data	FADN
FSA	IACS/LPIS data	FADN
Economic size	IACS/LPIS data	FADN
Soil quality	European soil database	European soil database
Farmers' attitude	DCE survey	Flash Eurobarometer 86 - The Farmers' Attitude towards CAP (15 EU countries)
Farmers' willingness to accept, i.e. their accepted payment level for specific	DCE survey	Not available

AES		
AES adoption data	IACS/LPIS data	FADN, JRC AES enrolment Europe data

Model validation

Model validation is critical for the EU level ABM. Firstly, we will continue applying pattern-oriented modeling methods to calibrate and validate the model. There is existing research focusing on AES adoptions. For example, Pavis et al. (2016) reported their case studies of AES participation in Netherlands, Denmark, Austria, Italy and Greece. Lastra-Bravo et al. (2015) reviewed ten research studies of farmers' participation in AES in different EU countries. A thorough literature review of AES adoptions will be carried out and used as patterns that the ABM output should match to. Secondly, to better understand the uncertainties of the model, we will apply uncertainty quantification techniques to the model in model calibration. Several approaches will be considered in this process: 1) Markov Chain Monte Carlo (MCMC) methods can be applied for parameter optimization in ABMs (Kattwinkel & Reichert 2016, Hooten et al. 2020). 2) Approximate Bayesian Computation (ABC) methods can be used to estimate the posterior distribution of specific parameter values given the observed data. (Turner & Van Zandt 2012) 3) Emulators can be used to perform model uncertainty analysis (Bijak et al. 2013, Klabunde & Willekens 2016 and Papadelis & Flamos 2018). We will test different approaches on the case study level ABM and apply the suitable approach to the EU level ABM.

7. Step F - linking outputs to indicators

New post-2020 CAP policy already presents its list of associated indicators to allow the Commission to assess and monitor the achievements of specific objectives of the policy. A new Performance Monitoring and Evaluation Framework (PMEF) is designed which includes the use of a set of common indicators: Context indicators (remain pertinent), Result indicators (annual performance), Output indicators (annual performance) and Impact indicators (multi-annual performance). Therefore, each CAP strategic plan presented by each State member of the EC should refer to some interventions linked to specific objectives that should be assessable through the indicators defined by the EC, for instance, Farmland Bird Index as an indicator of Contribution to the protection of biodiversity, enhance ecosystem services and preserve habitats and landscapes. All the indicators are listed in the Annex I of COM(2018) 392 final (https://ec.europa.eu/commission/sites/beta-political/files/budget-may2018-cap-strategic-plans-annex_en.pdf). Last version (17/06/2021) of indicators discussed by the Expert Group for Monitoring and evaluating the CAP can be found in:

Context and impact:
https://ec.europa.eu/transparency/expert-groups-register/core/api/front/document/53039/download
Results:
https://ec.europa.eu/transparency/expert-groups-register/core/api/front/document/53040/download

The EC will provide specific fiches for each indicator in which the definition, the type of intervention associated, the methodology and the units of measurement and other comments will be included. A draft example of such fiches can be consulted in

Context indicator fiches (v. 10/2020):
https://ec.europa.eu/info/sites/default/files/food-farming-fisheries/key_policies/documents/context-indicator-fiches_en.pdf

Impact indicator fiches (v. 10/2020):
https://ec.europa.eu/info/sites/default/files/food-farming-fisheries/key_policies/documents/impact-indicator-fiches_en.pdf

In the context of BESTMAP, indicators relevant for the model outputs have been identified with the aim to identify possible derived impacts on ecosystem services when a selected agri environmental scheme is present or absent.

Table 7: Impact indicators linked to the biophysical modeling of BESTMAP

Ecosystem services /models	**Linked impact / result indicator (v. 17/06/2021)**
Food production	I.2 Comparison of agricultural income with non-agricultural labour costs I.3 Agricultural factor income
Carbon sequestration	I.11 Soil organic carbon in agricultural land
	R.14 Carbon storage in soils and biomass
Water quality	I.15 Gross nutrient balance on agricultural land - Nitrogen and phosphorous
Biodiversity / habitats	I.18 Farmland Bird Index I.19 Percentage of species and habitats of Community interest related to agriculture with stable or increasing trends

Apart from the post-2020 official CAP indicators listed in Annex I of COM (2018) 392, BESTMAP has reviewed additional interesting metrics provided by the EU Sustainable Development Goals or the Water Framework Directive that are also available. Indeed, the EU SDG indicators set is aligned with the UN list of global indicators but also relevant for the EU, given that UN SDG indicators are selected for a global level reporting and not always relevant for the EU. Indicators of SGD 2 (Zero hunger) and SDG 15 (Life on land) are the most relevant for the objectives of BESTMAP modeling.

Figure 11: Sustainable Development Goal 2 (Zero Hunger)

Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture						
New indicator "Harmonised risk indicator for pesticides (HRI1)" replacing sdg_02_50 "Gross nutrient balance on agricultural land" provided that data is made publicly available in time for drafting the 2020 monitoring report.						
02_10	mpi -> 3	Obesity rate	No modification.	more than 3 years	EU aggregate & all MS; plus other countries	Eurostat
02_20		Agricultural factor income per annual work unit (AWU)	No modification.	every year	EU aggregate & all MS; plus other countries	DG AGRI
Code	*MPI*	*Indicator name*	*Comments*	*Frequency of data collection*	*Geographical coverage*	*Data provider*
02_30		Government support to agricultural research and development	No modification.	every year	EU aggregate & all MS; plus other countries	Eurostat
02_40		Area under organic farming	No modification.	every year	EU aggregate & all MS; plus other countries	Eurostat
~~02_50~~ (del)		~~Gross nutrient balance on agricultural land~~	Replaced by new indicator "Harmonised risk indicator for pesticides (HRI1)"	every year	EU aggregate & all MS; plus other countries	Eurostat
new		Harmonised risk indicator for pesticides (HRI1)	New indicator replacing sdg_02_50 "Gross nutrient balance on agricultural land" provided that data is made publicly available in time for drafting the 2020 monitoring report.	every year	EU aggregate & all MS	DG SANTE
02_60		Ammonia emissions from agriculture	No modification.	every year	EU aggregate & all MS; plus other countries	EEA
Multi-purpose indicators: Supplementary indicators of other goals which complement the monitoring of this goal						
06_40	mpi -> 2	Nitrate in groundwater	No modification; however no longer evaluated as multi-purpose indicator under SDG 15.	every year	EU aggregate & most MS; plus other countries	EEA
15_50	mpi -> 2	Estimated soil erosion by water - area affected by severe erosion rate	Revised time series consisting of 2000, 2010 and 2016 data points expected to be evaluated for 2020 EU SDG monitoring.	a-periodic	EU aggregate & all MS	JRC
15_60	mpi -> 2	Common bird index	No modification. To be noted that index of farmlandbirds (including MS data if available) is used as multi-purpose indicator for SDG 2 monitoring.	every year	Only EU aggregate; no MS data available.	European Bird Census Council

Figure 12: Sustainable Development Goal 15 (Life on Land)

Goal 15. Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss						
Indicators sdg_06_40 'Nitrate in groundwater' and sdg_11_31 'Settlement area per capita' no longer evaluated as multi-purpose indicator under SDG 15.						
15_10		Share of forest area	No modification.	every 3 years	EU aggregate & all MS	Eurostat
15_20		Surface of terrestrial sites designated under NATURA 2000	No modification.	every year	EU aggregate & all MS	EEA / DG ENV
15_41		Soil sealing index	No modification.	every 3 years	EU aggregate & all MS	EEA
15_50	mpi → 2	Estimated soil erosion by water	Revised time series consisting of 2000, 2010 and 2016 data points expected to be evaluated for 2020 EU SDG monitoring.	a-periodic	EU aggregate & all MS	JRC
15_60	mpi → 2	Common bird index	No modification. To be noted that index of farmlandbirds (including MS data if available) is used as multi-purpose indicator for SDG 2 monitoring.	every year	Only EU aggregate, no MS data	European Bird Census Council
15_61		Grassland butterfly index	No modification. To be noted that currently, no MS data are available.	every year	Only EU aggregate, no MS data	EEA (Butterfly Conservation Europe)
Multi-purpose indicators: Supplementary indicators of other goals which complement the monitoring of this goal						
06_30	mpi -> 15	Biochemical oxygen demand in rivers	No modification.	every year	EU aggregate & most MS; plus other countries	EEA
06_50	mpi -> 15	Phosphate in rivers	No modification.	every year	EU aggregate & most MS; plus other countries	EEA

Intercomparison between CAP post-2020 indicators and EU SDG has been made in order to identify the common indicators and therefore the most relevant ones:

Table 8: CAP post 2020 indicators comparison to EU SDG indicators

CAP post 2020 indicator (v. 17/06/2021)	EU SDG indicator
R17. Afforested land: Area supported for afforestation, agroforestry and restoration, including breakdowns R.26 Supporting sustainable forest management: Share of forest land under commitments to support forest protection and management of ecosystem services	15_10 Share of forested area
R.28 Improving Natura 2000 management: Share of total Natura 2000 area under supported commitments	15_20 Surface of terrestrial sites designated under NATURA 2000

I.13 Reducing soil erosion: Soil erosion by water - Percentage of agricultural land in moderate and severe soil erosion	15_50 Estimated soil erosion by water
I.18 Increasing farmland bird populations: Farmland Bird Index	15_60 Common bird index
I.16 Reducing nutrient leakage: Nitrates in groundwater - percentage of ground water stations with Nitrates concentration over 50 mg/l as per the Nitrate Directive	06_40 Nitrate in groundwater
I.27 Sustainable and reduced use of pesticides: Risks,use and impacts of pesticides R.37 Sustainable and reduced use of pesticides: Share of Utilised Agricultural Area (UAA) concerned by supported specific commitments which lead to a sustainable use of pesticides in order to reduce risks and impacts of pesticides such as pesticides leakage	NEW Harmonised risk indicator for pesticides (HRI1)

8. Step G - provide a dashboard to visualize and allow policy-makers to explore scenarios

Given the complexity of PIAMs, BESTMAP offers an interactive dashboard where end-users such as stakeholders, scientists or regular citizens, are able to use, analyse and report the results of models that simulate future scenarios. This decision-support tool allows easy interaction and comparison of policy alternatives by visualizing geospatial distributions of the positive and negative impacts on each case study. The first version of the dashboard is available at: https://www.ogc.grumets.cat/bestmap/ (Figure 2). One single dashboard showing the European situation and the possibility of zooming in into the 5 case studies has been implemented.

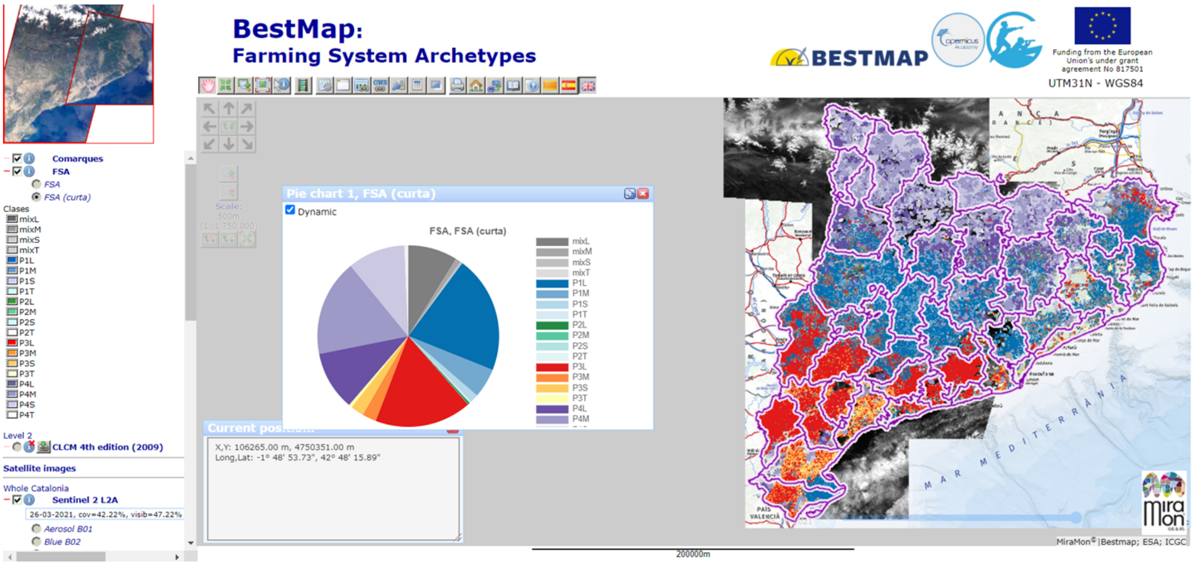


Figure 13. BESTMAP dashboard on ongoing development

The dashboard has been co-designed in a first meeting with stakeholders and project members to ensure its usefulness. Key messages of this meeting were collected and are being implemented. For instance, the concept of Storylines/Story Maps as narratives to explain the results is already a reality. The storyline/narrative based on the dashboard enables modelers to share a narrative based on model result dynamic maps and other multimedia content (Figure 3).

The story includes a narrative text in the local language that is associated with a specific area of the CS, so as the narrative is progressing, the map is moving to the focus area. The narrative will be built around key questions such as "how sensitive is the result to payments level above income forgone?".

Figure 14. Storyline on the distribution of the FSA around the Catalan CS visualized through the dashboard

Other several co-design sessions are scheduled to be performed during the first part of 2022 at each CS. Details of these sessions are included in section XX of this document.

At technical level, the dashboard is a configurable system designed to allow simple replacement of content as soon as the project is generating new models or pre-computed results. The visualization includes maps to easily identify spatial distributions of impacts, graphs or tabular data. It allows on-the-fly computation of several statistics, it will show data quality indicators (e.g uncertainty) and is provided with user-friendly controls that allow the selection of different narratives or scenarios.

The data architecture that includes the project dashboard is composed of 4 components (Figure 4). First, the GeoNetwork provides a Metadata Catalogue and also stores the data. Models run in a Virtual environment using GeoNetwork data as inputs and its output results are data sources for the GeoServer (WMS / WFS). All possible scenarios are precomputed as possible results. Complex indicators are also precomputed and stored in the GeoNetwork. GeoServer provides responses to the dashboard queries that are presented to the users as graphical or numerical values. Simple indicators such as statistical overalls are computed directly on the dashboard.

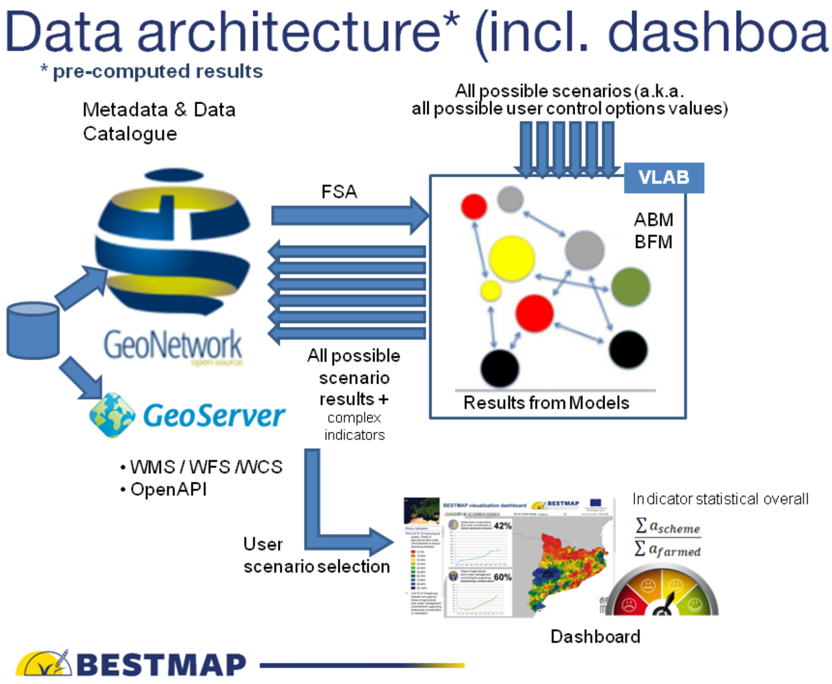


Figure 15. Data architecture including dashboard.

The dashboard will evolve with new functionalities to meet new requirements that could eventually appear during the project life.

9. Co-design in the framework

BESTMAP has always cared about the needs of policy makers and stakeholders. That's why co-design and co-development is part of the conceptual framework.
Indeed, BESTMAP has collected EU and local stakeholders' opinions to select relevant AES and co-design the project dashboard, with the aim to ensure that results of the project are meaningful and relevant for Case Studies.
A process of interaction with stakeholders has been developed at EU level and in each CS. The involvement of stakeholders is pursued in different ways tailored to the specific CS context, such as: phone/online interviews, surveys, structured meetings, co-design workshops, etc. All these interactions are carried out using local languages and are conducted by CS partners. For instance, a set of co-design of the dashboard sessions at each CS are scheduled to be performed during the first part of 2022.

Each session will include a demonstration / technical presentation of the dashboard and its functionalities (statistics) based on models preliminary results and first impressions on the model results major deviations will be collected and respective modifications will be made to the dashboard to fulfill stakeholders needs.
This approach demonstrates the project willingness to collaborate with EC representatives and other stakeholders in design and testing of applications, thus indicating their potential value and impact.

10. Remote Sensing as a datasource to complement FSA mapping

To inform and/or complement the two FSA dimensions, the applicability of remote sensing data was investigated. Three relevant domains of remote sensing applications were identified:

- Crop type mapping: Mapping crop types from remote sensing data directly informs the farm specialization dimension of FSAs because the type of farm specialization is determined based on the extent of individual crops grown at a farm.
- Yield mapping: The estimation of field-level yield from remote sensing data can serve as a complement to the Standard Output Coefficients (SOCs) selected in D3.5 to inform the economic size dimension of FSAs. Yield is heavily dependent on yearly weather conditions etc. and as such can reflect the temporal dynamics of a farm's economic output.
- Extraction of field boundaries: Applying a spatially independent algorithm to extract field boundaries from remote sensing data reduces the dependency on member state specific IACS/LPIS and solves the inconsistency of field definitions identified in D3.5.

These domains were analyzed at CS level and are reported in detail in D5.4. This section provides an overview of the key findings.

10.1 Crop Type Mapping

Crop type mapping is typically realized by a discrete classification of a time-series of satellite imagery. Data products exist at different scales and from different providers, e.g. the Land Cover Plus: Crops dataset by the UK Centre for Ecology and Hydrology (UKCEH) covering the area if the United Kingdom or the European crop map product by the Belarusian company OneSoil. These datasets were compared to LPIS and implications for FSA mapping were analyzed. While the OneSoil dataset has poor agreement with LPIS in the Czech case study region, FSA farm specialization mapping based on the Land Cover Plus: Crops dataset resulted in 77.5% agreement compared to the reference FSA farm specialization as mapped in D3.5. Here, the identification of grassland by combining multiple years of data was crucial to correctly map the farm specialization grazing and livestock (P4).

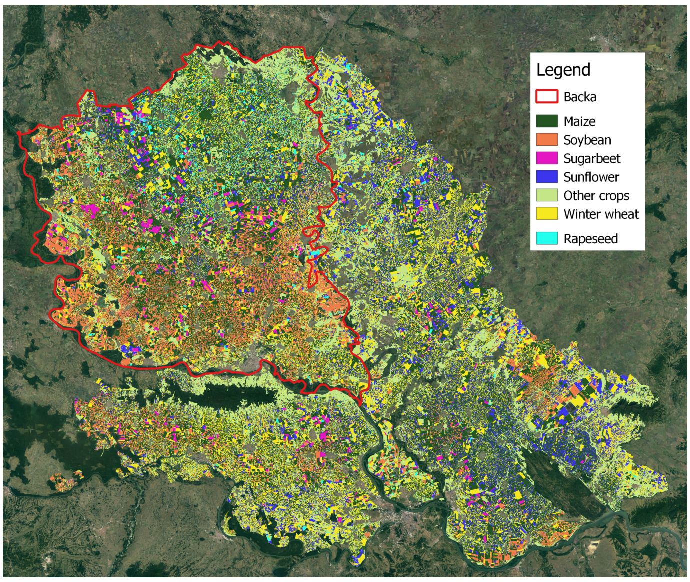


Figure 16: Crop classification map of the Serbian case study region

Additionally, a Random Forest crop classification map was generated using a Sentinel-2 time-series for the Serbian case study region, where no LPIS data is available (see Figure 16). Reference data from the voluntary platform AgroSens was used for this purpose. High classification accuracies of > 90% could be achieved across years and crop types. From these analyzes we conclude that remote sensing crop classification products can be used to inform the FSA farm specialization dimension with a high accuracy, provided the classification product is optimized for the region of interest. This means that the accuracy across case study regions needs to be analyzed in detail for new large-scale crop classification products that become available (e.g. d'Andrimont et al. 2021).

10.2 Yield mapping

Two analyses with different focus were conducted with regard to yield mapping: One in-depth analysis of remotely sensed vegetation indicators and their relationship to yield and the generation of an experimental yield product based on soil and weather data. For the first approach, a thorough literature review was conducted to find the maximum GNDVI (Green Normalized Difference Vegetation Index) of a growing season to be the strongest single predictor of yield. For FADN region 412 (East England), a three-year Sentinel-2 time-series was generated and different indicator metrics were compared to reference yield from the ASSIST dataset held by CEH (see also Hunt et al. 2019). Although only a weak to moderate correlation could be found, the maximum GNDVI was indeed the most stable and best correlated indicator to yield across years and crop types. An example of the linear relationship is shown in Figure 17.

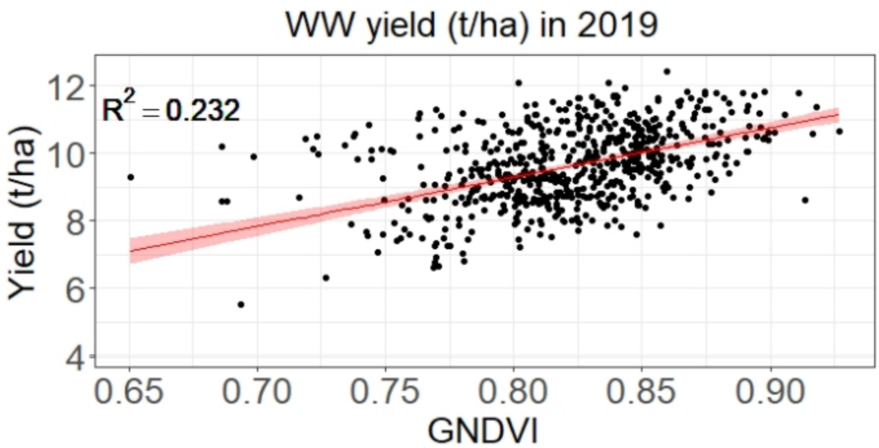


Figure 17: Linear regression between the field-level maximum GNDVI value of the 12/2018 - 07/2019 growing season of winter wheat (WW) and reference yield

This work is ongoing and several options are being explored in order to potentially apply a yield estimation approach with minimized need for reference data. This requirement is crucial for the application of the envisioned approach to other regions as the availability of spatially disaggregated reference data on yield is very limited.

The second yield mapping approach employed weather and soil data only and was realized for the Serbian case study region. It depends heavily on reference yield data and has a limited spatial resolution, but can produce large-scale yield estimates if input data is available. A possible combination of both approaches is also being investigated.

10.3 Field boundary mapping

The work on field boundary mapping is ongoing, but the envisioned approach employs a multi-task based convolutional neural network (CNN) based on Sentinel-2 imagery. The proposed architecture jointly learns two semantically similar tasks: Boundary delineation and segmentation of parcels (see Figure 18). This multi-task network outperforms a single CNN dedicated to boundary delineation only (Masoud et al. 2020).

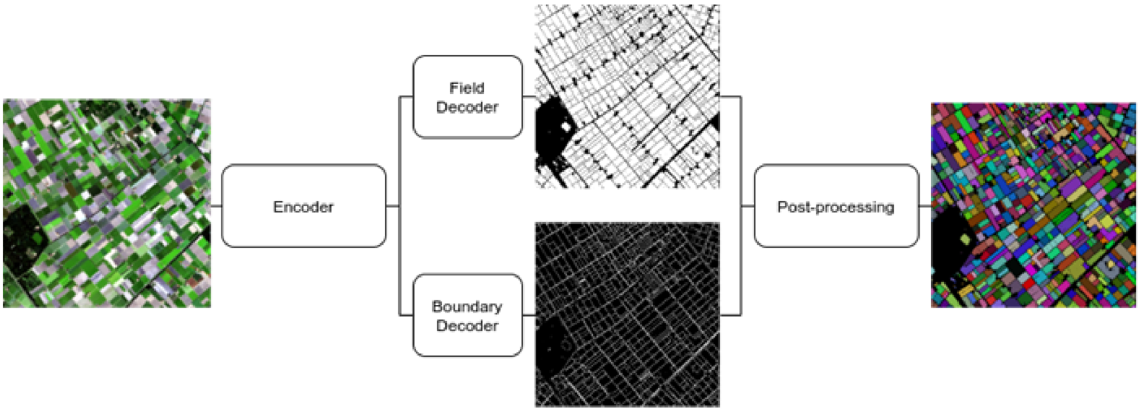


Figure 18: Multi-task convolutional neural network for detecting production parcels

This remote-sensing based approach has the advantage that it can be consistently applied to any region of interest such that the issues of parcel data unavailability and inconsistency in parcel/field definitions can be overcome.

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Appendix

Table A1 Grouping of AES and EFA schemes into the seven AES groups for the German CS Mulde River Basin.

Measures group	Scheme (AES/EFA)	Code	Description (German)	Description (English)	Notes
Cover crops	AES	AL4	Anbau von Zwischenfrüchten	Catch/cover crops	
	EFA	52	Zwischenfrucht/ Gründecke	Catch crop/green cover	
Maintaining permanent grassland	AES	GL1(a-c)	Artenreiches Grünland Ergebnisorientierte Honorierung	Species-rich grassland Results-oriented payment	GL1 (with no letters) was one single scheme up until 2016
	AES	GL2(a-h)	Biotoppflegemahd mit Erschwernis	Biotope maintenance mowing with difficulty	
	AES	GL4(a-b)	Naturschutzgerechte Hütehaltung und Beweidung	Conservation-oriented herding and grazing	
	AES	GL5(a-e)	Spezielle artenschutzgerechte Grünlandnutzung	Special species-compatible grassland use	
Buffer areas	AES	AL1	Grünstreifen auf Ackerland	Green strips on arable land	
	AES	AL5c	Mehrjährige Blühflächen	Perennial flowering areas	
	AES	AL5d	Einjährige Blühflächen	Annual flowering areas	

	EFA	54	Streifen am Waldrand (ohne Produktion)	Stripes at the edge of the forest (without production)	
	EFA	56	Pufferstreifen AL	Buffer strips on cropland	
	EFA	57	Feldrand / Pufferstreifen GL	Field edge / buffer strips on grassland	
	EFA	58	Feldrand / Pufferstreifen auf AL	Field edge / buffer strips on cropland	
	EFA	65	Bienenweide einjährig	Annual bee pastures	
	EFA	66	Bienenweide mehrjährig	Perennial bee pastures	
	EFA	78	Feldraine CC	Field border	
Organic farming		OEBL	Ökologischer Landbau	Organic farming	
Land use conversion to permanent grassland		K1	Stilllegung von Ackerland für Zwecke der Biotopentwicklung	Decommissioning of arable land for biotope development	does not occur anymore in IACS data after 2017
		K2	20jährige Ackerstilllegung für Zwecke der Biotopgestaltung und des Umweltschutzes	20-year set-aside of arable land for biotope creation and environmental protection	does not occur anymore in IACS data after 2018
		N3-AL	Langfristige Stilllegung landwirtschaftlicher Nutzfläche zur Biotopentwicklung auf Ackerflächen	Long-term set aside of agricultural land for biotope development on arable land	

		N3-GL	Langfristige Stilllegung landwirtschaftlicher Nutzfläche zur Biotopentwicklung auf Grünland	Long-term set-aside of agricultural land for biotope development on grassland	
	AES	G 10	Umwandlung von Ackerland in Dauergrünland	conversion of arable land into permanent pasture	does not occur anymore in IACS data after 2017
Land use conversion to forest	EFA	61	Aufforstungsflächen	Afforestation areas	
		EVP groß	Einkommensverlustprämie groß	Large income loss premium	
		EVP klein	Einkommensverlustprämie klein	Income loss premium small	
Fallow land	AES	AL5a	Selbstbegrünte einjährige Brache	Self-greened one-year-old fallow land	
	AES	AL5b	Selbstbegrünte mehrjährige Brache	Self-greened perennial fallow land	
	AES	GL3	Bracheflächen und Brachestreifen im Grünland	Fallow land and strips in grassland	
	EFA	62	Brachen ohne Erzeugung	Fallow without production	

Table A2 Grouping of AES and EFA schemes into the seven AES groups for the Czech CS South Moravia.

Measures group	Scheme (AES/EFA)	Code	Naming in LPIS data	Description (Czech)	Description (English)	Notes

Cover crops	EFA	VYM_OP_PP_MPL	VYM_OP_PP_MPL	Meziplodina	Catch crop	
Maintaining permanent grassland	AES	10.1.4		Ošetřování travních porostů	Grassland maintenance	
	sub AES	10.1.4.1	VYM_OP_AEKO_ZAKL	Obecná péče o extenzivní louky a pastviny	General extensive meadow and pasture maintenance	
	sub AES	10.1.4.2	VYM_OP_AEKO_MVLH	Mezofilní a vlhkomilné louky hnojené	Mesophilic and hygrophilic meadows fertilized	
	sub AES	10.1.4.3	VYM_OP_AEKO_MVLN	Mezofi lní a vlhkomilné louky nehnojené	Mesophilic and hygrophilic meadows non-fertilized	
	sub AES	10.1.4.4	VYM_OP_AEKO_HSLH	Horské a suchomilné louky hnojené	Mountain and arid meadows fertilized	
	sub AES	10.1.4.5	VYM_OP_AEKO_HSLN	Horské a suchomilné louky nehnojené	Mountain and arid meadows non-fertilized	
	sub AES	10.1.4.6	VYM_OP_AEKO_PODM	Trvale podmáčené a rašelinné louky	Permanently wet and peat meadows	
	sub AES	10.1.4.7	VYM_OP_AEKO_MODR	Ochrana modrásků	Protection of Lycaenidae butterflies	

	sub AES	10.1.4.8	VYM_OP_AEKO_CHRAS	Ochrana chřástala polního	Corn crake protection	
	sub AES	10.1.4.9	VYM_OP_AEKO_SSTAV	Suché stepní trávníky a vřesoviště	Dry steppe meadows and heaths	
	sub AES	10.1.4.10	VYM_OP_AEKO_DBP	Druhově bohaté pastviny	Species-rich pastures	
Buffer areas	AES	10.1.6		Biopásy	Biobelts (vegetated strips)	
	sub AES	10.1.6.1	VYM_OP_AEKO_KBP	Krmný biopás	Fodder vegetated strip	
	sub AES	10.1.6.2	VYM_OP_AEKO_NBP	Nektarodárný biopás	Pollinators vegetated strips	
Organic farming	AES	10.1.1	VYM_OP_AEKO_IPO	Integrovaná produkce ovoce	Integrated fruit production	
	AES	10.1.2	VYM_OP_AEKO_IPV (VYM_OP_AEKO_NOV)	Integrovaná produkce révy vinné	Integrated grapevine production	
	sub AES	10.1.2.1	VYM_OP_AEKO_ZOV	Základní ochrana vinic	Basic vineyard protection	
	sub AES	10.1.2.2	VYM_OP_AEKO_IPV (VYM_OP_AEKO_NOV)	Nadstavbová ochrana vinic	Additional vineyard protection	

	Organic farming	M11	VYM_OP_EZ_EZ	Ekologické zemědělství	Organic farming	
Land use conversion to permanent grassland	AES	10.1.5		Zatravňování orné půdy	Conversion of arable land into grassland	Conversion to grassland is not permanent, but limited to 5 years.
	sub AES	10.1.5.1	VYM_OP_AEKO_ZBS	Zatravňování orné půdy běžnou směsí	...using normal seed mixture	
	sub AES	10.1.5.2	VYM_OP_AEKO_ZDOS	Zatravňování orné půdy druhově bohatou směsí	...using species-rich seed mixture	
	sub AES	10.1.5.3	VYM_OP_AEKO_ZDRS	Zatravňování orné půdy regionální směsí	...using regional seed mixture	
	sub AES	10.1.5.4	VYM_OP_AEKO_ZBSV	Zatravňování orné půdy podél vodního útvaru běžnou směsí	...along water body using normal seed mixture	
	sub AES	10.1.5.5	VYM_OP_AEKO_ZDOSV	Zatravňování orné půdy podél vodního útvaru druhově bohatou směsí	...along water body using species-rich seed mixture	
	sub AES	10.1.5.6	VYM_OP_AEKO_ZDRSV	Zatravňování orné půdy podél vodního útvaru regionální směsí	...along water body using regional seed mixture	

land use conversion to forest						
Fallow land	EFA	VYM_OP_PP_UHOZ	VYM_OP_PP_UHOZ	Úhor s porostem	Fallow with vegetation cover	

Table A3 Grouping of AES and EFA schemes into the seven AES groups for the UK CS Humber River Basin.

Measures group	Scheme (AES/EFA)	Code	Description (English)
Cover crops	AES	SW6	Winter cover crops
	EFA	CA01	catch crop
	EFA	CA02	cover crop
Maintaining permanent grassland	AES	GS2	Permanent grassland with very low inputs (outside SDAs = severely disadvantaged areas)
	AES	GS5	Permanent grassland with very low inputs (in SDAs)
	AES	GS6	Management of species-rich grasslands
	AES	GS7	Restoration towards species-rich grassland
	AES	GS9	Management of wet grassland for breeding waders

Buffer areas	AES	SW1	4 to 6 metre buffer strip on cultivated land
	AES	SW2	4 to 6 metre buffer strip on intensive grassland
	AES	SW3	In-field grass strips
	AES	SW4	12 to 24 metre watercourse buffer strips on cultivated land
		SW11	Riparian management strip
		AB1	Nectar flower mix
		AB3	Beetle banks
		AB8	Flower rich margins and plots
		WT2	Buffering in-field ponds and ditches on arable land
	EFA	BF15	A buffer strip of permanent grassland and field margin of temporary grassland or fallow land that you want to use as part of your ecological focus area.
Organic farming	AES	OT1	Organic land management - improved permanent grassland
	AES	OT2	Organic land management - unimproved permanent grassland
	AES	OT3	Organic land management - rotational land
	AES	OT5	Organic land management - top fruit

	AES	OR1	Organic conversion – improved permanent grassland
	AES	OR2	Organic conversion – unimproved permanent grassland
	AES	OR3	Organic conversion – rotational land
	AES	OR5	Organic conversion - top fruit
Land use conversion to permanent grassland		SW7	Arable reversion to grassland with low fertilizer input
Land use conversion to forest		WGC	Woodland Creation Grant
Fallow land	EFA	FA01	Land lying fallow
	AES	GS1	Take small areas out of management

Table A4 Grouping of AES and EFA schemes into the seven AES groups for the Spanish CS Catalonia.

Measures group	**Scheme (AES/EFA)**	**Code**	**Description (Catalan)**	**Description (English)**	**Notes**
Cover crops	AES	AES_367	Producció integrada	Integrated production	

Maintaining permanent grassland	AES	AES_363	Gestió i recuperació de prats de dall	Management and recovery of meadows and pastures	
	AES	AES_368	Conservació de races autòctones	Conservation of native breeds	
Buffer areas					No AES for the Catalan CS
Organic farming	AES	AES_372	Agricultura Ecològica	Organic farming	
	AES	AES_373	Ramaderia ecològica	Organic livestock	
	AES	AES_366	Sistemes alternatius a la lluita química	Alternative systems to chemical control	
Land use conversion to permanent grassland					This measure group is excluded for the Catalan case study
Land use conversion to forest					No AES for the Catalan CS

Fallow land	AES	AES_364	Millora dels hàbitats esteparis de Xarxa Natura 2000	Improvement of the steppe habitats of the Natura 2000 Network	
	EFA	CODI_PROD = 24	Guaret sie/ sup. lliure sembra	Fallow land EFA / area free of sowing	