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D5.2 InVEST Models at the European scale

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InVEST Models at the European scale

Deliverable D5.2

31 Dec 2023

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

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Preface

This Deliverable provides a report on the biodiversity and ecosystem services (ESS) meta-models generated in Work Package 5 (WP5) - Upscaling, detailing how the outputs of biophysical models (BPMs) adapted for sub-country case studies (CS) were upscaled to represent the entirety of the European Union (EU) and some Associated Countries. A general overview of the research goals and guiding principles under which the BPMs were developed is given, followed by a detailed description on the theory and methodology for the meta-models. The Deliverable also discusses the obstacles and challenges encountered during the model adaptation and implementation, and how the meta-model outputs will be used in various other tasks within the project.

The output from this Deliverable is linked to Deliverable 5.1 - 'Analysis of the representativeness of CS in EU context', and both documents should be read in conjunction. The content of this document mostly focuses on the meta-model regression approach that was used, while Deliverable 5.1 presents the results of the meta-models, subsequent analysis, and the transferability process.

Originally, the intention for this Deliverable was to include code designed to execute the InVEST models throughout Europe. However, there were some issues with that approach, which were discovered during the early stages of the BESTMAP project. The main problem was that, in the process of determining how to best use the InVEST suite of models to simulation ESS for the individual case studies (CS), it was discovered that such models could not be used in general due to their inability to discern the subtle variations in land use denoted by the presence of AES. For this reason, other models, as described in D3.3 were used, with the only InVEST model being that for nutrient export. In addition, running models across Europe raises challenges associated with determining model parameter values for different geographic areas.

As the InVEST models were not in general used for modelling the ESS in each CS, this effectively ruled out using the InVEST model suite to upscale the results across the whole of Europe, due to two issues: the different parameter values that would have been required across different parts of Europe, which we had no knowledge of due to those models not being run at finer scales; and the final output of the models which would have shown different ESS results, in terms of the metric used, at the CS and European levels, making interpretation much less straightforward (i.e. different models will likely give different ESS estimates (e.g., Willcock et al., 2019). Therefore, we required another method that would enable Europe-wide modelling of the ESS, with each ESS being modelled using the same methodologies as in the CS. Consequently, the approach to upscaling deviated from the initial plan of creating Europe-wide InVEST models. This Deliverable is thus a written document detailing the methodology employed for upscaling, specifically through meta-modelling techniques. An added advantage of using the meta-modelling method as opposed to using InVEST is that it could be applied to upscale across Europe for any ESS that was modelled in any way (i.e., not only using InVEST) in any CSs across Europe.

Summary

In this Deliverable, the outputs from the BESTMAP biodiversity and ESS models, necessary for this Deliverable, are briefly described. Second, the data used for meta-modelling is listed. Third, the process behind meta-modelling - the main focus of this Deliverable - is described in detail, specifying the logic of the technique, the steps that were taken within the context of this work, and how the models were fitted and tested. Fourth, we present the results of the meta-models in terms of the number of times different predictors were significant, to give an idea of the important predictors. Finally, the challenges that were faced are discussed, as well as the final potential uses for the outputs.

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1. Research goals

Upscaling the CS BPMs was one of the core tasks in WP5 - Upscaling, specifically Task 5.2 European-wide modelling. It is therefore closely linked to activities in WP3 - Farming System Archetypes, which included the creation of the CS-level BPMs. The goal of Task 5.2 was to model the suite of ESS across Europe. Here, Europe includes Turkey, because all countries that have territories in the NUTS classification system were used. Additionally, an aim was to determine whether Agri-environment Schemes have a significant impact on ESS delivery. The results of this work will be visualised via an interactive dashboard (Task 6.4), and will be available to policymakers both in the dashboard and in this Deliverable.

2. Background

This Deliverable details the work undertaken as part of Task 5.2 - 'European-wide modelling'. It builds upon previous BESTMAP work, specifically Deliverable 3.3, and feeds into the work described in Deliverable 5.1. The flowchart of interrelated activities can be seen in Fig. 1, where the middle section outlines the work reported in this Deliverable.

2.1. Case study results

ESS data used in the upscaling process were derived from the earlier stages of the BESTMAP project. Detailed descriptions of the ESS models that were used can be found in Deliverable 3.3, 'Ecosystem service, biodiversity and socio-economic models for each case study'. The ESS modelled were food and fodder production, measured in terms of standard economic output (€); carbon sequestration (t C/ha); and two measures of water quality (also known as 'nutrient export' herein) (kg N/year and kg P/year). Biodiversity was also modelled, and for the purposes of this document will be considered an ESS. Each ESS was modelled in five different case studies across the EU and Associated Countries: the Mulde river basin in Germany, Catalonia in Spain, the Bačka region in Serbia, the Humber in the UK, and South Moravia in Czechia.

Outputs of the CS-level ESS models were aggregated at the farm level, meaning that each farm had an individual ESS result. Due to stringent data-sharing agreements, the data were provided to WP5 in tabular form with no associated spatial information so that specific farms could not be located, i.e. ensuring anonymity of the data. For each ESS, two scenarios were modelled - one with the current level of Agri-environment Practices (AEPs), which were a specific combination of Agri-environment Schemes (AES), Ecological Focus Areas and organic farming (please see Deliverable 3.3 for the AEPs included), and one with an alternative-now scenario of no AEPs. Therefore, each farm had two results for the same ESS. Farm-level data were also collated on the proportion of each AEP on the total farm area; economic size (€) of the farm, measures of uncertainty related to the BPM outputs, the farm size (area, in hectares) and the NUTS3 region the centroid of the farm was within.

Moreover, employing a consistent approach, each CS gathered environmental data for individual farms. Initially, the environmental data was averaged at a sub-NUTS3 level, utilising zonal statistics to coarsen the data compared to the farm-level abstraction. The coarsening approach ensured the protection of anonymity by preventing the identification of individual farms. Each farm was converted to its centroid coordinates, for which the

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associated environmental variables were extracted. This approach ensured that all farms within the same coarsened region shared identical values for all environmental variables. The sub-NUTS3 levels were represented by spatially explicit farm typologies known as Farm Spatial Mapping Units (FSUs), which are clusters of Homogeneous Spatial Mapping Units (Elbersen et al., 2006). The creation of FSUs, as done by Elbersen et al. (2006), involved utilising information from the Farm Accountancy Data Network (FADN), which is a dataset containing financial, physical, and economic information from agricultural holdings across Europe. For details on specific variables, please refer to the Europe-wide predictor data section.

For the upscaling of the biodiversity models, we only considered models for five individual bird species. Due to different ecologies, and sometimes even contrasting habitat preferences, the species were considered separately. Five species were chosen based on their presence in all or most of the CS model regions: Northern lapwing (*Vanellus vanellus*), Eurasian skylark (*Alauda arvensis*), yellowhammer (*Emberiza citrinella*), common linnet (*Carduelis cannabina*), and common whitethroat (*Sylvia communis*). The Northern lapwing was modelled in all five CS datasets, while the other four were modelled in four CS, but not in the Serbian CS due to lack of data. However, for this Deliverable, the Lapwing was not mapped as an ESS in the UK because the biodiversity model evaluation metrics were below the minimum acceptable threshold, meaning that the model outcomes are not trustworthy.

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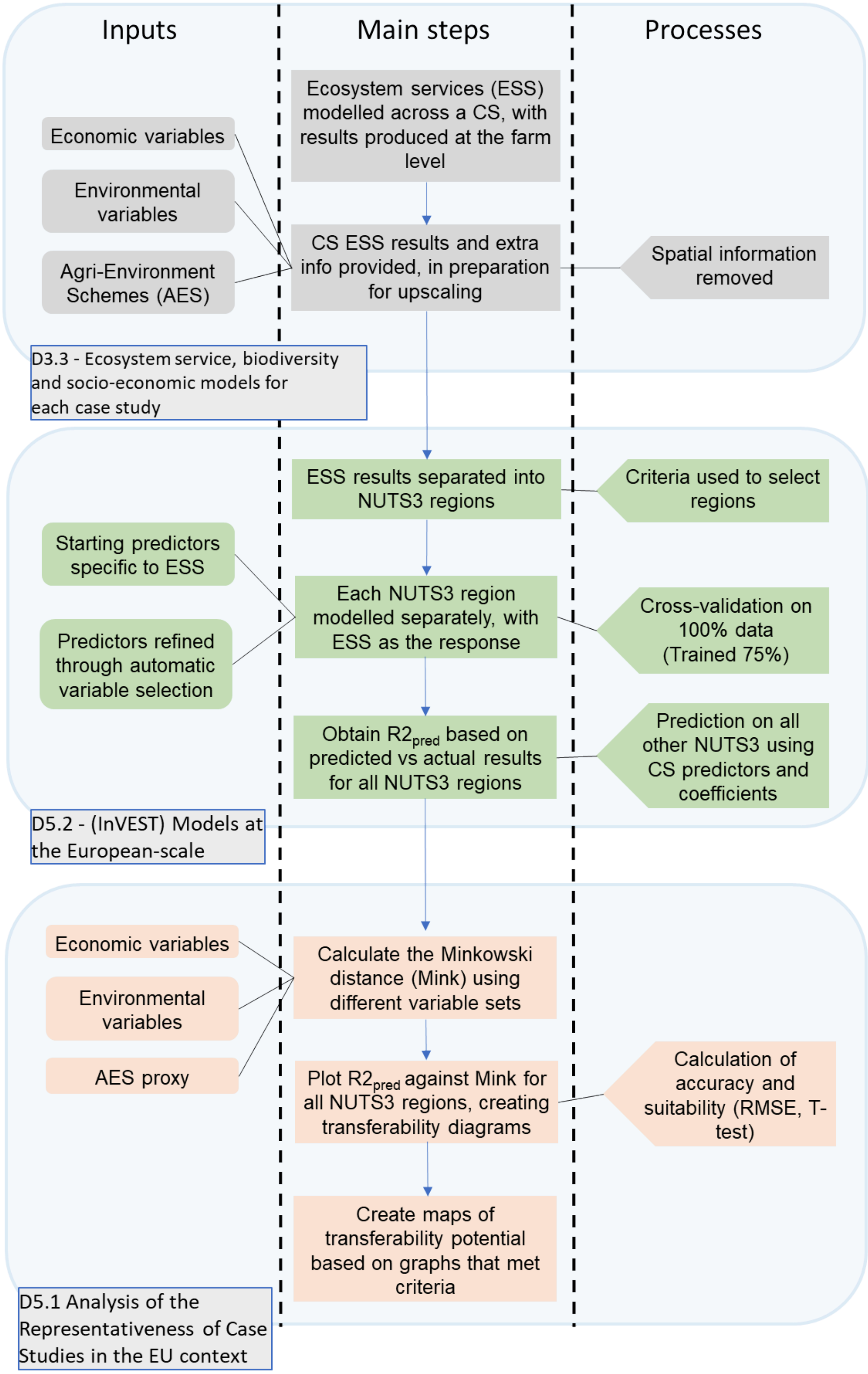

Figure 1: *Flowchart showing where the work described in this Deliverable fits in context to the other work done in BESTMAP and the related Deliverables.*

2.2. Europe-wide predictor data

The data used in the CS ESS models were generally at a fine spatial resolution, with country-level extents. The process of upscaling, however, required the type and source of data to be consistent across all of Europe. Therefore, only data that covered the whole extent of Europe were used in the meta-models. These data had various resolutions and extents (Table 1). The used predictor data were FSU-averaged covariates representing topography, climate, and soil properties.

Table 1: Bioclimatic variables extracted for each farm in the five CS, and used in the upscaling analysis.

Environmental variable	Unit	Spatial resolution	Spatial extent	Temporal extent	Reference
pH	pH (x 10)	250 m^2	Global	2017	Poggio et al. (2021)
Bulk density	g cm^{-3}	1 km^2	EU	2013	Hiederer (2013)
Clay content	g kg^{-1}	250 m^2	Global	2017	Poggio et al. (2021)
Available water capacity	volume fraction	500 m^2	EU	2013	Ballabio et al. (2016)
Topsoil organic carbon	%	1 km^2	EU	2013	Hiederer (2013)
Temperature (min, max)	degrees C	1 km^2	Global	1980 - 2019	Karger et al. (2020)
Precipitation	kg m^{-2} $month^{-1}$	1 km^2	Global	1980 - 2019	Karger et al. (2020)
Solar radiation	W/m^2	0.25°	EU	2015-2019	Karlsson et al. (2020)
Potential evapotranspiration	kg m^{-2} $month^{-1}$	1 km^2	Global	1980 - 2019	Karger et al. (2020)
Land cover	Land cover class	10 m^2	EU	2017	Malinowski et al. (2020)
Small woody features	m^2	100 m^2	EU	2015	Copernicus Land Monitoring Service (2020)
Soil moisture	m^3 m^{-3}	~700 m^2	EU	2015 -	Bauer-Marschallinger

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				2019	and Paulik (2019)
Elevation	m	25 m^2	EU	2011	Copernicus Land Monitoring Service (2016)
Hydrology of soil type (HOST) soil group	Hydrologic soil groups	250 m^2	Global	2018	Ross et al. (2018)
Rooting depth	cm	1 km^2	EU	2013	Hiederer (2013)

Numeric data
Most of the predictors were numeric and thus continuous, with differing temporal extents. For pH, bulk density, clay content, available water capacity, topsoil organic carbon, small woody features, elevation, and rooting depth data were available only for a single year (see Table 1). Data for temperature, precipitation, solar radiation, and potential evapotranspiration were available across multiple years. Daily temperature data were extracted and maximum and minimum values obtained for each three-month season between 2010 - 2019. These values were then averaged, giving a single mean value per season. For precipitation and potential evapotranspiration, values were summed across seasons between 2010 - 2019, and then averaged. Solar radiation was also calculated using the same methodology, but using data between 2015 - 2018.

Categorical data
Land cover and hydrology of soil types were categorical environmental data. These were reduced to fewer categories than in their original form, to reduce the variables input to models (an issue when using categorical rather than continuous data). The final per-FSU values of these data were the percentage cover of each one of the classes, calculated using zonal statistics.

The initial land cover map was the land cover classification based on Sentinel-2 data by Malinowski et al. (2020). These data consisted of 14 land cover types, which we combined to form six classes for the meta-model regression analysis:

- Artificial surfaces and constructions (initial code 62; classified as ‘lcm_62’);
- Vineyards and cultivated areas (73 + 75);
- Tree cover (82 + 83, ‘lcm_tree’)
- Herbaceous / Moors and Heathland / Sclerophyllous vegetation (102 + 103 + 104, ‘lcm_shrub’)
- Marshes / Peatbogs (105 + 106, ‘lcm_bog’)
- Natural material surfaces (121; ‘lcm_121’)

In addition, ‘Permanent snow covered surfaces’ and ‘Water bodies’ (codes 123 and 162, respectively) were removed because they never appeared in any of the farm data received.

The different hydrology of soil types were obtained from Global Hydrologic Soil Groups (Ross et al., 2018). There were eight original soil types, defined by five names: low runoff potential (HSG-A; >90% sand and <10% clay); moderately low runoff potential (HSG-B; 50-90% sand and 10-20% clay), moderately high runoff potential (HSG-C; <50% sand and 20-40% clay), high runoff potential (HSG-D; <50% sand and >40% clay), and high runoff potential unless drained. The final category was split into four sub-groups, based on soil composition: HSG-A/D (>90% sand and <10% clay), HSG-B/D (50-90% sand and 10-20% clay) HSG-C/D (<50% sand and 20-40% clay), and HSG-D/D (<50% sand and >40% clay). The 'high runoff potential unless drained' sub-group categories were condensed, with HSG-A/D, HSG-B/D, HSG-C/D, and HSG-D/D added together to make one category, 'HOST_10plus'.

Meta-modelling

There are different approaches to upscaling. One method is known as meta-modelling, where a complex model is simplified and run using its most important parameters and variables. Meta-modelling methods reduce the requirement for time and computing resources, and thus are useful when upscaling to larger regions. Meta-modelling methodology also means that models can be used in places where data is sparse or missing. In BESTMAP, we only have farm-level data for five CS, meaning that similar data are missing (or not generally accessible to the BESTMAP team or others) from all other countries and regions across Europe. Therefore, meta-modelling can be done to provide knowledge about those countries' ESS. There are two types of meta-modelling: i) a model of a model (e.g. Moorcroft et al., 2001); or ii) a faster statistical emulator. The meta-models described in this paper are a form of the latter approach, i.e. a statistical approximation of the original model (Marie and Simioni, 2014). Technically, this approach (Eq. 1) can be described as

(Eq. 1) $g(x) \cong f(x) \ = \ y$

where, *g(x)* represents a statistical approximation of the output *(y)* from the model defined by *f(x)* = *y,* utilising the identical input *x* (Marie and Simioni, 2014).

This statistical emulation meta-modelling approach originated within engineering, but has begun to be used within ecology (Marie and Simioni, 2014). Previous examples include simplifications of the Agricultural Production Systems sIMulator (APSIM) to determine differences in soil organic carbon (Luo et al., 2013); a calculator that links the CAPRI agro-economic dataset with the DNDC-EUROPE bio-geo-chemical model to determine N leaching (Villa-Vialaneix et al., 2012; Britz and Leip, 2009); and the CENTURY model to determine soil organic carbon changes (Kwon and Hudson, 2010). Using the principles applied in these examples, Marie and Simioni (2014) presented a methodology for conducting meta-model analyses, including their validation.

Marie and Simioni (2014) presented meta-modelling steps for more ecologically-relevant data and objectives based on 'a model of a model', which were adapted to the faster statistical emulator approach for this work. The steps were:

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1. *Defining a general strategy*
2. *Identifying Input/Output relationship*
    a. Reducing the number of inputs can be done based on a sensitivity analysis and/or input aggregation
3. *Creating a dataset*
    a. Construct a dataset obtained from simulations with the original model, following a design of simulation determined by the number of inputs and computing constraints
4. *Fitting the meta-model(s)*
    a. Madu (1990) suggests starting with a basic model and adding more complexity if necessary
5. *Testing the meta-models(s)*
    a. a multi-scale error analysis

3. Model logic, theory, and construction

3.1. Meta-model logic

The main aim of our meta-modelling approach was to determine ESS provision at the farm level across the EU and its Associated Countries within Europe. The rationale for using meta-modelling in the upscaling stage of BESTMAP was to derive simplified relationships, i.e. meta-models, from the CS-level process-based model outputs. This enables estimates of ESS provision outside the modelled CSs without the need for high-resolution CS-level input information, which is not available across Europe as a whole.

3.2. Meta-modelling steps

Defining the meta-modelling strategy

We used a 'fragmented' meta-modelling strategy, by which we treated each CS as providing a different submodel, rather than as a single model across all CS. We further fragmented each CS into sub-CS regions, giving more spatial detail to the results than there would have been if only the five CS regions were modelled individually. The justification for this was to aid in the transferability process (see Deliverable 5.1 for details).

All regions of the EU (and some other European countries, along with Turkey) are divided into sub-country administrative regions, known as 'nomenclature of territorial units for statistics' (NUTS). The smallest categorisation of these is NUTS3, which were initially conceived as small regions for specific diagnoses of policy issues. As the boundaries of the NUTS3 regions and the CS regions intersected, we used the NUTS3 regions as the sub-CS areas in which to undertake the individual meta-modelling.

We developed a set of criteria to select objectively which NUTS3 regions were to be used to sub-divide the CS and which not. First, we removed any non-CS NUTS3 region. Second, NUTS3 regions where the number of farms was <5% of the total amount for that CS were also removed, but only if the cumulatively removed data equated to <10% of the overall number of farms in that CS. Table 2 indicates which NUTS3 regions were removed within each CS. Nineteen NUTS3 regions remained after the selection criteria were applied (Fig. 2).

Table 2: Results of the NUTS3 reduction criteria. The 'Non-CS NUTS3 removed' indicates which NUTS3 regions were removed due to the farm centroids falling within a non-native NUTS3 region. 'NUTS3 removed with < 5% (% of overall farms)' indicates how many NUTS3 regions were removed due to containing <5% of the number of CS farms, and 'Total data removed (%)' indicates what percentage of data (i.e. farms) were removed from a whole CS dataset due to the criteria. 'Final NUTS3 regions' lists all the NUTS3 regions retained for the meta-modelling.

Case Study	Starting NUTS3 regions (farms)	Non-CS NUTS3 removed	NUTS3 removed with < 5% (% of overall farms)	Total data removed (%)	Final NUTS3 regions
UK	6 (3525)	0	2 (2.8%, 4.7%)	7.52%	UKE31 UKE13 UKE12 UKE22 UKF30
DE	11 (3121)	2 (CZ041; 6 farms / CZ042; 25 farms)	4 (0.83%, 1.57%, 2.53%, 4.58%)	9.52%	DE53 DE52 DE45 DE42 DE43
ES	7 (42379)	0	3 (0.002%, 0.04%; 0.23%)	0.27%	ES512 ES511 ES513 ES514
CZ	2 (1103)	0	0	0%	CZ072 CZ064
RS	6 (1316)	1 (HR025; 2 farms)	2 (0.30%, 0.53%)	0.83%	RS125 RS121 RS123

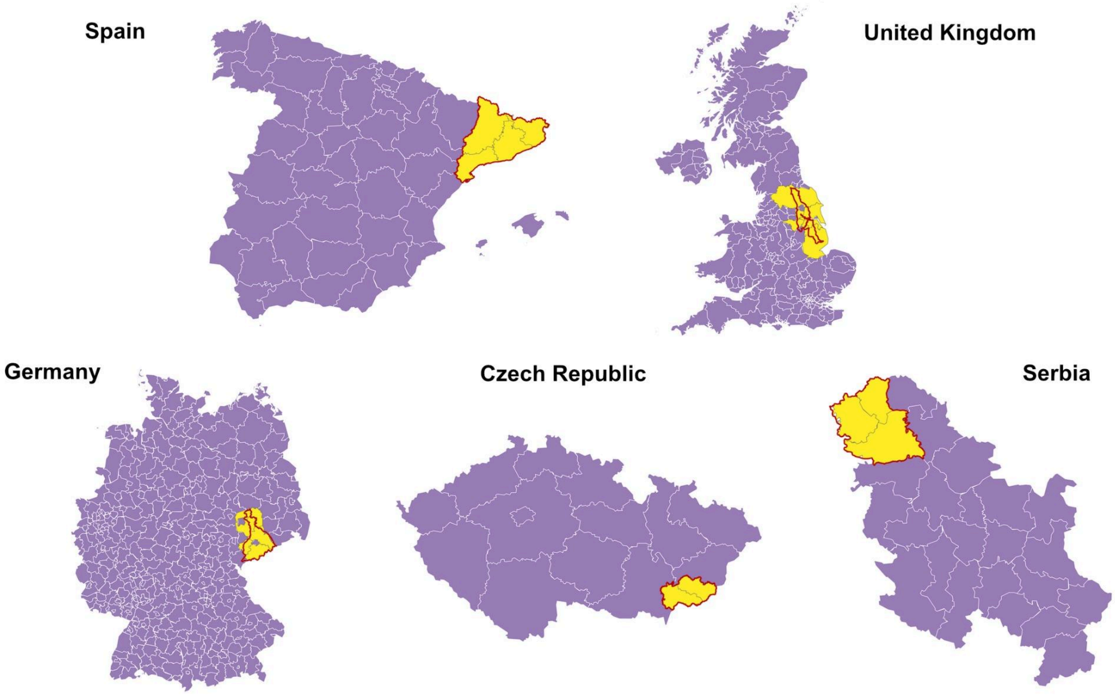

Figure 2: *Overview of the BESTMAP case studies (red outlines) and the overlapping NUTS3 regions retained in the analysis (yellow separated by grey lines; see Table 2) at a scale of 1:4,500,000 (Spain, United Kingdom, Germany) and 1:2,000,000 (Czech Republic and Serbia).*

Identifying relationships

Reducing the number of inputs is important for the meta-modelling process, as simple models are preferred over complex ones to aid interpretability (Marie and Simioni, 2014) and avoid over-fitting. For each NUTS3-level meta-modelling, we achieved this by first using an automated variable selection process, followed by a model selection process.

The initial set of input predictors to be used as independent variables in the meta-modelling were different for each ESS. The predictor set was chosen from a list of candidate predictors (Table 1) based on expert opinion of the BPM modellers. The initial predictors for each ESS are found in Table 3, and included both mean and standard deviation of all numeric predictors.

Table 3: The initial predictors that went into the variable selection process for different ESS. 'Yes' indicates that a variable was initially included, and 'MV (Yes)' indicates that the variable was an original CS model input variable, and was also included in the upscaling variable selection process. Where possible, the exact MV variables used in BPM models were used across Europe, although most had to be derived from similar variables that were available at the continental extent.

Environmental variables	Upscaling ESS model			
	Food	Carbon	Nutrient export	Biodiversity

pH	Yes	MV (Yes)	-	-
Bulk density	Yes	MV (Yes)	-	-
Clay content	Yes	MV (Yes)	Yes	-
Available water capacity	Yes	-	-	-
Topsoil organic carbon	Yes	MV (Yes)	-	-
Temperature	Yes	MV (Yes)	Yes	Yes
Precipitation	Yes	MV (Yes)	MV (Yes)	Yes
Solar radiation	Yes	-	-	Yes
Potential evapotranspiration	Yes	-	Yes	Yes
Land cover	MV (Yes)	MV (Yes)	MV (Yes)	MV (Yes)
Small woody features	-	-	Yes	MV (Yes)
Soil moisture	Yes	Yes	Yes	-
Digital Elevation Model	Yes	-	MV (Yes)	MV (Yes)
Hydrology of soil type (HOST) soil group	Yes	Yes	Yes	-
Rooting depth	Yes	-	-	-

The variable selection process first determined the variance inflation factor (VIF) of all of the numeric variables considered as candidate predictors for the meta-modelling (see Table 3 for the variables). VIF measures the degree of multicollinearity of all independent variables in a regression, which can drastically alter estimates of parameter variance (O'brien, 2007). A predictor with a VIF below 5 suggests a weak correlation with other independent predictors, and therefore suitable for use (James et al., 2013). One or more of the predictors being above 5 lowers the chance of the independent variables showing a statistically significant fit due to increased standard errors in the model.

If the VIF of any predictors were >5, those variables were then plotted against each other and also against the ESS estimate. Of these, the predictor that had the lowest correlation to all other predictors and the highest correlation to the ESS value was kept. This was repeated until one predictor variable was left, which was then removed. The whole process was then repeated until all predictors had VIF <5. This process was undertaken for each ESS, for each different NUTS3 region, regardless of CS.

Creating a dataset

Two different initial datasets were used for the meta-modelling of each ESS. The first was produced using the method described in the previous section. These data contained the ESS result; farm size, which was log-transformed; and the predictors that had lower collinearity. These data only included environmental variables (herein 'Env'), as identified in Table 3. The second dataset consisted of the environmental variables, used also in the first dataset, with additional 'economic' variables (herein 'EnvEco'). These economic predictors were farm specification, economic size, and whether a farm had any AES or not ($AES_{present}$ hereafter). AES are subsidies that farmers receive to cover the costs of applying more sustainable farming practices (Directorate-General for Environment and University of the West of England, 2017). Economic size was included as a numeric predictor that indicated the income of a farm in Euros per year. This predictor was included in the VIF-based variable selection process. Farm specialisation was a categorical predictor which classifies farms into five categories (general cropping [P1], horticulture [P2], permanent crops [P3], grazing livestock and forage [P4], and mixed farming [mixed]; see D3.5 - 'Farming System Archetypes for each CS' for further details on this classification), based on the main crops produced by each farm. Due to the extremely low numbers of farms with 'P2' classification, they were removed prior to analysis, leaving four categories. $AES_{present}$ had two categories, 0 or 1, with the latter indicating a farm had some AES. Farm specialisation and $AES_{present}$ were excluded from the VIF process as they are categorical variables.

The CS BPM models were built using AES data, economic size, and farm specification from local CS sources, but Europe-wide data were required for the upscaling. This Europe-wide data came from a synthetic FADN dataset created by the Thünen Institute, and were not exactly the same measures as used in the CS, but proxies. The initial FADN dataset was tabular, with each row representing a number of similar farms in that FADN region. Each row included a NUTS3 variable indicating the region to which the farm belongs. However, it is important to note that this NUTS3 region is not universally applicable to all the farms represented in a given row. Instead, it serves as a sample for similar farms. Consequently, the BESTMAP team did not have information about the NUTS3 region for each individual farm within the FADN. Thünen created probabilities of most likely NUTS3 designations for farms in FADN regions (ref). Using the probabilities from that methodology and the SYS08 variable, the NUTS3 region of each farm represented in a row was determined. For example, if SYS08 equaled 10, 10 synthetic farms - all of which contained the same values of other FADN variables, but different NUTS3 designations - were created, allowing upscaling using NUTS3 regions. From that data, the proxies used for upscaling were 'Agri-environment and animal welfare payments Value' for AES, and 'SE005' for economic size in Euros. In addition, 'Total Utilised Agricultural Area' was used as a proxy for farm size for both datasets.

Fitting the meta-models

Meta-models were fitted using multiple linear regression, to understand and quantify the relationship between the specific ESS and two or more environmental and/or economic predictors. A logarithmic transformation was applied to the ESS results ('ESS_{log}'), as this resulted in better fitting models. ESS results were treated as the response variable, while all the predictors from the variable selection process were independent variables (Eq. 2).

(Eq. 2) $ESS_{log} = \beta_0+\beta_1 \cdot v_1+\beta_2 \cdot v_2+\ldots+\beta_n \cdot v_n+\epsilon$

where, $v_1, v_2, \ldots, v_n$ are the independent predictor variables; β_0 is the intercept term; $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients corresponding to each independent variable; and ϵ is the error term, representing unobserved factors influencing the dependent variable.

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Following the initial fitting of the meta-model, a stepwise approach was employed to enhance the performance of the model. This iterative method, based on Efroymson (1960), evaluates the statistical significance of individual independent variables within a linear regression model. The sequential replacement method was specifically applied, wherein the most contributive predictors are successively added, eliminating variables that no longer contribute significantly to the model's accuracy. The evaluation of each step involves assessing the lowest Akaike information criterion, as outlined by Burnham and Anderson (2002).

To determine the accuracy of the meta-model in a region, train-test cross-validation was used, with the data partitioned into training (75% of the data) and testing (25%) datasets. Therefore, 75% of the farms were included in creating the meta-models. Once the meta-model had been fit, it was used to predict both the testing dataset (i.e. the remaining 25%), and the full dataset (i.e. 100% of the data). The cross-validation gave a R^2, which helped to identify how well the model fit the data.

Biodiversity was modelled differently to the other ESS, because the results were in the proportional form, signifying how suitable a farm was for each bird species. These proportional data were converted into binary variables, with a species considered 'present' if the proportion was >0.5. Binomial logistic regression with a logit link function was used to model the binary data, meaning the response data were transformed using the natural logarithm of the odds ratio as part of the analysis. Instead of using R^2 to evaluate model fit, a measure which is not directly applicable to logistic regression (Hosmer et al., 2013), we derived the area under the receiver operating characteristic curve (AUC). AUC is a commonly used metric to evaluate the performance of a model, due to its robust ability to discriminate between different classes (e.g. Manel et al, 2001), including in presence-absence models (Fielding and Bell, 1997).

Testing the meta-models

The final meta-model fit was evaluated for a specific NUTS3 by using it to predict the ESS estimates of all of the other NUTS3 regions for which we had ESS values estimated by the CS BPMs. This assesses the spatial error propagation that can occur when fitting meta-models (Marie and Simioni, 2014). For the full details of the method and results, please see Deliverable 5.1.

4. Final model results

Below is a brief summary of all the final meta-models that were produced as output from the work described in this document. To see the full results in context of the rest of the BESTMAP project, especially WP5, please refer to Deliverable 5.1.

4.1. Carbon sequestration, food production, and nutrient export

The carbon sequestration, food production, and nutrient export meta-models were all modelled with the log-converted respective ESS as the response variable. With the exception of carbon, logged farm size was always selected as one of the predictors in the 19

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final meta-models - one for each NUTS3 region - for both the Env and EnvEco models. Whenever farm size was a predictor, it was significant. A model predictor was considered to be significant if its p-value was < 0.05. For the full results, see Tables 4 and 5.

Carbon sequestration

For carbon, farm size was a predictor in 14 of the 19 meta-models. For the carbon Env meta-models specifically, the mean and standard deviation (SD) clay content of the soil, and the soil moisture standard deviation were significant nine times; eight times for natural material surfaces percentage, SD precipitation, mean soil moisture, and mean topsoil organic carbon. For the carbon EnvEco meta-models, the P1, P3, and P4 farm specialisations were significant 17, 16, and 14 times, respectively. The presence of AES was significant in 10 meta-models. Clay content mean and SD were significant in more than 50% of cases, at 10 each, while percentage of HOST 10 plus and pH SD were significant nine times each.

Food production

The food meta-models had far fewer predictors that were consistently significant across the 19 NUTS3 region meta-models than did the carbon meta-models, with the exception of the aforementioned farm size. For the Env meta-models, clay content SD was the only other predictor that was significant in >50% cases, at 11. The predictors of mean clay content, mean topsoil organic carbon, mean pH, and the annual water content (AWC) mean and SD were significant in seven regions (36.84%). For EnvEco, the P1, P3, and P4 farm specialisations, and AES presence were significant 17, 14, 16, and 14 times, respectively. Economic size was significant >50%, for 11 meta-models. Clay mean and SD, AWC mean, and natural material surfaces percentage were significant in six NUTS3 meta-models.

Nutrient export

Nutrient export was recorded by two measures: the export of i) nitrogen (neN) and ii) phosphorus (neP). For the Env meta-models of neN, other than farm size, there was only one predictor significant in more than half of the meta-models, which was natural material surfaces percentage. Clay SD and summer evapotranspiration SD were the next highest, at eight times significant each. For neN EnvEco, AES presence, and P1, P3, and P4 farm specialisations were the most consistently significant across the 19 meta-models, at 15, 14, 13, and 13, respectively. All other predictors were significant in fewer than 10 cases, with natural material surfaces percentage, HSG-B percentage, and soil moisture SD being the highest, at nine, eight, and seven, respectively.

For the Env meta-models of neP, no predictors were consistently significant other than farm size. Soil moisture SD and the mean cover of woody features were significant nine times each, while natural material surfaces percentage cover, clay content SD, and percentage of woodland (lcm_tree) were found to be significant in eight meta-models each. For EnvEco, AES presence, and P1, P3, and P4 farm specialisations were again the most consistently significant across the 19 meta-models, although AES was significant in fewer cases than for neN, at 12 out of 19. Economic size, moisture SD, and HSG-A and HOST 10 plus percentages were significant nine times each.

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Table 4: The number of times each predictor was significant for the ESS (carbon = carbon sequestration; Food = food production; neN = nutrient export of nitrogen; and neP = nutrient export of nitrogen) when using the Env predictors.

	Ecosystem service			
Predictor	Carbon	Food	neN	neP
awc_mea		7		
awc_std		7		
bulkd_mea	3	2		
bulkd_std	6	6		
clay_mea	9	7	6	4
clay_std	9	11	8	8
dem_mea			3	1
dem_std			5	5
evap2010_d.f_mea		1	5	4
evap2010_d.f_std		1		
evap2010_j.a_mea		1	3	3
evap2010_j.a_std		6	8	6
evap2010_m.m_mea		2		
evap2010_m.m_std			1	
evap2010_s.n_mea		1		1
evap2010_s.n_std				
farm_size_log	14	19	19	19
host_1				
host_10plus	7	4	6	7
host_2	5	6	6	6
host_3	5	3	3	6

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host_4	4	2	4	4
lcm_121	8	6	10	8
lcm_62	2			
lcm_arab	2	4	1	3
lcm_bog	6	5	7	6
lcm_shrub	3	6	3	3
lcm_tree	4	3	6	8
maxt2010_d.f_mea				1
maxt2010_j.a_mea	1			1
maxt2010_j.a_std				1
maxt2010_m.m_std		1		
maxt2010_s.n_mea				
maxt2010_s.n_std				1
mint2010_d.f_mea	2			
mint2010_d.f_std				
mint2010_j.a_mea				
mint2010_j.a_std	1			
mint2010_m.m_mea	1			
mint2010_s.n_mea				
mint2010_s.n_std		1		
moisture_mea	8	6	4	2
moisture_std	9	6	7	9
ph_mea	4	7		
ph_std	7	6		
prec2010_d.f_mea	2		1	1
prec2010_d.f_std	2		1	
prec2010_j.a_mea	2	2	2	4

prec2010_j.a_std	8	2	4	3
prec2010_m.m_mea	2			
prec2010_m.m_std				
prec2010_s.n_mea	3	4	4	3
prec2010_s.n_std	3	1	1	
rootdep_mea		4		
rootdep_std		2		
srs_j.a_mea				
srs_j.a_std				
topsoil_mea	8	7		
topsoil_std	6	4		
woodyf_mea			7	9
woodyf_std			4	5

Table 5: The number of times each predictor was significant for the ESS (carbon = carbon sequestration; Food = food production; neN = nutrient export of nitrogen; and neP = nutrient export of nitrogen) when using the EnvEco predictors.

	Ecosystem service			
Predictor	Carbon	Food	neN	neP
aes_present1	10	14	15	12
awc_mea		6		
awc_std		5		
bulkd_mea	3	2		
bulkd_std	6	4		
clay_mea	11	6	4	3
clay_std	10	6	6	7
dem_mea			2	
dem_std			2	1
econ_size	8	11		9

evap2010_d.f_mea			3	1
evap2010_d.f_std				
evap2010_j.a_mea		1	3	4
evap2010_j.a_std		4	6	5
evap2010_m.m_mea		1		
evap2010_m.m_std			1	1
evap2010_s.n_mea		1		1
evap2010_s.n_std				
farm_size_log	14	19	19	19
farm_specp1	17	17	14	15
farm_specp3	15	14	13	14
farm_specp4	16	16	13	14
host_1				9
host_10plus	9	3	7	9
host_2	5	5	8	8
host_3	5	3	2	7
host_4	3	3	3	4
lcm_121	8	6	9	7
lcm_62	2			
lcm_arab	2	4	1	
lcm_bog	7	5	6	6
lcm_shrub	1	5	2	2
lcm_tree	3	4	6	8
maxt2010_d.f_mea				1
maxt2010_j.a_mea	2			1
maxt2010_j.a_std				2
maxt2010_m.m_std				

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maxt2010_s.n_mea				1
maxt2010_s.n_std				
mint2010_d.f_mea				
mint2010_d.f_std				
mint2010_j.a_mea				
mint2010_j.a_std	1			
mint2010_m.m_mea				
mint2010_s.n_mea				
mint2010_s.n_std				
moisture_mea	7	5	6	5
moisture_std	7	5	7	9
ph_mea	4	5		
ph_std	9	4		
prec2010_d.f_mea	2			1
prec2010_d.f_std	2		2	
prec2010_j.a_mea	2	1		2
prec2010_j.a_std	8		3	3
prec2010_m.m_mea	2	2		1
prec2010_m.m_std		1		
prec2010_s.n_mea	3	3	5	2
prec2010_s.n_std	2	3		
rootdep_mea		2		
rootdep_std		3		
srs_j.a_mea				
srs_j.a_std				
topsoil_mea	8	3		
topsoil_std	7	5		

woodyf_mea			6	7

4.2. Biodiversity

The biodiversity meta-models for the different bird species are fewer due the lack of biodiversity data in the three CS of Serbia, meaning most species were modelled for 16 NUTS3 regions. For the full results, see Appendix Tables 6 and 7.

Alauda arvensis

In the Env meta-models for the skylark, farm size was always significant, i.e. 16 out of 16 models. The only other predictors that were significant in >50% meta-models were percentage of tree cover, being significant 10 times, and woody features SD, nine times. Natural material surfaces percentage was significant in eight out of 16 meta-models. For EnvEco meta-models, three farm specialisations were almost consistently significant, with P4 and P1 being significant 15 times, and P3 13 times. Percentage of tree cover was significant in nine out of 16 meta-models, while logged farm size was significant in 50% (eight out of 16).

Carduelis cannabina

In the Env meta-models for the linnet, farm size was the most consistently significant, at 13 out of 16. Small woody features SD, percentage of arable cover, and summer solar radiation SD were significant nine times each, while mean summer solar radiation was significant eight times. For EnvEco, there were no consistently significant predictors. The predictors that were most significant in nine meta-models each were small woody features SD, percentage of arable cover, summer solar radiation SD, and farm specialisations P4 and P1.

Emberiza citrinella

The Env meta-models for the yellowhammer had no predictors that were significant in more than 50% meta-models. In half of the meta-models, natural material surfaces percentage, farm size, percentage of shrub (lcm_shrub) and bog (lcm_bog), and summer evapotranspiration SD. For EnvEco, the farm specialisations P4 and P1 were significant 13 out of 16 times, while small woody features SD and farm specialisation P3 were significant 11 times each. Natural material surfaces percentage was significant in nine meta-models, while mean summer solar radiation, percentage of bog, and summer evapotranspiration SD were significant eight times each.

Sylvia communis

Farm size was the predictor that was significant in most Env meta-models for the whitethroat, in 11 out of 16 meta-models. Mean woody features, summer evapotranspiration SD, and percentage of arable were significant in nine out of 16 meta-models. For EnvEco, the farm specialisations P4 and P1 were significant 12 out of 16 times, while mean small woody features were significant 11 times, and farm specialisation P3 and cover of arable were significant 10 times. Farm size was significant nine out of 16 times.

Vanellus vanellus

Due to the lack of trustworthy CS BPM model results for the lapwing in the UK CS, only 11 meta-models were fitted for this species. Of the 11 meta-models for Env, only two predictors were significant in >50% (six meta-models), which were percentage of arable cover and woody features SD. The percentage cover of woodland and natural material surfaces, and mean summer solar radiation were significant in five meta-models (45%). For EnvEco, P1, P3, and P4 farm specialisations were almost entirely consistently significant, being significant in 10 out of 11 meta-models. Small woody features SD was significant in seven meta-models, while four predictors were significant in six out of 10 meta-models, which were all percentages of different land covers: arable, bog, woodland, and natural material surfaces.

Table 6: The number of times each predictor was significant for the biodiversity ESS when using the Env predictors.

	Ecosystem service				
Predictor	Skylark	Linnet	Yellowhammer	Whitethroat	Lapwing
dem_mea		2	1		1
dem_std	3	3	3	4	
evap2010_d.f_mea	2		1	1	
evap2010_d.f_std	1	1			1
evap2010_j.a_mea	4	4	4	5	1
evap2010_j.a_std	5	7	8	9	
evap2010_m.m_mea					
evap2010_m.m_std				1	
evap2010_s.n_mea	2	2	2	2	3
evap2010_s.n_std		1			1
farm_size_log	16	13	8	11	4
lcm_121	8	7	8	8	5
lcm_62	4	3	6	5	2
lcm_arab	7	9	7	9	6
lcm_bog	5	4	8	6	4
lcm_shrub	7	7	8	5	4

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lcm_tree	10	7	7	8	5
maxt2010_d.f_mea					
maxt2010_j.a_mea					
maxt2010_j.a_std					
maxt2010_m.m_std					
maxt2010_s.n_mea					
maxt2010_s.n_std					
mint2010_d.f_mea		4	2	2	
mint2010_d.f_std				1	2
mint2010_j.a_mea			1		
mint2010_j.a_std			1	1	
mint2010_m.m_mea					
mint2010_s.n_mea	1				
mint2010_s.n_std					
prec2010_d.f_mea	1	3	1	3	2
prec2010_d.f_std	2				
prec2010_j.a_mea	5	1	4	3	4
prec2010_j.a_std	3	5	4	6	
prec2010_m.m_mea	1	2	4	3	2
prec2010_m.m_std	1				
prec2010_s.n_mea	2	1			
prec2010_s.n_std	1		1	1	2
srs_j.a_mea	7	8	7	5	5
srs_j.a_std	7	9	7	8	4
woodyf_mea	6	3	7	9	4
woodyf_std	9	9	6	7	6

Table 7: The number of times each predictor was significant for the biodiversity ESS when using the EnvEco predictors.

	Ecosystem service				
Predictor	Skylark	Linnet	Yellowhammer	Whitethroat	Lapwing
aes_present1	8	8	7	7	5
dem_mea		1	1		1
dem_std		4	3	5	2
econ_size	7	6			4
evap2010_d.f_mea	2		1		
evap2010_d.f_std	1	1	3		1
evap2010_j.a_mea	5	5	5	6	2
evap2010_j.a_std	4	5	8	9	
evap2010_m.m_mea					
evap2010_m.m_std				1	
evap2010_s.n_mea	2	3	2	1	1
evap2010_s.n_std		1			1
farm_size_log	8	7	4	9	5
farm_specp1	15	9	13	12	10
farm_specp3	13	7	11	10	10
farm_specp4	15	9	13	12	10
lcm_121	8	8	9	9	6
lcm_62	4	4	5	3	2
lcm_arab	6	9	7	10	6
lcm_bog	6	4	8	7	6
lcm_shrub	6	7	7	6	5
lcm_tree	9	8	6	7	6
maxt2010_d.f_mea					
maxt2010_j.a_mea					

maxt2010_j.a_std					
maxt2010_m.m_std					
maxt2010_s.n_mea					
maxt2010_s.n_std					
mint2010_d.f_mea		3		2	
mint2010_d.f_std				1	1
mint2010_j.a_mea			1		
mint2010_j.a_std			1	1	
mint2010_m.m_mea					
mint2010_s.n_mea	1				
mint2010_s.n_std					
prec2010_d.f_mea	1	2	1	3	2
prec2010_d.f_std	2				2
prec2010_j.a_mea	5	2	3	2	4
prec2010_j.a_std	4	5	4	6	
prec2010_m.m_mea	1	2	3	1	2
prec2010_m.m_std					
prec2010_s.n_mea	1	2			
prec2010_s.n_std			1	1	2
srs_j.a_mea	6	7	8	6	4
srs_j.a_std	5	9	7	7	3
woodyf_mea	7	3	11	11	3

5. Obstacles and challenges

Integrated Administration and Control System and Farm Accountancy Data Network data

Restrictions relating to the FADN and Integrated Administration and Control System (IACS) data was a challenge for this work. Access to IACS data initially delayed the original CS models, which pushed the analysis for this Deliverable back as well. For the upscaling part of the project, when trying to create synthetic farms from data from the initial FADN data, there were issues with UK and Serbia not being included in the data, limiting the scope of the meta-modelling analysis with the EnvEco predictors. For the UK, this could be overcome by using the coarser resolution NUTS2 values, but Serbia had to be excluded.

Data-sharing and inconsistency of CS-level data

Some of the CS-level data, especially data relating to IACS/LPIS, were subject to data-sharing agreements with local data providers, which meant that they could not be transferred to the upscaling team. Getting access to certain farm-level variables was therefore highly time-consuming, with all modellers for all CSs having to run code, sometimes several times, which otherwise could have been run a single time. Due to the differences in the data structures of all the CS, the script had to be amended by the upscaling team without sight of the original data, making the task much more challenging.

Differences in the CS

There were differences in the quantity of farms, i.e. data points, within each CS, which affected the meta-modelling analysis. This was most prominent in the Catalonian CS, which had >42,000 farms, while the other four CS had <4000 farms. Also, a majority of crops grown in Catalonia (e.g. fruits, olives) do not match those grown in the other CS, and could not be modelled as part of the WOFOST model (the model used to model the food production). This has ramifications when trying to upscale, because not all crops are found in every location, which affects the standard economic output, i.e. the measure of food production used, differently.

Lack of appropriate datasets

No fieldwork was planned as part of BESTMAP, meaning no new data was collected and existing datasets had to be sought. While the search for high-quality, Europe-wide data yielded some good data with many advantages, it also came with limitations. Due to the scale of data needed, and the general paucity of validated datasets that cover Europe's extent, other predictors that may have had significant effects in our meta-models were not available. This is especially true when considering other socio-economic factors that might have been included, such as high-resolution crop yield data.

6. Outlook

The output from this Deliverable, combined with that of Deliverable 5.1, and the outputs from the work packages WP3 and WP4, are important results for the BESTMAP project that will hopefully be used to inform the ESS results across the EU and Associated Countries, and ultimately help to shape aspects of the next generation of the EU's Common Agricultural Policy. The output included in D5.1. will also be added to the BESTMAP dashboard, making the results easily accessible to interested parties.

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