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Deliverable D2.2 BESTMAP Conceptual Framework Design & Architecture

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BESTMAP Conceptual Framework Design & Architecture

Deliverable D2.2

23rd December 2020

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

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Summary

This deliverable provides a General Framework for the BESTMAP Policy Impact Assessment Modelling (BESTMAP-PIAM) toolset. An update of the framework will be provided later in the project in Deliverable 2.4. The BESTMAP-PIAM is based on the notion of defining (a) a typology of agricultural systems, with one (or more) representative case study (CS) in each major system; (b) mapping all individual farms within the case study to a Farm System Archetype (FSA) typology; (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 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; (e) upscaling the CS level results to EU scale; (f) linking the outputs of these models to indicators developed for the post-2020 CAP output, result and impact reports; (g) visualizing outputs and providing a dashboard for policy makers to explore a range of policy scenarios, focusing on cost-effectiveness of different AES. Each of these steps are detailed in a separate section below.

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 likelihood 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 A).

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

1. Farming System Archetypes

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To allow linkages between CS and EU level to work, the set of attributes defining FSAs within each CS 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 characteristics of 'farmer agents' which individually "decide" if they adopt the set of AES, based on the same relationships found in the CS ABM.
- Be either available in Farm Structure Survey scientific-use files (SUF) (to be able to create a weighting for FADN microdata records) or use weighing coefficients based on Standard Output (economic size) and Farm Specialization (type of farm) which FADN already includes.
- 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).
- 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).

After discussing possible attributes given the data in IACS/LPIS and FADN, BESTMAP made the decision to keep the FSA classification simple, and follow the FADN approach of farm specialization and economic size (see Other Farmer's Attributes for discussion).

(1) Farm specialization - fit to farm practice was highlighted in BESTMAP interviews, and we operationalized that using a farm typology. BESTMAP-PIAM will use a simplified version of FADN that is defined in Annex IV of EU regulation 2015/220. We choose to reduce TF8 to five types - field crops (area-based rule: P1 > 2/3, see definition of P1 below), horticulture (P2 > 2/3), permanent crops (P3 > 2/3), grazing livestock (P4 > 2/3) and mixed.

To map spatial IACS/LPIS data to these five classes, we will use the area based rules defined in EU regulation 2015/220. For completeness, the definitions of P1, P2, P3 and P4 are given below based on FADN microdata field names. For each CS, we will map the crop classification in the IACS/LPIS to these fields (a mapping is provided in Step B for BESTMAP CSs):

[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 modelling agricultural systems, so would advice policymakers to keep collecting such data even if regulations are simplified and monitoring EFA is not mandatory.

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P1 General cropping = P15 (cereals) + 2.01.02. (dried pulses and protein crops) + 2.01.03. (potatoes) + 2.01.04. (sugar beet) + 2.01.06.01. (tobacco) + 2.01.06.02. (hops) + 2.01.06.03. (cotton) + P16 (oilseeds) + 2.01.06.09. (flax) + 2.01.06.10. (hemp) + 2.01.06.11. (other fibre crops) + 2.01.06.12. (aromatic plants, medicinal and culinary plants) + 2.01.06.99. (other industrial crops not mentioned elsewhere) + 2.01.07.01.01. (fresh vegetables, melons, strawberries — outdoor or under low (not accessible) protective cover — open field) + C1 2.01.10. (arable land seed and seedlings) + 2.01.11. (other arable land crops) + 2.01.12. (fallow land) + FCP1 (forage for sale)

P2 Horticulture = 2.01.07.01.02. (fresh vegetables, melons, strawberries — outdoor or under low (not accessible) protective cover — market gardening) + 2.01.07.02. (fresh vegetables, melons, strawberries — under glass or other (accessible) protective cover) + 2.01.08.01. (flowers and ornamental plants — outdoor or under low (not accessible) protective cover) + 2.01.08.02. (flowers and ornamental plants — under glass or other (accessible) protective cover) + 2.06.01. (mushrooms) + 2.04.05. (nurseries)

P3 Permanent crops = 2.04.01. (fruit and berry plantations) + 2.04.02. (citrus plantations) + 2.04.03. (olive plantations) + 2.04.04. (vineyards) + 2.04.06. (other permanent crops) + 2.04.07. (permanent crops under glass)

P4 Grazing livestock and forage = GL (grazing livestock) + FCP4 (forage for grazing livestock)

The farm specialization in FADN is given by Type of Farming as either 8 classes (TF8) or 14 classes (TF14), both are available per farm in the microdata, and used to stratify regional standard reports (see below). For BESTMAP-PIAM, we will combine TF classes 3 (wine) and 4 (other permanent crops) as a single 'permanent crop' type. We will also combine class 5 (milk) and class 6 (other grazing livestock) as a single 'grazing livestock' type. We combined class 7 (granivores) and class 8 (mixed) as 'other'. In the former case, it is likely possible to separate wine and other permanent crops in IACS/LPIS, but we choose to avoid adding another farm type (which has a knock-on effect on survey). IACS/LPIS does not have information on livestock density of cows vs other livestock, hence separating milk and other livestock is not possible with the spatial data we have.

To get the Farm Specialization in a online survey, farmers can easily answer the following question -
Q. roughly what percentage of your farm is:
_____ % field crops
_____ % grazing and silage
_____ % horticulture
_____ % permanent crops, vineyards, orchards
_____ % other (incl. granivores)

(2) Economic size - income is a well-known factor affecting decision making. The economic size of farms is given as variable SE005 in Standard Result in FADN microdata. To define classes of economic size, we adopt a simplified version of FADN ES6 (6 classes), which is available in the microdata:

FADN ES6

1	2 000 - < 8 000 EUR
2	8 000 - < 25 000 EUR
3	25 000 - < 50 000 EUR
4	50 000 - < 100 000 EUR
5	100 000 - < 500 000 EUR
6	>= 500 000 EUR

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We decided to classify economic size as small, medium and large. The thresholds for these *for each farm specialization* were determined by analysis of the 2018 'farms represented' (SYS02) within YEAR.COUNTRY.SIZ6.TF8.zip standard report, and combining ES6 classes for each of the five Farm Specializations (FS) to get as close as possible to 33%/33%/33% -

FS	ES6 classes included (% of farms in 2018 FADN for FS)
field crops	small = 1 (23.6%); medium = 2 (35.6%); large = 3-6 (40.7%)
horticulture	small = 1-2 (32.9%); medium = 3-4 (35.8%); large = 5-6 (31.4%)
permanent crops	small = 1 (15.3%); medium = 2 (48.2%); large = 3-6 (36.5%)
grazing livestock	small = 1-2 (43.3%); medium = 3-4 (33.8%); large = 5-6 (22.9%)
other	small = 1 (35.2%); medium = 2 (28.6%); large = 3-6 (36.3%)

Economic size is not directly available from IACS/LPIS, but can be calculate using FADN Standard Output coefficients (EUR per hectare for ~90 crop types) available for 2013 in Eurostat[2]. The average per crop area can be easily computed by linking the pseudonymized LPIS/IACS farm data across years using a method based on maximizing intersect-over-union across consecutive years. Step B (below) describes this process for the CSs included in BESTMAP.

We can ask farmers how much is their total income, but this seemed to be too sensitive and many farmers may prefer not to answer (or not submit the whole survey). To overcome this, we propose to build on the strong correlation between Economic Size and UAA for each Farm Specialization. Farmers are likely to be much more in ease reporting what is their total UAA. To convert those, we compare FADN UAA available as SE025 standard result[3] and Economic Size (SE005). Using the same YEAR.COUNTRY.SIZ6.TF8.zip standard report the Pearson correlation between UAA (SE025, in hectare) and economic size (SE005, in units of 1000 euro) for all farms is 0.55, but that correlation is much higher when considering individual Farm Specializations[4]. We calculate the coefficient converting SE025 (UAA) = alpha * SE005 (economic size) for each:

Pearson correlation alpha*

[2] Standard output coefficients are the average monetary value of the agricultural output at farm-gate price, in euro per hectare or per head of livestock. For 2013 SO coefficients per regions calculated using the average of 2011-2015 prices in 2016 Farm structure survey data see https://ec.europa.eu/eurostat/web/agriculture/so-coefficients

[3] RI/CC 1750 defines SE025 as Total utilised agricultural area of holding. Does not include areas used for mushrooms, land rented for less than one year on an occasional basis, woodland and other farm areas (roads, ponds, non-farmed areas, etc.). It consists of land in owner occupation, rented land, land in share-cropping (remuneration linked to output from land made available). It includes agricultural land temporarily not under cultivation for agricultural reasons or being withdrawn from production as part of agricultural policy measures. It is expressed in hectares (10 000 m2). As from 2014, it includes kitchen gardens.

[4] This correlation is not too surprising, given economic size is calculated based on multiplying different areas by crop-specific (but also region-specific) coefficients. Hence, farms of similar farm type have similar crops and compositions thus the correlation arises. 'Other' farms are much more heterogeneous in composition, thus having lower correlation.

	between economic size	UAA and
Crop fields	0.856171042	0.876
Horticulture	0.742337305	0.024
Permanent crops	0.743932219	0.130
Grazing livestock	0.754230673	0.420
Other	0.524681123	0.234

* smaller alpha means *higher* economic value per hectare. Fresh vegetables make the largest value (and also profit and gross margin) but are limited to small area of highly productive land

With these we can define the *UAA thresholds* for the three economic sizes we defined (per FS):

	UAA threshold [hectare]		
	small farms	medium	large
Crop fields	< 7	< 22	> 22
Horticulture	< 0.6	< 2.4	> 2.4
Permanent crops	< 1	< 3.2	> 3.2
Grazing livestock	< 10.5	< 42	> 42
Other	< 1.8	< 5.9	> 5.9

Last, farmers may know better their total farm size (including non farmed area, wooded land etc.). The relationships between different variables is given in the diagram below:

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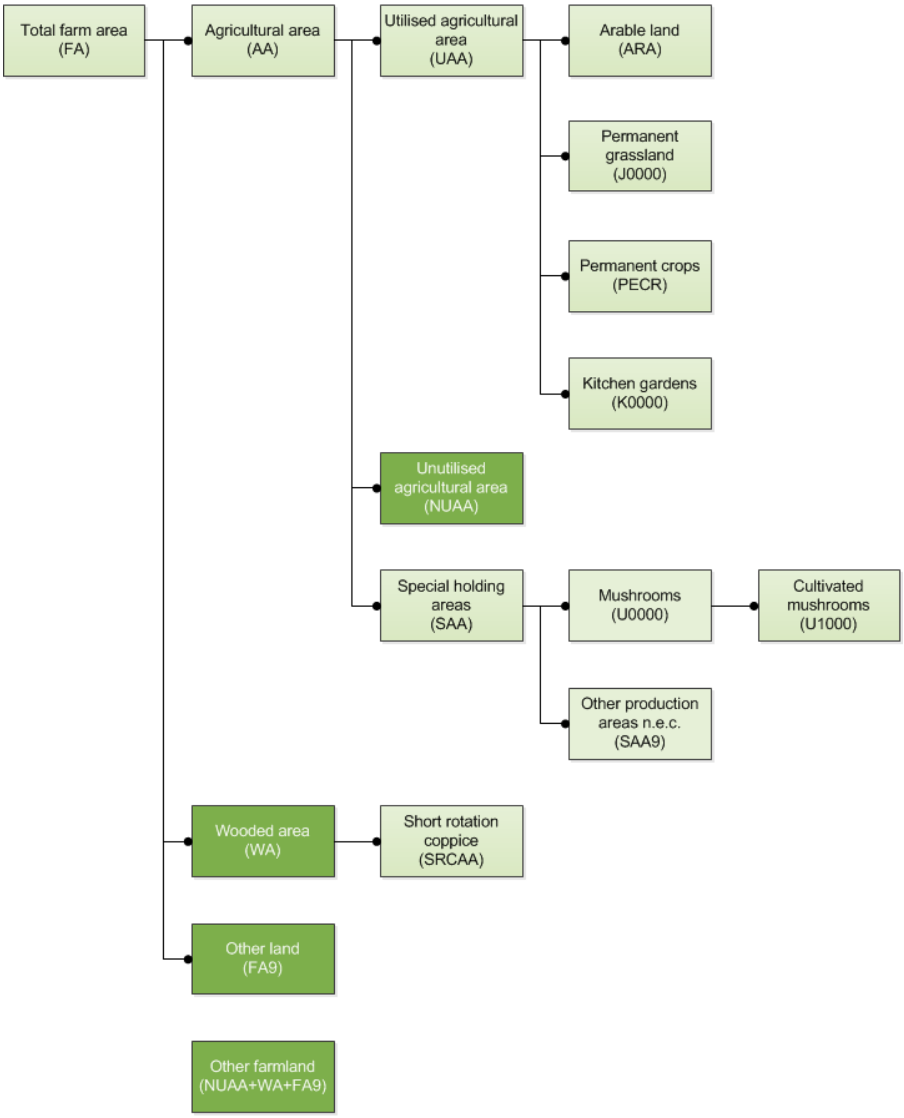

For some of the CSs, we can make a relationship between UAA and Total Farm Area as the IACS/LPIS provide complete coverage. This will be explored and revised in the next update of the Conceptual Framework.

1.1 Reducing number of FSAs

The previous section describes a top-down approach for FSAs that end up with at most 15 FSAs - 5 Farm Specializations X 3 Economic Sizes. Getting a representative sample of farmers to survey per FSA in each CS would still be very difficult with 15 FSAs - both achieving representativeness and resource requirements would make this hard. BESTMAP-PIAM approach, therefore, relies on reduction by merging of those 15 FSAs based on the agricultural system (step A) - see in relevant section below for further details.

1.2 Other Farmer's 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, available in FSS SUF to derive weights, easy for farmers to answer). 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.

Past participation in AES - 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'[5] 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 some farms repeat across multiple years, but it is not designed as a longitudinal study. Of course, asking the farmers is rather simple for this attribute. More importantly, the FSS SUF exclude all subsidy data, in particular environmental subsidies - hence we can't make a weight for FADN microdata with this as a strata.

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 as 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.

[5] 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)

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Average distance between groups of fields managed by the same famer as a proxy of mechanisation 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. It is also not clear if FSS SUF includes only area or also yields of crops.

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[6] sources[7] (averaged over FADN polygons). 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

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

[7] 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.

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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 farms data provided by IACS/LPIS to FSAs follows the procedure detailed above to calculate Farm Specialization based on a rule-based procedure by crop area (e.g. P1 > ⅔ ➡crop field) and weighing each farm field by Standard Output region/crop coefficients from Eurostat, followed by thresholding to small/medium/large. The final step uses the per agricultural system mapping (Step A) to reduce to a minimal set of FSAs, which is key to allow sufficient sampling of farmers in survey and building regressions from biophysical/socio-economic models.

Full details on the construction of FSAs from IACS/LPIS data will be provided in a future Deliverable 3.5. The table below show an example for Humber CS of linking the spatial data source, FADN classification and Eurostat:

Table 1: The ten most predominant crop types within the Humber region for 2019. Data source: UK Rural Payments Agency

Code	Original name	Is P1/P2 /P3 /P4 ?	Mapped SO coefficient name	2013 SO coefficient value (EUR/ha]
AC66	Wheat (winter)-type arable crop	P1	Common wheat and spelt	1,618.67
PG01	Permanent grassland	P4	Permanent grassland and meadow - pasture and meadow	237.28
AC67	Oilseed (winter)-type arable crop	P1	Other oil seed crops	755.24
AC63	Barley (winter)-type arable crop	P1	Barley	1,270.85
AC01	Barley (spring)-type arable crop	P1	Barley	1,270.85
TG01	Temporary grassland	P4	Forage plants - temporary grass	254.48
LG03	Field beans (spring)-type leguminous and nitrogen fixing crop	P1	Pulses - total	1,149.96

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AC03	Beet-type arable crop	P1	Sugar beet	2,668.01
AC44	Potato-type arable crop	P1	Potatoes	5,987.86
AC17	Maize-type arable crop	P1	Grain maize	1,522.13

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

1. vegetables are not specified to be 'garden market' or not, which makes them difficult to classify as P1 or P2. We decided in most CSs to assign them to P1, which meant very few farms were horticulture specialists.
2. forage for sale (P1 in FADN) vs forage for grazing (P4 in FADN) cannot be distinguished from LPIS data. For the ES we got a farm-level field weather the farm holds livestock. In that case, we assigned all grasslands (temporary and permanent) to grazing, otherwise to sale. In the UK we attempted to use the presence of 'livestock shelters' but we found this data to be missing on many livestock farms. Hence for the CSs other than ES, we assigned permanent grassland for grazing (P4) and temporary grassland for forage for sale (P1).
3. SO coefficient is used based on the NUTS region. For example, the DE case study spans 3 NUTS units hence the range of values in the last column of the DE data above. For each farm, we used the SO coefficients in the NUTS unit where the farm centroid is.

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

To identify what determines the spatial allocation of AES adoption, BESTMAP-PIAM uses an agent-based modelling (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 five selected agri-environmental schemes (cover crops, maintaining grasslands, field margins, conversion to woodland/wetland, conversion to organic farming). 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. It is planned to develop first a stylized ABM, which in a later step will be specified for the five case studies.

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4.1 Entities, state variables and scales

The temporal scale is assumed to be characterised by an annual resolution and a time span of 20 years, starting 2020. To allow for a systematic analysis of spatial influence factors, in a first approach, we create a virtual landscape based on a regular grid. In a second step, we will consider the case study regions explicitly and assume a spatial resolution at field level. The output of the ABM will be the yearly land use pattern related to the actual implementation of the five AES on a field level.

We will incorporate 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). 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 their individual identity (e.g. pro-environmental value and the weighting of the different influence factors), external conditions (e.g. the availability of consultancy) or to specific AES (e.g. willingness to change and years of prior adoption). An overview of the included state variables and sources that we plan to use 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
	Availability of consultancy	Switched on or off to test influence, if switched on available to all farmers or a selected proportion (e.g. based on farm size with large farms having more resources to pay advisors)
	Pro-environmental value (high/low)	Existing reviews on AES adoption, e.g. Lastra-Bravo et al., 2015; Dessart et al., 2019; Brown et al., 2020 Existing discrete choice experiments for different influence factors such as availability of consultancy (Hasler et al., 2019; Espinosa
AES specific**	Willingness to change (high/low)	
	Specific years of adoption of AES*	
Weighting factors	Susceptibility to	

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	previous experience (*w1*), social influence (*w2*), consultancy (*w3*)	et al., 2010), bureaucracy (Ruto & Garrod, 2009), change to established farm practices (Christensen et al., 2011; Latacz-Lohmann & Breustedt, 2019)
	Importance of economic factors (F), environment (E), knowledge (K), bureaucracy (B), change to established farm practice (P) for AES decision: β_i with $i = F, E, K, B, P$	Potentially own discrete choice experiment/survey on CS level (see below)

*Specific years of adoption of AES is an emerging property of the system and not parameterized through discrete choice experiments. The initial state in the first simulation step will be derived from LPIS.
**In BESTMAP that would be five values per farmer for each of the five AES we model, i.e. 5 values for willingness to change, 5 values for years of adoption of each specific AES

Fields are characterised by state variables which may be changing (soil conditions) or constant (size and topography) (see Table 3). Furthermore, we include the spatial distribution of the fields, i.e. their location. In a first approach, we allocate fields to farmers based on spatial proximity (potentially including some randomness to account for more distant fields) and randomly assign field characteristics to individual grid cells. In a second step, the ABM will have 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, soil and terrain characteristics will be incorporated in the model to determine expected yields (cf. step 3 of decision-making framework). For a later model revision, we might also include a tighter coupling to biophysical models and include for each annual time step the actual conditions of biophysical state variables such as yield, water quantity and quality, sediment loss, soil carbon or biodiversity stemming from the biophysical models and weather conditions (e.g. using a random generator based on climate projections). These state variables are needed if they influence farmers' choice of AES such as economic aspects (yield, biocontrol) or farmers' perception of the environmental state of the farm (e.g. biodiversity, water quality, at least for certain types of farmers with high environmental awareness). For BESTMAP, we decided not to include climate change of the simulated time span of 20 years as our empirical observations during farmers interviews (see Deliverable 3.4) did not reveal that this is a main driving factor for farmer behavior.

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	Size	LPIS/IACS

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	Topography	LPIS/IACS
	Location	LPIS/IACS
	Land use	LPIS/IACS
	Intensity (organic/conventional)	LPIS/IACS
	Soil conditions	LPIS/IACS (in later model versions potentially changing over time depending on AES adoption)

The five selected AES differ in several attributes which will in combination with the farmer characteristics determine farmers' decision on adopting a specific AES or not (Table 4). These characteristics include spatial properties, i.e. the minimal field size required to implement a specific AES. Furthermore, they specify temporal properties which determine the duration of an AES contract and reflect whether a scheme involves a more fundamental change and hence has a multi-year perspective. Additional characteristics involve the level of change of management needed compared to the current farm practice and the level of bureaucracy that is required to apply for, implement and monitor the scheme. Change to farm practices and level of bureaucracy are discretized in three classes (low/medium/high) and are framed in a way that "low" is positive, i.e. favors the adoption, and "high" is negative and restricts the adoption. In contrast to the identity driven farmer characteristic "willingness to change", the AES characteristic "change to farm practices" is focusing more on the economic aspects that an AES adoption bears.

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)
	Duration	AES regulations (CS level)
	Change to farm practices (low/medium/high)	Depending on specific AES, specialization and production on individual fields (three dimensional look-up table). Classification to be determined in exchange with farmers/consultancy

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	Level of bureaucracy (low/medium/high)*	To be determined in exchange with farmers/consultancy

* For 'Large' farms (based on Economic Size), we assume Level of bureaucracy to be one lower than other size classes. For AES rated with low level of bureaucracy, the rating remains low in that case.

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. 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 practices	high	included
Farm size	high	included
Soil quality / productivity	high	included
Past experience with AES	high	included
Farmer-landlord relationship	medium	excluded*
(Potential) External influence on AES outcome	medium	excluded*
Inflexibility of AES	medium	excluded**
Automatization / digitalization of AES placement on land	medium	potentially in later model versions***
Duration of AES	medium	potentially in later model versions***
Duration of lease contracts	medium	potentially in later model versions***
Influence of other farmers	low	included#
Lack of knowledge about AES	low	included##
Authorities or subsidy system perceived as corrupt	low	excluded

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*excluded due to missing data availability
**excluded in the sense of the interview analysis (“a decision to adopt AES is perceived as a decision to give up independent decision-making”, c.f. D3.4), however included as part of fit with established farm practices
***to be included in later model versions depending on data availability
#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 considered social influence through information of farmers about AES, potentially it will also be included with respect to diffusion of knowledge, societal reputation or as social capital with influence on pro-environmental value.
##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.

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 five 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 (developed by 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 for our context, some aspects of the CONSUMAT approach such as social influence and uncertainty are given too high weight which does not match to 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 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 1). The different processes to be run in one time step include:

1. **Openness to specific AES:** Decision-making at farm level on whether at all the farmer is open to consider adoption of a specific AES
2. **Subset suitable fields:** Selection at field level which locations are available for AES adoption
3. **Deliberation**: Deliberation on which AES to adopt on which field based on economic utility and transaction costs

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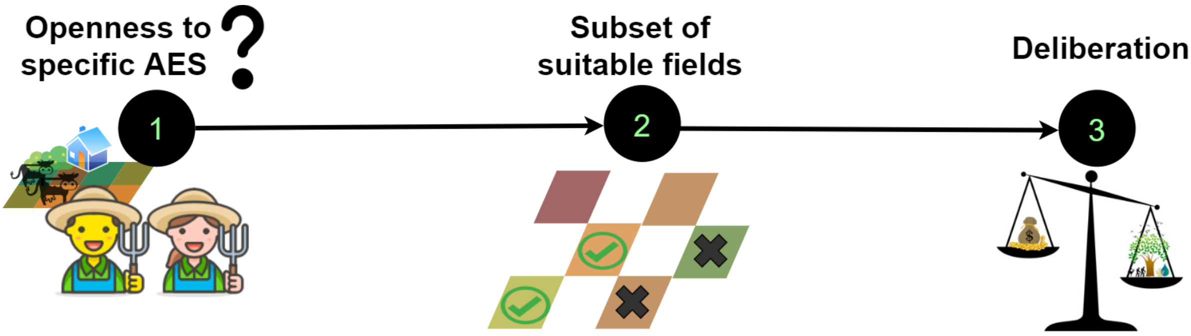

Figure 1: Schematic representation of the three steps of the decision-making process: (1) openness to specific AES, (2) subsetting suitable fields and (3) deliberation.

When the ABM is more closely linked to the biophysical models, previous to these steps, yield and other field characteristics would be updated. 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 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 to apply 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. Therefore, the first decision-making step will depend on the following three variables: Willingness to change, prior knowledge on AES, pro-environmental value.

For all of the three farmer-specific variables we assume a division in two distinct categories (high/low). Whereas pro-environmental value is constant and willingness to change is constant for every AES, prior knowledge is variable and depends on different influence factors. This could, for example, result in prior knowledge as being composed of (1) own prior experience, (2) prior experience of other farmers and (3) influence from consultancy on specific AES. Different implementations including influence from other sources are however also conceivable. The three suggested factors can be additively combined and weighted with weighting factors $w_1 + w_2 + w_3 = 1$that denote the susceptibility of a farmer to the respective influence factors and are given as farmer-specific characteristics. "Own experience" is in a first model version equal to one if the farmer has participated in the specific AES before (considering the whole time span of the simulation) and zero otherwise. In later model refinements, we envision an evaluation of applied AES which would allow us to weight farmers' own experience based on the rate of success of previous participation. As we do not have the respective data available, this could be based on a probabilistic assumption on how successful an AES application was with lower probabilities for AES that are highly dependent on external influences over which the farmer has no control. Unsuccessful AES could, for example, implicitly 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. The experience of others is based on similar assumptions. Here, the rate of participation of a subset of farmers is calculated. This subset can, for example, consist of other farmers in the CS area that are in the same FSA, i.e. farmers with similar farm sizes and specializations, and/or farmers that are in spatial proximity e.g resembling belonging to a village where farmers regularly meet during social activities. This could be implemented, for example, by following the idea of social circles (Hamill and Gilbert, 2009). For influence via consultancy we assume that if consultancy is present (a property assigned to individual farmers, see table x1), this value is one and zero otherwise. In total, the calculation of prior knowledge sums up to a value between zero and one and can be transferred to low/high categories by assuming a threshold at 0.5.

Based on these three dimensions, we derive simple probabilistic relationships that denote the probability for taking specific AES into account. By using a probabilistic approach, we try to reflect that the complex decision-making already in the first step whether or not to be open for an AES at all cannot be mapped to strict yes/no decisions based on only three influence factors. This leaves room for rather unexpected or uncommon behavior that might arise from other influence factors not explicitly included in the three factors, i.e. a farmer with "low" rating in all categories may still with a low probability consider adopting AES. In a later model version and with more empirical knowledge from the existing literature and, if needed, a follow-up online survey in our CS (see below), we might be able to replace this simplistic approach by more precise functional relationships, e.g. using regression models on empirical data. To derive the decision tables, we calculate all eight possible combinations of the three variables (Table 6). In a first approach, we assume that the willingness to change has the highest importance for farmers to decide whether to adopt followed by prior knowledge and pro-environmental value as this resembles our observations from the interviews. The relevance of the influence factors can for a later model version also be derived from further empirical studies (see below). Each farmer is open to consider a specific AES, i.e. proceed to step 2 and 3 of the decision model for that AES, with the probability that emerges from this table. For a first approach, specific values for the range of probabilities can be derived from reviews on farmer decision making that rate the importance of different influences, e.g. Lastra-Bravo et al., 2015 or Brown et al. 2020, or from discrete choice experiments, e.g. Hasler et al. 2019 or Ruto & Garrod, 2009. For more details on specific values of the probabilities see paragraph on

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parameterization below.

Table 6: Probability table to derive chance that a farmer considers taking specific AES into account based on willingness to change, prior knowledge and pro-environmental value.

Willingness to change	Prior knowledge	Pro-environmental value	Probability of considering AES application
high	high	high	High*
high	high	low	
high	low	high	
high	low	low	
low	high	high	
low	high	low	
low	low	high	Low*
low	low	low	

* There will always be some probability a farmer is not open to accept an AES, and a possibility he is open to it. For example, the range can be from 0.9 (for High) to 0.1 (for Low)

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 will be based on results from regression models parameterized from available CS data (on EFA declarations) but due to the mandatory nature of the EFAs, explicit decision-making (as for AES adoption) is not included. To comply with the rules for the minimum field size needed for application of specific AES, farmers furthermore exclude fields that are too small. Farm level schemes such as organic farming are only applied on the whole farm and therefore decisions are taken at farm level (see below).

Based on data availability in the CS, we might additionally also consider the duration of lease contracts (to compare with duration of AES) and specific administrative restrictions that inhibit the application of certain AES on some fields (e.g. DIANAweb in DE) in the selection of suitable fields in later model versions. 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 are not considered in

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this version.

Step 3: In the third step, farmers consider whether it is profitable for them to adopt AES. This calculation is done separately for every suitable field and AES. Below, we describe how this affects farm-level schemes such as organic farming. In their decision-making, farmers include different elements:

- **Financial gains from AES:** Subsidies that farmers receive for AES application.
- **Financial costs of implementation:** Costs that occur in addition to existing farm practices, e.g. when farmers are required to learn new skills or buy new technology to implement AES.
- **Opportunity costs:** Forgone income that farmers could have achieved by following their regular cropping strategy without considering AES.
- **Environmental gains from AES:** Environmental benefit of AES comprise both private and public benefits, e.g. increase in soil quality due to cover crops or perceived contribution to biodiversity through flower strips, respectively.
- **Transaction costs:** For transaction costs, farmers consider two different aspects, namely (1) available knowledge and (2) bureaucracy required to apply for, fulfill and monitor the AES.
- **Fitness with established farm practices:** Farmers compare their regular farming activities with what is required to implement the AES.

The general assumption is that farmers consider a scheme for adoption for which holds:

$$\begin{aligned}&\mathit{financial\ gains\ from\ AES} - \mathit{financial\ costs\ of\ implementation} - \\ &\mathit{opportunity\ costs} \\ &\qquad + \mathit{environmental\ gains\ from\ AES} - \mathit{transaction\ costs} \\ &\qquad - \mathit{fitness\ with\ established\ farm\ practices} > 0\end{aligned}$$

Farmers calculate for each field whether the adoption of AES is profitable and include AES that fulfill the general assumption of positive overall gain (see above) in a list of options. We assume that farmers decide to adopt that scheme on their list with the largest overall gain. In a first approach, we consider farm-level AES such as organic farming to be taken into account when they fulfill the condition on a majority of the fields. Later this might be revised to take into account the specific requirements of such far-reaching changes to established farm practices.

Here, we present a first approach on how to formalize the different influence factors and combine them to calculate the overall gains or losses of AES application at field level. For the moment, we do not present concrete ways of implementation but rather highlight the functional relationships for the main effects that determine the decision-making and their dependence with farmer, field and AES characteristics. More precise relations might be derived from further empirical studies (see below) or through an exchange with agro-economists.

- AES remuneration is designed in a way that on average, farmers are subsidized for incurring costs and forgone income, i.e. the overall financial profit *F* of AES application is zero for a farm with average soil quality, topography and size and conventional farming: Expectation[F] = Ex[financial gains from AES - financial costs of implementation - opportunity costs] = 0. Note that this generally holds at national scale, and not necessarily true within the CS scale. As the soil quality and topography differs between individual fields or farms, and farm size and farming intensity also affects net profit (economy of scale), *F* depends on the deviation of these factors from the average in the respective region, i.e. *F = f(soil quality - Ex[soil quality], topography - Ex[topography], farm size - Ex[farm size], intensity - Ex[intensity])*.
- Environmental gains *E* depend on the specific AES but also on the pro-environmental value of a farmer, i.e. *E = f(pro-environmental value, AES)*. We assume that farmers with a high pro-environmental value assign a higher environmental gain to AES in general which implicitly implies that they also weigh public benefits such as improved biodiversity higher. Furthermore, we assume that some AES are more beneficial for the environment (e.g. organic farming) than others (e.g. cover crops) and therefore more interesting to farmers with high pro-environmental value.
- Available knowledge *K* is part of the transaction costs and comprises costs for getting information It is AES-specific and might be changed by e.g. consultancy i.e. *K = f(AES, consultancy)*. It can be calculated similarly to 'prior knowledge' as in decision step 1 or include further sources of influence, e.g. via the media.
- Bureaucracy *B* is the second part of transaction costs. It is AES-specific (see Table 4) and depends on the farm size, *B = f(AES, farm size)*. As a first approach, we assume that for each AES bureaucracy is assigned to one of three classes (low, medium, high). We assume that larger farms have more capacities to deal with bureaucratic issues. For simplicity, we therefore lower the ranking of the administrative burden of an AES for large farms by one category, e.g. the high effort for applying organic farming is only medium for large farms (for classification of farm size in small, medium, large see above). AES that are rated with "low" bureaucracy would remain "low" for large farms .
- Fitness with established farm practices *P* is based on the farm specialization and the land use on the field, meaning for example whether a field can be used as grassland or for crop cultivation, and is AES specific, i.e. *P = f(AES, specialization, land use)*. As a first approach, we plan to create a three-dimensional look-up table from which the respective classification can be derived (cf. Table 4).

In the decision-making process, each of these elements is combined and weighted with a factor β_i with $i = F, E, K, B, P$reflecting the importance of the different aspects

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that are considered and additionally converting all functional relations to unitless numbers. We assume that the weighting differs between FSAs. Here, we however have not yet a specific functional relationship in mind but rely on further insights from empirical data (see parameterization).

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 is to use an existing open-source Python-based ABM environment. This would allow easy scripting and interchange of data between the two platforms. Our current implementation plan builds on Mesa (https://mesa.readthedocs.io/en/master/index.html), a modular framework for building, analysing and visualizing agent-based models. There is also an extension to Mesa which allows to incorporate GIS data into models called mesa-geo (https://github.com/Corvince/mesa-geo) that will be used in the project. BESTMAP will explore existing open-source Python libraries to perform calibration/validation and sensitivity analysis - for example using SALib (https://github.com/SALib/SALib) package. High Performance Cluster resources to perform the analyses are available in several consortium organizations. If, during the implementation phase, we encounter insurmountable challenges with Mesa, BESTMAP will adopt the more commonly used NetLogo ABM environment (which most ABM modellers, including our own, have experience with). The tight integration with python-based biophysical models can, in that case, be achieved by using 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). As with Mesa, this environment supports the use of python packages to sample and analyze a suitable experimental design for sensitivity analysis and to parallelize the simulations. Additionally, a NetLogo extension is available that provides the ability to load GIS data in NetLogo models

(https://ccl.northwestern.edu/netlogo/docs/gis.html).

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.

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Field characteristics can be derived from spatial datasets on the CS level (Table 3). This includes soil quality, field size, topography, spatial distribution, land use and intensity as well as ownership (included as the farmer characteristic 'set of fields') which leads to information about the set of fields a farmer manages. Furthermore, information on land use and land cover can be used to derive the crop type and intensity that is applied on each field. This information can then be incorporated into the calculation of yield that is needed to derive the opportunity costs of AES application.

The properties of the selected AES are listed in Table 4. Minimal field size and duration can be derived from the design of the AES policies in the different CS. In a first model version, 'change to established farm practices' and 'level of bureaucracy' are based on the assessment of the BESTMAP CS experts. For later model versions, we plan to check this classification with farmer experts or farmer consultants to make sure that our rating captures farmers' assessment of the important influence factors.

The parameters that describe the farmer agents (Table 2) can be divided into three different types: spatial variables, identity-based properties and AES-specific characteristics. Spatial variables include the variables related to the FSA classification (farm size and specialization) and information about managed fields (which are described by further spatial variables on the field level, see above). These variables can be derived from spatial datasets at CS level. For identity-based properties such as pro-environmental value and willingness to change CS-wide dataset do not exist. Similarly, farmers' susceptibility to different influences (w_i) in the first step of the decision-making and their weighting of the importance of factors (β_i) in the last step to decide on AES adoption are not captured by available datasets. Here, we have to rely on empirical data. Existing discrete choice experiments that derive the importance of various factors such as the availability of consultancy (Hasler et al., 2019; Espinosa et al., 2010), bureaucracy (Ruto & Garrod, 2009) or changes to established farm practices (Christensen et al., 2011; Latacz-Lohmann & Breustedt, 2019) on the decision for specific AES can be used as a first source to gain more insights into these variables.

In addition to the parameters that are included in the model, we assume functional relationships between the farmer, field and AES characteristics and farmers' decision-making. First, we use a probability that farmers consider application of specific AES based on their willingness to change, prior knowledge and their pro-environmental value (step 1 of the decision-making framework) and second, we calculate the functional relationships between these characteristics to calculate financial profit, environmental gains, transaction costs and fit to farm practices of specific AES (step 3 of the decision-making framework).

To derive these relationships and the respective weighting factors, we envision to conduct a second online survey campaign which might be either framed as a questionnaire or a discrete choice experiment. A questionnaire would allow to expand

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the quantitative part of the first interview campaign on reasons for AES adoption and could be used to derive relationships between farmer characteristics, a broad range of influence factors and their decision-making, e.g. by using regression analysis. With discrete choice experiments the range of factors that could be tested would be limited, for the selected aspects, however, stronger results than from a normal questionnaire could be obtained. The experiments could be framed in a way that for each AES, farmers chose the option they prefer based on a given set of options with different influence factors. These options would reflect different levels of attributes of the scheme (see decision step 3) and would therefore allow to reveal and measure trade-off between the different choices and the ranking of importance. An additional questionnaire following the discrete choice experiment would provide basic information on farmers' characteristics. This information could be used to derive the distribution of certain farmer characteristics (such as pro-environmental value) across a CS which can be used as a basis for the parameterization of the farmers. Difficulties with regard to the discrete choice experiment could be that we would need to find and incentivize a sufficient number of farmers to obtain reliable results. However, BESTMAP CS experts are confident that by distributing the requests via farmer associations and as the experiment will be conducted online and will not take much time, we would be able to reach enough participants. To provide additional incentives, we are furthermore considering a lottery where farmers can participate after completing the online survey.

4.6 Validation

The BESTMAP ABM aims at developing a model that helps with understanding the policy-farmers-environment system rather than a model that allows predictions (Grimm et al., 2020). Validation is fundamentally important for an ABM. According to Sargent (Sargent 2017), the model validity concerns conceptual model validity, data validity and model operational validity. We will carry out validation work through all stages of the ABM development.

As discussed above, our conceptual model of farmers' decision making process is developed based on well-established decision-making theories, together with insights obtained from the qualitative analysis of our case studies across Europe. In the ABM development phase, we will take advantage of the datasets, e.g. survey data, FADN, GIS data, that are discussed in the previous chapters, statistical and machine learning methods to inform agent design and parameters. Furthermore, parameter sensitivity analysis will be carried out to test the model's robustness.

For the operational validity, we will apply a pattern-oriented modelling (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 multiple observed patterns in the data. BESTMAP will define the patterns the ABM results will be matched against, which could be important observations, measures or statistics in data, such as land use changes and the adoption of AES. A set of scenarios will be designed to test the model operationality against the patterns.

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 therefore 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 latter 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 modelling task (see Step E below) rather than an upscaling of the models developed at the CS level.

Model selection is based on previously selected AES 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. Data availability varies across the CSs, and affects model selection at the CS level, e.g. when lack of data prevents model development in one/several CS. One of the challenges in the modelling 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). Moreover, all input data including geospatial information about AES participation are pooled for multiple years (typically 4-5); and

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information about the physical environment, such as climate and terrain geodata, comes from multi-year averages which do not necessarily meet the exact timeframe for which the IACS/LPIS data have been retrieved. Harmonisation obstacles arise also from inherent differences in the AES in different countries. To overcome this, selected AES are grouped into higher-level measures with similar management purpose (e.g. maintaining low-intensity grassland, land-use conversion, etc.), but such categories are broad and may need to be further differentiated (e.g. land-use conversion measures include conversion from arable land to grassland as well as afforestation of previously open land). Finally, certain EFA schemes (e.g. cover crops, field borders, buffer strips) are very similar in management and purpose to some of the selected AES, and should therefore be included as input data in the biophysical models. This will require an additional step in the modelling framework, as the effects of AES and EFA in the model outputs will need to be disentangled. The simultaneous inclusion of AES and EFA in the models will otherwise entail increased effort and complexity of the Agent Based Models.

BESTMAP aims to model socio-economic impacts of adoption of the five AES, particularly on issues such as farm labour. The conceptualization of these models is still ongoing, but they would likely be regression based models using FADN microdata. As BESTMAP is yet to get FADN data, we postpone further elaboration on those models to the update of this Deliverable.

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

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 a subset of FADN regions across Europe, where we consider at least one of BESTMAP case study models to be adequate for transferring ABM and impact models.*

There are a few approaches that could be used when upscaling from the CSs to the EU region. Three options relate to deriving either model parameters (for an ecosystem service (ES) model such as InVEST) or model results from spatial analysis of the CS land covers and archetype maps. These options are titled Parameter Averaging (PA), Results Averaging (RA), and Results Metamodeling (RM) respectively. As this part of the work is only starting, the Conceptual Framework here proposes all options - we expect to be able to select the best approach in the update Deliverable 2.4 of this framework.

In brief, PA involves tailoring land cover model input parameters to archetype parameters prior to running an ecosystem service (ES) model. The tailored parameters would be based on weightings derived from the land covers each archetype (what BESTMAP will be using as the base map layers (herein known as FSAs)) overlays in space. Alternatively, RA involves ES models to be run using the original land cover maps and original parameters tables, with the results giving a value to each FSA delineated in space. RM is similar to RA, but instead of assigning a value to each FSA, we build a regression (meta-model) for each FSA based on the results maps and variables at the farm-level.

Parameter Averaging (PA)

For an ES model like InVEST, parameter tables are required to link each land type of a map with a set of unique properties (biophysical parameters). Thus, there is a requirement that each land cover has one row in the appropriate input table. Due to specificity of each FSA, appropriate parameter values may be extremely difficult to find or obtain via a literature review. PA can address this issue by deriving the necessary parameters from the underlying land covers (which are much easier to find parameter values for). The methodology of PA would require the original land cover map to be delineated by each spatially-aligned FSA. The land cover area that the specific FSA covers would then be analysed in terms of its composition. For example, if FSA1 covered 5 pixels of LC1 (which had a parameter value of 1) and 15 pixels of LC2 (which had a value of 10), the final weighted parameter value would be 7.75 because:

$$WM(p) = \sum_{i=1}^{n} (xi * wi) / \sum_{i=1}^{n} (wi)$$

where *WM(p)* is the weighted mean of a parameter, *x* is the value of the land cover pixel, and *w* is the weight (number of pixels). Then a final value for all the parameters based on the weighted value of each of the land cover parameters can be obtained.

Once the values for all the parameters for the specific models have been obtained, ES models can be run at the EU-scale with the tailored parameters.

Results Averaging (RA)

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The RA approach differs from PA in that averaging comes subsequent to the ES modelling of the land cover map (as opposed to the FSA map) in a certain case study region. The basis of this RA approach requires ES models to be run with the original case study land cover layer. Once those models have been run, the output will be overlaid with the FSA map. All the pixels (i.e. the total area) of the archetype of interest will then be delineated and a mean of the underlying values will be obtained. This way each archetype is composed of various land covers. Resulting, each archetype would have an average value of the ES services, creating an ES profile.

The basic methodology for RA would involve modelling ESs using the land cover maps and their associated parameters and then defining ES values of FSAs by spatially-aligning and delinetating the ES results by each FSA. The summed values in the delineated ES result layer would then be calculated and divided by the number of pixels to get a mean per pixel ES value for a single FSA. This would make calculation of ES at lower resolutions or larger extents (i.e. those outside the case studies) easy to calculate as each FSA would be assigned an ES value based on the RA results.

Results Meta-modelling (RM)

The RM extends the RA approach, replacing the single mean value assigned to the archetype by a regression model parameterized by (a) the overlaid ES model outputs masked by specific FSA map; (b) set of farm level parameters (which we expect to have available from FADN microdata); (c) other spatial gridded data e.g. precipitation. For each FSA, we will create a regression model, and those will be used later replacing GIS layers with FADN individual farm records data.

RM vs. RA vs PA

Each of the methods described above have benefits and disadvantages. The advantages of PA are that it would allow for (possibly) more spatially-explicit modelling, thereby highlighting regional differences better. The disadvantages of PA are that it would require a new model to be run for each scenario, which is both time-consuming and requires much more computational effort.

The main benefit of RA is that, when modelling a different scenario, only simple calculations are required - i.e. no extra models have to be run. Also, RA uses the results from the case study FSAs and thus may be more representative due to their incorporation. The disadvantage of the RA approach is that, in the current method, incorporation of more spatially-explicit results (e.g. those with extreme topographies) will not be as well represented; however, with post-processing this should be able to be corrected to some degree.

The advantage of RM is that it can, if the regressions explain more of variance than a constant value (which is RA) produce better results which also capture environmental and farm-level controls. A priori, we don’t know which farm-level variables would be

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significant in such a regression, which is a risk. Furthermore, if we use environmental gridded data (which are often also in the ES model, so it is very likely they will be picked up in e.g. backward stepwise regression, we will face a challenge as FADN data is only provided at NUTS3 level. We will likely need to average ("degrade") gridded data to NUTS3 level before trying to generate the regressions. MIND STEP, a sister project to BESTMAP with Thunen and JRC as partners, is working on R package to analyze FADN micro-data, and a streamlined method to probabilistically assign FADN microdata to 1x1km grid cells (HSU units) see e.g. https://susfans.eu/system/files/public_files/Publications/Reports/SUSFANS-Deliverable-D4.6-UBO.pdf . Depending on their progress, BESTMAP may take advantage of those two developments by MIND STEP.

Next steps: deciding which method to use

The decision about which method will be used could be assessed using a decision matrix, with each requirement or criterion given a different level of priority/ influence in the decision-making process (Table 1). It is important to note that the decision of which method to use could be different for the different ecosystem services modelled.

The requirements with the highest priorities (i.e. those labelled 1) would focus on whether trials of the method had proved sensitive to changes in AES, which is the aim of BESTMAP to test and therefore essential, and also whether correlations to any accessible validation data resulted in high scores (e.g. ≥0.9). These two factors are essential when deciding on the most appropriate method, and therefore any method could be invalidated if it did not meet these criteria.

The second level priorities are that there is low uncertainty of the results of the models, how representative the rest of the EU is compared to the case study regions, and whether the method is achievable using computational power and time available. Uncertainty is a fundamental characteristic of modelling, 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. The uncertainty of each model run will be made explicit regardless of where it is considered in the decision matrix priority.

Representative the rest of the EU is compared to the case study regions may be important for some methods more than others. In the PA vs RA situation, RA would possibly perform better if there was a high level of representativeness between CSs and the EU at large. This is because the values used for RA would incorporate values

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from all the CSs, and therefore would require a high representativeness to be able to model ecosystem services at the larger extent to an accurate degree.

The considerations of computational and time resources are important as without these the method may not be possible; however, it would not be the main factor in deciding, hence why it has the lowest priority level in the decision-making process.

Table 7: Decision matrix for deciding which method will be used for different ecosystem services

Requirements and criteria	Priority (1 = highest)
Sensitive to AES changes	1
High correlation with validation data (if available)	1
Low uncertainty	2
Representativeness of case studies to rest of EU	2
Achievable using computational power and time available	2
Lowest time cost	3
Lowest computational cost	3

6.1 ABM Upscaling

ABM upscaling is aimed to develop an approach that allows our ABM to be applied in other regions of EU members of states.

We will first demonstrate the operationality of our ABM by developing a valid model that produces meaningful results for the five different case study areas across Europe (Step C). In this stage, a methodology of setting up and calibrating the model will be developed for using the model in other EU regions, where required data is available or can be derived from other datasets.

In the ABM upscaling stage, we aim to apply the decision-making ABM to another EU region. The major challenge for the upscaling is model validation due to lack of data. As it is discussed in Step C, the ABM parameterisation will use different data sources. Although existing in each Member State, LPIS/IACS data is not harmonized to the same schema/data structure, so using it for each EU region would require attention when applying to different EU regions. It is also very difficult and time consuming to get access to IACS/LPIS because of confidentiality requirements of each responsible organization within the Member States. Instead, BESTMAP-PIAM builds on using FADN microdata - which is still not trivial to get, but there exists a process to request FADN data, it is harmonized and available for all EU regions and across multiple years. However, some information available in IACS/LPIS at field and farm level is not available in FADN records.

To overcome this data challenge, we propose a hybrid modelling approach which integrates statistical modelling into ABM. Existing research suggests using Markov Chain Monte Carlo (MCMC) methods for parameter optimization in ABMs (Kattwinkel & Reichert 2016, Hooten et al. 2020). MCMC is a family of algorithms used for random sampling from high-dimensional probability distributions. Another approach is to perform model uncertainty analysis using statistical emulators (Bijak et al. 2013, Klabunde & Willekens 2016 and Papadelis & Flamos 2018). We will need further investigation to decide the approach once the ABM development for case studies is completed. We will use distributions estimated in the CS level, from IACS/LPIS, and use one of those approaches to incorporate those missing data into the FADN regions level ABM analyses (with error propagation).

In the upscaling stage, we will also carry out a thorough literature review of the farmers' decision-making research on AES and categorize the existing research data and findings based on region/country. These data can be used for the ABM tuning when implementing a scenario of an EU region that is out of BESTMAP case study regions. For example, Pavis et al. reported their case studies of AES participation in Netherlands, Denmark, Austria, Italy and Greece (Pavlis et al. 2016). Lastra-Bravo et al. (Lastra-Bravo, X. B.2015) reviewed ten research studies of farmers' participation in AES in different EU countries.

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).

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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 https://ec.europa.eu/transparency/regexpert/index.cfm?do=groupDetail.groupMeetingDoc&docid=43860.

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. As explained above, different types of models will be used, Agent based models (ABM) or biophysical models. The firsts would produce mainly output indicators while the seconds would produce mainly impact indicators. Table 8 presents a selection of indicators linked to the biophysical modelling that would assess some ecosystem services (ES).

Table 8: Impact indicators linked to the biophysical modelling of BESTMAP

Ecosystem services	**Linked impact indicator**
Water quantity	I.17 Reducing pressure on water resource: Water Exploitation Index Plus (WEI+)
Water quality	I.15 Improving water quality: Gross nutrient balance on agricultural land
Carbon sequestration	I.11 Enhancing carbon sequestration: Increase the soil organic carbon
Biodiversity / habitats	I.18 Increasing farmland bird populations: Farmland Bird Index I.19 Enhanced biodiversity protection: Percentage of species and habitats of Community interest related to agriculture with stable or increasing trends

.

On the other hand additional interesting metrics provided by the EU Sustainable Development Goals or the Water Framework Directive 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.

Code	MPI	Indicator name	Comments	Frequency of data collection	Geographical coverage	Data provider
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
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

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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:

CAP post 2020 indicator	EU SDG indicator
R17. Afforested land: Area supported for afforestation and creation of woodland, including agroforestry R.25 Supporting sustainable forest management: Share of forest land under management commitments to support forest protection and management. R.26 Protecting forest ecosystems: Share of forest land under management commitments for supporting landscape, biodiversity and ecosystem services	15_10 Share of forested area
R.28 Supporting Natura 2000: Area in Natura 2000 sites under commitments for protection, maintenance and restoration	15_20 Surface of terrestrial sites designated under NATURA 2000
I.13 Reducing soil erosion: Percentage of land in moderate	15_50 Estimated soil

and severe soil erosion on agricultural land	erosion by water
I.18 Increasing farmland bird populations: Farmland Bird Index	15_60 Common bird index
1.16 Reducing nutrient leakage: Nitrate in groundwater - Percentage of ground water stations with N concentration over 50 mg/l as per the Nitrate directive	06_40 Nitrate in groundwater
I.27 Sustainable use of pesticides: Reduce risks and impacts of pesticides R.37 Sustainable pesticide use: Share of agricultural land concerned by supported specific actions which lead to a sustainable use of pesticides in order to reduce risks and impacts of pesticides	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 will offer an interactive dashboard where end-users such as stakeholders, scientists or regular citizens, will be able to run (or use pre-computed outputs), analyse and report the results of models that simulate future scenarios. This decision-support tool will allow easy interaction and comparison of policy alternatives by visualizing geospatial distributions of the positive and negative impacts on each case study.

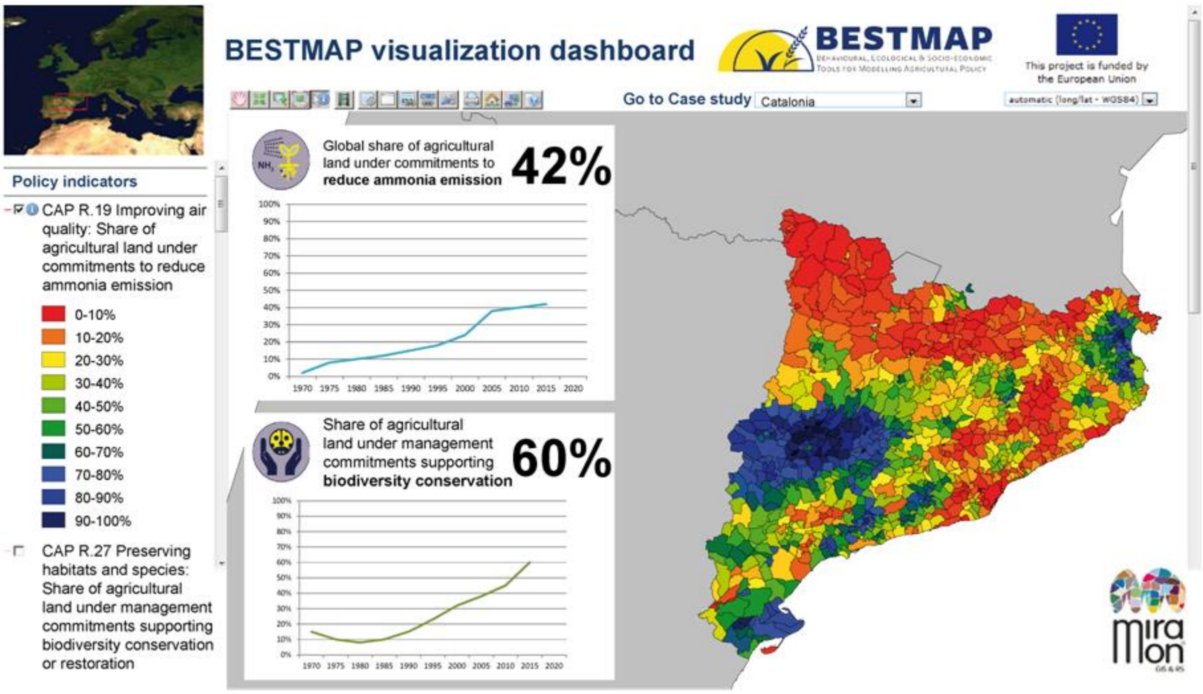

Figure 2. Mock-up of BESTMAP dashboard.

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The dashboard will be co-designed with stakeholders and project members to ensure its usefulness through the organization of at least one virtual / face-to-face meeting among these actors.

At technical level, the dashboard will be 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 will include maps to easily identify spatial distributions of impacts, graphs or tabular data. It will allow on-the-fly computation of several statistics, it will show data quality indicators (e.g uncertainty) and will be provided with user-friendly controls that will allow the selection of different scenarios (e.g. sliders).

The data architecture that includes the project dashboard is composed of 4 components (Figure 2). 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.

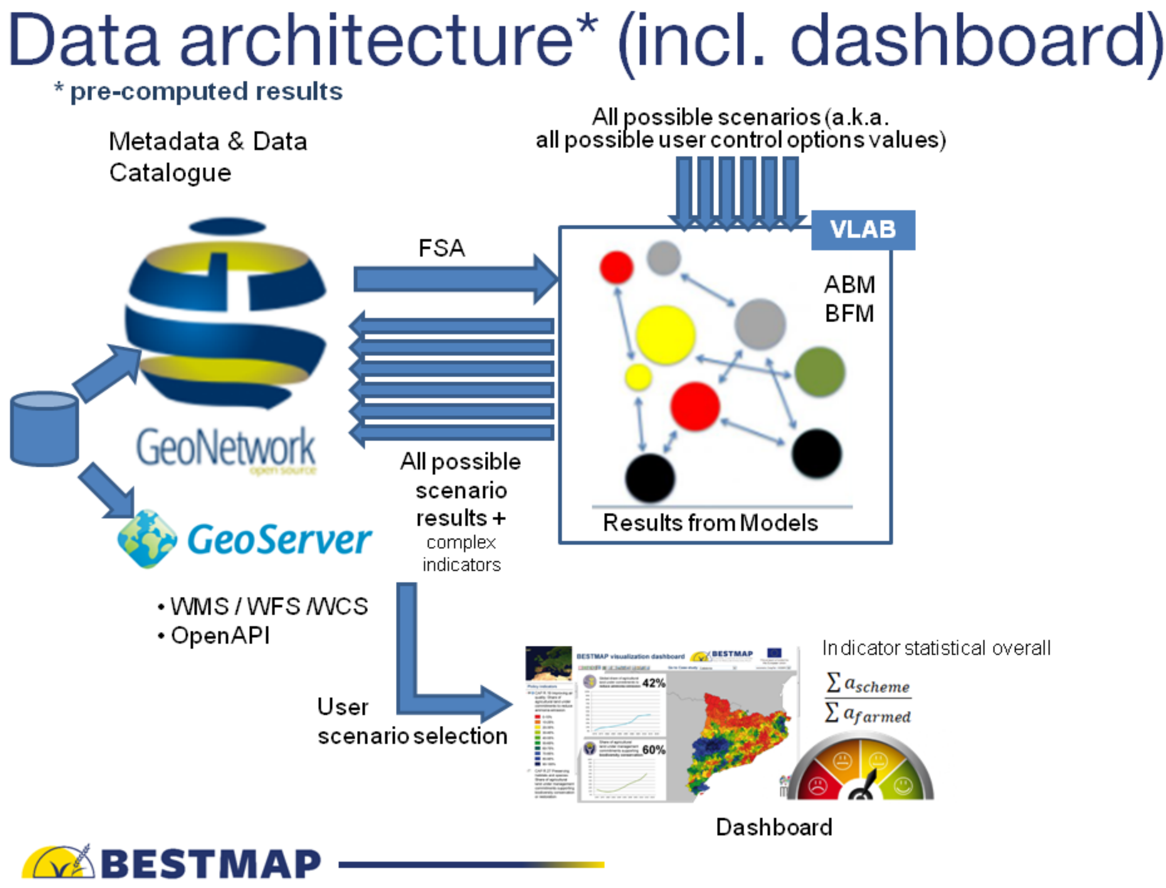

Figure 3. Data architecture including dashboard.

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

References

Bijak, J., Hilton, J., Silverman, E., & Cao, V. D. (2013). From agent-based models to statistical emulators. In Joint Eurostat/UNECE Work Session on Demographic Projections, October, 1–12. http://www.demographic-research.org

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

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

Coelho, L. A. G.; Pires, C. M. P.; Dionísio, A. T. & Serrão, A. J. d. C. The impact of CAP policy in farmer's behavior – A modeling approach using the Cumulative Prospect Theory. Journal of Policy Modeling, 2012, 34, 81-98

Despotović, J.; Rodić, V. & Caracciolo, F. Factors affecting farmers' adoption of integrated pest management in Serbia: An application of the theory of planned behavior. Journal of Cleaner Production, 2019, 228, 1196-1205

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

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

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

Grimm, V.; Johnston, A. S. A.; Thulke, H.-H.; Forbes, V. E. & Thorbek, P. Three questions to ask before using model outputs for decision support. Nature Communications, 2020, 11, 4959

Groeneveld, J.; Müller, B.; Buchmann, C. M.; Dressler, G.; Guo, C.; Hase, N.; Hoffmann, F.; John, F.; Klassert, C.; Lauf, T.; Liebelt, V.; Nolzen, H.; Pannicke, N.; Schulze, J.; Weise, H. & Schwarz, N. Theoretical foundations of human decision-making in agent-based land use models – A review, Environmental Modelling & Software, 2017, 87, 39-48

Hamill, L. & Gilbert, N. Social circles: A simple structure for agent-based social network models. Journal of Artificial Societies and Social Simulation, 2009, 12, 3

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

Hooten, M., Wikle, C., & Schwob, M. (2020). Statistical Implementations of Agent-Based Demographic Models. International Statistical Review, 88(2), 441–461. https://doi.org/10.1111/insr.12399

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

Jager W. Modelling consumer behavior, Doctoral Thesis. University of Groningen, Universal Press, 2000

Jager W., Janssen M. A. An updated conceptual framework for integrated modeling of human decision making: the Consumat II. In: Paper presented at Workshop Complexity in the Real World @ ECCS 2012—from policy intelligence to intelligent policy. Brussels, 5th & 6th September 2012, 2012

Janssen, M. A. & Jager, W. Fashions, habits and changing preferences: Simulation of psychological factors affecting market dynamics. Journal of Economic Psychology, 2001, 22, 745-772

Jaxa-Rozen, M. & Kwakkel, J. H. PyNetLogo: Linking NetLogo with Python. Journal of Artificial Societies and Social Simulation, 2018, 21, 4

Kattwinkel, M., & Reichert, P. (2016). Bayesian parameter inference for individual-based models using a Particle Markov Chain Monte Carlo method. https://doi.org/10.1016/j.envsoft.2016.11.001

Klabunde, A., & Willekens, F. (2016). Decision-Making in Agent-Based Models of Migration: State of the Art and Challenges. European Journal of Population, 32, 73–97. https://doi.org/10.1007/s10680-015-9362-0

Kuemmerle T, Hostert P, St-Louis V, Radeloff VC. Using image texture to map farmland field size: a case study in Eastern Europe. Journal of Land Use Science. 2009 Feb 13;4(1-2):85-107.

Lastra-Bravo XB, Hubbard C, Garrod G, Tolón-Becerra A (2015). What drives land managers' participation in EU agri-environmental schemes? Results from a qualitative meta-analysis. Environmental Science & Policy 54: 1–9. doi: 10.1016/j.envsci.2015.06.002

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

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

Metzger M.J., Bunce R.G.H, Jongman R.H.G, Mücher C.A. & Watkins J.W. (2005). A climatic stratification of the environment of Europe. Global Ecology and Biogeography 14: 549-563.

Papadelis, S., & Flamos, A. (2018). An application of calibration and uncertainty quantification techniques for agent-based models. Understanding Risks and Uncertainties in Energy and Climate Policy: Multidisciplinary Methods and Tools for a Low Carbon Society, 79–95. https://doi.org/10.1007/978-3-030-03152-7_3

Pavlis, E. S., Terkenli, T. S., Kristensen, S. B. P., Busck, A. G., & Cosor, G. L. (2016). Patterns of agri-environmental scheme participation in Europe: Indicative trends from selected case studies. Land Use Policy, 57, 800–812.

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

Sargent, R. G. Verification and validation of simulation models. Journal of Simulation, 2013, 7, 12-24

Václavík, T., Langerwisch, F., Cotter, M., Fick, J., Häuser, I., Hotes, S., Kamp, J., Settele, F., Spangenberg, J., Seppelt, R. (2016) Investigating potential transferability of place-based research in land system science, Environmental Research Letters, 11, 9.

Van der Zanden, Emma H., et al. "Representing composition, spatial structure and management intensity of European agricultural landscapes: a new typology." Landscape and Urban Planning 150 (2016): 36-49.

Van Eupen, M., Metzger, J., Pérez-Soba, M., Verburg, P.H., Van Doorn, A., Bunce, G.H. (2011) A rural typology for strategic European policies. Land Use Policy, 29, 473-482