MODELLING INDIVIDUAL DECISIONS TO SUPPORT THE EUROPEAN POLICIES RELATED TO AGRICULTURE

Deliverable D 2.6: Literature review of methods for linking economic and bio-physical databases

AUTHORS	Jörg Rieger (THUENEN), Alexander Gocht (THUENEN), Adrian Leip (JRC)
APPROVED BY WP MANAGER:	Gocht, Alexander
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GLOSSARY

ALTZ	Altitude Zones
CAP	Common Agricultural Policy
CO	Constraint optimization approach
CO	Constraint Optimization Approach
CLC	Corine Land Cover
EU	European Union
FAOSTSAT	FAO Statistics
FADN	Farm Accountancy Data Network
FMU	Farm Mapping Units
FSS	Farm Structure Survey
AROPAj	French optimisation model
HSMU	Homogenous Mapping Units
IACS	Integrated Administration and Control System
LUCAS	Land Use and Coverage Area frame Survey’
LFA	Less Favoured Areas
MLN	Multinomial logit model
N2O	Nitrous Oxide
NUTS	Nomenclature of Territorial Units
MINDSTEP	Project acronym

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EXECUTIVE SUMMARY

This report summarizes the literature in the field of linking economic and bio-physical data. Recent CAP reforms have introduced farm-specific measures whose uptake and economic effects differ significantly between individual farms. Consequently, there is an increasing demand for micro level assessment. While for some indicators the farm location is not an issue for others accurate information of bio-physical endowments of the farm is necessary, e.g., soil erosion, landscape diversity, biodiversity or GHG emissions. However, a general limitation is that although often collected, spatial location of the farms in underlying databases are not available due to confidentiality regulations. This is also the case for the predominant data base FADN used in MINDSTEP to develop single farm models and modules. To overcome this shortcoming researchers have developed in the past different strategies to adjust their models to address spatially relevant topics. This report provides a review of existing approaches. Particular of interest for MINDSTEP are approaches at the EU scale but also approaches with a more regional focus have been reviewed. For EU wide approaches, the locations of farms are estimated as a probability estimate in a spatial unit with homogenous conditions. Land use shares and expected yields from the FADN database were assigned to spatial unit by a statistical procedure combining observations on land use and herd sizes with available aggregated information on land use, animal herd sizes or number of farms of a particular specialization in a region. Such approaches at EU scale are computationally demanding but necessary to more realistically model farmers behaviour and to better assess economic and environmental impacts of EU policies.

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1. INTRODUCTION

The Common Agricultural Policy (CAP) has increasingly been adapted to integrate environmental concerns and one of the core objectives of the CAP is to ensure a sustainable way of farming and the provision of environmentally beneficial public goods and services. One important lesson from previous CAP evaluations is that some policy effects are difficult to assess at national or even regional levels. Moreover, recent CAP reforms have introduced a set of farm-specific measures whose uptake and economic effects differ significantly between individual farms. Consequently, there is an increasing demand for micro level assessment to fully understand farmer responses to CAP instruments and market signals and to better grasp the net effect of policy measures.

To assess such effects, individual farm models have been developed which require detailed input data. For the EU the Farm Structure Survey (FSS) collects information on the whole population of farms each 2nd or 3rd year and publishes results for administrative regions. The Farm Accountancy Data Network (FADN) contains currently around 80,000 farms, representing a population of about 5,000.000 farms in the EU and about 90% of the total agricultural production. Most farm level models for the EU represent the farm population using a sample of individual farms recorded in FADN to enhance the capability in providing scientific support for CAP impact analyses at farm micro level (Offerman et al., 2005; Kellermann et al., 2008; OECD, 2010; De Cara and Jayet, 2011; Gocht and Britz, 2011; Gocht et al., 2013; Louhichi et al., 2015; Louhichi et al., 2018; Ciaian et al., 2020).

Besides capturing economic impacts, those models also aim to contribute to assessing the environmental impacts of the CAP. Therefore, a set of agri-environmental indicators have been developed to enable the environmental assessment of policy measures. While for some agri-environmental indicators the location is not an issue (e.g. energy use), for some others, accurate information of bio-physical endowments of the farm is necessary (e.g. soil erosion, landscape diversity, or biodiversity or GHG emissions). For some indicators, such as N2O emissions from cultivated soils, a strong dependence on environmental conditions such as soil type exist. However robust data bases to develop emission factors by soil types are not yet available. Process-based models introduce further data demand and uncertainties, so that generally simple methods are preferred (Leip et al., 2011a,b). A general limitation for agricultural models is the non-availability of spatially explicit farm data, particularly for models that simulate spatially dependent ecological-economic relationships or try to capture decision-making of actors in a spatial context (Uthes and Kiesel, 2020). Although in the monitoring activities of the EU member states spatially explicit farm data are collected, they are not publicly available due to confidentiality regulations (Schmit et al., 2006).

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2. LITERATURE REVIEW

Without such data, researchers have developed different strategies to adjust their models to address spatially relevant topics. This problem can be addressed by combining economic and bio-physical modelling as bio-physical models use spatial information (such as climate, soil or slope …) usually available at higher spatial resolution (e.g. grids at different level of resolution – from few meters for the elevation to several kilometres for the climate). A spatial allocation of farms would make it possible to extend the analytical capabilities to agri-environmental evaluation, replacing some proxy indicators with more direct calculation and improving the aggregation of the results to more representative environmental zones.

In the literature for non-EU countries several approaches were developed to link both the farm unit with the spatial location. Kruska et al. (2003) describe a methodology for mapping livestock-oriented agricultural production systems for the developing world. Since statistical data on livestock production are often completely missing, the location was assigned based on expert rules and allocated using spatially explicit climate, soil and socio-economic criteria. Neumann et al. (2008) proposes a modelling approach spatially distributing regional livestock data using an expert-based approach defining allocation rules, and compared the results with an empirical approach. Van der Steeg et al. (2010) presented a methodology to derive a spatially explicit distribution of farming systems in the Kenyan Highlands. Their approach starts with the definition of farming systems based on a sample of about 3.000 farms. The advantage of this approach was that the exact location of each holding was known. A regression model was estimated to predict the probability to observe a farming system based on relevant environmental and socio-economic drivers. The estimated model was used to predict the farming systems for the out of sample area.
For EU related studies authors have developed different techniques for downscaling economic model results to lower spatial scales for larger regions such as the entire EU and smaller regions such as specific NUTS 3 regions.

Kempen et al. (2011) developed a method to link the farms in the FADN sample to their environmental endowment (climate, soil attributes …) at the EU-wide scale using a constraint optimization approach (CO). The locations of farms from the FADN are estimated using small-scale spatial units with homogenous conditions for farming also known as Farm Mapping units (FMU). The spatial unit was defined as an aggregation of the so-called Homogenous Mapping Units (HSMU) defined as areas within an administrative unit with homogeneous location factors (Leip et al., 2008). The dataset of HSMU was developed in the CAPRI-DynaSpat project. Within this project Homogeneous Spatial Mapping Units (HSMUs) were defined using a Geographical Information System (Kempen et al., 2007 and Leip et al., 2008). Land use shares and expected yields were assigned to each HSMU by a statistical procedure combining grid observations on land use with available aggregate information at regional level. Information on less favoured areas (LFA) and altitude zones (ALTZ) can be added by overlaying HSMU

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boundaries with specific thematic maps. Kempen et al. (2011) aggregated the relevant attributes of the HSMUs to approximately 15,000 FMUs for the EU-15. The estimation allocates farms with the same ALTZ and LFA status. They estimated a matrix, indicating the percentage of a farm located in a FMU. As a single farm in the FADN sample represents many similar farms, this percentage can also be understood as the share of these farms being allocated to a specific FMU. The farm production mix and yields in FADN should match with the highest possible consistency with those of the spatial units using an optimisation approach by maximizing the probability. For the estimation of the probability, whether or not a farm is located in a certain FMU, Kempen et al. (2011) applied a constrained optimization model. This approach first measures the statistical fit between similar variables (e.g. yields for wheat (py0), share of wheat (ps0)) in FADN and the corresponding land mapping unit. The second step ensures consistency by maximising the similarity over all farms and the spatial unit. For this purpose, a Bayesian highest posterior density concept (see Heckelei et al., 2008) is applied allowing to measure “similarity” with respect to several criteria simultaneously satisfying regional consistency constraints. The resulting spatial allocation of FADN holdings including spatially dependent environmental indicators, extend the analytical capabilities to agri-environmental evaluation and improves the aggregation of the results to more representative environmental zones (e.g. Nitrate Vulnerable Zones, Areas with Natural Constraints).The authors of the study concluded that the used prior information was insufficient to allocate certain farm types and proposed to further develop the spatial unit such that it represents homogenous regions of farming systems, instead of single production systems. Results showed that the suitability of prior information seems to depend on the characteristics of the farm as the prior information on land use shares improves the allocation results for arable and dairy systems, which have a strong land dependence and land use share. However, for farming systems with low or no link to land-use (e.g. pigs, poultry) or farm types with low UAA per farm (horticulture, permanent crops), results were quite weak.

The approach by Kempen et al. (2011) has been used by other studies at EU-scale. Andersen (2017) investigates the scope of perceiving the agricultural landscapes of the European Union as patterns of different farming systems and landscape elements in homogeneous biophysical and administrative endowments. The link of the spatial framework and the typology of farming systems is based on the constrained optimisation approach, matching farm attributes and spatial characteristics subject to consistency constraints. In this study farming systems are a group of farms with the same size, intensity and land use class within an area with homogenous administrative, climatic and soil conditions for farming which can is used to map the farming component of the European agricultural landscapes, to describe the pattern of farming systems in each landscape and to calculate indicators of the spatial organisation of the farming systems.

The mentioned shortcomings in Kempen et al. (2011) have been addressed in several projects for the European Commission conducted by the JRC, Eurocare and Thuenen-Institute to

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further improve the allocation mechanism. Major improvements to the study of Kempen et al. (2011) include the usage of the statistical representation factor attached to each FADN farm to allocate them to the spatial units instead of allocation of a particular FADN farm exclusively to the one spatial unit. Instead of HSMU a new initial spatial unit HSU (Homogeneous Spatial Unit) is used to define farm mapping untis (FMU). HSUs have a finer-scale spatial clustering driven by the search for homogeneity with regard to selected environmental factors (see Lamboni (2016) for further details). In addition, data from Eurostat containing information about the share of UAA (utilised agricultural area) per farm type on a $10km^2$ grid level is integrated as an additional constraint and used as prior information in the CO model. The estimation results for the whole EU were compared with data from FSS to validate the modified allocation procedure. Results showed that the additional prior information on farm types greatly improved the allocation for farm types particularly for “land-independent” farm types with low UAA per farm throughout whole Europe.

Also using the data calculated with the method from Leip et al. (2008) as a basis, Hutchings et al. (2012) developed an approach to extend the data to field operation timelines. Briefly, the crop shares per HSMU were processed by a ‘crop rotation generator’ estimating plausible crop sequences. Livestock density time series were generated using FAOSTSAT trends. Using climate data weather data and crop phenology data from the MARS meteorological database[1], a timeline model calculated for each spatial unit tillage, sowing, fertilizer application, grazing and cutting, and harvesting dates. This information was then used by process-based biophysical models running at (sub) daily time steps.

For the EU-15 based on FADN data from 2002, Cantelaube et al. (2012) use geographical downscaling to map outputs provided by an economic optimization model AROPAj (Galko and Layet, 2011; Jayet 2020) by estimating FADN farm-group probabilities within EU-regions. The definition of farm groups is based on altitude level, farm type and economic size unit. To downscale results from AROPAj a two-step procedure is used. The FADN regions are divided into 100 x 100 m grid cells. In the first step remote sensing data for land from Corine Land Cover (CLC) is combined with land use survey data from the ‘Land Use and Coverage Area frame Survey’ LUCAS carried out by Eurostat[2], weather data from the European MARS meteorological database[3] and soil characteristics from the European Soil Database[4]. Then a multinomial logit model (MLN) is estimated separately for every FADN region relating the land cover/type of crops with the other physical data, consisting of the CLC classes (altitude, slope,

[1] https://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx

[2] https://ec.europa.eu/eurostat/web/lucas

[3] https://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx

[4] https://esdac.jrc.ec.europa.eu/content/european-soil-database-v20-vector-and-attribute-data

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climatic parameters and soil characteristic parameters) resulting in prior estimates of crop location. In this step information provided by the FADN database such as the regional proportion of land cover related to the various crops is not considered. The second step consists of estimating the likely location of regional farm-groups through prior estimates for crop location in the preceding stage by minimising the difference between the estimated land use share, derived from probabilities by the MLN model and the observed land use share which is derived from the FADN data. For this, a cross-entropy approach is used so that probabilities of presence of different crops are attributed to each grid cell (see Chakir (2009) for further details). The mapping of the farm groups and hence the linkage between farm-groups and geo-referenced indicators of activities is based on the area devoted to the different agricultural activities (crop categories) for each farm group. In other words, the probability of a farm group to be located in a specific grid cell refers to the relative contribution of a farm-group (within a region) to the share of agricultural activities present into one specific cell belonging to the regional territory (with convenient altitude restriction). In contrast to Kempen et al.(2011) focusing on agricultural activities mapping from homogeneous soil mapping units (HSMU) influenced by economic agents, the approach of Cantelaube et al. (2012) focuses on the mapping of economic agents representative of agricultural activities observed at a certain period. However, the approach of Cantelaube et al. (2012) in comparison to Kempen et al. (2011) does not provide information about the quality of results for “land-independent” farm types with low UAA per farm and the approach has not been evaluated with regard to the actual distribution of farm types using the FSS data base.

In the literature many case specific studies not aiming at developing general spatial allocation methods for farms in the EU exist. Temme and Verburg (2011) proposed a disaggregation approach for assessing changes in agricultural land use intensity for changes in the CAP between 2000 and 2025. In this study the LUCAS data on nitrogen inputs are related from outputs of the CAPRI model as a first step. Afterwards nitrogen inputs are spatially disaggregated using 49 environmental co-variates at 1 km × 1 km. In a study of Guiomar et al. (2018) a map of Europe has been developed showing regions where small farms have different degrees of importance, in relation to the regional context of agriculture and the territorial characteristics on a NUTS-3 level. In contrast to previous studies estimating the distribution of different farm types in Europe (e.g. Kempen et al., 2011; Andersen, 2017) this study aims at better considering the particular context of each region for small farms in the EU.

The discussed studies how that different options are available for relating spatial and economic scales. Uthes and Kiesel (2020) state that the usefulness of different approaches depends on the focus and the geographical scale of analysis. They argue that from an EU perspective, it is tolerable to create homogenous entities and to assume that a region is managed by one representative FADN farm type (e.g. Kempen et al., 2011; Andersen, 2017).

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However, for lower scale spatial analyses the differences within these entities, differences in the behaviour of farm types as well as the interactions between farms become increasingly relevant. Particularly for smaller regions, studies use a synthetic landscape approach (Saura and Martinez-Millan, 2000; Li et al., 2004; Kellermann et al., 2008). Farms are placed on a grid of the area under study by ensuring that the localization of the farms fulfils the area claims of the farms e.g. using the share of land of a particular type in the total area of farms or farm types (Happe et al., 2006). The synthetic landscape approach was used in the literature for estimating the relationship between on-farm compliance costs and environmental effects of grassland extensification for a regional farm population in Germany (Uthes et al., 2010), or to assess the impacts of changes in the direct payment regime of the EU's agricultural policy on the land market activities of farm populations in different EU regions (Happe et al., 2008; Uthes et al., 2011).

In the literature current synthetic landscape approaches use a relatively coarse resolution (1ha x 1ha) and simple techniques by considering only the grassland share in the total area of farms or farm types (e.g. Uthes et al., 2010, Uthes et al., 2011).

In a recent study of Uthes and Kiesel (2020) the authors aim at improving the synthetic landscape approach in terms of resolution (25m x 25m), by considering landscape parameters in the allocation of farms as well as allocation quality indicators that allow for an assessment of the overall allocation result. The main data source is the Integrated Administration and Control System (IACS) by the State Office for Consumer Protection, Agriculture and Land Re-Planning in Brandenburg. This dataset includes an identification system for all farms in an administrative area, covering information on the type of farming, type of business, aggregated spatial information (such as total area, arable area, grassland area, individual crop areas etc.). In addition, it contains the Land Parcel Identification System (LPIS) covering all agricultural land parcels managed by these farms. For the spatial allocation procedure various variables are used such as the total arable area, total grassland area, average arable land quality (measured by the German Ackerzahl) and grassland quality (measured by the German Grünlandzahl), number of hectares located in protected areas for meadow birds and Natura 2000, and the Landbaugebiet to which a farm belongs which is a larger area with similar conditions for farming e.g. soil for agricultural use is suitable for wheat and sugar beets. Based on the actual spatial distribution of the IACS farm parameters it is assumed that a farm can only be located within a certain circle, in which the real landscape parameters are highly consistent with those reported in the IACS farm data set. Each pixel of the arable and grassland is assumed to be a potential centre point for each farm. As a first step in the allocation procedure all spatial data were converted to raster format (25 x 25 m), separately for arable and grassland and 30 radii were predefined representing the frequency distribution (quantiles) of farm sizes in the study area. For each pixel of arable land and grassland, and each of the predefined radii, the area shares of the landscape parameters from the IACS farm data set in the resulting circles were calculated. In the second step quality indicators are

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calculated which express the degree of equivalence between aggregated spatial farm characteristics reported in the IACS farm data set with the landscape parameters assigned to the farms through their spatial allocation. In this step the optimal arable land and grassland radii for each pixel and farm is identified by choosing the radii with the highest equivalence between area of arable and grassland observed in the circles with data reported in the IACS. Following this principle additional quality indicators are calculated by comparing allocated landscape parameters with those reported in the IACS farm data set. As a last step the weighted allocation quality for each pixel and farm is calculated by summation of the individual quality indicators multiplied by their assigned weights which sum up to one. Based on the pre-calculated weighted allocation quality the spatial allocation of the farms to the land is an iterative process. The allocations are carried out with decreasing potential weighted allocation quality. For each farm, the potential centre points are grouped according to their weighted allocation quality and sorted in descending order which reduces the available area for subsequent farms. The overall allocation quality was relatively high for the considered German case study region Ostprignitz-Ruppin (NUT3 level).The authors conclude that this approach is well suited for smaller regions with sufficient data quality and suitable to link farm data and spatial data to generate a more realistic synthetic landscape of farm locations for use by agro-economic models, such as mathematical optimization models and/or agent-based models, compared to other studies that used simpler spatial allocation procedures. However the computational time of this approach is high and it has not been tested yet in other regions.

3. CONCLUSION

In MIND STEP the method of Kempen et al. 2011 will be used as it is the only approach covering the whole EU-27, particularly land-independent farm types (pig poultry) and farm types with low UAA per farm (horticulture, permanent crops) and where the results have been evaluated with European FSS data. Other studies using methods such as the synthetic landscape approach (e.g. Uthes and Kiesel 2020) for a specific region could be better suited for smaller regions but require highly dissaggregated data with sufficient data quality and have not been tested yet in other regions throughout Europe. The CO model used in Kempen et al. 2011 will be further improved in MIND STEP by updating the FADN data from 2012 to 2018 and replacing the HSU (Homogeneous Spatial Unit) with a new initial spatial unit FSU (Farm structure unit) which are part of exactly one FSS 10 km^2 grid cell and provide detailed information about nutrients flows. The prior data for the CO approach containing information about the share of UAA per farm type on a 10km^2 grid level will be based on FSS data from 2010. The computed probabilities for a specific FADN farm to be located in a spatial unit allows to link economic behaviour to climatic, soil and landscape information and will be used by other models like IFM-CAP in task 2.6 as well as for spatial econometric or machine learning approaches.

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ANNEX I MIND STEP WP2 TEAM

Mr Alexander Gocht (THUENEN)
Mr Jörg Rieger (THUENEN)
Mr Adrian Leip (JRC)
Mr John Helming (WEcR)
Mr Marc Müller (WEcR)
Mr Thomas Heckelei (UBO)

CONSORTIUM DESCRIPTION

The consortium of MIND STEP consists of 11 partners from 7 countries in Europe (the Netherlands, Germany, Austria (IIASA), Italy, France, Spain (JRC-Seville), Norway and Hungary). It includes partners from the private and public sector representing:

- Academia and higher education (UBO, UCSC, WU).
- SME dealing with research consultancy, data collection, strategic advice, normalization and policy in the field of energy, environment and sustainable development. This SME has also a strong track record in the field of communication, stakeholder engagement and exploitation (GEO)
- Public government bodies dealing with agricultural and environmental research and data collection and building agricultural models at different scales (WR, IIASA, IAMO, THUENEN, INRA, NIBIO, JRC)

The consortium has been carefully constructed in such a way that it is capable of jointly managing all activities and risks involved in all project stages. Each partner contributes its own particular skills, (inter) nationally wide network and expertise, and has a critical role in MIND STEP. Partner expertise smoothly complements each other and all together form the full set of capabilities necessary to lead MIND STEP to a success. Achieving the overall objective is determined by all partners in the consortium as well as their ability to involve other interested stakeholders in the process of developing, validating and disseminating the IDM models, indicators and methodologies (WR, UBO, IAMO, UCSC, WU, THUENEN and INRA) and linking IDM models to current agricultural policy models (WR, IIASA, UBO) included in the MIND STEP model toolbox. Dissemination and communication activities are steered by partner GEO who has graphic design, IT and marketing communication teams to deliver out-of-the-box and novel solutions for dissemination and communication and JRC who has a large network with policy makers. GEO has experience in leading comparable activities in H2020 projects as UNISECO and COASTAL. The coordinator WEcR is part of Stichting Wageningen Research (Wageningen Research Foundation, WR). WR consists of a number specialised institutes for applied research in the domain of healthy food and living environment. WR collaborates with Wageningen University (WU) under the external brand name Wageningen University & Research. One of the strengths of Wageningen University & Research (including WR) is that its structure facilitates and encourages close cooperation between different disciplines. The institutes Wageningen Economic Research (proposed coordinator of MIND STEP, WEcR) and Wageningen Environmental Research (WEnR) are involved in this proposal. The One-Wageningen approach will also be applied to MIND STEP. WEcR has a long standing reputation of leading large scale EU projects, such as SUPREMA, Foodsecure, SUSFANS, FLINT, SAT-BBE, and SIM4NEXUS.

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