MIND STEP

MODELLING INDIVIDUAL DECISIONS TO SUPPORT THE EUROPEAN POLICIES RELATED TO AGRICULTURE

Deliverable Report D5.2

Report on improvements to the current EU and global models

EDITED BY	Tamas Krisztin (IIASA), Felicity Addo (IIASA), Elisa Bardazzi (WEcR), Esther Boere (IIASA), Stefan Frank (IIASA), Alexander Gocht (Thuenen), Petr Havlik (IIASA), John Helming (WEcR), Niklas Hinkel (IIASA), Dimitrios Kremmydas (JRC), Ipsita Kumar (IIASA), Marc Mueller (WEcR), Sebastian Neuenfeldt (Thuenen), Leopold Ringwald (IIASA), David Schaefer (University Bonn), Hugo Scherer (WEcR), Davit Stepanyan (Thuenen), Michael Woegerer (IIASA)
APPROVED BY WP MANAGER:	Petr Havlik (IIASA)
DATE OF APPROVAL:	17 July 2023
APPROVED BY PROJECT COORDINATOR:	Hans van Meijl (WR)
DATE OF APPROVAL:	xx
CALL H2020-RUR-2018-2	Rural Renaissance
WORK PROGRAMME Topic RUR-04-2018	Analytical tools and models to support policies related to agriculture and food - RIA Research and Innovation action
PROJECT WEBSITE:	https://mind-step.eu

This document was produced under the terms and conditions of Grant Agreement No. 817566 for the European Commission. It does not necessarily reflect the view of the European Union and in no way anticipates the Commission's future policy in this area.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Change records

Version	Date	Who	Changes

ABBREVIATIONS

AgriPolis	Agricultural Policy Simulator	**HI**	High input system
BAB	Bundesanstalt für Agrarwirtschaft und Bergbauernfragen	**IAEI**	Institute of Agricultural Economics and Information
BART	Bayesian Additive Regression Trees	**IDM**	Individual Decision-Making model
BMEL	German Federal Ministry of Food and Agriculture	**IFM CAP**	Individual Farm Model for Common Agricultural Policy Analysis
CAP	Common Agricultural Policy	**IFPRI**	International Food Policy Research Institute
CAPDIS	CAPRI Spatial Disaggregation module	**IIASA**	International Institute for Applied Systems Analysis
CAPRI	Common Agricultural Policy Regionalised Impact Modelling System	**INRAE**	Institut national de la recherche agronomique
CES	Constant elasticity of substitution	**IOT**	Input-Output Table
CGE	Computable General Equilibrium	**IR**	Irrigated system
CH4	Methane	**JRC**	European Commission - Joint Research Centre
CLC	Corine Land Cover	**KTBL**	Kuratorium für Technik und Bauwesen in der Landwirtschaft

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

CO2	Carbon Dioxide	**LC**	Land Cover
CoESM	Co-development of Earth System Models	**LI**	Low input system
COP	Specialist cereals, oilseeds and protein crops	**LU**	Land use
CrpLnd	Cropland	**LUC**	Land use change
DG AGRI	Directorate-General for Agriculture and Rural Development	**MACC**	Marginal abatement cost curve
DG CLIMA	Directorate-General for Climate Action	**MAGNET**	Modular Applied GeNeral Equilibrium Tool
DG ENV	Directorate-General for the Environment	**MAPA**	Ministerio de Agricultura, Pesca y Alimentación
DG SANTE	Directorate-General for Health and Food Safety	**MENA**	Middle-East and North Africa
DM	Dry matter	**MS**	Member State
EC	European Commission	**N**	Nitrogen
EEA	European Environment Agency	**N2O**	Nitrous oxide
entGWP	Enteric fermentation	**NEIO**	New Industrial Organization
EPA	Environmental Protection Agency	**NEL**	Net energy for lactation
EPIC	Environmental Policy Integrated Model	**NotRel**	Not relevant land
ESD	Effort Sharing Decision	**NRW**	North-Rhine Westphalia
EU	European Union	**NUTS**	Nomenclature of Territorial Units for Statistics
EUR	Euro	**OLS**	Ordinary least squares
Euro Cordex	European branch of the international Coordinated Downscaling Experiment	**OthAgri**	Other agricultural land
FADN	Farm accountancy data network	**PE**	Partial equilibrium
FALMCO	Forestry and Agricultural Land-use and Management Costing	**PPE**	Perceived price elasticity
FAO	Food and Agriculture Organization of the United Nations	**RCP**	Representative Concentration Pathway

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

FAOSTAT	Statistics Division of the Food and Agriculture Organization of the United Nations	**RMSD**	Root mean squared deviation
FarmDyn	A dynamic mixed integer bio-economic farm scale model	**RUMINANT**	Animal-level model that simulates the effects of nutrition
FSS	Farm Structure Survey	**SAM**	Social Accounting Matrix
G4M	Global Forest Model	**SFP**	Single farm payment
GAEZ	Global Agro-Ecological Zones	**SNA**	System of National Accounts
GAMS	General algebraic modeling system	**SPAM**	Spatial Production Allocation Model
GCM	General circulation model	**SSP**	Shared Socioeconomic Pathways
GDP	Gross Domestic Product	**SUR**	Seemingly unrelated regression
GHG	Greenhouse gas	**TF**	Grouping of agricultural holdings by type of farming
GLOBIOM	Global Biosphere Management Model	**UAA**	Utilized agricultural area
GrsLnd	Grassland	**USD**	United States Dollar
GTAP	Global Trade Analysis Project	**ÚZEI**	Ústav zemědělské ekonomiky a informací
GWP	Global warming potential	**XP**	Raw protein

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

1 EXECUTIVE SUMMARY

This deliverable (D5.2) focuses on improving EU-wide and global models (i.e., CAPRI, GLOBIOM) that the European Commission uses for policy evaluation in the agricultural sector. The goal is to enhance the representation of farm-level behaviour and its impact on the environment and climate by linking macro-level models with micro-econometric models. The deliverable highlights various improvements, including harmonising production systems and farm typologies, calibrating behavioural parameters, representing structural changes, improving risk representation, addressing greenhouse gas emissions, and enhancing market power parameters and price transmission elasticities.

Overall, this deliverable documents technical adjustments to the MIND STEP toolbox, enabling better policy evaluation, identification of policy options, scenario development, and assessment of their impact on European agricultural production systems. The improvements aim to enhance the accuracy and relevance of models by incorporating farm-level data, improving decision-making representation, and addressing key factors such as risk, adoption of new technologies, and market dynamics.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

2 INTRODUCTION

Agricultural land management has a direct impact on the environment and climate. In order to assess specific agricultural policy instruments and their impact on farm business and the agricultural sector in general, these models need to be enhanced by the improved representation of individual decision-makers behaviour. This deliverable (D5.2) focuses on improving current EU-wide and global models used at the European Commission through aspects such as risk or structural change behaviour, building on integrating the tools developed in WP3 and WP4, focussing on the individual farmer and on interactions among farmers and within the supply chain, respectively. Specifically, it reports upon the improvements made in WP5 following the harmonisation of production systems, sectors, and farm types based on the MIND STEP-data framework developed in WP2. Moreover, it presents an improved representation of individual decision-making in macro-scale models, improved elasticities of transformation/impacts on productivity coefficients, improved elasticities of substitution/transformation between land uses, improved risk representation, enhanced adoption of mitigation technologies, and improved market power parameters and price transmission elasticities.

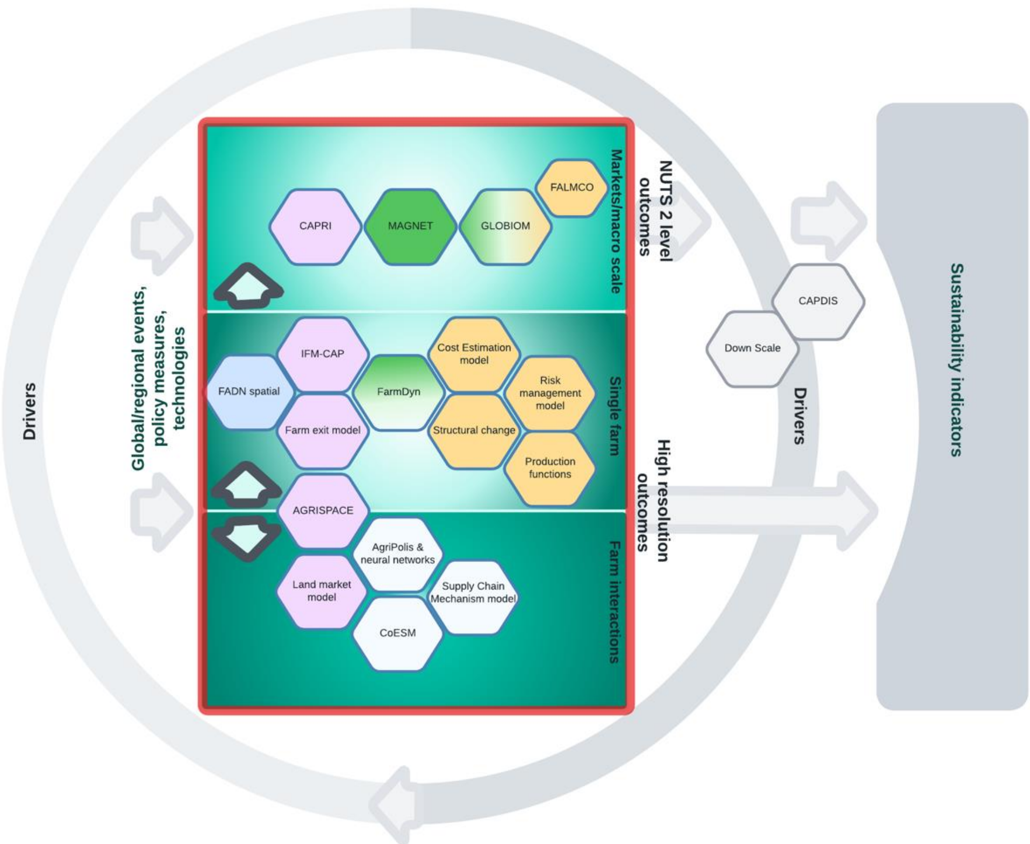


Figure 1 Technical innovations of this deliverable in the MIND STEP toolbox (adapted from D5.1).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Overall, this deliverable presents the necessary technical adjustments to the MIND STEP modelling tools for the policy evaluation in Task 6.4, which aims to identify policy options, develop coherent scenarios, and assess their impact on European agricultural production systems. **Figure 1** contains an overview of the main improvements and innovations of this deliverable in the MIND STEP toolbox. The main work areas are highlighted in red. The work within Task 5.2 focused on improving existing models and the *bottom-up* connection of single farm (and farm interaction) models. This includes establishing clear links to the models in WP3 (throughout sections 3 and 4) and WP4 (sections 6 and 7).

This deliverable is structured along the main subtasks of the work package (WP):

- **Section 3 (Task 5.2.1)** focuses on harmonising production systems and farm typologies within the MIND STEP model toolbox. The harmonisation focuses on the crop and livestock sectors. The objective is to enhance the representation of farm types specified in the GLOBIOM and MAGNET models and to thus align these two models with the ones developed in WP3 and WP4. While GLOBIOM already operates at a high spatial resolution and differentiates alternative production systems for crops and livestock to ensure seamless interfacing with the individual decision-making models, it is necessary to review and refine the production system and sector classification, as well as parameterisation to accurately reflect the farm types identified in the newly developed models. For MAGNET, this required a split of animal herds as stock from capital for improved linkages to IDM models explicitly including the substitution between labour, capital and land. To accomplish this, the modelling teams relied on, among other things, the well-established FADN database.
- **Section 4 (Task 5.2.2)** deals with calibrating behavioural parameters for the choice of agricultural output and input levels and their substitution for macro-level models, specifically GLOBIOM. The micro econometric models of crop and livestock production decisions developed in Task 3.4 are used as input to macro-level models. Within GLOBIOM, parameters entering land allocation equations (elasticities of substitution/transformation between land uses) are improved, coupled with parameters characterising crop management. This section outlines the improvements to GLOBIOM by first aligning GLOBIOM’s database with an explicit representation of land-use change. Second, bottom-up linkages between farm-level models and GLOBIOM are established by linking observed farm-level crop and crop-management changes to GLOBIOM’s representation of technological change. Finally, a validation tool, as well as a statistical framework to link econometric model estimates (such as those produced by INRAE in Task 3.4) to GLOBIOM is introduced.
- **Section 5 (Task 5.2.3)** focuses on the representation of structural change in current models. The current EU/global models represent the farm structure implicitly (CAPRI,

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

MAGNET), and some of them more or less explicitly (IFM-CAP, GLOBIOM), and the aim is to incorporate the influence of structural change and related land market developments on the supply side response of the agricultural sector.

- **Section 6 (Task 5.2.4)** aims to improve the risk representation in current macro-level models, specifically on the example of GLOBIOM. The impact of farmers' risk attitudes on production decisions is explored by putting forward a framework to integrate the findings from Tasks 3.5 and 4.4 in GLOBIOM. The aim is to examine the impact of climate change, particularly through increased climate variability, on the agricultural sector by making changes in elasticities or cost markups in the current large-scale models.
- **Section 7 (Task 5.2.5)** focuses on enhancing the macro-level models to make them fit to support policy assessments related to the urgent need to mitigate greenhouse gas (GHG) emissions in the agricultural sector within the framework of the European Green Deal and the European Climate Law. Economic modelling plays a crucial role in evaluating climate change mitigation strategies. Micro-level models, such as single-farm level models, provide detailed insights into specific mitigation measures, while macro-level models offer a broader perspective on cost-efficiency and mitigation potential. However, macro-models often lack consistent and region-specific data on abatement costs, leading to the omission of important measures. To address this, the linkage of FarmDyn with GLOBIOM and MAGNET allows for the incorporation of farm-level data and country-specific factors, enabling more accurate assessments of the abatement potential and costs of the agricultural sector.
- **Section 8 (Task 5.2.6)** focuses on enhancing the market power parameters and price transmission elasticities in existing models, specifically CAPRI and MAGNET. This section builds upon the models developed in Task 4.4, aimed at improving the parameterisation of CAPRI and MAGNET by incorporating conjectural elasticities and price transmission elasticities at a disaggregated product level. While Task 4.4 is limited to a few supply chains, this section provides a concept for the potential of this approach.

The final section concludes.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

3 HARMONISATION OF PRODUCTION SYSTEM, SECTOR, AND FARM TYPE

This section focuses on harmonising production systems and farm typologies within the MIND STEP model toolbox. The harmonisation focuses on the crop and livestock sectors. The objective is to enhance the representation of farm types specified in the GLOBIOM and MAGNET models and to thus better align these two models with the ones developed in WP3 and WP4.

While GLOBIOM already operates at a high spatial resolution and differentiates alternative production systems for crops and livestock to ensure seamless interfacing with the individual decision-making models, it is necessary to review and refine the production system and sector classification, as well as parameterisation to accurately reflect the farm types identified in the newly developed models.

The novelty of the work presented in this chapter is the integration of the FALMCO (Forestry and Agricultural Land-use and Management COsting) module in GLOBIOM. FALMCO is a costing module to estimate and allocate production costs associated with diverse land uses across multiple management dimensions. On the one hand, top-down econometric and statistical techniques are applied to the farm-level FADN data to classify farms' management systems and estimate the associated production costs. On the other hand, in regions where data is scarce or lacking, a bottom-up engineering-descriptive approach is employed, using open-source production data to quantify input use and associated costs, which are then extrapolated to these data-scarce regions. The overall aim of the FALMCO module is to establish and publish an open-source database of production associated with diverse land use classes and management and input use intensities. In Subsections 3.1 and 3.2, we present the main methods behind the FALMCO module, especially how production costs associated with crop farming in the EU are estimated. Subsection 3.3 established a link between the FALMCO module and WP3 by comparing cost estimates to the micro-econometric model developed there.

The novel contribution to MAGNET is a split of animal herds as stock from the capital for improved linkages to IDM models explicitly including the substitution between labour, capital and land. To accomplish this, the modelling teams relied on, among other things, the well-established database.

The following subsections delve into the specific subtasks and objectives of this harmonization effort, including the improvement of crop sector and production system classification for GLOBIOM, estimation and validation of input-output coefficients using national datasets,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

parameterisation of GLOBIOM with validated cost estimates, and the enhanced livestock sector classification for MAGNET.

3.1 An improved management system classification of the EU crop sector for the macro-level model GLOBIOM

3.1.1 Introduction

An important distinction in farming systems is the management practices associated with producing crops, livestock, and forests. These management differences are reflected in the variations in the intensity of input use, the nature of field operations, and the production costs associated with the management systems. Therefore, this subtask aims to classify and parameterise production systems, creating a more straightforward interface of the larger-scale market models (e.g., GLOBIOM model) with other IDM models developed in WP3 and WP4. In the GLOBIOM model, this translates to classifying the management systems associated with crop farming in the EU at the NUTS 2 spatial resolution. The FADN database is used to classify the production of major crops to obtain an accurate representation of the management systems related to crop farming in the EU. Specifically, to model how intensive inputs are applied.

The starting point defines the old management systems (sometimes referred to as production systems) adopted from SPAM 2000 based on the Global Agroecological Zones (GAEZ) (IIASA/FAO, 2012) and Spatial Production Allocation Model (SPAM) methodologies (Wood-Sichra et al., 2016; You et al., 2014; You and Wood, 2006). Building on these works, the GLOBIOM model characterises and distinguishes crop production by four management systems based on water supply conditions (irrigated vs. rainfed) and input use (low vs. high) globally. Therefore, the management systems are:

- **Rainfed - subsistence (SS):** Under this system, crop producers are typically small-scale and produce mainly for their own household consumption. Here, production is rainfed with low inputs. This type of management characterises traditional production techniques, less mechanisation, and little to no fertilisers and crop protection or application. This management system is rare in the EU. This type of system cannot be identified in the FADN as the FADN includes agricultural holdings considered commercial.
- **Rainfed - low input (LI):** Rainfed low input applies traditional seed varieties without (or with little) application of fertilisers or plant protection. This system uses traditional tools and is typically labour-intensive. In parts of the EU (i.e., Romania), this translates to less machinery use, lower average productivity, poorly technically equipped and limited access to credit, among others (European Commission, 2022).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

- **Rainfed – high-input (HI):** In this system, crop production is rainfed and uses high-yield varieties, optimal application of fertilisers and crop protection, and may be fully mechanised.
- **Irrigated - high input (IR):** Here, crop production areas are typically equipped for irrigation, and crop production uses modern high-yield seed varieties, optimal fertiliser, and crop protection applications. In this analysis, this translate to HI farms with irrigated area.

Generally, different crop management practices often result in different yields, associated production costs, and gross margins. The GLOBIOM model accounts for these management systems relating to production (i.e., fertiliser use and water use), production costs, and output (i.e., yield) of crops cultivated. However, as Wood-Sichra et al. (2016) noted, global datasets on management system shares for each crop were largely absent. Therefore, the SPAM model relied extensively on expert judgment, making the classification more subjective and qualitative. In this task, the management systems with respect to the EU crop sector are re-defined using the EU farm intensity indicator. This approach has multiple benefits. First, it applies the harmonised EU FADN survey data, the reference for most relevant micro-econometric models. Second, it allows for incorporating the estimates of these micro-econometric models into GLOBIOM. Third, although the SPAM model has a global representation, the present approach presented here focuses on EU management systems and highlights differences in crop production based on a standardised EU indicator, thus capturing variations across MS in a more standardised manner.

The remainder of this section is presented as follows: the following section presents the conceptual framework, which describes the farm intensity methodology, how it is applied in this task, and the data used. The subsequent sections present the main findings and conclusion remarks.

3.1.2 Conceptual Framework

EU farms are heterogeneous regarding production intensity and practices. To model this heterogeneity among crop producers in GLOBIOM, it is essential to associate management systems with individual crops. However, in the FADN data, input and resource use are reported at the farm level. For example, the FADN data presents information on the total fertiliser expenditure of the farm, with no additional information on how farms apply these fertilisers among crops produced on the farm. Therefore, we made the following three key assumptions to parameterise and classify crop production under the management systems. First, rather than directly classifying individual crops under the different management systems, we categorise the farms' overall production instead. Here, we assume that, e.g., a high-input farm will typically produce all crops under this system. Second, based on the definition of the subsistence system and the criteria for sampling farms in the FADN (i.e.,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

considering only commercial agricultural holdings), there is no subsistence farming in the new re-classification among the EU crop producers. Third, as EU farms are typically diverse in their production, the clustering analysis focuses on farms with crop farming as their main production.

Based on these assumptions, we apply the FADN data and cluster analysis to classify farms into rainfed low- and high-input and irrigated management systems. Although several econometric methods persist for cluster analysis, we use the more straightforward and consistent EU-based farming intensity indicator (indicator C33) from the agri-environmental indicators jointly developed by the Directorate-General for Agriculture and Rural Development (DG AGRI), the Directorate-General for Environment (DG ENV), Eurostat, the Joint Research Centre (JRC), the European Environment Agency (EEA), the Directorate-General for Health and Food Safety (DG SANTE) and, the Directorate-General for Climate Action (DG CLIMA). This method uses the readily available FADN data to classify farms into low, mid, and high intensities based on fertiliser, crop protection, and feed use in two steps[1].

However, to make it applicable to our analysis, which focuses on crop farms, we adapted this clustering methodology by using crop-specific costs. In other words, crop-specific costs such as fertiliser and plant protection expenditures per hectare were used as a proxy for clustering the input-use intensity of crop farms. Within this methodology, farm input intensity is defined as the level of inputs the farm uses per unit of production factor (i.e., land). **Figure 2** presents the modelling framework.

The starting point of this analysis is the FADN data, which uses harmonised bookkeeping principles to collect financial, economic, and physical farm-level data for a representative sample of farms across the EU. Farms in the FADN sample are stratified according to production orientation (i.e., farm type), farm economic size, and farm topography. The empirical analysis applies an unbalanced panel of crop farms from the FADN database covering the EU 27 Member States (MS) and the UK from 2007 to 2018. To capture variations in management between different farm types related to crop farming (i.e., specialised vs. mixed), we use the EU TF 14 classification. For the specialised crop farming systems, we focus on the cereal, oilseeds, and protein crop farms (TF15) and ii) other field crop farms (TF 16). For the mixed crop farming systems, we focus on: i) mixed crop farms (TF60) and ii) mixed crop and livestock farms (TF80)[2].

---

[1] More on the methodology as applied by the European Commission can be found here.

[2] Farms in the FADN are stratified based on their standard output according to production orientation (i.e., farm type), farm economic size (measured in standard output-SO), and farm topography.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Table *1* presents a distribution of our utilised data per farm type, comprising over 75000 farms covering the period from 2007-2018. Farms are, on average, seven years in the sample. Although the sample size increases across most farm types over time, mixed crop farms show an opposite trend. The majority of sampled farms are classified as specialised crop farms (i.e., COP or other specialised field crop farms), representing over 70% of the sample. Mixed cropping systems, on the other hand, were the least common production orientation. The data distribution per member state (MS) presented in **Table *2*** shows that the largest share of sampled crop farms are concentrated in Poland and Italy, representing over 25% of the sample. Conversely, Luxembourg and Ireland had the least number of crop farms in the sample.

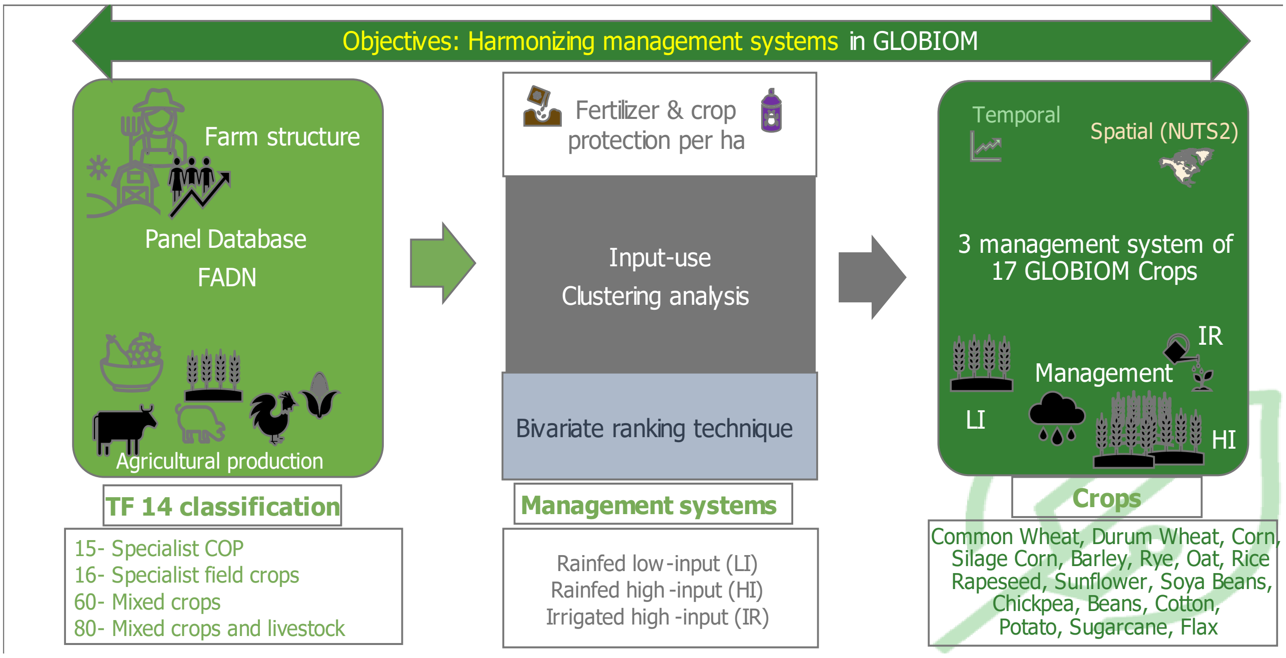


Figure 2 A modelling framework for harmonising management systems of crop production.

The next step focuses on the clustering analysis based on input use. As input volumes/quantities are not reported in the FADN, a necessary step is to create a proxy for input quantities used per hectare of utilised agricultural area (UAA). We divide input expenditures per hectare by the input price index for the year and country in question, with 2010 as the base year. Specifically, the input used is expressed in constant input prices per ha. Therefore, fertiliser expenditure is divided by the country and year-specific fertiliser price index provided by Eurostat to estimate the volume used. Similarly, plant protection expenditure is converted into a volume measure by dividing it by the plant protection price index. This approach accounts for inflation and price fluctuations, thus reflecting the trend in the volume of inputs used.

Table 1 Distribution of farms per farm type.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

TF14	Number of farms	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
15	27,498	8,393	9,331	10,746	11,790	12,136	12,983	13,786	12,930	12,838	13,220	13,426	13,396
16	22,731	8,241	7,386	7,685	7,876	8,213	8,325	8,533	8,355	8,141	8,480	8,890	8,864
60	9,994	3,110	2,690	2,832	2,933	2,829	2,958	3,097	2,810	2,701	2,745	2,757	2,682
80	15,176	3,830	4,008	4,623	4,422	4,376	4,774	4,938	4,784	4,622	4,673	4,753	4,443
Total	**75,399**	**23,574**	**23,415**	**25,886**	**27,021**	**27,554**	**29,040**	**30,354**	**28,879**	**28,302**	**29,118**	**29,826**	**29,385**

Once the farm-specific input volumes have been estimated, the bivariate ranking method is employed to categorise farms into farming intensities. Here, a rank is assigned using the fertiliser and crop protection per ha values calculated in the previous step. Ideally, the UAA distribution by the ranked input intensity can be calculated per various geographical levels (EU, MS, NUTS) for a specific reference year. As the input intensity indicator analysis in the present study aims to provide insights into EU farms in general, we classify farms based on the EU-wide quantiles, with 2010 as the reference year. In other words, to compare farms across the EU, a consistent indicator of intensity (i.e., cutoff points of the quantiles) is applied rather than a member-state-specific quantile. It is important to note that the cut-off values are flexible and represent a reference value in 2010. This changes depending on the reference period. With this reference value, we can assess the development of farms' input use intensity over time.

Table 2 Distribution of farms per member state.

FADN country codes	MS	No. of farms	No. of obs.	Per cent	FADN country codes	MS	No. of farms	No. of obs.	Per cent
BEL	Belgium	486	2,565	0.77	LTU	Lithuania	2,192	7,620	2.29
BGR	Bulgaria	2,707	11,508	3.46	LUX	Luxembourg	98	388	0.12
CYP	Cyprus	506	1,741	0.52	LVA	Latvia	999	5,309	1.60
CZE	Czech Republic	1,663	8,914	2.68	MLT	Malta	267	957	0.29
DAN	Denmark	2,296	6,652	2.00	NED	The Netherlands	426	2,744	0.83
DEU	Germany	6,644	31,249	9.40	OST	Austria	824	5,211	1.57
ELL	Greece	3,896	22,520	6.78	POL	Poland	12,432	54,072	16.27
ESP	Spain	5,192	30,406	9.15	POR	Portugal	907	3,776	1.14
EST	Estonia	575	3,004	0.90	ROU	Romania	8,347	23,852	7.18
FRA	France	4,798	27,941	8.41	SUO	Finland	497	3,200	0.96
HRV	Croatia	763	2,642	0.79	SVE	Sweden	516	3,009	0.91
HUN	Hungary	2,096	13,586	4.09	SVK	Slovakia	775	4,250	1.28
IRE	Ireland	193	1,090	0.33	SVN	Slovenia	415	1,465	0.44
ITA	Italy	13,094	43,419	13.06	UKI	United Kingdom	1,795	9,264	2.79
					Total		**75399**	**332,354**	**100.00**

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Based on this, three classes of intensity (low, high, irrigated) are defined, corresponding to the input use intensity in the 33rd and the 66th UAA quantiles. A farm is classified as low intensity if its cost-specific input level is less than or equal to the intensity value associated with the 33rd quantile of UAA. On the other hand, a high-intensity farm has an intensity value above the 66th quantile of UAA. Therefore, a farm is classified as low-input if its input level is below or equal to € 142.11/ha and high-input greater or equal to €273.56/ha. We define a medium-intensity farm between the 33rd and 66th quantiles to ensure a clear input use delineation between the low and high intensities. The idea is to clearly distinguish between low input (i.e., levels below the 33rd quantile) and high input (i.e., levels above the 66th quantile).

The last category focuses on high-input irrigated crop management systems. We classify these as farms with high input levels (i.e., greater than €273.56/ha) and irrigated areas. Categorising irrigated farm systems presented three interesting features. First, there is a limited number of irrigated farms in the sample. Only about 23% of the total sampled farms reported any irrigated area. Second, our *a priori* expectation that irrigated farms are managed as high input was only met partially. In other words, approximately 53% of farms with irrigated areas were classified as high input. For consistency, only farms categorised as high-input with an irrigated area are classified as high-input irrigated. This implies that farms with irrigated areas classified as low input are still considered under the low input system class, as the irrigated management system class aims to capture high input use with partial or full irrigation.

Third, some countries reported no irrigated area (e.g., Germany, Luxembourg, and Ireland), although Eurostat maps show irrigated/irrigable areas. This could point to missing data. To account for this, we used the average EU irrigated farm per year to calculate a measure of irrigation technology for these countries. This corresponds to crop-specific costs greater or equal to €655.65/ha. Based on this, the irrigated management system in these countries was assigned.

3.1.3 Key findings

3.1.3.1 ***Temporal dynamics and spatial distribution of management systems***

The results show that about half of the sampled farms are classified under the low-input management system. Farms classified as high input and irrigated systems constitute 32% and 19% of the sample, respectively. One of our aims is to investigate whether farming intensity is homogeneous across the EU and over time. In other words, are specific management systems concentrated in certain parts of the EU? To understand these dynamics and patterns spatially and over time, we split the study period into three main aggregate periods: i) 2007 – 2009 (labelled initial), ii) 2010 – 2014 (labelled mid), and iii) 2015 – 2018 (labelled final).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Figure 3 presents the shares in total UAA of management systems across the EU over the three periods. Figure 3 merely depicts the share of farming systems and does not reflect how much the high-input or low-input farming area has increased. For example, the UAA of high input or irrigated farming might have increased over the observed period. Still, the share of high-input would decrease if this is accompanied by a proportionally higher increase in low-input areas. As expected, the results show that farm intensity and management vary across the EU. A larger share of low-input farms is concentrated among Northern countries (i.e., Sweden and Finland), above the 75th percentile. Furthermore, in southern (i.e., Spain, France) and eastern Europe (i.e., Romania, Bulgaria), we observe a large proportion of low-input farms above the 50th percentile. As expected, high-input farms are concentrated in central and western Europe.

The irrigated management system is concentrated in Central Europe. The shares are highest in Germany, Italy, and Greece. There is a minimum concentration of irrigation farm systems in northern Europe, and this trend has remained consistent over time. In Germany, as initially stated, irrigated area is not reported and needs to be extrapolated. The overly high shares of irrigated areas in Germany could indicate an overestimation in the extrapolation step. Hence, results need to be cautiously interpreted.

Regarding the temporal dynamics of the management systems, we observe that the share of low-intensity farming has increased in most Eastern European countries. Most apparent is the shift in production from high-input to low-input management systems. This results in a decrease in the share of high-input systems in Eastern Europe over time. Specifically, farm intensity seems to be more or less split in the initial period between low-input and high-input systems. However, toward the final period, the relative share of low-input systems has increased. This effect is predominant in Poland, Romania, and Bulgaria.

Conversely, farms in northern Europe shifted towards high-input systems over time. A general trend observed is the increased share of irrigated farm systems over time, particularly among southern EU and Mediterranean countries (i.e., France, Greece, Spain, and Portugal). However, the patterns of irrigated farm systems remain unchanged for most of the EU.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

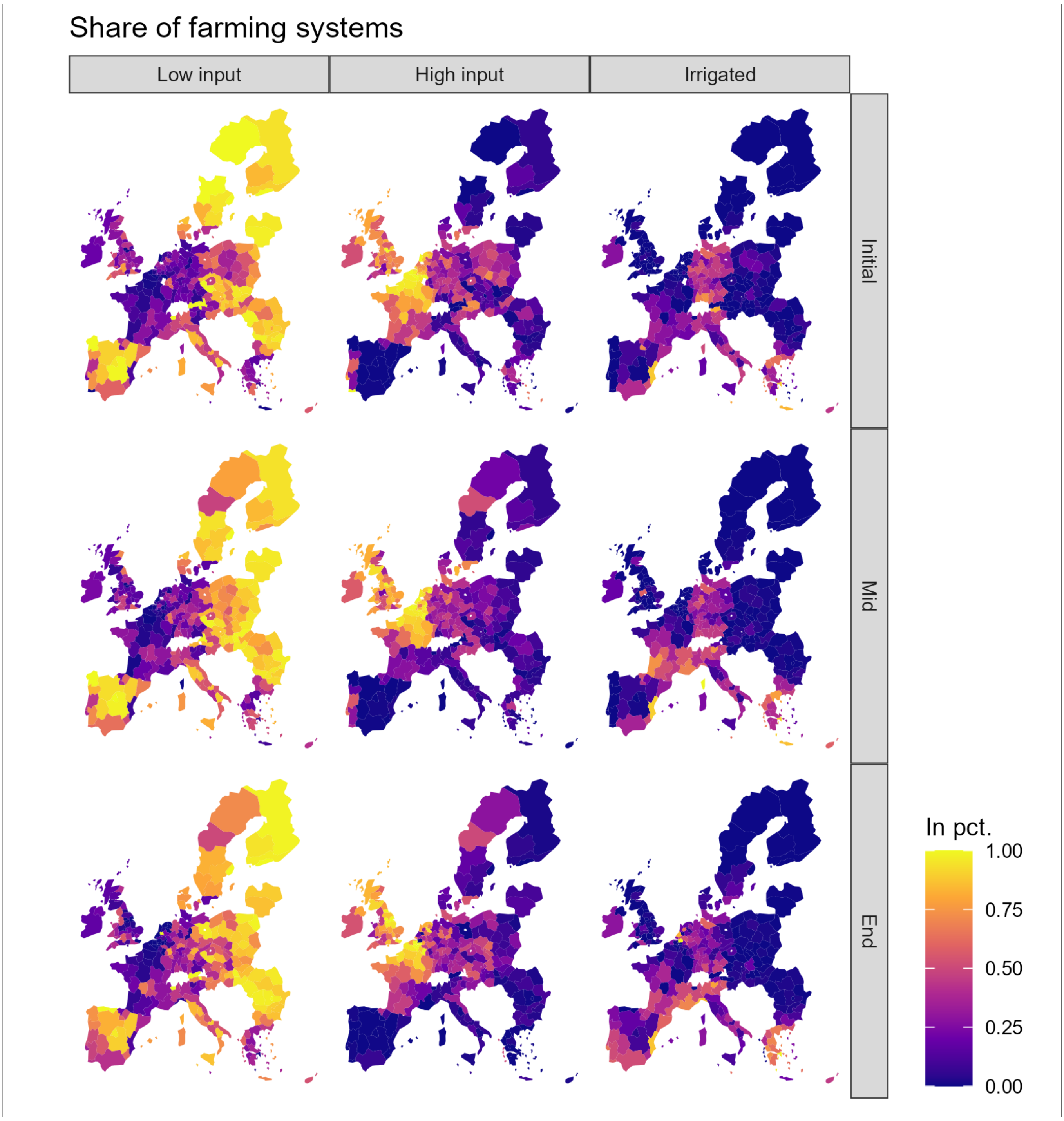


Figure 3 Share of management systems across the EU (spatial) over time (temporal).

3.1.3.2 *Management system patterns across farm typologies*

Another interesting aspect of the analysis is the distinction in farming intensities across farm typologies. **Figure 4** compares the share of management systems across crop farm typologies across the different EU member states. Management systems are different in countries and types. While some farm types are managed entirely by a specific farming intensity, others are

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

more diverse. For example, specialised COP farms in Belgium, Luxembourg, and the Netherlands are almost entirely managed as high-input systems, while in Bulgaria and Romania, they are primarily low-input. Apart from Belgium, Malta, and the Netherlands, mixed crops and livestock farms (TF80) are predominately managed as low-input systems. In most countries, the shares are above 50%. This is unsurprising and could point to much less crop-specific input use among mixed crop and livestock farms, although this pattern is dissimilar for mixed crop farms.

A plausible explanation could be that as mixed farms typically have a larger share of grasslands, this implies lesser use of chemical fertilisers in many countries. This is particularly true if farms apply more manure instead of chemical fertilisers. Thus, they need less chemical fertiliser, although the N-fertilizer input use and equivalent yields are high. Therefore, an important component that still needs to be resolved is how to distinguish these from low-input farms and classify them appropriately as high-input, as they will not necessarily be low-input simply because they substitute manure for fertilisers.

Specialist field (TF16) and mixed crop farms (TF60) are vastly diverse across the EU, with all management systems represented to some extent. Across the EU, all the management systems are observed across the different farm typologies. However, in some countries, irrigated systems are more predominant across the different farm typologies (i.e., Malta and Luxembourg). At the same time, others are predominantly low-input across farm types (i.e., Romania and Lithuania).

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement N° 817566.

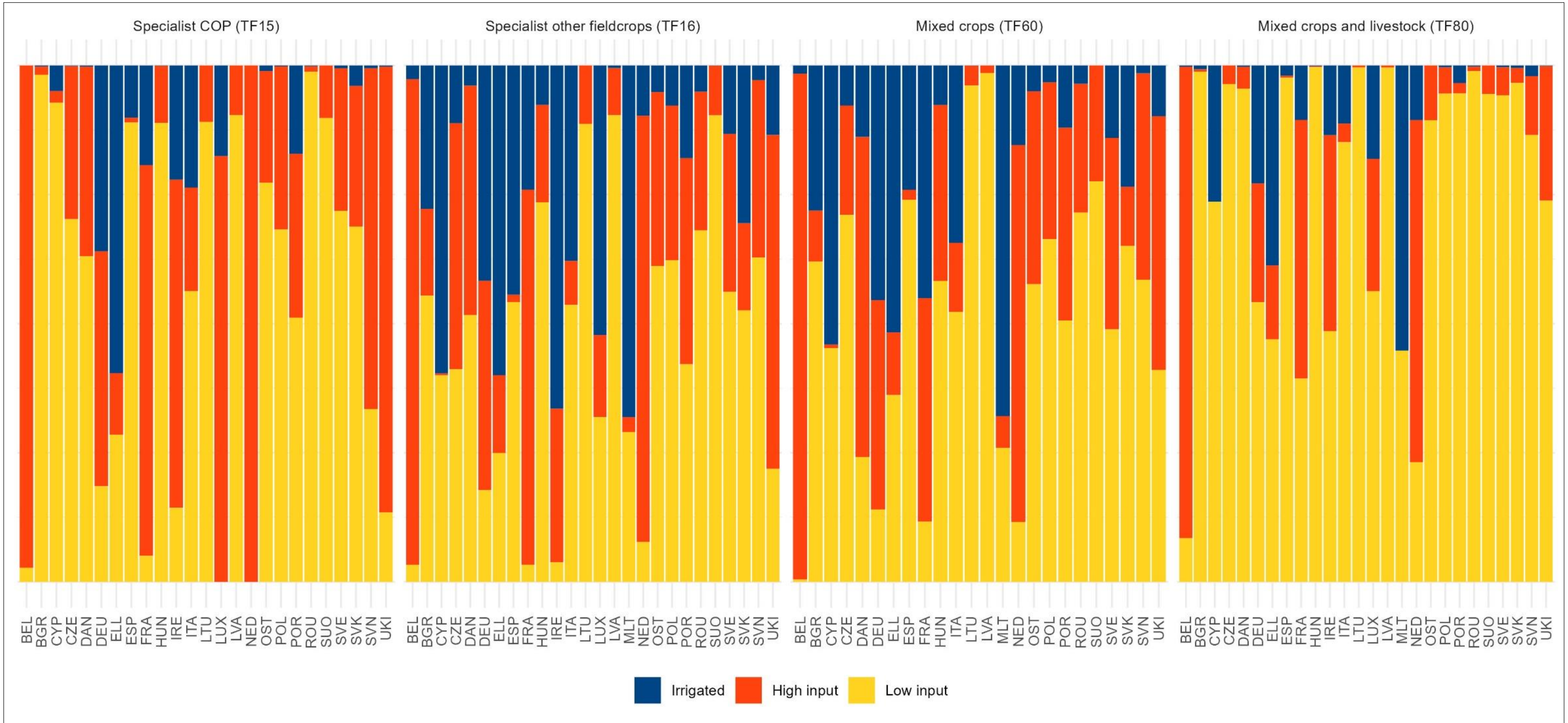


Figure 4 Share of management system patterns across the EU's crop farm typologies.

3.1.3.3 FADN-SPAM management systems comparison and dynamics: Lessons learnt

Cropland shares under different management systems across the EU

Given that this analysis is a stepping stone to improving the producer-specific heterogeneity in the GLOBIOM model, we assess the fit of the FADN-based management system definition to the SPAM model used for management system classification in GLOBIOM [3]. We evaluate this in three dimensions. First, the distribution of cropland shares managed under the different management systems is compared across the EU. This evaluates whether the definitions and approximation of farming intensities are consistent. An important consideration is that in SPAM, crop management systems are defined according to the activity/crop, while in the FADN-based approach applied here, they are defined per farm.

Figure 5 compares the distribution of cropland shares under different management systems based on the FADN approach developed in this study and the SPAM model in the initial period. We compare the development of cropland management spatially and temporally. Between the 2000 and 2020 periods, we do not observe much change in the cropland management at the NUTS2 level in both GLOBIOM and the present FADN approach. In aggregate terms, the share of cropland managed under the different systems remained relatively constant over time. In terms of management system representation, we find that the irrigated management system is the most consistent between the two approaches, even when disregarding the interpolated irrigated cost data for Germany, Luxembourg, and Ireland. Particularly for most of the EU, the shares of cropland under the irrigated system are similar. Slight differences are observed for central EU (i.e., Germany, Belgium, France) and parts of southern EU (i.e., Greece), where the FADN approach estimates slightly higher shares of irrigated croplands.

Regarding high-input managed croplands, we observe fairly consistent and similar shares (ranging between 75-100%) in northern France, the Netherlands, Belgium, the UK, Ireland, Denmark, and Poland. The most discrepancies are observed in the north and south, where SPAM data reports almost 100% shares of high input systems in Sweden, Finland, and Greece, and FADN reports range between 25-50%. Furthermore, in SPAM, almost no low-input croplands are reported in the EU. Nearly all EU croplands were managed as high input except for a few shares reported in Italy, Romania, and Latvia. In contrast, the FADN method reports large shares of low-input managed croplands in northern EU (i.e., parts of Finland and Sweden) and eastern EU (i.e., Hungary, Bulgaria, and Poland).

[3] In GLOBIOM harvested areas are based on FAOSTAT statistics but spatially allocated using data from the Spatial Production Allocation Model (SPAM), see You and Wood (2006).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

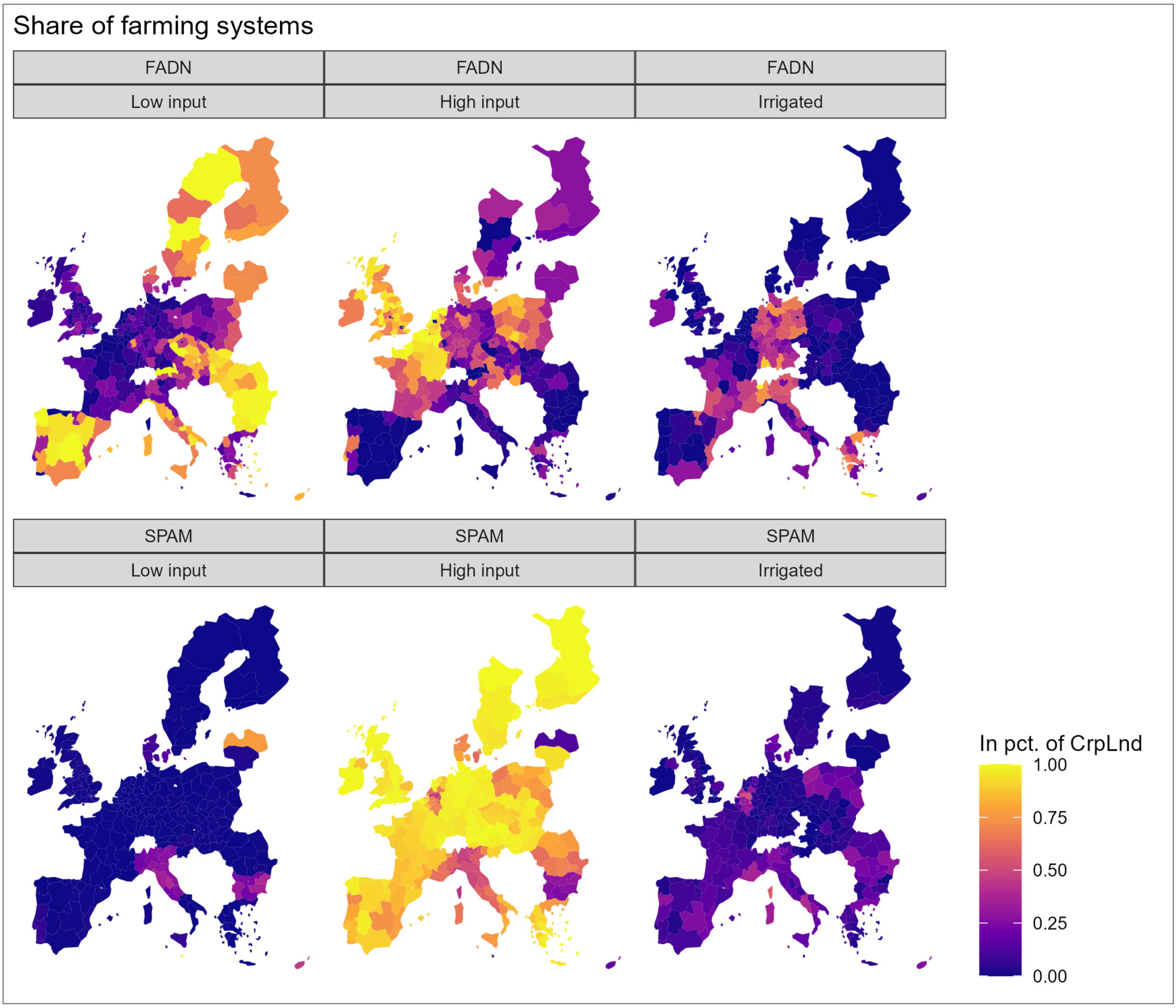


Figure 5 Cropland distribution in the EU per management system: A SPAM-FADN comparison (initial period).

Selected crop shares under different management systems across the EU

The second dimension is an extension of the share of cropland under the different management systems over selected crops. Here, we compare the percentages of cropland producing major crops under different management systems. Although over 18 crops are reported in GLOBIOM and covered in our analysis, we present results for two main crops produced in the EU to explore and illustrate this comparison due to the lack of space. We focus on two cereal crops (i.e., wheat and spelt and barley). **Figure 6** presents the GLOBIOM-FADN comparison of cropland shares for wheat and barley production in the EU per management system. The results are presented as follows:

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

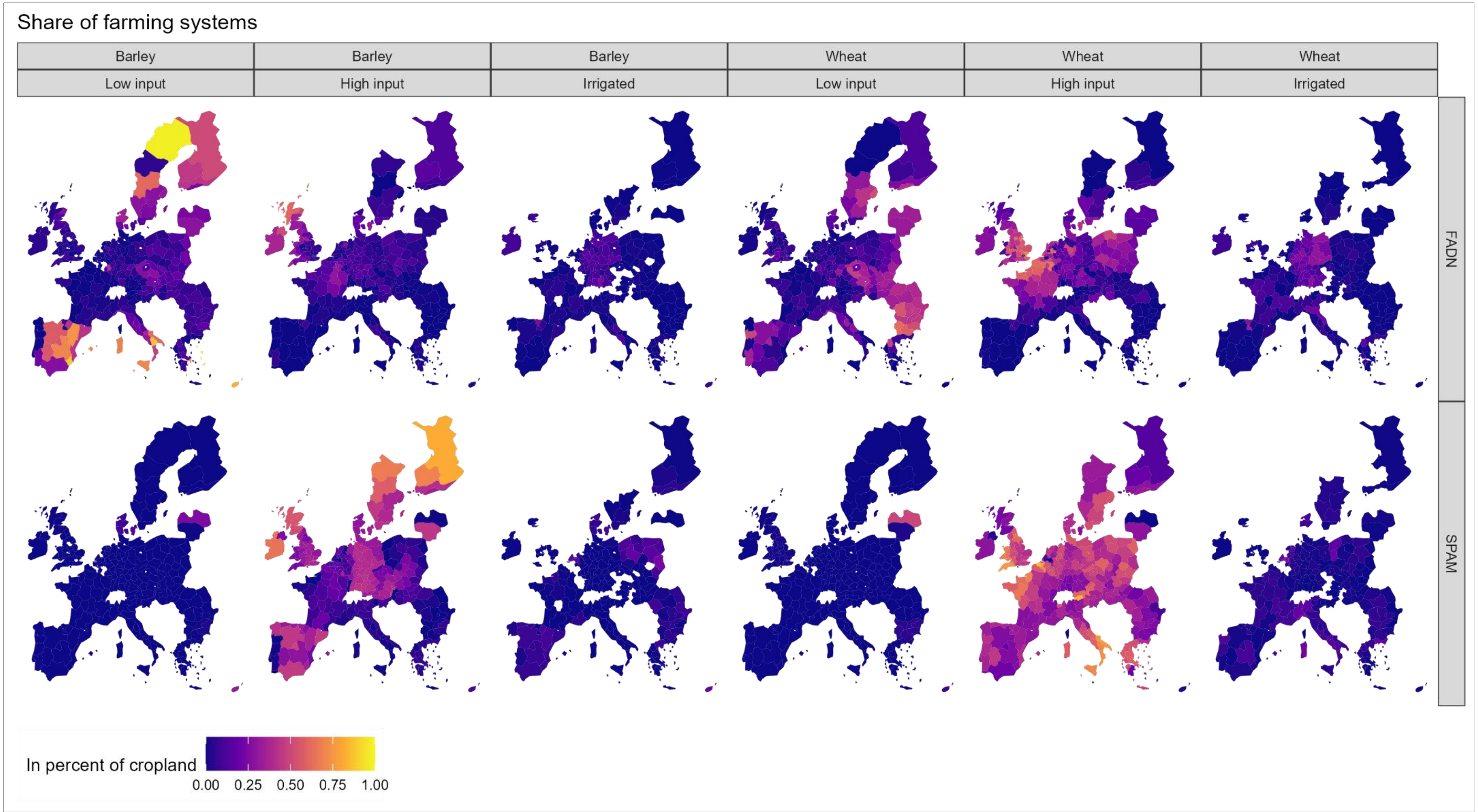


Figure 6 SPAM-FADN comparison of barley and wheat cropland shares in the EU per management system (initial period).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Wheat

Wheat is produced in almost all EU countries. As expected, the distribution of management systems is significantly different between SPAM and FADN. EU wheat production is predominately rainfed, with slight shares (under 20%) of irrigated wheat reported in parts of the EU. The majority of rainfed wheat production is largely cultivated under high-input systems. This is concentrated in the central and western EU (i.e., the UK, Ireland, France, Belgium, and Poland). We observe varying percentages of low-input systems across the EU, particularly in Eastern EU and parts of Sweden.

Barley

Similar to wheat production, there is a contradiction in the distribution of barley production systems under both approaches. However, we observe higher shares of low-input barley production in parts of northern and southern EU countries (i.e., Finland, Sweden, Spain, and Italy.). High-input barley production is concentrated in central EU and parts of northern EU (i.e., the UK and Ireland). We observe almost no irrigated barley production in the EU.

3.1.4 Concluding remarks

Understanding how farmers produce crops and how farm resources are deployed in the fields significantly impacts yields, productivity, profitability, and overall performance of farms. Large-scale sectoral and economic models (i.e., GLOBIOM) differentiate these management systems to explore the evolution of land use over time and the competitiveness of intensive and extensive production systems in terms of meeting demand in the agricultural and forestry sectors, the associated production costs differentiated by these management systems and how this translates in gross margins across space (i.e., different land uses, management, and regions).

This subsubsection discussed the typology for the novel GLOBIOM costing module FALMCO, which allows for scenarios of varying input costs in GLOBIOM. A new typology was necessary to establish the linkage of GLOBIOM costs to observed farm-level FADN data, which is used to parametrize the costing module (see the next subsubsection for details).

To accomplish this, it was necessary to ensure that crop production distribution reported in FADN can be mapped to GLOBIOM's production quantities and is comparable to them. In GLOBIOM, crop data and statistics used are obtained from FAOSTAT. Given that FAOSTAT reports country-level production without considering the management systems, the distribution of crop production and management systems applied in the GLOBIOM model was

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

taken from the IFPRI SPAM model (Wood-Sichra et al., 2016; You and Wood, 2006) for the base year, 2000.

Based on a modified version of DG-AGRI's farm intensity indicator, we estimated the management systems associated with crop production using the FADN data to stay close to the SPAM model definitions. This harmonization step would be crucial for estimating activity and management-specific production costs in the subsequent section. Although not covered in this subtask, a potential expansion could be replacing the SPAM management classification in GLOBIOM with classifications estimated here. However, ensuring consistency in applying this EU-based management classification globally will be necessary. Would it be a better reflection of global cropping production patterns? Alternatively, management shares per NUTS 2 regions could be used to update the SPAM model for the EU.

Two main features of the analysis need to be clarified as part of examining cropping systems in this subtask. First, the comparison between FADN and SPAM concerns the global version of GLOBIOM and not the GLOBIOM-EU version[4], often used in EU policy impact assessments. This choice was made because the crop systems representation in the global version is closer to the classification we wanted to develop here. Second, although the systems are labelled HI, the yields and input use are harmonized at the country level. Thus, the input use and yields would, depending on the shares in the country, correspond more to a medium or low input system, albeit the label.

The results show that farm management systems vary across the EU, with a larger share of low-input farms concentrated among northern (i.e., Sweden and Finland) and southern (i.e., Spain, France) and eastern EU member states (i.e., Romania, Bulgaria), while high-input farms are concentrated in central and western Europe. The irrigated management system is concentrated in Central Europe. Regarding the temporal dynamics of the management systems, we observe that Eastern European countries showed the most evolution in farming intensity. Most apparent is the shift in production from high-input to low-input management systems over time. A general trend observed is the increased share of irrigated farm systems over time, particularly among southern EU and Mediterranean countries. Overall, the biggest discrepancy between SPAM and FADN-based classification is among high-input systems. The

[4] The global version of GLOBIOM focuses on the major food production crops and is used in the context of global assesment. This version was used within MIND STEP to focus on global spillovers of EU policies and trade linkages. Note, that this is not the EU version of GLOBIOM which was used for policy assessments in the EU and thus includes additinal managment systems relevant for the EU (i.e., tillage practicies and crop rotations), as well as a NUTS region specific resolution.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

SPAM model reports larger shares of high-input crop production in northern EU than the FADN-based approach.

Although the FADN presents a consistent source of data on farms in the EU, a few challenges still persist with using it to categorise production systems. First, the lack of physical input use information in FADN presents challenges to quantifying input use, particularly as price shocks and other market fluctuations create problems when using input expenditures as a proxy for input use. This study used price indices to develop a pseudo input using quantity. Next, very small farms deemed uncommercial are excluded from the FADN. Although these might be a minority in the EU context, this still implies that the subsistence management system is not still represented.

3.2 Estimating costs of crop production under different management systems using FADN data for the Forestry and Agricultural Land-use and Management Costing (FALMCO) Module

3.2.1 Background

Although farm activity-specific costs are necessary for analysing agricultural policy and welfare impacts, providing technical coefficients on producers' behaviour and production technologies, and simulating agricultural supply assumptions and shocks in market models, such as GLOBIOM, MAGNET, IFMCAP, CAPRI, they are often rare, limited and in most farm survey and accounting databases (i.e., FADN). Additionally, most farm survey data report on aggregate farm-level cost expenditures rather than the activity level input use. For example, fertiliser expenditure captures expenses related to all types of fertiliser products (e.g., ammonium, potash, phosphorus) applied at the farm. Moreover, input quantities or input price information are rarely available.

Consequently, studies have often tried using a diverse array of methods to allocate aggregate production costs reported in farm surveys to specific activities performed on the farm. However, most studies in the EU focused on specific costs (i.e., crop-specific and livestock-specific costs) rather than allocating all costs, including overheads. Furthermore, most EU analyses were limited to a specific MS or region. In this subtask, we aim to use econometric models to allocate aggregate farm-level variable costs (crop-specific costs and overheads) to crop-specific activities/outputs produced at the farm across the entire EU. An end product is a database reflecting the production costs of major crops across the EU. This has three advantages. First, due to the flexibility of the models, a more comprehensive set of costs are allocated with computational ease. Second, this application covers a wider geographical area and presents cost allocation at the NUTS-2 spatial resolution. Third, temporal cost dynamics can be examined. Finally, as the estimations are based on the EU FADN, these costs can be

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

used by other market models. The current application is linked to improvements in the supply side of the GLOBIOM model.

Currently, GLOBIOM has a limited representation of detailed costs. Besides the few explicit cost categories (a general cost component, costs of land use change, trade and transport costs, and the marginals of resource constraints on land and irrigation water), production costs stem from a calibration step for the base period, 2000. Based on the assumption of perfect competition with price-taking producers, in this step, the observed market price (from FAOSTAT) is matched by all suppliers' costs via the addition/subtraction of an unobserved cost component on top of the sum of the explicit cost categories.

In principle, the relation between individual cost items and the comparative advantage of activity is straightforward. Reducing a cost item would increase the comparative advantage of the activity, depending on the share the costs represent in the total activity cost. Decomposition into individual cost items would allow us to analyse how cost components respond to trends and shocks. For example, how would the currently modelled costs react to observable trends (e.g., changes in prices of natural gas/oil/fertilisers/labour)? Therefore, implementing explicit cost items (i.e., fertiliser costs, energy, labour) with obvious links to these observed trends or policy shocks (e.g., taxes, subsidies) in GLOBIOM presents significant improvement of the model.

Explicitly relevant to the GLOBIOM modelling framework, this sub-task aims to estimate production costs associated with crop production under the management systems defined above (LI, HI, IR) at the EU NUTSII resolution using the FADN dataset. The estimated costs will replace the general cost component in GLOBIOM and are expected to reduce the size of the calibrated cost component. This has two advantages. First, for GLOBIOM to allocate the production of a specific crop to a spatial unit, data for the crop production process in the unit is necessary. As one of these required data points is the cost of production, the current approach, based on calibration to observed activity levels, does not allow the model to produce a crop in a spatial unit where this crop was not produced in the calibration period. Implementing explicit costs could overcome this lack of data. Second, improving cost representation in GLOBIOM would also improve consistency with other technologies represented through engineering bottom-up cost approaches (i.e., forestry-specific costs and technological mitigation options).

3.2.2 Methods and data

Estimating activity-specific cost applies the least squares regression technique (i.e., random-effects model). This approach has been widely used to analyse and allocate variable production costs of the agricultural sector panel and cross-sectional data sources (Cesaro et

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

al., 2013; Hallam et al., 1999; Just et al., 1990). This method estimates a functional relationship between aggregated costs (inputs) and the outputs produced at the farm level based on a system of equations.

Our econometric approach follows the work of Cesaro et al. (2013) and Hallam et al. (1999). It explores the benefit of panel data of the FADN data to control for these individual farm and year effects while applying the random effect estimation of seemingly unrelated regressions as follows:

$$x_{ikt} = \sum_{j=1}^{J} \beta_{jk} y_{ijt} + \beta_{0k} + \alpha_{ik} + \varepsilon_{ikt} \tag{1}$$

where x_{it} denotes the k-th input cost (along input cost categories $k = 1, \dots, K$) of farm i at time t. y_{ijt} is the observed j-th output (with $j = 1, \dots, J$) by farm i in time t, and β_{jk} is the corresponding unknown technical coefficient (to be estimated) and is defined as the average cost of input required to produce a unit of output. Theα_{ik} term captures unobserved farm heterogeneity and is assumed to be random. The ε_{ikt} term is statistical noise (iid Gaussian distributed with zero mean and σ_k^2 variance). The cost of production c_{jit} per unit of output y_{jit} produced by farm i in time t is calculated using a vector of farm-specific price per ton of output (p_{jit}) and yield per hectare (z_{jit}) and as:

$$c_{jit} = \beta_j p_{jit} z_{jit} \tag{2}$$

This modelling framework is easy to implement, flexible, and readily adapted to aggregate farm overheads (i.e., depreciation, energy costs) and specific costs (i.e., crop- or livestock-specific costs). Furthermore, it is simple and does not require sophisticated econometric procedures in its implementation (Surry et al., 2013). Additionally, this model can easily be applied to small regions (i.e., NUTS 2 regions) or larger ones (i.e., the entire EU region).

However, applying this approach introduces some interesting econometric features. First, given the structure of the model, each equation is composed of a dependent variable (i.e., cost component) and a set of explanatory variables. The set of regressors could be similar for all equations or unique. As Cesaro et al. (2013) noted, the simple ordinary least squares (OLS) is a suitable estimator if the regressors are the same for all equations and no correlation of the error terms persists. However, if the equations have different regressors and significant correlations between the error terms persist, then the seemingly unrelated regression (SUR) technique is preferred to the OLS (Cesaro et al., 2013).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Second, estimated technical coefficients could have implausible magnitudes, and negative signs are sometimes statistically significant (Hallam et al., 1999). The authors note that these issues could be attributed to heterogeneity among farms. Heterogeneity can originate from significant farm-to-farm variations pertaining to inputs and outputs resulting from factors related to differences in production conditions (i.e., quality of land resources) and managerial skills of farmers. Another source of heterogeneity is the yearly variations influenced by climatic and environmental conditions (i.e., rainfall patterns, droughts, and pests).

The empirical analysis applies an unbalanced panel of crop farms from the FADN database from 2007 to 2018. It focuses on the EU 27 Member States (MS) and the UK. Our utilised sample focuses on farms with crop farming as their primary production and is selected based on the EU's Type of Farm (TF14) grouping. This includes specialised cereal, oilseed, and protein crop (COP) farms (TF14= 15), other field crops (TF14= 16), mixed crop farms (TF14= 60), and mixed crop and livestock farms (TF14 = 80) (European Commission, 2008). As specialised farms use inputs differently from mixed farms, it is interesting empirically to assess if costs vary among farms.

Table 3 and **Table 4** provide an overview of the input and output variables used in the analysis. This analysis focuses on allocating crop-specific costs and farm overheads to crop outputs produced on the farm. In this respect, three crop-specific costs are considered, and 13 overheads. The crop-specific costs are seeds and seedlings, fertilisers and soil improvers, and crop protection. The overheads are broadly categorised as: i) energy costs which include motor fuels, electricity, and heating fuels; ii) maintenance and upkeep costs which capture building and machinery maintenance; iii) financial costs, including rent, interests, and taxes paid, iv) depreciation, and v) wages.

Table 3 Overview of costs.

Costs (EUR)	FADN Common Name	FADN description
Crop-specific costs		
Seeds	SE285	Seeds and plants. It relates to agricultural and horticultural crops.
Fertilisers and soil improvers	SE295	Purchased fertilisers and soil improvers (excluding those used for forests)
Crop protection	SE300	Plant protection products, traps, baits, bird scarers, anti-hail shells, frost protection, etc. (excluding those used for forests).
Farm overheads		
Energy costs		
Motor fuels	IFULS_V	Motor fuels and lubricants
Electricity	IELE_V	Electricity
Heating fuels	IHFULS_V	Heating fuels Farming overheads Value

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Maintenance and upkeep costs		
Building maintenance	IUPKPLND_V	Current upkeep of land improvements and farm buildings
Machinery maintenance	IUPKP_V	Current upkeep of machinery and equipment
Farm depreciation		
Depreciation	SE360	Depreciation of capital assets estimated at replacement value
Financial cost		
Interests paid	SE380	Interest and financial charges paid on loans
Taxes	SE390	Farm taxes and other dues (excluding VAT and the personal taxes of the holder) and taxes and other charges on land and buildings.
Agricultural insurance	IINS_V	Agricultural insurance
Rent paid	SE375	Rent paid for farmland and buildings and rental charges.
Wages		
Wages	Family Wages[5] + Paid Wages	
Family wages	(SE370/SE020) × SE015	Average wage rate * unpaid labour inputs Wage rate = (se370/se020) SE370 is wages paid to wage earners SE020 is paid labour input SE015 is the unpaid labour units
Wages paid	SE370	Wages and social security charges (and insurance) of wage earners. Amounts received by workers considered as unpaid workers (wages lower than a normal wage) are excluded.

All cost variables are directly in FADN data, either aggregated under the standard results variables (commonly referred to as SE variables) or individually denoted under the cost category of the variables. As expected, wages and social security charges, particularly relating to unpaid labour, are not captured. Wages accrued to the farm must be represented in the estimation, even if it is the farmers' own labour and thus is unpaid. To this, three proxies have been suggested. First, the paid wages recorded under SE370 could be used as a proxy for the value of unpaid labour. However, this proxy poses a significant challenge in the context of FADN as most farms are family-run and predominantly rely on unpaid family labour and thus do not report any use of hired labour. Second, net farm income can be used. However, this can yield negative values if farms report a loss and, therefore, become unsuitable as a proxy for cost. Thus, in this study, we use a yearly average wage rate at the MS level calculated using the mean per unit wage of labour. However, unpaid labour faces the same wage rate and is therefore treated as homogenous, which may not necessarily reflect reality. The calculated mean wages per MS are then multiplied by unpaid labour used to generate a proxy cost associated with family labour costs.

[5] This is proxy measure, self-calculated from the data.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Regarding the crops, we mainly focus on the major crops produced in the EU and represented in the GLOBIOM model (see **Table 4**). These are grouped into three main categories: i) cereals, ii) oilseeds and protein crops, and other crops. However, to appropriately allocate overhead costs to all farm activities and enterprises, it was necessary to include other crops produced, livestock, and farm activities.

Table 4 Overview of crops.

Crops	Short name used in figures	FADN Common name	FADN Description
Cereals			
Barley	brl	CBRL_TO	Barley Total output
Common wheat	whtc	CWHTC_TO	Common wheat and spelt Total output
Durum wheat	whtd	CWHTD_TO	Durum wheat Total output
Grain maize	mze	CMZ_TO + CCRNSWT_TO	Grain maize and corn-cob mix + Sweet corn Total output
Fodder maize	fmze	CFODMZ_TO	Green maize Total output
Rye	rye	CRYE_TO	Rye and winter cereal mixtures (maslin) Total output
Oats	oat	COAT_TO	Oats and spring cereal mixtures (mixed grain other than maslin) Total output
Rice	rice	CRICE_TO	Rice Total output
Oilseeds and protein crops			
Rapeseed	raps	CRAPE_TO	Rape and turnip rape seeds Total output
Sunflower	sfl	CSNFL_TO	Sunflower Total output
Soya	soy	CSOYA_TO	Soya Total output
Chickpea	chkp	CLNTL_TO	Chickpeas, lentils, and vetches Total output
Flax	flx	CFLAX_TO	Flax Total output Value
Field peas	pea	CPEA_TO	Field peas, beans, and sweet lupins Total output
Other crops			
Cotton	ctn	CCOTN_TO	Cotton Total output
Potato	pto	CPOT_TO	Potato Total output
Sugarcane	sgcn	CSUGCN_TO	Sugarcane Total output
Aggregated crop and livestock production necessary for the estimation of overhead costs			
Other cereals		CCEROTH_TO	Other cereals for the production of grain Total output
Vegetable and flower		SE170	Vegetables and flowers
Fruit, excluding citrus fruits		SE175	Fruit trees and berries grown in the open (including tropical fruit), excluding citrus fruit orchards and grapes.
Citrus fruit		SE180	Citrus fruit
Wine and table grape		SE185	Wine and grapes
Olive and olive oil		SE190	Olives and olive oil
Fodder crops		SE195	Forage crops (i.e., roots and brassicas, other fodder plants, meadows and permanent pastures, rough grazing, fallows).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

All other crops		SE200	Other crop output, including other arable crops (not covered by specific headings) and permanent crops grown under shelter.
Cattle meat		SE220	Beef and veal
Sheep and goat meat		SE230	Sheep and goats
Pig meat		SE225	Pigmeat
Poultry meat		SE235	Poultry meat
Cattle milk		SE216	Cows' milk and milk products
Sheep and goat milk		SE245	Ewes' and goats' milk
Poultry eggs		SE240	Eggs
Other livestock products		SE251	Other livestock and products (i.e., Meat of equines and other animals, wool, other animal products).

A final step necessary before the cost estimations is the outlier analysis, which identifies and omits observations with unrealistic values to ensure that the estimation results are unaffected or skewed by outliers and extreme and implausible data points (Bahta et al., 2011; Cesaro et al., 2013). Billor et al. (2000) presented a complete overview of the outlier algorithm applied in this study and implemented using the STATA 15 software. Additionally, crop farms with no utilised agricultural area are omitted. Third, the expenditures and total output values used in the estimations are deflated with relevant input and output price indices from Eurostat using 2010 prices.

3.2.3 Key findings

This section presents the results of production costs of major crops across the management systems defined in Section 3.1 above across the EU, focusing on crop-specific costs and selected overheads. To present the main findings succinctly, the EU is categorised into five regions based on the GLOBIOM region classification: i) Central-East (covers Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Slovenia, Slovakia), ii) Baltic (Estonia, Latvia, and Lithuania), iii) Mid-West (Austria, Belgium, Germany, France, Luxembourg, and The Netherlands), iv) North (Denmark, Finland, Ireland, Sweden, United Kingdom), and v) South (Cyprus, Greece, Italy, Malta, Portugal, and Spain).

3.2.3.1 Distribution of production cost shares across the EU regions

Figure *7* presents the average percentages of cost categories across the EU. On average, expenses for fertiliser and other soil improvers constitute the largest share of total costs (approx. 22%) among crop farms in the EU—other substantial costs are energy costs and depreciation.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

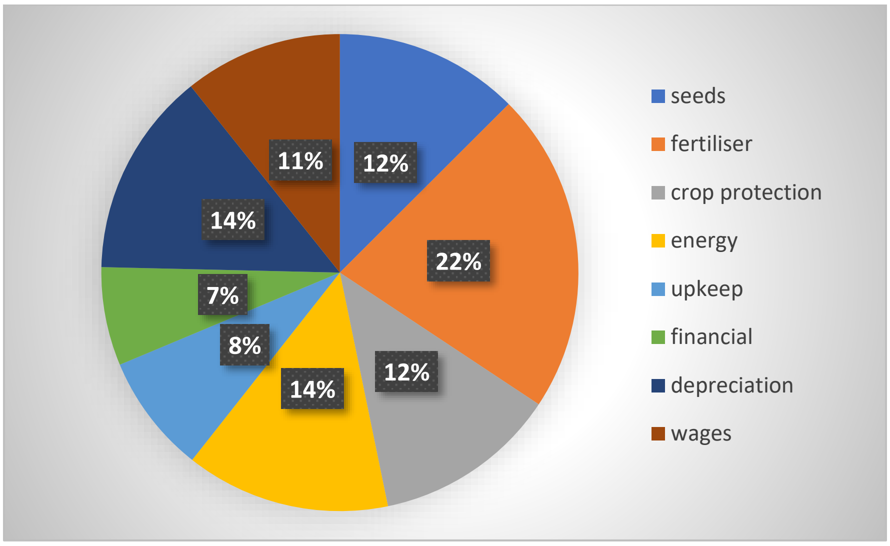


Figure 7 Average shares of production costs.

To delve deeper, we analyse the distribution of costs across the five EU regions, as presented in **Figure 8**. Results show that although the distribution differs, fertiliser costs are still substantial and dominate the cost accrued by farmers. The share was highest in the Baltic region (approximately 30%) and lowest in Central East and North EU regions (approximately 19%). The subsequent ranking differs; while depreciation costs ranked second among Baltic (21%) and Mid-West (19%), energy costs ranked second among Central East and South EU regions. In the North region, maintenance and upkeep costs ranked second to fertiliser costs.

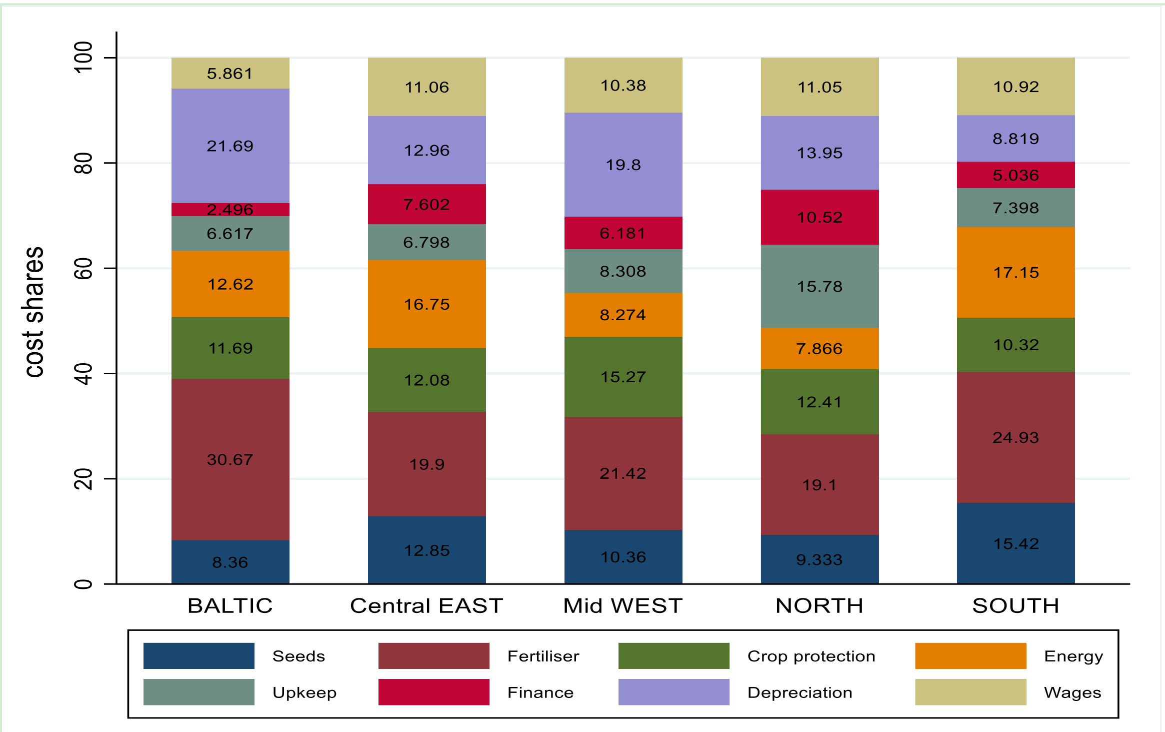


Figure 8 Distribution of costs across the five EU regions

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

3.2.3.2 Production crop costs under different management systems

An essential aspect of this study assesses the cost of crop production, reflecting the various management practices and systems. **Figure *9*** captures the difference in expenses (in €) between management across the EU regions. Results show that costs are highest among crop farms in North and Mid-West EU (i.e., total costs exceed €1000/ha).

Furthermore, across the EU regions, costs are lowest among low-input production systems. Costs among irrigated systems are highest in the Baltic, Central-East, and North EU regions. This trend is, however, not observed among Mid-West and South EU regions.

Figure *10* presents the production cost of 17 crops under diverse management systems. Sugar cane production has the highest cost, predominantly driven by depreciation and wages (exceeding over €2000/ha under all management systems, followed by flax and potato production. Although a relevant crop globally and therefore captured in the global version of the GLOBIOM model, sugarcane is not predominately cultivated in the EU, with production restricted to parts of France, Portugal, and Spain.

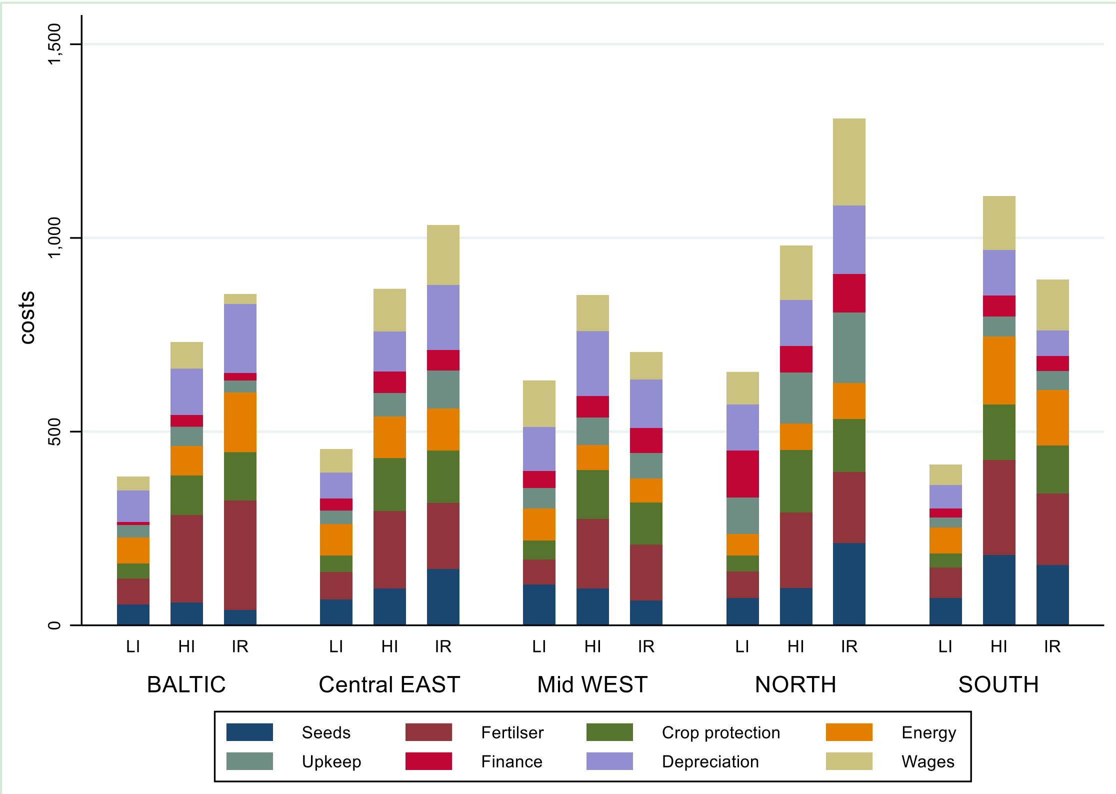


Figure 9 Capturing differences in costs (€) across the EU regions and management systems.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

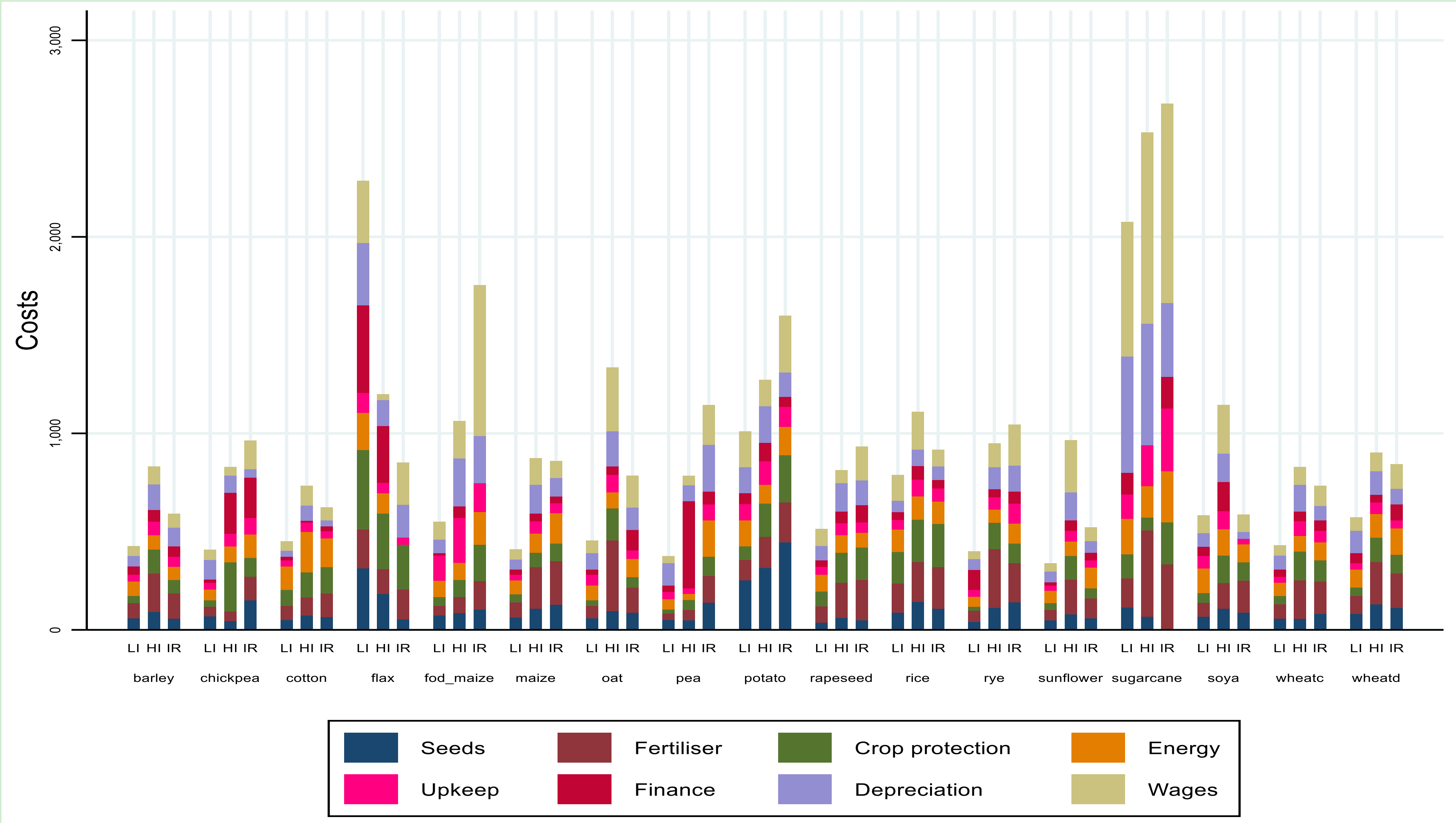


Figure 10 Costs of production across selected crops under different management systems (LI, HI, IR).

Regarding cereal production, results show that rice production costs were the largest (approx. €878/ha), driven by fertiliser and crop protection costs. This is followed by durum wheat (€846/ha) and maize production (approx. €719/ha), with fertiliser costs constituting the main driver. Oat production is the least costly (approx. €350/ha).

Regarding oilseeds and protein crops, soybeans production costs the most (€614/ha), followed by rapeseed (€487/ha) and sunflower seed production (€395/ha). Concerning industrial and other crops, chickpea (€931/ha) and cotton production (€656/ha) are the highest, driven by financial and energy costs.

Assessing the costs across management systems, results show that except for flax, low-input systems had the lowest expenses. Irrigated production systems are more expensive for most crops than high-input systems (i.e., maize, rye, rapeseeds). However, this trend is not persistent across all crops. A plausible explanation is that irrigated systems had fewer observations for most crops.

3.2.3.3 Crop yields under different management systems across the EU

Here, we study three dimensions. First, we examine the distribution of crop yields across the EU regions, presented in **Figure 11**. Results show production and yield variations across the EU. Among most crops, average yields are highest in the West EU. Lower yields are typically observed in the Baltic and Central East. Furthermore, although certain crops are produced widely across the EU, others are concentrated. For example, although common wheat and maize production are widespread across the EU, crops such as rice and sunflower seeds are concentrated in Central East, South, and parts of Mid-West EU regions.

Moreover, the distribution of yields in **Figure 11** shows that while some crops are dense around the mean, most crops (such as rice, barley, and maize) are sparsely distributed across the regions. Interestingly, most crop yields in the Mid-West are densely distributed, while the Baltic and Central East distribution is largely sparse.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Figure 11 Distribution of crop yields across the EU regions based on the FADN sample.

Second, we compare the average yields based on our FADN sample and Eurostat. The results in **Figure 12** compare the yields of: i) cereals (i.e., barley, common wheat, maize, rye, oat, rice and durum wheat), ii) oilseeds and protein crops (i.e., rapeseeds, sunflower, soya beans and peas) and iii) root crops (i.e., potatoes and sugar beet). We observe a positive correlation between Eurostat and FADN yields for all crops. The positive relationship is strongest among oilseed and protein crops, with very few extreme values for pea and sunflower production. Although the yields for cereal crops are generally consistent, we still observe some discrepancies among maize, rye and rice crops, where FADN yields are more than Eurostat yields. Potato yields are largely consistent, while sugar beet yields show more discrepancies.

Lastly, we examine the relationship between yields and total costs across the different management systems. **Error! Reference source not found.** presents the resulting curve calculated as the prediction for crop-specific yield from a linear regression of the yields on crop-specific total costs under diferentmanagement systems. The results show a positive correlation between costs and yields among all crops, capturing the marginal physical product. As expected, the marginal physical product of total costs increases until a point where an additional unit of total input cost spent results in decreasing yields, exhibiting a diminishing marginal product.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

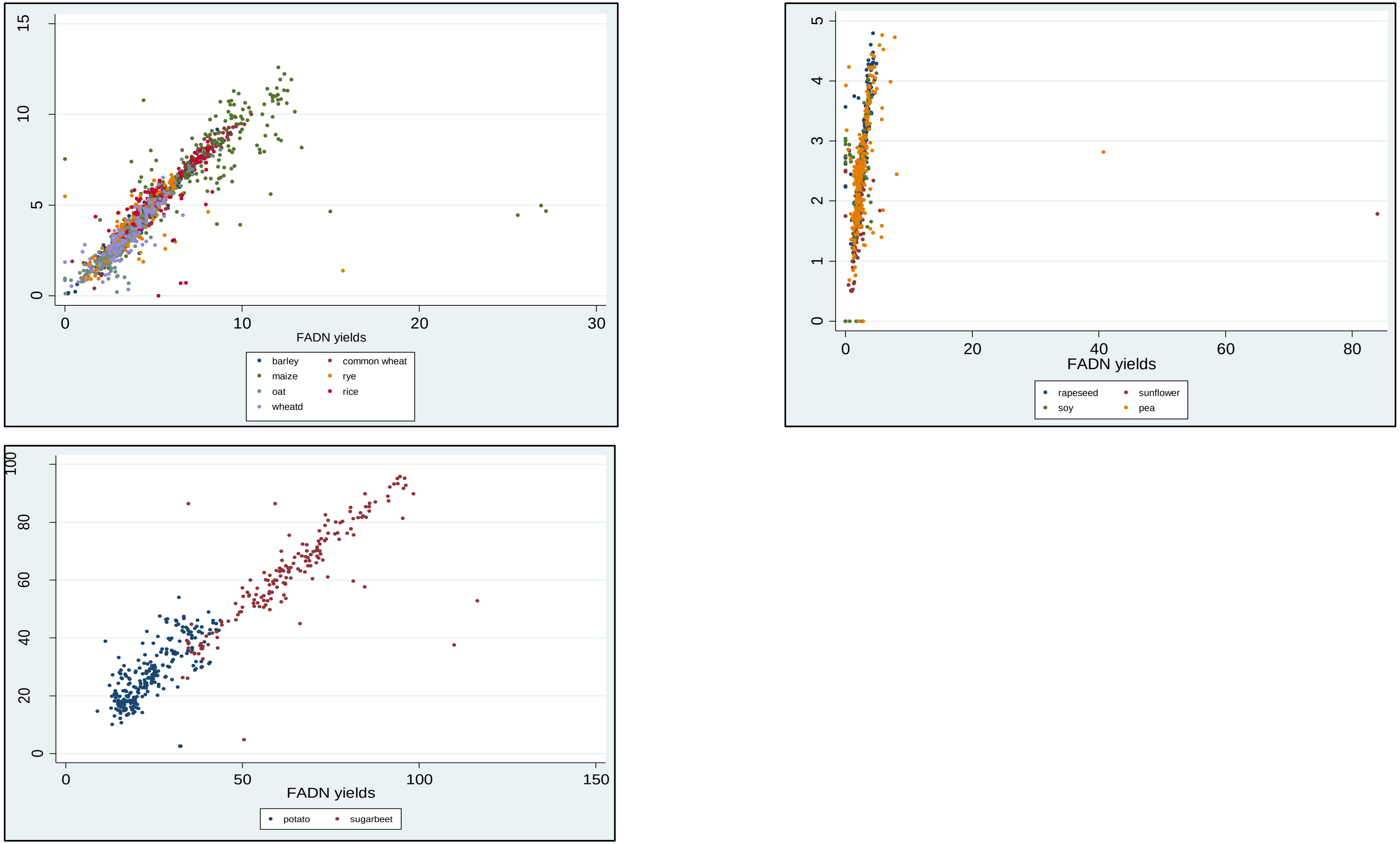
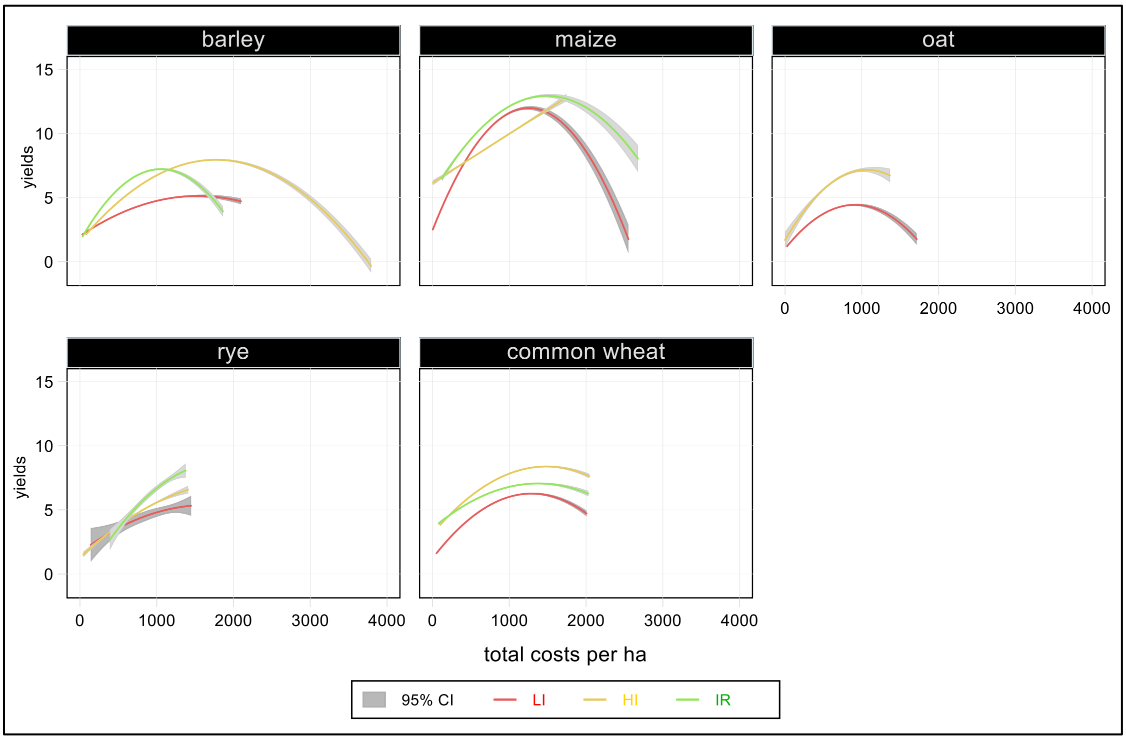


Figure 12 Comparing Eurostat and FADN crop yields across the EU regions.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.



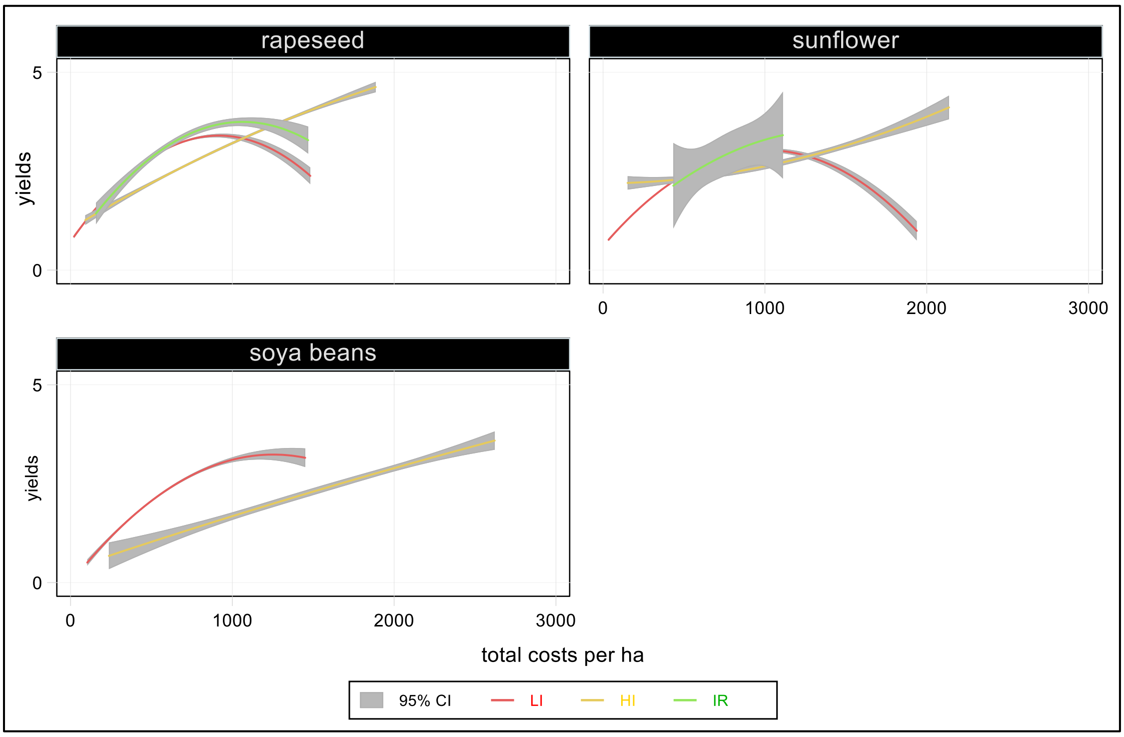


Figure 13 Cost and output dynamics across management systems of cereal and oilseeds crops

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

3.2.4 Concluding remarks

This section estimates and disaggregates farm-level costs among crops produced on the farm. This analysis primarily focuses on providing estimates that improve the heterogeneity of crop production systems in GLOBIOM. To accomplish this, we apply econometric techniques using FADN farm-level data on specialised COP, field crop, mixed crop, and mixed livestock and crop farms to capture varying input uses and reflect the management systems captured in Section 3.1 above.

The results show that although the distribution of costs differs across the EU regions, fertiliser costs are still substantial and form the lion's share of costs. Second, the production costs are highest in the North EU region, with the irrigated systems having the highest costs. Moreover, cereals such as rice, durum wheat, and maize have the highest production costs, primarily driven by fertiliser expenditure.

Lastly, results show a positive correlation between crop yields and total costs. This implies that an increase in input use and, thus, costs results in a proportionate higher yield. However, for most crops, results show an inverted U-shaped graph. This result suggests that the benefit of increasing input use (production costs) decreases once the optimal crop yield is achieved. At this point, an additional increase in input use does not improve yields and, in some cases, results in lower yields (i.e., maize, barley).

3.3 Validation of production costs using national datasets

To validate the results of the estimated costs, we compile open-source benchmark data on the cost components of crop production (e.g., wheat, maize, barley). The validation data for production cost components have been compiled for four EU countries: Austria, the Czech Republic, Germany, and Spain. The temporal dimension, crop activities, cost compositions, and spatial coverage differ. **Figure *14*** describes the validation data.

It is important to note that the bottom-up nature of the data for Austria and Germany (profit loss calculator dataset) supplies valuable information on prices and quantities to implement bottom-up costs.

3.3.1 Austria

This data is based on a webpage calculator developed by “*Bundesanstalt für Agrarwirtschaft und Bergbauernfragen*” - BAB (abbreviation in German), which translates to Federal Institute of Agricultural Economics. It is an economic and social science research institute under the Austrian Federal Ministry of Agriculture, Forestry, Environment, and Water Management

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

(BMLFUW). The production data is available as single national data points (no time series) as 5-year averages (2015-2019 or 2016-2020, depending on activity). The calculation is based on prices and quantities (bottom-up).
The GLOBIOM crop production activities represented in the BAB data include wheat, durum wheat, corn, soya, sugar beets, sunflower, rye, rapeseed, potatoes, barley, oats, and peas. Although not processed, online production activities include organic options for the mentioned crops, silage corn, wine, and livestock. The dataset represents variable crop-specific costs, e.g., fertiliser, seeds, and crop protection. Other variable costs included in the database are drying, cleaning, machinery, and other costs.

Validation data description

country	regions	activities	cost components	time
AUT (BAB)	• **NUTS-0 / national granularity**	• **GLOBIOM crops processed:** Barl, Corn, Dwht, Oats, Peas, Pota, Rape, Rye, Soya, SugB, Sunf, Whea • **Further crops:** various available online (incl. organic options, CSil, wine, …) • **Livestock** available online	• **var cost fertilizer** • **var cost seed** • **var cost plant protection** • **various others, e.g.:** •var cost drying •var cost cleaning •var cost machinery •var cost other	• **single 5-year-average data points** • **averages for 2015-2019 or 2016-2020 (dependent on activity)**
CZE (UZEI)	• **NUTS-0 / national granularity** • additionally crop zones: •corn and sugar beets •potato •potato, oats, and mountains	• **GLOBIOM crops processed:** Barl (spring & winter), Corn, CSil, Flax, Oats, Peas, Pota, Rape, Rye, SugB, Sunf, Trit, Whea (spring & winter) • **Further crops:** various available & processed (e.g., hops, fruits like apples) • **Livestock** available & processed	• **fertilizers (own & purchased)** • **plant protection products** • **seeds (own & purchased)** • **various others, e.g.:** •administrative overhead •depreciations •others direct material •wage & personnel	• **annual data** • **2002 to 2015**
ESP (JRC)	• **NUTS-2 (ES24, -41, -42, -43, -51, -61)**	• **GLOBIOM crops processed:** Barl, Corn, Dwht, Oats, Pota, Rape, Rye, SugB, Sunf, Whea	• **var cost fertilizer** • **var cost plant protection** • **var cost seed** • **var cost other**	• **annual data** • **2010 and 2016**
GER (KTBL)	• **NUTS-0 / national granularity** • **NUTS-2**	• **GLOBIOM crops processed:** Barl, Corn, CSil, Fallow, Flax, Oats, Pota, Rape, Rye, Soya, SugB, Sunf , Whea • **Further crops:** various available & processed (e.g.: hops, tobacco, and aggregates ("other cereals", …))	• **var costs fertilizers** • **var costs pesticides** • **var costs seeds and planting stock** • **var costs others**	• **seasonal data** • **2000/01 to 2019/20**

Figure 14 Summarizing the validation data

3.3.2 Czech Republic

The costs of production are calculated by the ÚZEI (abbreviation in Czech of "*Ústav zemědělské ekonomiky a informací*," which translates to the Institute of Agricultural Economics and Information) (IAEI, 2018). The annual data is based on surveys and includes crop and livestock production costs. It is available as national averages for "crop zones" (corn and sugar beets zone, potato zone, potato, oats, and mountains zone) from 2002 through 2015.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

The cost components included in the dataset are fertiliser (owned and purchased), plant protection, seeds (owned and purchased), and various other costs (e.g., administrative overhead, depreciations, other direct material, wage and personnel). This data represents the following GLOBIOM crops: corn, flax, oats, peas, potatoes, rapeseed, rye, silage corn, barley (spring and winter), wheat (spring and winter), sugar beets, sunflower, triticale. Further activities in the dataset include hops, livestock, and fruits.

3.3.3 Germany

The validation dataset for Germany is provided by the KTBL (abbreviation in German of "*Kuratorium für Technik und Bauwesen in der Landwirtschaft*," which is translated to Curatorship for Technology and Engineering in Agriculture). This institute is supported by the German Federal Ministry of Food and Agriculture (BMEL). Two datasets are available. First is the **profit and loss calculation dataset** based on a bottom-up online calculator. This captures various production parameters (e.g., field size), which can be specified to generate different cost data points. The second is the **standard gross margin dataset**.

The latter dataset is used for validation, is regionally available for NUTS-2 regions (changes in NUTS-2 borders over time must be considered), and covers seasons 2000/2001 through 2019/2020. Cost components included in this dataset are fertilizer costs, pesticide costs, costs of planting stock and seeds, and other variable costs. Crops represented in GLOBIOM are barley, corn, wheat, fallow land, flax, silage corn, oats, potatoes, rapeseed, rye, soya, sugar beets, and sunflowers. The dataset also includes other crops (e.g., hops and tobacco) and aggregates (e.g., other cereals, protein crops).

3.3.4 Spain

Validation data for Spain are based on publications by the MAPA (abbreviation in Spanish for "Ministerio de Agricultura, Pesca y Alimentación," which translates to Spanish Ministry of Agriculture, Fisheries and Food) (MAGRAMA, 2013; MAPA, 2020). The data are available at the NUTS-2 level for the years 2010 and 2016. Represented cost components include seeds, fertilizers, plant protection, machinery (contract work, fuel, and lubricants, maintenance), human labour, and others. Crops represented in GLOBIOM are Barley (irrigated and rainfed), common and durum wheat (irrigated and rainfed), maize (irrigated), oats (rainfed), potatoes (irrigated), rape seed (irrigated and rainfed), rye (irrigated and rainfed), sugar beets (irrigated), and sunflowers (irrigated and rainfed).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

3.3.5 Key Findings

This section presents the results of the estimated costs (in Section 3.2) cross-validated with the benchmark data from Austria, the Czech Republic, and Germany. One of the main challenges of cross-validation is the consistency of the costs. As described in **Figure *15*** above, the different sources of validation data calculated the various production costs differently. Given this, we focus the cross-validation analysis on crop-specific expenses (i.e., seeds, fertilizers, and crop protection).

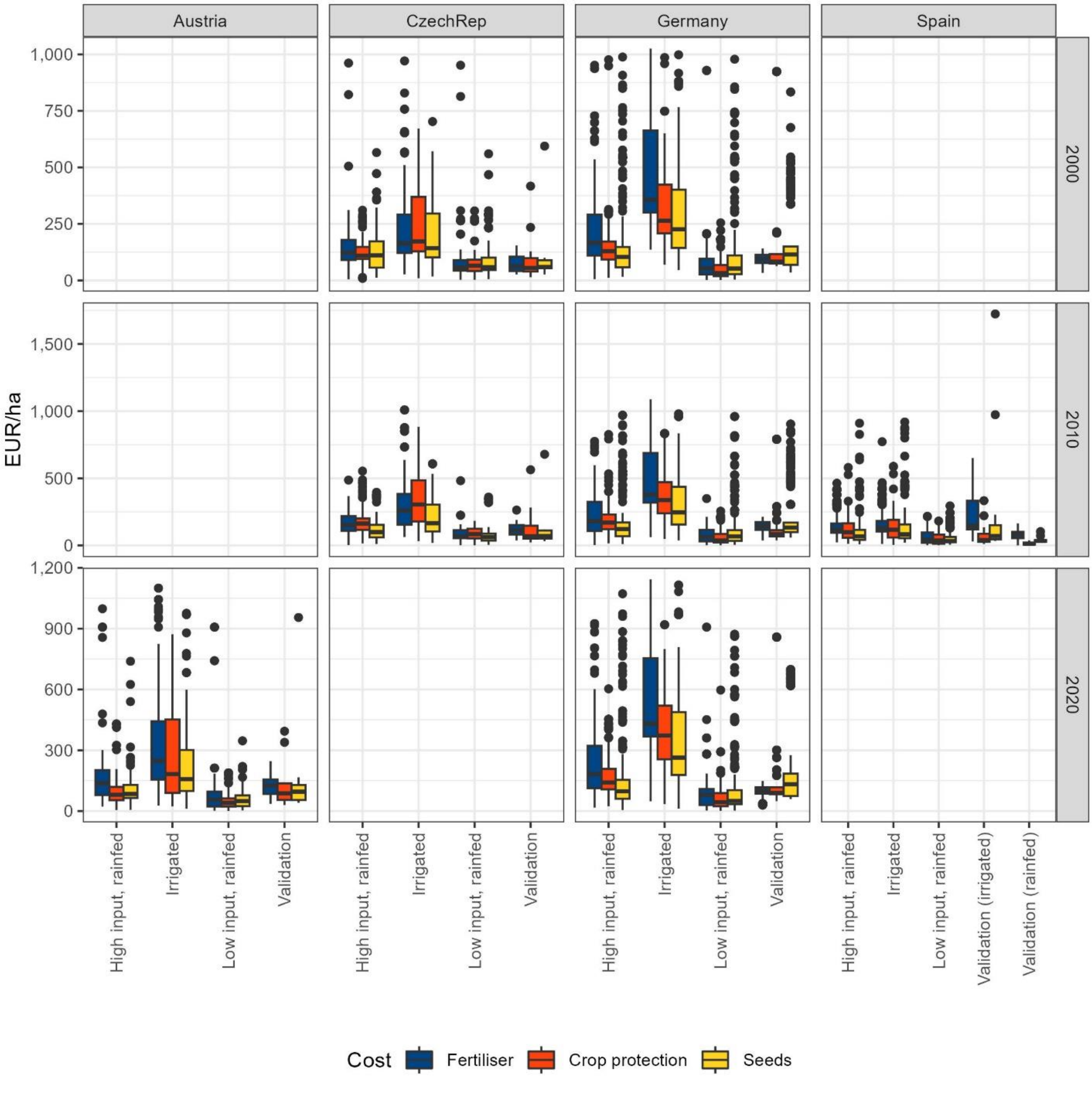


Figure 15 Comparison of estimated costs with validated data across all crops. *The validation data is based on 5-year averages.*

Figure *15* summarises the validation of the estimated cost data. The x-axis contains the estimates of costs in the categories of fertilizers, crop protection, and seeding costs. Moreover, the validation datasets are also depicted. For Austria, the Czech Republic, and Germany, only an overall validation dataset is available, while for Spain, detailed validation data on irrigated and rainfed crop management is available. Overall, the plot confirms that the cost estimates align with bottom-up datasets, especially for rainfed crop costs. This is not entirely surprising, as the irrigated costs have an explicit markup, as outlined in the cost estimation method in the previous subsections.

3.4 Parametrization of the macro-level model GLOBIOM with validated cost estimates

This section describes the GLOBIOM parameters to be updated, indicating the mapping to GLOBIOM of estimates and preliminary results (including stylized graphics). The GLOBIOM version to be used is a new EU light version. It is based on the global TRUNK version but differs from it in two points: First, the **demand side** is more granular. Instead of 5 EU regions, all 27 EU Member States (MSs) are represented individually. Second, **trade** is explicit between MS and countries outside the EU.

3.4.1 How do cost estimates from Section 3.2 enter GLOBIOM?

Cost estimates for each crop activity are estimated per NUTS 2 region (based on the 2016 Eurostat NUTS-2 classification). The global version of GLOBIOM used in this report is run on a resolution of a grid of 2-degree pixels (roughly 200 by 200km at the equator). To map the NUTS-2 level costing database to the 2-degree grid, an area-weighted mapping was developed based on the 1:1 million shapefile of NUTS-2 regions available from Eurostat.

Given that FADN is a sampled dataset of farms, there are regions where no observations on GLOBIOM crops are present, even though theoretically, production would be possible. This is because production in these regions is relatively small, with few observations and no farms producing these crops were included in the sample. Alternatively, the current production in these regions is low but could be expected to increase in the future (due to market dynamics or the effects of climate change on crop yields).

When using the cost data in GLOBIOM, it is crucial to have broader coverage than is strictly observed from the sample. In the initial econometrically estimated costing database, 38.45% of cost data specific to GLOBIOM grid cells, crops, management systems and activity dimensions are missing. To have 100% coverage, the following rules were used:

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

1. As an initial step, if observations were missing for a specific grid cell, crop, management system and cost type combination, these were replaced by the respective average values of non-missing observations within the same country. After this step, 20.68% cost estimates remain missing.
2. The remaining missing values for specific crop, management system and cost type combinations are replaced by EU averages of the same crop, management system and cost type. After this step, 2.21% remain missing.
3. If no exact match of crop, management system and cost type is found in the same country, the average across all management systems within a country is inputted for the same crop and cost type combinations. After this step, 1.68% of estimated data points remain missing.
4. For the remaining missing data, the average across crops (while keeping the management system and cost type dimensions) is inputted within the same country. The percentage of missing observations is reduced to 1.47%.
5. As a next step, the average of all crops across the EU is taken (while keeping the management system and cost type dimensions). This results in 0.86% of observations remaining missing.
6. For the last remaining cost components, an average across countries, management systems and crops is inputted. There are no more missing data after this step.

Additionally, four crops observed in the FADN data are mapped to five unobserved crops present in GLOBIOM to approximate cost estimates for the unobserved crops.[6] The mapping is based on general similarities of the crops.

3.4.2 Cost dynamics

The estimated costs in Section 3.2 are reported in EUR_{2010}, while GLOBIOM uses USD2000 as currency. Hence, the FADN-based estimates are converted and deflated to USD_{2000}. The average annual EUR/USD exchange rate for the year 2000 is used for the conversion. The European Central Bank estimates this average exchange rate of 0.924 USD/EUR. A general price index provided by Eurostat between 2010 and 2000 is used to deflate the cost estimates, with a deflation factor of 0.817.

FADN data is available annually from 2007 through 2018. This overlaps only with one of the decadal GLOBIOM periods (2010). Other historical GLOBIOM periods (2000 and 2020) and future periods (2030, 2040, and 2050) lie outside the temporal range of FADN data.

[6] chickpeas → dried beans; corn → sorghum, millet; peas → groundnuts; potatoes → sweet potatoes

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

In GLOBIOM, using estimates from a single year could create confounding effects, especially in cases where the estimates are affected by single-effect shocks related to that single year. To reduce this risk, an average of cost estimates based on a symmetric time frame around 2010 is used to smoothen the parameters (2010 +/- 2 years, i.e., 2008-2012). For other historical (2000 and 2020) and future GLOBIOM periods (2030, 2040, …), shifted 2010 cost parameters are used. In GLOBIOM, conventionally, costs are shifted between periods using yield growth data, leading to growth paths for costs. The shifting applied to the cost estimates uses these growth paths together with the cost parameters for 2010 as a base to extrapolate cost parameters for all other periods. Deviating from these cost growth paths offers options for scenario analyses.

3.4.3 Proof of concept

After implementing the cost estimates in GLOBIOM, the resulting additional granularity of cost modelling is used to simulate an exemplary policy scenario where a single cost component is shocked. Specifically, the cost of nitrogen fertilizer is increased homogeneously in all EU-27 Member States to simulate a hypothetical policy to reduce this input via taxation. When comparing this policy scenario with a business-as-usual baseline scenario, the difference between the scenarios reveals the impact of the policy intervention, i.e., the tax on nitrogen fertilizer. The exemplary policy simulation uses a shock in the form of a tax of 132% on the cost of nitrogen fertilizer that is applied from 2020 onwards[7] to all cropping activities in all management systems and agro-ecological zones throughout the EU. This shock corresponds to a hypothetical emission price of 200 EUR/tCO_2eq on the emissions from the production and application of nitrogen fertilizer. In this exemplary scenario, the money raised by the newly introduced tax is assumed not to re-enter the modelled sectors.

The evaluation, as a comparison of the baseline and policy scenarios, is based on the GLOBIOM simulation for 2030. It shows that, due to the policy, the input quantity of nitrogen fertilizer decreases on average by 28% EU-wide (see **Figure 16**). This corresponds to an average reduction of surplus nitrogen (i.e., inputs less withdrawals from the soil) of 25% EU-wide (see **Figure 17**).

The policy impacts the profitability of European agricultural production. Member States compete with non-EU producers that are not affected by the hypothetical tax. This becomes apparent when looking at changes in the use of cropland in the EU and elsewhere (see **Figure 18**). EU use of cropland shrinks by 25.6 million ha compared to the baseline in 2030. At the

[7] GLOBIOM simulates annual equilibria every ten years, starting in 2000.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

same time, cropland use outside the EU increased by 10.3 million ha, stepping in for lost European capacities but not fully compensating them. A closer look at changes in cropland use per Member State reveals that in absolute terms, Spain, Italy, and Poland are impacted most by the tax, as they each use over 3.5 million ha cropland less (see **Figure 19**).

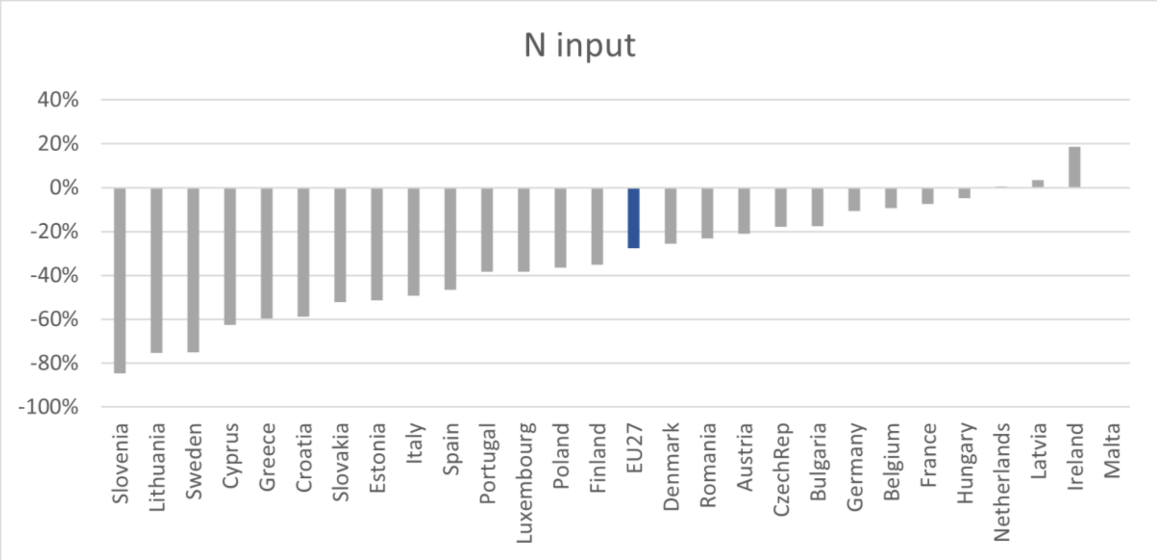


Figure 16 Change of nitrogen fertilizer use in the policy scenario compared to the baseline in 2030. *(Note: results for Malta are not meaningful.)*

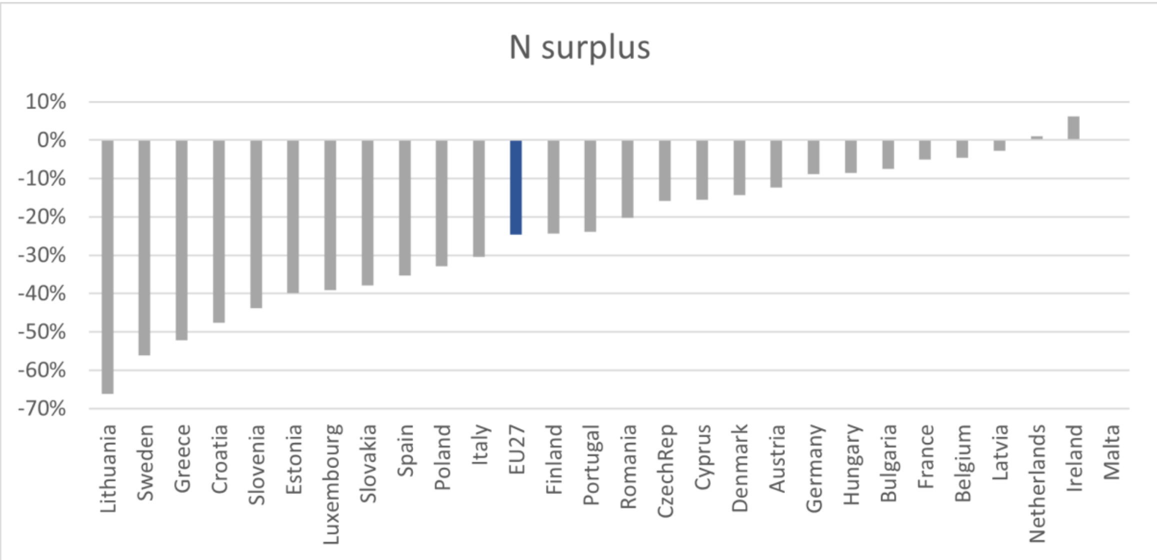


Figure 17 Change of nitrogen fertilizer surplus in the policy scenario compared to the baseline in 2030. *(Note: results for Malta are not meaningful.)*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

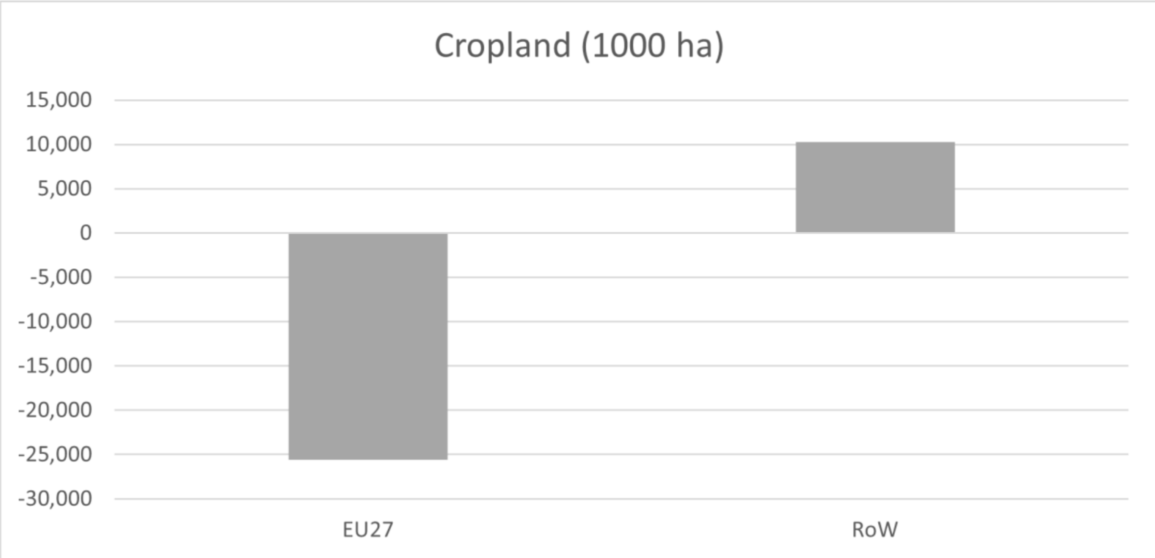


Figure 18 Change in cropland in the policy scenario compared to the baseline in the EU and the rest of the World (RoW) in 2030.

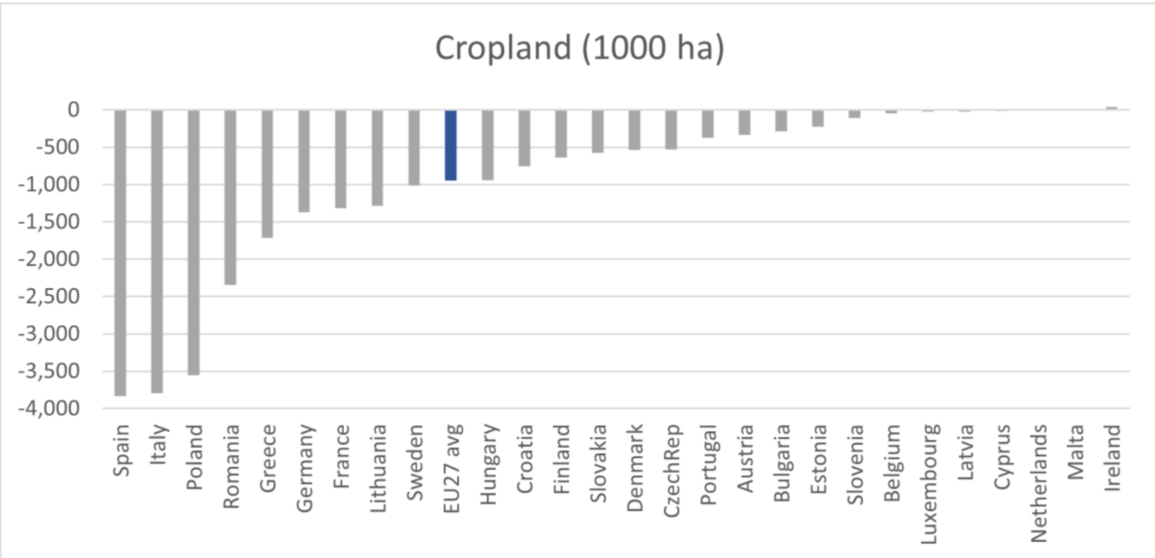


Figure 19 Change in cropland per Member State in the policy scenario compared to the baseline in 2030.

3.5 Improved livestock sector classification for the macro-level model MAGNET

Splitting animal herds from the capital and estimating the substitutability of animal herds against other primary factors of production is, in principle, possible using the FADN database. This requires two distinct work steps. First, to derive the share of animal herds in total farm assets at the national level, such that the types of considered animal herds are consistent with

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

the definition of agricultural activities in the MAGNET models. Second, to devise an estimation procedure that identifies the needed substitution elasticities, again consistent with the definitions and factor combinations used in MAGNET.

3.5.1 Agricultural primary factors in the MAGNET model

Like many other global Computable General Equilibrium (CGE) models, the MAGNET model is built on the GTAP database. In principle, each country's database is structured as a commodity-by-commodity Input-Output Table (IOT). Productive sectors in GTAP distinguish between the production activities with their input requirements and the associated commodity outputs. Due to the commodity-by-commodity structure of the underlying IOTs, activities are defined by their commodity outputs, so that, e.g., the commodity raw milk is produced by a raw milk activity. A conceptual problem arises due to the fact that some primary factors available at the farm level may not be strictly attributable to a specific production activity, e.g., a cow herd can produce animals for fattening as well as for milk production. Hence, allocating factors to activities requires calculating the portion of the fixed, in principle, the non-allocatable asset needed by the respective outputs.

The primary factors used by the agricultural activities in the GTAP databases are listed in **Table 5**. Labour is split into skilled and unskilled, while capital distinguishes land and other physical capital. In the GTAP default aggregation, the three animal production activities that rely on standing herds as the main factor of production are “Bovine cattle, sheep and goats, horses,” “Animal products n.e.c,” and “Raw milk” production. Alternative aggregation levels are possible, provided that the data is available.

Table 5 Agricultural activities and primary factor shares in GTAP.

		Labour		Capital	
		Non-skilled	Skilled	Other	Land
Paddy rice	PDR	0.32	0.10	0.22	0.36
Wheat	WHT	0.39	0.10	0.25	0.25
Cereal grains nec	GRO	0.38	0.09	0.24	0.29
Vegetables, fruit, nuts	V_F	0.41	0.10	0.26	0.24
Oil seeds	OSD	0.38	0.10	0.25	0.27
Sugar cane, sugar beet	C_B	0.35	0.09	0.24	0.31
Plant-based fibres	PFB	0.27	0.04	0.22	0.48

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

Crops nec	OCR	0.35	0.12	0.27	0.26
Bovine cattle, sheep and goats, horses	CTL	0.33	0.12	0.35	0.20
Animal products nec	OAP	0.38	0.10	0.52	0.00
Raw milk	RMK	0.37	0.13	0.28	0.22

3.5.2 Capital assets and animal herds in FADN

The farm accountancy data network (FADN) monitors farms' income and business activities. It is also an important informative source for understanding the impact of the measures taken under the common agricultural policy. It is currently the only source of microeconomic data based on harmonized bookkeeping principles. It is based on national surveys and only covers EU agricultural holdings, which can be considered commercial due to their size.

FADN includes a range of indicators related to farm-level assets. The first group, total assets, measures fixed and current assets at their closing value, as shown in **Figure *20***.

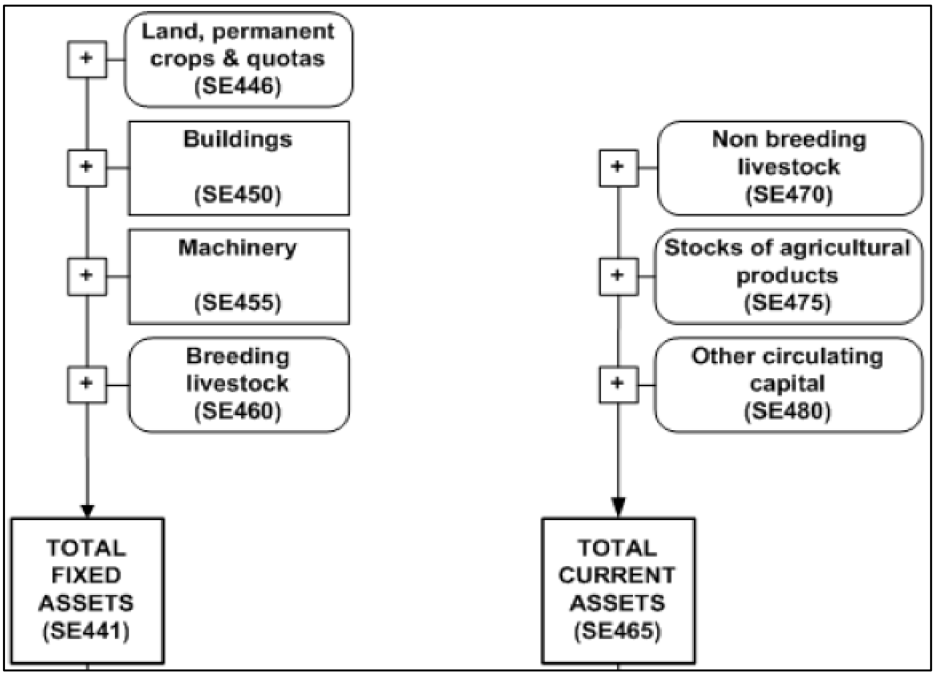


Figure 20 Components of fixed and current assets in FADN.

Alternatively, the farm endowments are expressed as average farm capital, measuring the averages of opening and closing values for each reporting period for the elements shown in **Figure *21***. As defined in Figure 16, farm capital also includes several items not included in total assets, such as cash and equivalents. The question, which of the two categories, total assets or average farm capital, should be used as a proxy for the primary factor shares required by

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

the MAGNET database, should be answered by comparing the accounting principles of FADN with those of the System of National Accounts (SNA), on which the GTAP IOTs are based. However, a pragmatic consideration is that the MIND STEP project has applied for all variables within the asset category and not for all variables in the average farm capital category. So, for pragmatic reasons and because FADN assets seem closer to the MAGNET database, the asset category will be used.

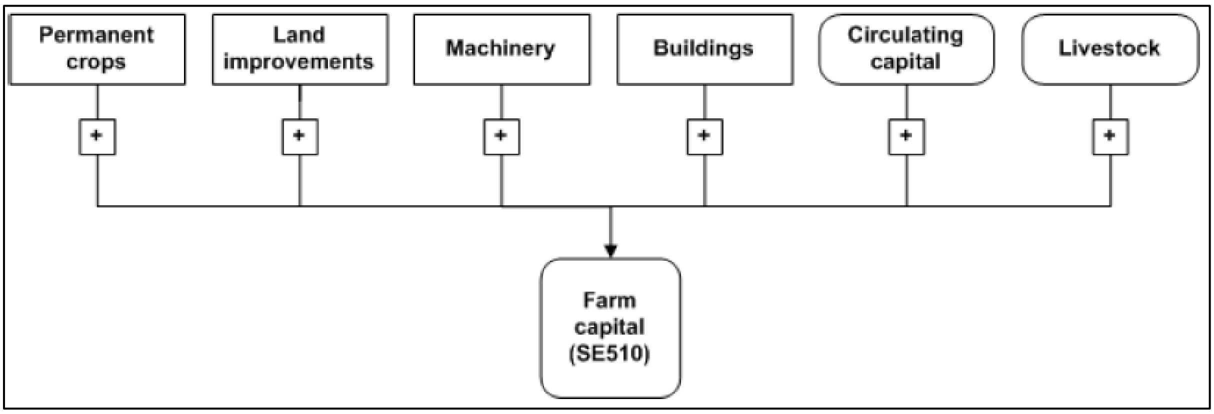


Figure 21 Components of farm capital in FADN.

3.5.3 Data Manipulation – splitting SAM

The SAM is the basis of the macroeconomic model and accounts for the total value of economic activities for the full economy for all the countries in the database and at the global level. Introducing Breeding Livestock as an input of production implies adapting the original SAM to account for this new element, splitting it from an existing one. Therefore, a new accounting line is introduced in the SAM to introduce the breeding livestock. The procedure to assign economic value to this account starts by collecting FarmDyn data on the associated value added at the sector level for all the targeted livestock sectors (Cows, Pigs, Milk, and other Cattle).

In particular, the following data is useful to operationalize the herds split from MAGNET:

- Shares of livestock in total capital stock and shares of sector-specific livestock from total livestock, ideally per each of the EU countries.
- Data on subsidies or taxes on herds capital assets -if available or comparable
- Depreciation rates – do we use one common depreciation rate like in GTAP (0.04) for all capital, or do we distinguish for the type of livestock asset – e.g., swine vs. cow?
- Substitution elasticity between herds capital and other production function
- Price and quantities of Livestock endowment

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

To maintain consistency with the remaining national accounts, using the share of livestock in total assets obtained by FADN was sufficient to carry out the SAM disaggregation. Nevertheless, other variables, such as the depreciation rates from FADN, were compared with depreciation rates in MAGNET to assess the consistency.

These values are calculated for each FADN farm type and then mapped to MAGNET sectors as described in **Table 6**. Then, the share of livestock is extracted from total capital assets, excluding the non-breeding livestock from livestock assets at the specialized farm level. Furthermore, the shares of livestock assets have to be calculated, excluding land from total assets, to be consistent with the capital stock in MAGNET.

Table 6 Agricultural activities and primary factor shares in GTAP.

MAGNET name	MAGNET code\	TF14 Code	TF14 Name
Raw milk	RMK	45	Specialist milk
Other cattle	othctl	48	Specialist sheep and goats
Beef cattle	bfctl	49	Specialist cattle
Pigs	pigpls	50	Specialist granivores (but without poultry!)

Even though GTAP provides sector values for capital income, it only provides regional capital stock. Sector capital stock is derived from data manipulation using proportional shares of capital income. These values are used to redirect the proper amount to the breeding livestock account. In particular, splits are necessary for the activities, endowment, and investment accounts. Concerning the activities section, it is essential to split the rows in the activities column (and endowment row) corresponding to capital and livestock payments from each activity and the related factor input taxes (or subsidies) from the employment of capital and livestock. For the endowment section, the sum of livestock factor payments from each activity must be distributed to livestock capital income, income taxes paid over capital income from livestock, and depreciation. Finally, another consideration must be made on the side of investment demand. Gross Capital Formation (investments) in the four livestock types must also be linked to the investment demand of those sectors that produce them. Knowing if the livestock is produced at home or purchased from abroad would be useful. The list of the new livestock accounts in the SAM is reported in **Table 7**.

Table 7 New breeding livestock accounts and relative accounting section.

Account Section	Adapted Variable

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Activities Column	Input Value Added, Taxation on Firm Endowment use
Endowment Colum	Regional Household Revenue (dependent on endowments), Total taxation, Total Investment account
Investment column	Import and domestic value of livestock sectors, taxation of imported and domestic livestock sectors

3.5.4 Modifications of the MAGNET model to account for livestock endowment

The procedure adopted to explicitly represent breeding livestock as a factor of production improves the pre-existing structure, assuming undifferentiated general capital as one of the factors of production. In detail, the new production structure of the relevant livestock (row milk, cattle, pigs, and other livestock) sectors is reported in **Figure *22***. Several assumptions were made about the behaviour of the new endowment. First, herd capital stock has been assumed to be sector-specific, as it is impossible to exchange one breeding livestock for another (i.e., cattle cannot be used for production in the goat sector). This implies that the livestock market is sector-specific and livestock price differs across the sectors. This is a deviation from the other capital markets where capital is mobile and allows reallocation across the sectors.

Furthermore, the new production input “lvcp” is introduced in the production structure at the same level as the other basic inputs (e.g., capital, labour, natural resources), and the elasticity of substitution is maintained as the one already estimated for primary inputs in the original MAGNET structure. This assumption can be changed in the future, assuming more data on the substitution between livestock and other production inputs.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

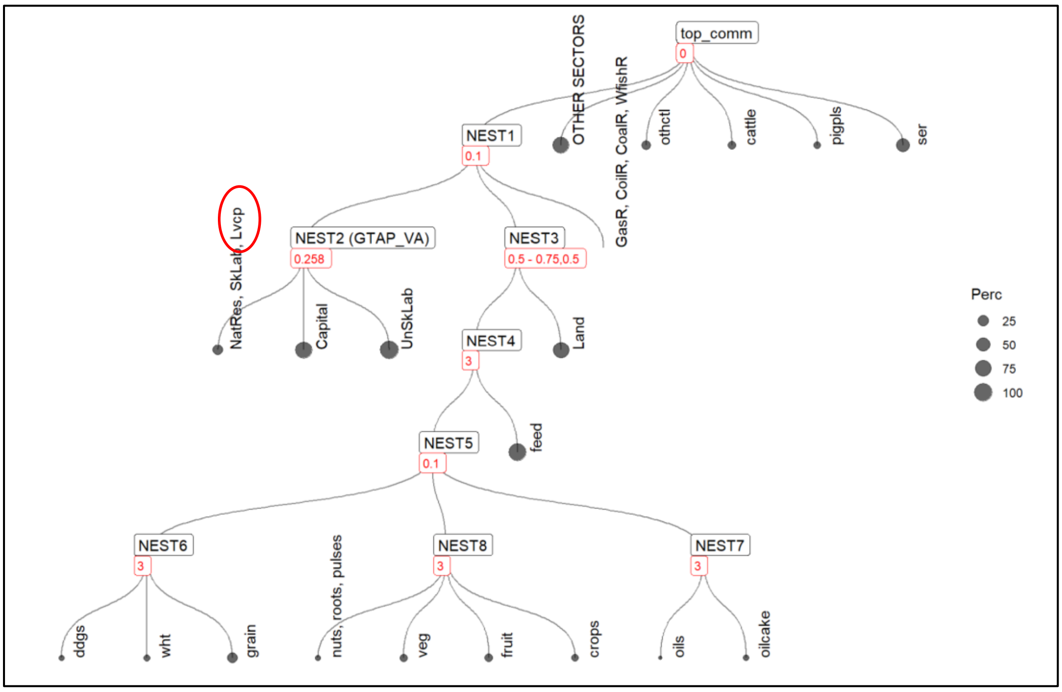


Figure 22 Production structure of Livestock sectors in MAGNET.

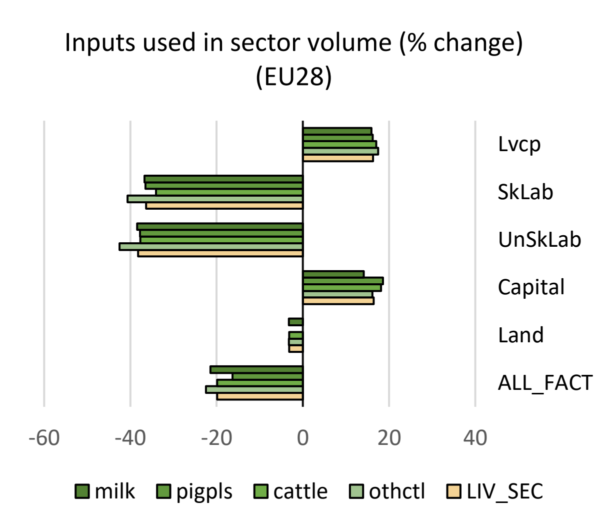
Having accommodated livestock in the production technology (the CES nested production structure) of livestock-using sectors allows for addressing the demand for endowment. The supply side of the endowment must be defined as well. Following the standard default MAGNET version, capital stock is set exogenously to follow the growth rate of GDP (constant capital-output ratio). Adopting a similar assumption for livestock would lead to excessive growth of livestock endowment supply. Thus, herd capital is assumed to grow as a percentage (25%) of the regional GDP growth. A similar assumption has been made for natural resources in MAGNET to mimic the possibility of maintaining/searching for more resources with more economic growth in the region. As the results in the previous subsection show, pegging livestock supply this way to GDP produces balanced results in terms of rates of returns (capital and livestock endowment prices evolve similarly).

There are several future expansions of this modelling approach. First, an explicit link between investment and herds capital stock should be established. This requires several modifications: i) calibrating the value of herd livestock and depreciation as a share of total capital stock (at this moment, livestock input only represents herd capital income, not stock), ii) distinguishing between physical capital investments and livestock investments and modelling its allocation, iii) linking livestock investment to livestock capital stock, iv) linking livestock investment to investment demand. Second, more attention could be spent defining the substitution between breeding livestock and the other production inputs (positioning in the production function nest).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

3.5.5 Baseline projections with livestock capital

Concerning the European Union overall, the volume and prices of the inputs of production are reported in **Figure** 23. Labour will be relatively scarce considering the relatively low level of reproduction of the EU (which is generally a demographic pattern shared with other developed regions). Capital and Livestock, on the other hand, are driven by investment and macroeconomic growth, which is positive in the European countries and, therefore, generates an increase in these input volumes. The prices reflect the overall scarcity (abundance) of the production factors and, accordingly, increase (decrease) over the period of observance.



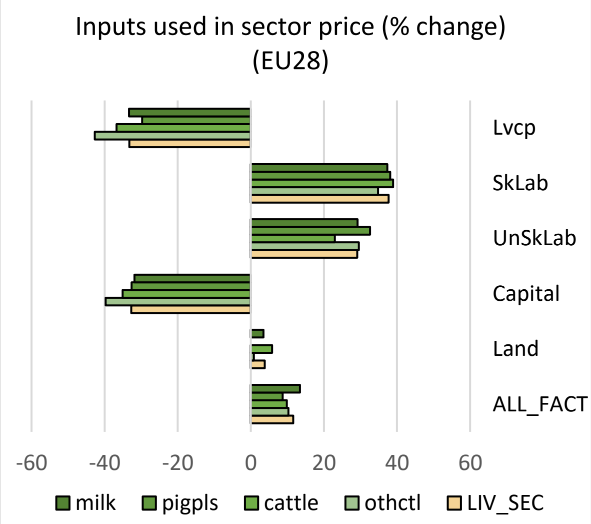


Figure 23 Volume and prices of livestock sectors for the EU 28 region.

The trends that emerge for the input analysis are confirmed by looking at the sectorial production at an aggregated world level (**Table 8**). Indeed, the production volume of the livestock sector is increasing, driven by economic growth and increasing availability of livestock driven by investments. Furthermore, its increase is comparable with the general trend of primary agricultural products in the region. On a sub-sector level, cattle and pig production increase relatively more as compared to other livestock sectors.

Table 8 Production and price projections in agricultural and livestock sectors.

	Production prices (% change) (EU28)						Production volume (% change) (EU28)					
	2014-2019	2019-2025	2025-2030	2030-2040	2040-2050	**2014-2050**	2014-2019	2019-2025	2025-2030	2030-2040	2040-2050	**2014-2050**
AGRI_PRIM	-5,2	-6,04	-5,28	-10,16	-10,85	**-32,43**	1,12	0,81	0,42	2,07	2,51	**7,12**
LIV_SEC	-4,54	-5,22	-4,58	-9,44	-10,2	**-29,79**	2,08	1,98	1,44	3,56	3,69	**13,38**
othctl	-4,87	-5,63	-4,99	-9,75	-10,32	**-30,97**	1,22	0,96	0,53	2,82	3,6	**9,44**
cattle	-4,61	-5,26	-4,66	-9,61	-10,31	**-30,15**	1,96	1,94	1,61	4,16	4,35	**14,78**
pigpls	-4,62	-5,36	-4,75	-9,93	-10,61	**-30,77**	2,62	2,37	1,58	3,8	3,75	**14,93**
milk	-4,44	-5,09	-4,41	-9,03	-9,89	**-28,93**	1,84	1,8	1,34	3,2	3,38	**12,09**

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

At the country level, different behaviour emerges in the use of the inputs for the livestock sector **Table 9**. Asian and Sub-Saharan countries expect a higher breeding input use, partially due to the reliance of developing countries on primary sectors and partially due to the higher expected economic growth to the 2050 horizon with respect to the European area.

Table 9 Production and price of Input projections for livestock sectors (disaggregated).

	Inputs Prices used in Livestock sector (% change)						Inputs Volume used in Livestock sectors (% change)					
	ALL_FACT	Land	Capital	UnSkLab	SkLab	Lvcp	ALL_FACT	Land	Capital	UnSkLab	SkLab	Lvcp
CAN	4,1	39,9	-25,3	17,4	20,3	26,5	3,79	0,84	35,2	-28,43	-28,89	20,23
USA	5,7	47	-29,9	0,2	4,9	28,1	3,71	1,26	37,73	-24,18	-25,08	18,41
BRA	4,5	55	-29,9	38,8	42,5	21,2	15,14	5,97	45,35	-48,56	-48,91	27,98
OSA	14	64,2	-44,6	15,2	22,3	26,2	2,05	10,61	62,18	-35,15	-36,12	33,34
FSU	22,5	34,8	-43,2	34	51,1	-36,7	-29	-1,78	34,1	-56,33	-57,8	29,34
REU	11,4	21,9	-27,2	34,9	37,3	-29,9	-14,16	-1,05	17,3	-45,07	-45,45	18,21
MENA	6,7	40,7	-44,4	18,4	25,9	89,5	14,14	0	90,53	-22,69	-22,85	39,17
SSA	23,3	323,9	-56,8	-19,6	1,6	256,3	31,89	0	193,32	-6,89	-13,78	70,78
CHN	68,8	17,8	-58,4	136,1	143,1	-7,8	-8,94	-3	75,15	-47,83	-48,22	44,99
AUT	13,9	-4	-31,7	31,5	38,2	-36,9	-23,2	-2,33	11,96	-37,97	-38,75	15,46
BLX	-6,5	-28,4	-40,8	8,8	20	-65,2	-22,4	-6	-3,07	-33,43	-35,1	18,9
IND	31,7	96,7	-70,2	5,5	15,4	-63,6	-5,03	8,94	71,65	-57,6	-58,58	65,67
BGR	39,9	-22	-67,3	111,3	143,9	-66,4	-19,44	-4,26	29,76	-48,54	-50,43	29,73
SEA	6,9	50,4	-40,4	14,6	22,3	4,3	2,8	-0,41	42,32	-21,65	-23,33	23,34
HRV	17,2	14,2	-24,3	42,3	53,9	-33	-24,39	-0,48	6,9	-50,77	-51,76	14,4
OAS	108,8	297	-65,7	-14,9	8,4	-39,1	-2,15	0	83,84	-43,56	-47,4	63,24
GCM	-3,1	-15,3	-18,8	7,6	34,6	-50,6	-40,79	-4,96	-0,8	-62,36	-64,03	19,13
ANZ	19,4	155,2	-38,7	1	3,1	60,8	6,69	0,28	56	-12,21	-12,66	25,16
CZE	20	-8,1	-55,3	60,2	65,1	-57,5	-12,43	1,97	28,99	-34,77	-35,28	28,68
DNK	-5,7	7,8	-22,9	14,3	19	-34	-1,85	-11,87	22,07	-30,78	-31,5	16,35
EST	46,8	10,4	-35,4	82,4	93,6	-51,7	-29,32	1,03	18,24	-55,04	-55,73	27,26
FIN	9,3	-1,2	-31,2	21,9	26,5	-1,1	-22,17	-2,87	15,41	-37,42	-38,03	16,76
FRA	0,5	12,7	-33,1	9	13	-27,6	-17,59	-0,95	23,6	-32,97	-33,59	18,16
DEU	17,2	1,6	-27,7	32,4	37,1	-32,8	-24,89	-6,36	9,3	-38,37	-38,93	10,98
HUN	5,5	-31,3	-56	55,8	65,1	-72,8	-25,6	-4,16	6,39	-54,35	-55,04	19,43
IRL	46,9	44,6	-20,9	59,4	64,7	22	-8,48	0,06	34,93	-21,74	-22,39	21,22
ITA	19,9	-7,8	-29,9	38,9	43,1	-26	-22,12	-2,17	13,92	-36,95	-37,43	12,26
LVA	21,8	-34,7	-56,2	62,8	87,6	-72,5	-26,94	-2,9	7,65	-46,22	-48,17	20,79
LTU	8,5	-36,7	-53,8	42,5	67	-66,5	-31,61	-6,63	6,57	-52,34	-54,26	17,31
NLD	5,7	9,4	-35,6	14,2	25,7	-25,5	-12,23	-3,17	20,46	-23,36	-25,24	16,08
POL	23,5	-0,9	-43,3	66	84,6	-52	-22,99	-3,53	15,93	-50,08	-51,44	19,94
PRT	25,3	-22,5	-31,6	51,9	61,6	-50,3	-31,16	0,24	7,44	-49,81	-50,61	17,18
ROU	17,3	-18,1	-53,2	61,4	97,8	-60,1	-27,05	-2,29	17,58	-56,76	-58,99	22,41
SVK	11,6	-35	-64,4	62,5	66,4	-69,7	-19,53	0,29	18,77	-44,41	-44,74	24
SVN	29,1	40	-39,2	48,1	52,6	-19,1	-15,67	-1,6	24	-37,52	-38	19,22
ESP	6,6	12	-31,2	19,9	24,6	-34,1	-24,84	-10,91	10,4	-39,52	-40,13	12,16
SWE	7,2	71,3	-32,4	11,7	14,9	-4	-9,99	-7,39	33,74	-25,03	-25,57	21,53
GBR	18,4	37,7	-25,6	25,6	27,4	-20,5	-20,94	-2,16	19,52	-35,66	-35,9	19,46

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Concerning the livestock sector production at the disaggregated regional level (**Figure 24**), different trends emerge. Indeed, countries like Belgium, Slovakia, and Latvia have a negative trend both in general livestock and primary agricultural production, while Lithuania and Hungary have negative trends in Livestock but slight increases in general primary agricultural production. Countries like Sweden, Ireland, France, Denmark, and Ireland show the strongest increases in the production of both livestock and agriculture. Interesting cases are Bulgaria and, more distinctly, the Netherlands, which expect an increase in the production of livestock but a decrease in primary agriculture.

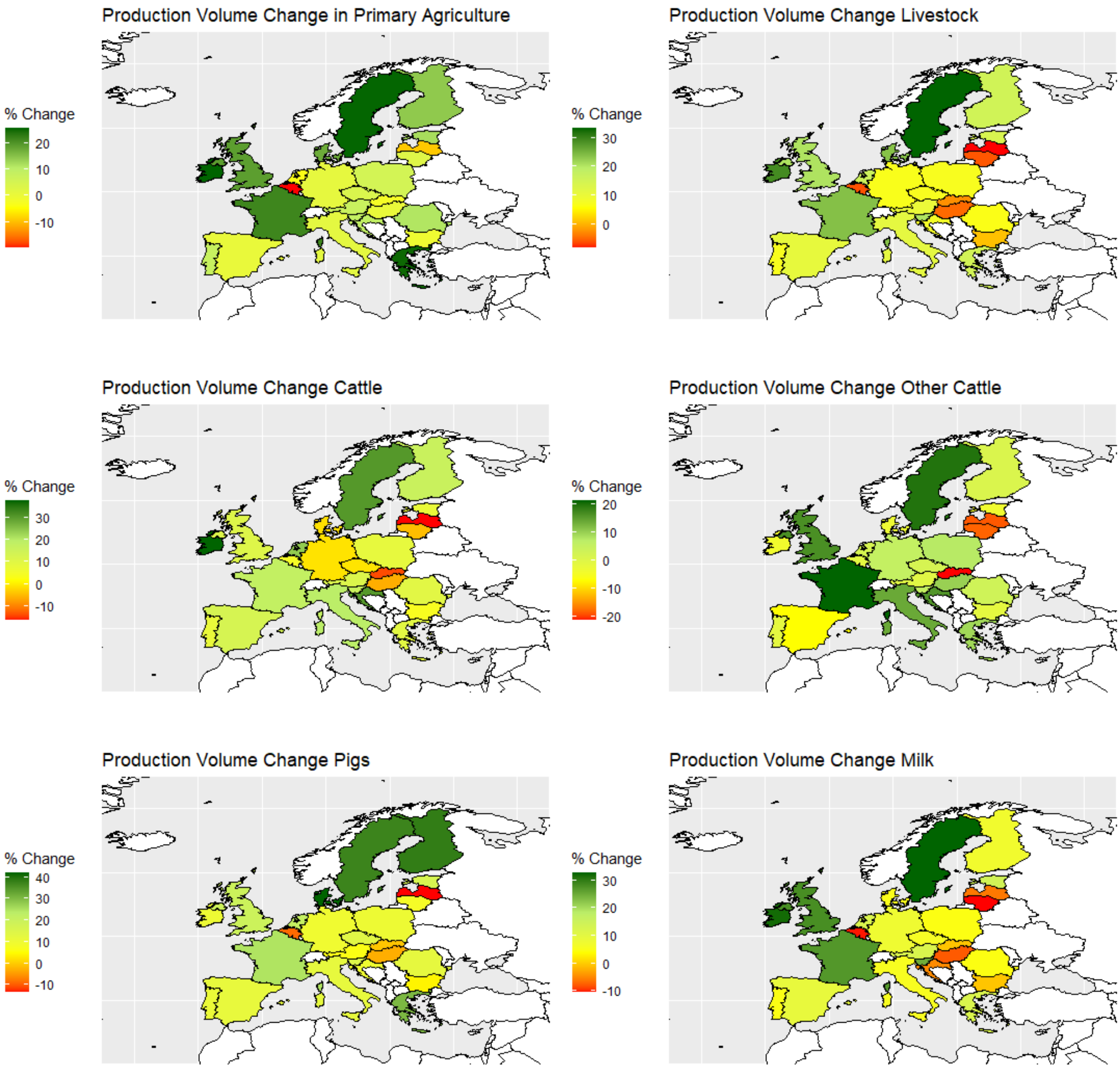


Figure 24 Production of Livestock related sectors for disaggregated Europe region (2014-2050).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

The price of breeding capital for livestock production at a disaggregated country level highlights concerning patterns in several regions **Figure 25**. For example, MENA and, even more, South Saharan Africa show a significant and consistent increase in breeding livestock prices. This trend is shared, in lower entity, also by other South Asian countries, Brazil, Canada, and the USA, with the latter showing a strictly increasing trend. Concerns also arise in Ireland, showing a sensible spike in livestock prices in the second half of the simulation period. Substantial increases in the price of breeding livestock can be associated with increases in food production costs and, therefore, higher risks in meeting the country or regional nutritional requirements.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

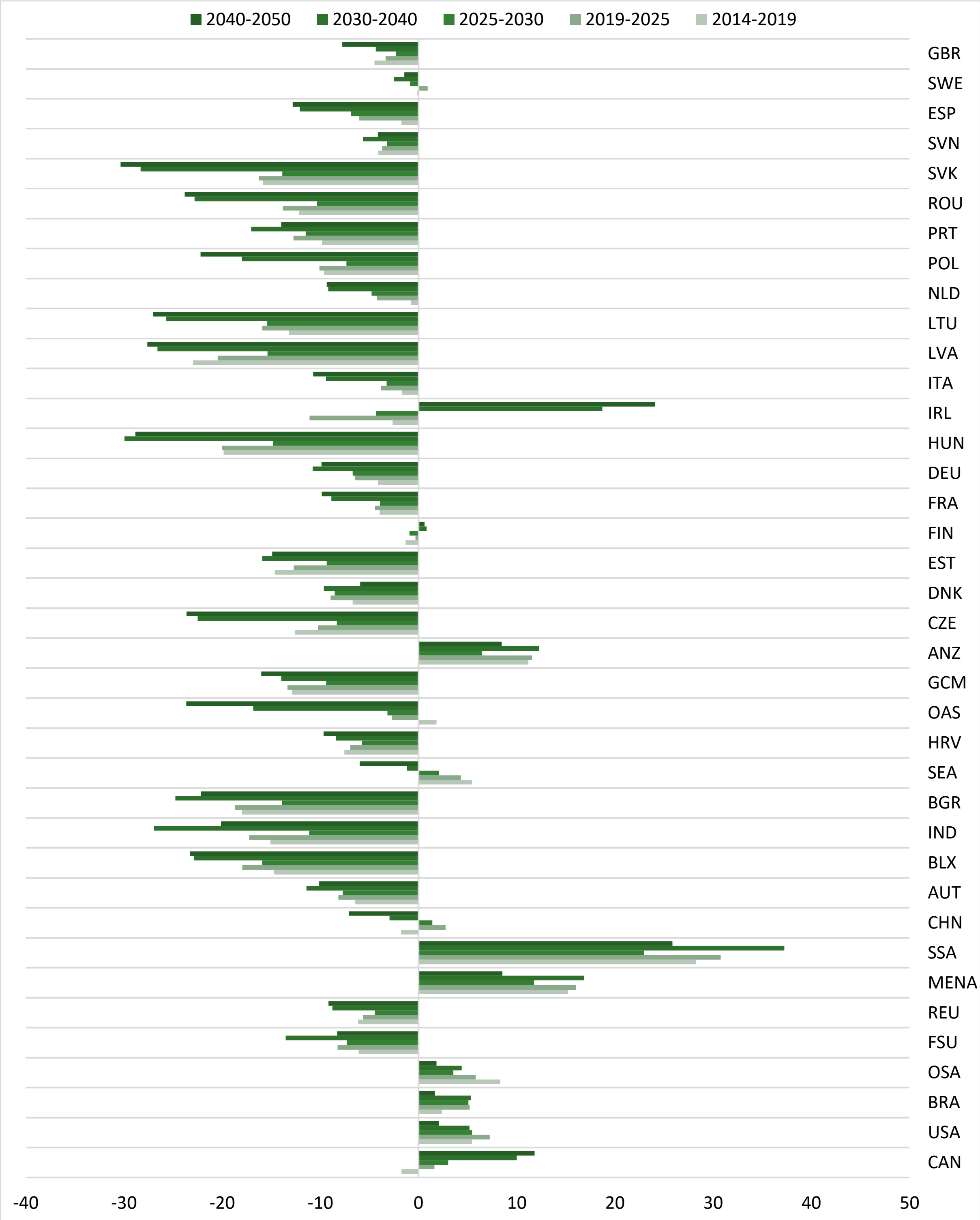


Figure 25 Breeding capital change price for Livestock sectors (% change).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

4 IMPROVED ELASTICITIES OF SUBSTITUTION/TRANSFORMATION BETWEEN LAND USES

4.1 A comparison of land-use and land-use change in Europe with GLOBIOM output

The partial-equilibrium model GLOBIOM, more specifically its global version (Havlik et al. 2014), represents main land use sectors, including agriculture and forestry. More specifically, six land use types are modelled endogenously: cropland (CrpLnd), grassland (GrsLnd), short rotation plantations, managed forests, unmanaged forests, and other natural vegetation lands (OthNatLnd). There are four additional land cover types represented in the model to cover the total land area: other agricultural lands (OthAgri), wetlands, not relevant (NotRel), and urban areas (Urban). These four categories are kept constant at their initial level and not modelled, hence exogenous. Economic activities are associated with the first four land cover types.

The model can switch from one land cover type to another depending on the profitability of primary, by-, and final product production activities. Land conversion over the simulation period is endogenously determined for each grid cell within the available land resources. Although a global model and, in particular, taking spatial interaction effects into account, GLOBIOM operates on a spatial grid. The spatial resolution of the supply side relies on the concept of Simulation units, which are aggregates of 5 to 30 arcmin pixels belonging to the same altitude, slope, and soil class, the same 30 arcmin pixel, and the same country.

Furthermore, countries are subsumed under supranational regions since certain parameters and features, such as international trade and demand side representation, apply to the supranational regions. See Annex **Table A*1*** for a list of the 37 GLOBIOM supranational regions and the corresponding countries they include.

The most important takeaway until now is that spatial information can flow through GLOBIOM from high resolution, i.e., simulation units, over lower resolution aggregates, i.e., countries, to broader spatial concepts in supranational regions. For instance, as represented by production in each grid cell, the cost of land use change (LUC) is one constraint that each supply-side producer faces. This cost is a function that quadratically increases (i.e. rising marginal cost) in the amount of LUC of a given transition pair accrued over all producers inside a supranational region. It is governed by an intercept and slope parameter and bound by a maximum parameter. Over its simulation period, this maximum parameter limits the total amount of a given endogenous land use (LU) class area to transition to another per simulation

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

region and timestep, e.g., cropland to grassland or other natural lands. Essentially, this maximum parameter is a weight between 0 and 1 of the initially present area, i.e., at the beginning of a simulation time step, of this LU class per simulation region. It acts as a safeguard to either meet policy constraints on the one hand or to cover potential outlier cases caused by the model's behaviour.

In this subtask, descriptive statistics on LUC observed between CORINE Land Cover (CLC) accounting layer[8] observations between the years 2000 and 2012 are used to compare if conditions enabling the aforementioned maximum parameter in GLOBIOM matches the observed data. The CLC accounting layer data is a modified product of the European Environment Agency (EEA) from the original CLC inventory data by the Copernicus Land Monitoring Service as part of the Copernicus Programme. The accounting layer harmonizes inconsistencies between the 6-year updates of the original data for the purpose of creating a more solid basis for statistical time series analysis of land cover changes with CLC data.

In the following, the underlying approach for rendering CLC accounting layer LC data comparable with GLOBIOM is outlined:

- **Method:** the CLC accounting layer data in raster format for 2000 and 2012 have been merged, i.e., one layer that reports per 100x100 meter pixel CLC classification code for 2000 and 2012. Hence, if $class_{i,2000} = class_{i,2012}$ no change and vice versa, if $class_{i,2000} \neq class_{i,2012}$ an LC change was observed, where $i \in \{All\ CLC\ Pixels\}$ and $class \in \{Level\ 3\ CLC\ Classification\}$.
- **Spatial aggregation:** LU class transitions in CLC from the original 100x100 meter resolution projected in CRS *EPSG:3035 - ETRS89-extended / LAEA Europe* have been aggregated to reprojected 5 arcminute resolution by area coverage of the former in the latter.
- **Thematic aggregation**: Level 3 CLC classification has been mapped to the thematic resolution of GLOBIOM, i.e., cropland (CrpLnd), other agricultural areas (OthAgri), forest (Forest), grassland (GrsLnd), other natural lands (OthNatLnd), not relevant (NotRel) and urban areas (Urban)[9].

In order to understand the background and differences of observed LUC and GLOBIOM in Europe, the following flow graphs in **Figure *26*** show transitions in total area in terms of GLOBIOM LU classes. On the left-hand side, based on CLC information aggregated to GLOBIOM

[8] https://www.eea.europa.eu/data-and-maps/data/corine-land-cover-accounting-layers

[9] See Annex **Table A1** for the mapping between GLOBIOM and CLC classification.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

classes, and on the right-hand side from a GLOBIOM simulation. In this representation, transitions from and to CLC forest classes *Broad-leaved forest*, *Coniferous forest*, and *Mixed forest* (Level 3 CLC classification code: 311, 312, 313) based on the CLC LC class *Transitional woodland-shrub* (324) have been excluded. This class inflates transitions from other natural lands (OthNatLnd) to forests and vice versa to such a degree that ambiguous identification from raw satellite imagery data to the forest classes and Transitional woodland-shrub in CLC Accounting Layer data cannot be ruled out with certainty.

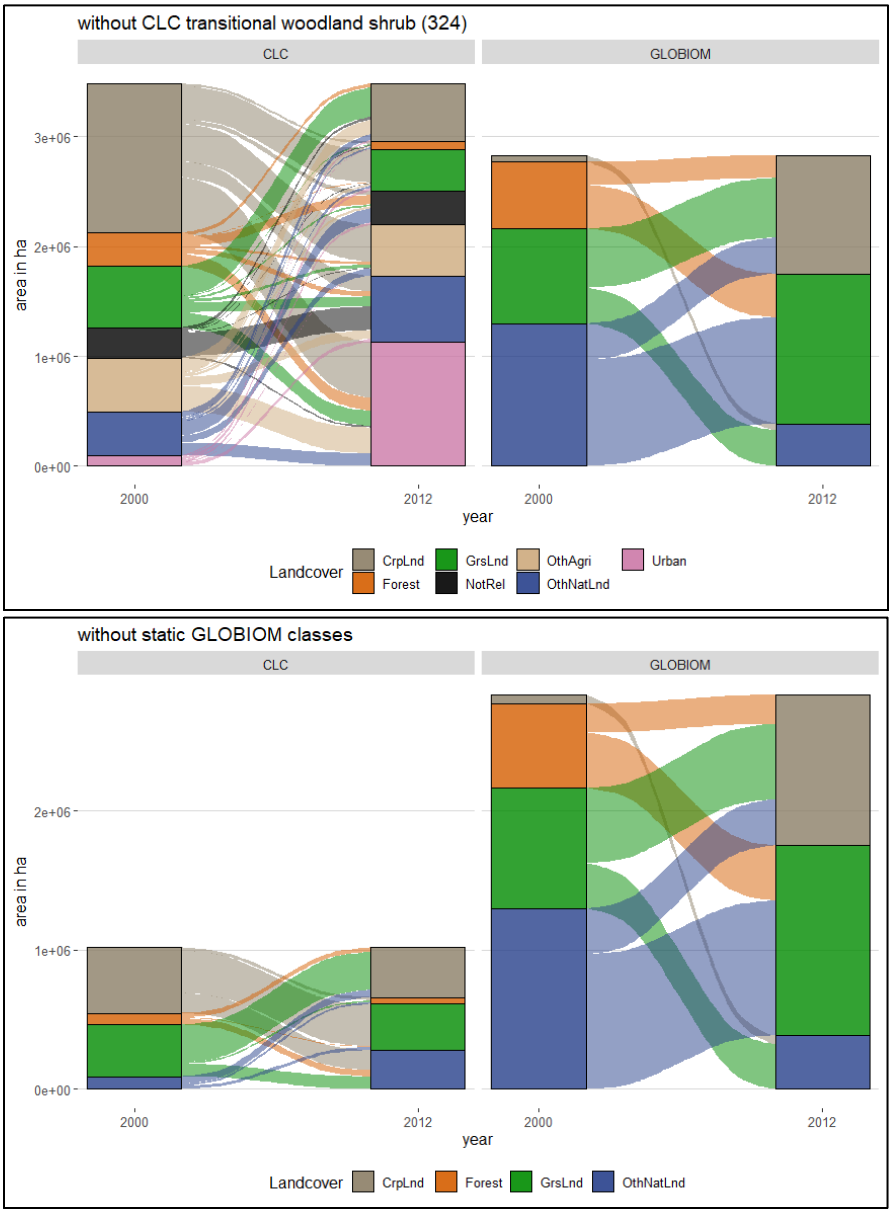


Figure 26 Flow graphs of CLC Accounting Layer data at GLOBIOM thematic aggregation (left) and GLOBIOM reference projection (right) between 2000–2012 time steps. *Flow graphs based on CLC data are without CLC class Transitional woodland and shrub. The top plot shows all GLOBIOM classes and the bottom plot focuses on endogenous GLOBIOM classes in CLC data.*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Figure *26* reaffirms the belief that urban expansion is a major driver of LUC in developed regions, e.g., Europe, and as such, displaces other LU types that might be expanding in other locations. For this reason and, in particular, considering GLOBIOM assumes urban areas to be static over time, adjusting LUC for the effect of urban displacement might lead to a more precise representation of actual LUC.

This adjustment is being calculated with the following assumptions in mind: i) transitions from urban to a given endogenous LU class are considered a direct compensation of urban expansion from this LU class, i.e., net urban displacement, ii) urban displacement is offset, not necessarily in the same *higher spatial resolution* location urban expansion can be identified to have occurred at but some other location inside some meaningful *lower resolution* aggregate, i.e., a country level, and iii) one particular transition from a given endogenous LU class to urban cannot be traced to a particular transition to this same LU class in some other location nor to some non-urban LU class from where it emerged.

Given these assumptions, the urban displacement adjustment is computed as follows:

i. Calculate the sum of transitions to urban by LU class from (and vice versa) for each and over the spatial aggregate country.
ii. Obtain net transition to urban per other LU class by subtracting inflows to urban from outflows from urban (per LU class) for each country.
iii. Allocate the urban net transitions within each country from a certain LU by subtracting their mean over the lower spatial aggregates within each country and all non-urban inflows from the latter.

The following plots (**Figure *27***, **Figure *28***, **Figure *29***, and **Figure *30***) report quantiles of the percentage share of area change from the initial area of the outflowing LU class in the year 2000 per European supranational GLOBIOM region for each transition pair, i.e., from a certain endogenous LU class in GLOBIOM to all other endogenous LU classes. Excluded are spatial units with less than 10 ha total area. Displaying quantiles[10] instead of visualizing the full sample of each European supranational region and transition pair adds clarity and transports some sense of their distributional properties.

The right-hand side panels report values based on the urban displacement adjustment, and the left-hand side panel values without urban displacement adjustment. Per row, the panels report the inflowing LU class per transition pair.

[10] More specifically, the 5^{th} ,16^{th} ,25^{th}, median , 75^{th}, 84^{th}, and 95^{th} quantiles.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Generally, one can observe that urban adjustment shifts the sample distribution to the left, i.e., less area transitioning and even to negative values, implying urban displacement is larger than the area inflowing to a LU class without adjustment.

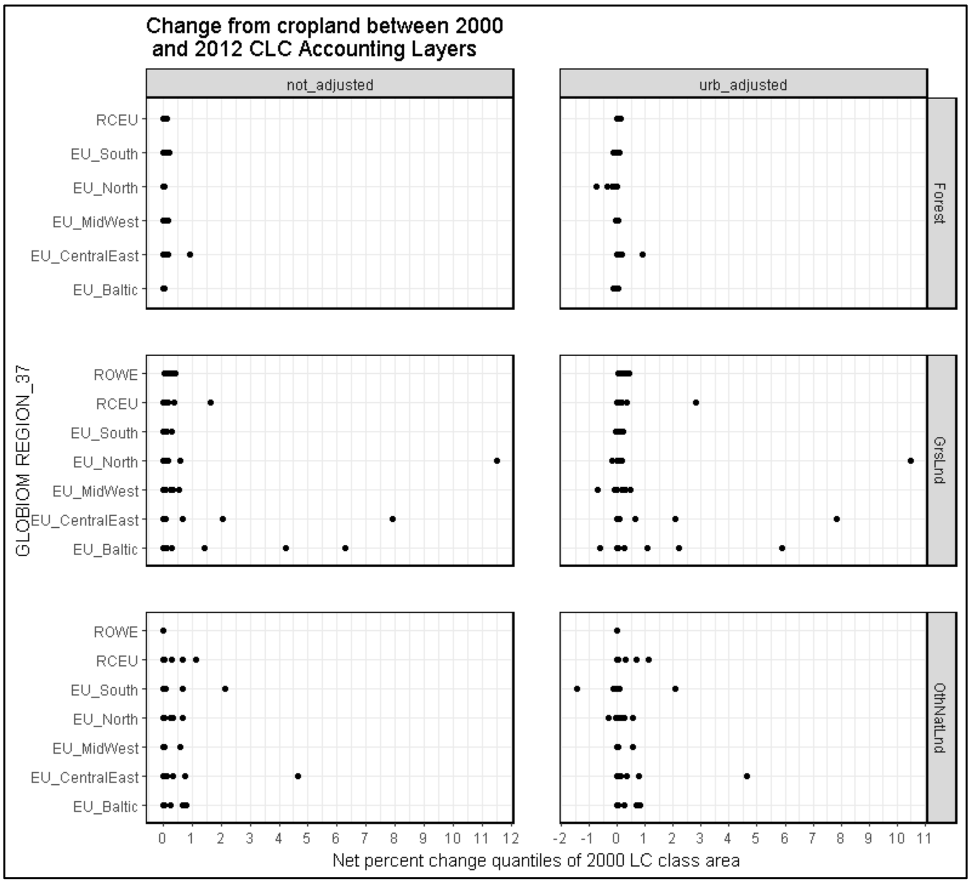


Figure 27 Quantiles of observed net per cent changes from cropland to forests, grasslands, and other natural lands. *Y-axes show European GLOBIOM regions and the x-axes value of net percentage change. The left-hand (right-hand) plots results are not adjusted (adjusted) for urban displacement.*

Looking in particular at outflow shares from cropland to forests, grasslands, and other natural lands and their unadjusted quantile values, it is evident that over all transition pairs and regions are a large part of their samples range between values of 0-1% of area change with some outlying 95th-quantile values. However, for the transition pair cropland to grassland and the Central east and Baltic regions, the sample distribution stands out as its more dispersed and ranges from the median to the 95th above 1% to 8%. Switching attention to the urban-adjusted samples, it appears that urban displacement has a limited effect on the share of area change from cropland as it shifts the distribution of the samples only marginally.

For GLOBIOM, the maximum allowed area to expand from cropland is globally set to 99% of the initial cropland area. Evidently, this magnitude is not captured in the observed range of all samples. This assumption is needed in the case of agricultural production, represented by

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

cropland areas in GLOBIOM, which becomes economically infeasible and, thus, cropland areas convert fully out of the simulation. Unsurprisingly, such a drastic situation has not been observed in Europe according to CLC data and, for that matter, is not expected to be occurring in GLOBIOM.

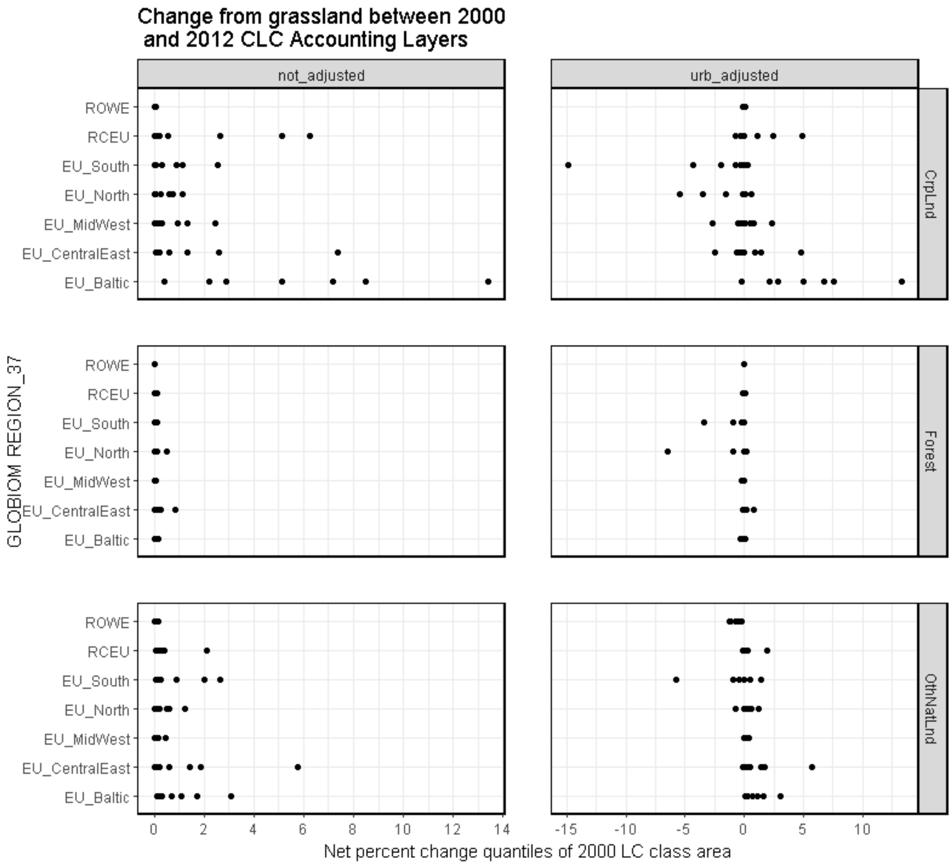


Figure 28 Quantiles of observed net per cent changes from grassland to cropland, forest, and other natural lands. *Y-axes show European GLOBIOM regions and the x-axes value of net percentage change. The left-hand (right-hand side) plots results are not adjusted (adjusted) for urban displacement.*

The general picture differs for the transition pairs grassland to cropland, forest, and other natural land. Apart from inflows to the forest, the sample values are more spread out, and most observations range between 0% and 2%. In particular, in northern Europe (EU_North and EU_Baltics) and transitions from grassland to cropland, quantile values indicate to a larger degree changes in the range of 2% to 8% of the initial grassland area. Moreover, the effects of urban expansion shift the sample distribution to the left to a larger degree than for cropland.

Specifically, for the set of EU27 countries in GLOBIOM, the multiplier governing the maximum allowed area to transition from grassland defaults to 2% of the initial total grassland area. In particular, for inflows to cropland and northern and eastern Europe (RCEU), this value sits well inside the range of their observed samples, with the 75th and 50th quantile, respectively,

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement N° 817566.

being close to 2%. This value is guided by European policy requirements, which, for instance, virtually prohibit conversion from permanent grasslands to cropland. In general, these empirical results suggest that the default assumption in GLOBIOM for transitions from grassland to cropland and other natural land are reasonably chosen. Nevertheless, they also suggest choosing different values in both directions, i.e., lower and higher, for the maximum area allowed for LUC in GLOBIOM might be worthwhile to explore for the LU class grassland, especially in certain regions.

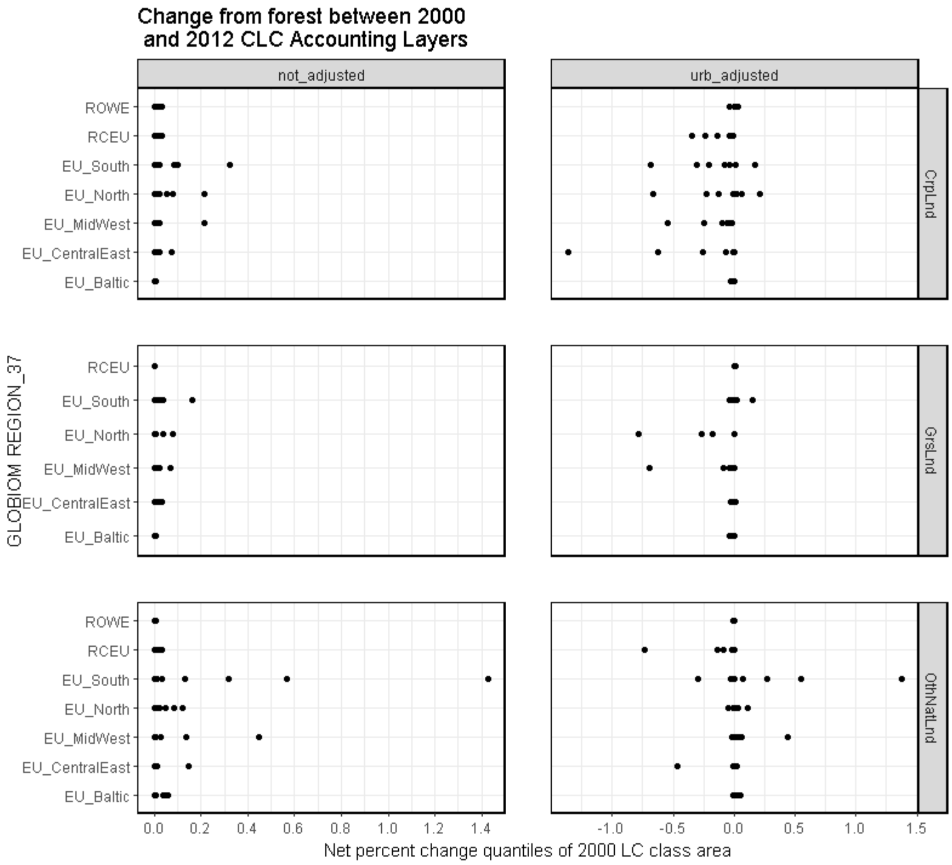


Figure 29 Quantiles of observed net per cent changes from forest to cropland, grasslandand, and other natural lands. *Y-axes show European GLOBIOM regions and the x-axes value of net percentage change. The left-hand (right-hand side) plots results are not adjusted (adjusted) for urban displacement.*

Not unexpected, the transition dynamics from forest to the remaining endogenous GLOBIOM classes are shallow across all samples and, excluding the 95th quantile outlier in the southern European region, are well below 1% of forest area change to all three other receiving LU classes: cropland, grassland, and other natural lands. Accounting for urban displacement, almost all observations are below 0.5%.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Depending on the version of GLOBIOM, outflows from forest to other endogenous LU classes, i.e., deforestation, are not allowed. The observed results are, to some degree, in accordance with the assumption of deforestation merely being a minor factor in Europe.

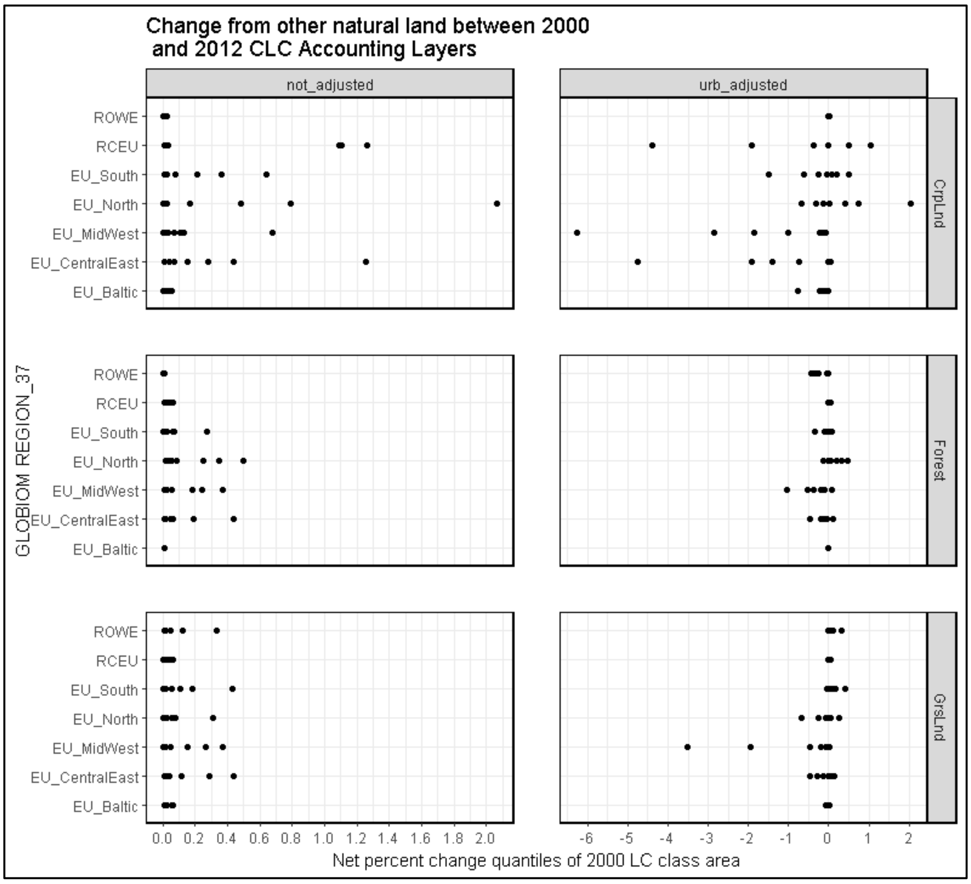


Figure 30 Quantiles of observed net per cent changes from other natural lands to cropland, forest, and grassland. *Y-axes show European GLOBIOM regions and the x-axes value of net percentage change. The left-hand (right-hand side) plots are not adjusted (adjusted) for urban displacement.*

Similar to the forest dynamics, observed changes from CLC classes considered as other natural lands in GLOBIOM rarely exceed 0.6% of initial coverage in the year 2000, and urban expansion drives that effect even further to the left.

As for grassland, the maximum parameter is set to 2% in GLOBIOM. In contrast to grassland, however, the above results indicate that observed LUC from other natural lands is solidly below 2%. Regarding reassessing this assumption in GLOBIOM, the results imply taking values between 0.2% and 0.8% into account when searching the parameter space and calibrating GLOBIOM to observed data.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

In summary, observed LUC from CLC Accounting layer data between 2000 and 2012 is generally less than 1% of the outflowing LU area. Nevertheless, dynamics from grassland, especially in north-eastern regions, show more dispersion in their samples. Unsurprisingly, the results from applying adjustment for urban areas strongly indicate urban areas as expanding and displacing endogenous LUC dynamics by reducing its magnitude as the distribution of observed LUC transitions as shares of initial outflowing LU area in the year 2000 shifts to left across all regions and transition pairs.

Shifting attention to the potential of calibrating the maximum parameter in GLOBIOM to observed data, results are most promising for endogenous LU classes grassland and andother natural lands. In both cases, the corresponding samples of observed LUC are in their range of values either reasonably close or include the default setting of GLOBIOM for European countries. However, the opposite is true for LUC outflowing from cropland. Here, the range of observed values and what is assumed in GLOBIOM differ to the degree that renders calibration questionable as it interferes with essential mechanics in the GLOBIOM model. Moreover, the special case in GLOBIOM of forest or, more specifically, deforestation being ruled out in Europe is largely in line with the observed quantities being close to zero over all samples.

Lastly, this exercise shows potential insights into how GLOBIOM can be adjusted to incorporate real-world observations regarding the maximum area allowed for transition. However, it must be noted that the assumption of the actual potential maximum area available for LUC might not have been fully exhausted in real-world processes as observed from CLC Accounting layer data or other satellite data. Hence, these results must be taken as a guiding exploration into the underlying assumptions of GLOBIOM and not a disproof of them.

4.2 Estimating crop substitution/transformation parameters based on FADN data

The macro-level land-use allocation model GLOBIOM explicitly covers the production of each of the 18 world major crops, though, within Europe, only ten are considered major crops. Each of these crops can be produced under four different management systems, depending on the individual profitability of each. The main management systems are *high-input irrigated*, *high-input rainfed*, *low-input rainfed*, and *subsistence* farming.

Each farming system and crop type is associated with a specific crop yield. The EPIC model generates crop yields at the grid cell level based on soil, slope, altitude, and climate information[11]. Within each management system, the input structure is fixed following a Leontief production function.

The main mechanism of how crop yields can change endogenously is by switching to another management system while producing the same crop in the same grid cell, switching the crop type while staying in the same management system and grid cell, or switching to a more or less productive grid cell outright while producing the same crop with the same management intensity. Besides the endogenous mechanisms, an exogenous component representing the long-term technological change is also considered. The endogenous crop conversion between two-time steps of the GLOBIOM model (covering ten years) can be summarised by the following boundary conditions of the model:

$$\begin{gathered}\sum_{m=1}^{M} x_{i,c,,r,m,t+1} \leq maxcrop_{r,c} \sum_{m=1}^{M} x_{i,c,r,m,t} \\ \sum_{c=1}^{C} x_{i,c,,r,m,t+1} \leq maxcropsys_{r,m} \sum_{c=1}^{C} x_{i,c,r,m,t}\end{gathered} \tag{3}$$

where $x_{i,c,r,m,t}$ denotes the area of crop c (with $c = 1, \dots, C$) at time t in grid cell i and region r under management system m (with $m = 1, \dots, M$). It is trivial to see that the exogenous parameters $maxcrop_{r,c}$ and $maxcropsys_{r,m}$ define the boundaries of crop and management system expansions within a given time step.

The goal of this subtask is to improve the consistency of the endogenous crop yield updates with farm-level models by calibrating coefficients regulating the maximum allowed crop substitutions ($maxcrop_{r,c}$), as well as the maximum allowed management system transitions ($maxcropsys_{r,m}$) based on observed farm-level data stemming from the FADN database.

For the empirical analysis to estimate GLOBIOM's parameters, we use the same dataset as detailed in Subsection 3.1. This is the observed crop farms from the FADN database from 2007 to 2018. Our dataset covers the EU 27 Member States (MS) and the UK. As with the costing analysis, our utilized sample focuses on farms with crop farming as their primary production and is selected based on the EU's Type of Farm (TF14) grouping. This includes specialized

[11] See https://iiasa.ac.at/web/home/research/researchPrograms/EcosystemsServicesandManagement/EPIC.en.html

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

cereal, oilseed, and protein crop (COP) farms (TF14= 15), other field crops (TF14= 16), mixed crop farms (TF14= 60), and mixed crop and livestock farms (TF14 = 80).

Regarding the crops, we mainly focus on the major crops within the GLOBIOM model and prevalent in the EU. These are barley, dry beans, corn, cotton, potatoes, rapeseed, rice, soybeans, sunflower, and wheat. The management systems are defined using the FADN data on fertilizer and crop protection expenditures, as outlined in Subsubsection 3.2.2. Our study covers 5 European supranational regions within the GLOBIOM model. These are: EU_Baltic, EU_CentralEast, EU_MidWest, EU_North, and EU_South.

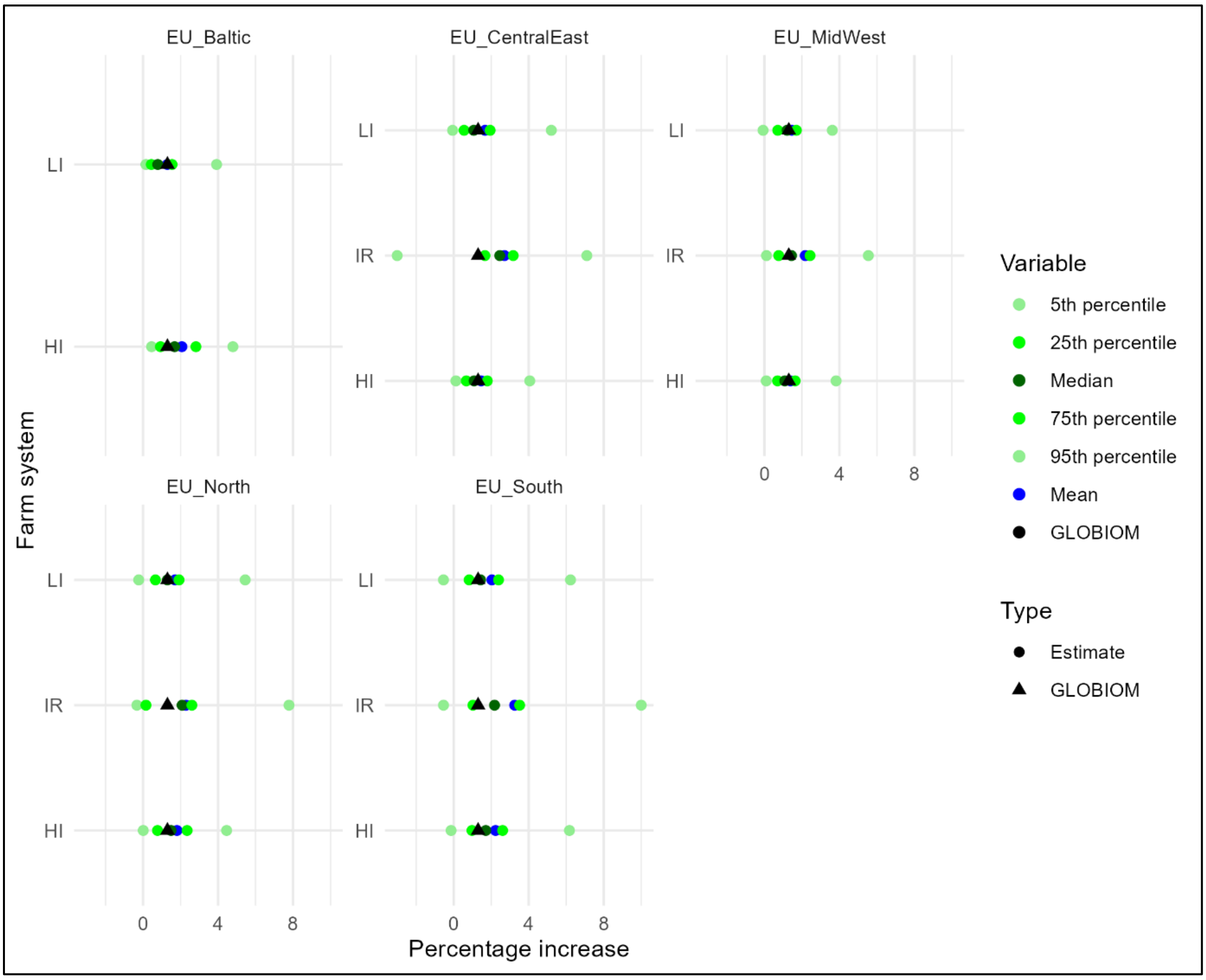


Figure 31 Estimation results of maximum crop system expansion parameter (MAXCROPSYS) based on FADN data between 2007-2010 and 2015-2018 averages. *Y-axes show crop systems, i) low intensity (LI), ii) high intensity (HI), and andiii) irrigated (IR), x-axes percentage change, and per European GLOBIOM region. The triangle symbol represents the GLOBIOM baseline value and the round dots quantiles and means of estimated values.*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

To empirically estimate the maximum crop conversion coefficients ($maxcrop_{r,c}$ and $maxcropsys_{r,m}$), we calculate the average crop area growth per farm j for the years 2007 – 2010 to the years 2015-2018. These are eight-year growth rates, which is close to the decadal representation of GLOBIOM. Averaging over the years is done to avoid counting multi-cropping or crop rotations as structural crop area changes. Note that the considered crop area is sample adjusted using FADN's sampling weights. This last step is necessary as FADN is only a survey of farms.

In a further step, we summarise all growth rates of farms in a given GLOBIOM region. As summary measures, we consider the mean, median, as well as 5th, 25th, 75th, and 95th percentiles. These summary measures serve as empirically estimated ranges of observed crop changes and can be used as extreme values for maximum allowed changes. **Figure *31*** and **Figure *32*** summarise the results, respectively.

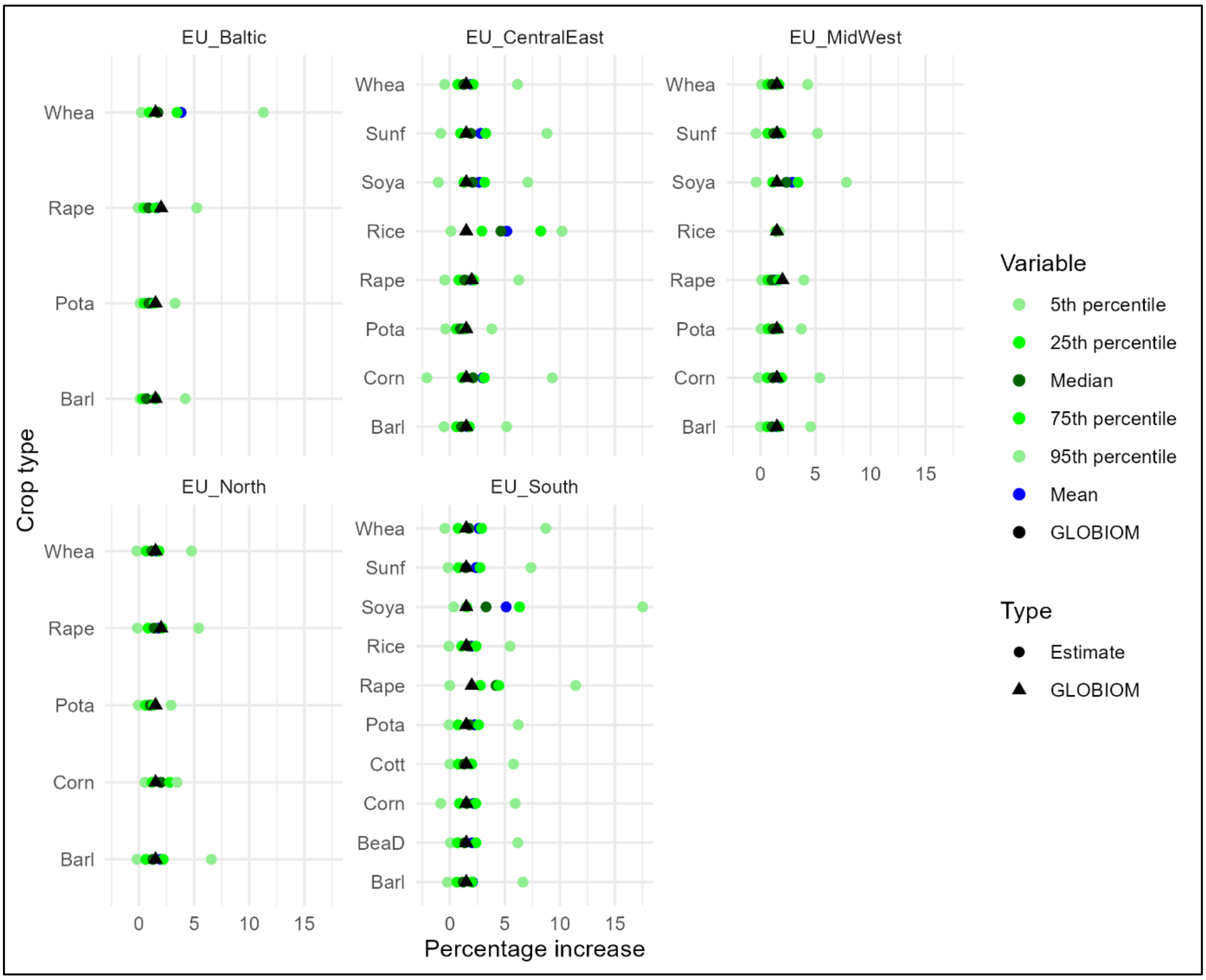


Figure 32 Estimation results of maximum crop type expansion parameter (MAXCROP) based on FADN data between the 2007-2010 average and 2015-2018 average. *Y-axes show crop types, x-axes percentage change, and per European GLOBIOM region. The triangle symbol represents the GLOBIOM*

baseline value, round dots quantiles, and mean of estimated values. Crop types considered are Barl (Barley), BeaD (dry beans), Corn (corn), Cott (cotton), Pota (potatoes), Rape (rapeseed), Rice (rice), Soya (soybeans), Sunf (sunflower), Whea (wheat).

The comparison between FADN and GLOBIOM maximum crop and management system parameters confirms that overall, GLOBIOM reproduces well the average of recent (2000 to 2020) developments across systems and crops in the EU. Nonetheless, there are some exceptions, such as the expansion of irrigated systems in the southern and eastern regions, where GLOBIOM's assumptions of maximum systems expansion are below even the mean and median observed expansion. The same is true for certain crops in the EU's south, baltic and eastern regions. While crops such as rapeseed and soybeans are only a small part of the production, it seems that wheat expansion in the Baltics was more pronounced over the study period as GLOBIOM would allow.

An additional note is that GLOBIOM "*maxcrop*" and "*maxcropsys*" parameters represent maximum expansion boundaries. Thus, it might be reasonable to set them higher as the observed mean or to allow for mechanisms of additional maximum expansion in reaction to more extreme climate change or socio-economic scenarios.

4.3 A validation tool for the macro-level model GLOBIOM dynamics to official datasets

GLOBIOM aims to capture the *real-world dynamics* of LU and LUC. Since its inception, it has been steadily improved to broaden its applicability for policy analysis and enhance its representation of reality. However, as with any scientific model, GLOBIOM necessarily abstracts from reality to simplify complicated systems, but at the same time, a desirable feature of any model is to predict real-world or empirical observations well, such as official datasets. Furthermore, GLOBIOM in itself is a complex model and outputs across many dimensions. This poses a problem for GLOBIOM modellers when deciding whether certain augmentations to the model improve its performance (with regard to matching official datasets) or not. In this subtask, a summary statistic for this purpose is presented, and its capability is showcased. Ultimately, GLOBIOM modellers are equipped with a validation tool to support their modelling choices.

The validation tool is essentially a script that compares the projections from an input GLOBIOM run to FAOSTAT data harmonized to GLOBIOM aggregates over intersecting (observed in both data sources) dimensions, i.e., items, variable types, units of measurement, and regions.

Since FAO data are reported on a yearly basis, ten-year time step projections from GLOBIOM are linearly interpolated to yearly observations. In this manner, the trend character of GLOBIOM projections is preserved by treating its 10-year projections as predictive of yearly observations. At the same time, a 5-year moving-average is applied to FAO yearly observations to extract the trend component of the time series data. While a rough estimate to the trend component, taking the moving average of the FAO data smooths out yearly spikes, which might not be representative of the trend dynamics GLOBIOM ultimately aims at reproducing. The chosen measure of performance is the root mean squared deviation (RMSD) given by:

$$RSMD_{(i,v,u,r)} = \sqrt{\frac{\sum_{t=1}^{T}\left(x_{(i,v,u,r,t)}^{FAO} - x_{(i,v,u,r,t)}^{GLO}\right)^2}{T}} \tag{4}$$

where $x_{(i,v,u,r,t)}$ denotes the value x of a given item i, of variable type v, and unit of measurement u, in GLOBIOM region r at time t and the superscripts FAO (respectively GLO) indicate their source. The time horizon $t = 1,2, \dots, T$ represents the shared data points of FAO and (interpolated) GLOBIOM observations. Currently, in this application, $t = 1$ indicates the year 2000 and $t = T$ year 2020 for almost all cases.

FAOSTAT data is taken from three FAO sources: i) supply and utilization accounts (SUA)[12], ii) food balance (FB)[13] sheets, and iii) the PRODSTAT (PS)[i14] database related to production statistics. The latter two augment, where necessary, the SUA database because the definition of the SUA products are no longer documented and reproducible. Taken together and harmonized to GLOBIOM regions and items, the final FAOSTAT dataset covers 978 unique combinations across types of variables, units of measurement, and items for 79 GLOBIOM regions/countries[15]. As stated above, even though some time series carry data before 2000, the time dimension for this application ranges from 2000–2020. The values from 2000–2019 are straight from the FAOSTAT dataset, and the 2020 values are linearly extrapolated. For an overview of available items, variable types, and units of measurement, as well as regions (and their constituting countries), the interested reader is referred to Annex **Table A*1*** and **Table A*2***.

[12] https://www.fao.org/economic/the-statistics-division-ess/methodology/methodology-systems/supply-utilization-accounts-and-food-balance-sheets-background-information-for-your-better-understanding/en/

[13] https://www.fao.org/faostat/en/#data/FB

[14] https://www.fao.org/faostat/en/#data/QCL

[15] The 978 unique combinations as well as the 79 unique combinations include double counting information, when one variable type is a combination of some others, e.g. import, export and net export, or some region is a superset of smaller regions, i.e. World, OECD, EU28, etc.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

In time series analysis, RMSD is a frequently used measure to summarize the deviation of predicted – here projected – and observed values, where larger deviations are magnified through the square term. Hence, it is sensitive to outliers.

The RMSD is always non-negative; a value of 0 (almost never achieved in practice) would indicate a perfect fit. In general, a lower $RMSD$ is better than a higher one. Usually, the $RMSD$ is used for models rather than data comparisons since it is dependent on the scale of the data used. This means comparisons across regions and items are being computed separately.

However, since the RSMD is usually applied to assess forecast performance of empirical time series models, its applicability to long-horizon partial-equilibrium models with many output variables across many dimensions, e.g., regions, items, units of measurement, such as GLOBIOM, is limited. For this reason, whether some model modification to GLOBIOM is improving its performance with regards to FAOSTAT data is being assessed in comparison to a baseline specification of GLOBIOM, i.e., without changes. Thus, given the $RSMD$ measure above, the model comparison is computed as follows:

$$M^{RMSD} = \frac{M^{adj}}{M^{base}} = \frac{\sum_{i=1}^{I} \sum_{v=1}^{V} \sum_{u=1}^{U} \sum_{r=1}^{R} RSMD_{(i,v,u,r)}^{adj}}{\sum_{i=1}^{I} \sum_{v=1}^{V} \sum_{u=1}^{U} \sum_{r=1}^{R} RSMD_{(i,v,u,r)}^{base}} \tag{5}$$

where the superscript adj indicates some modified GLOBIOM specification and $base$ its baseline version. The $RMSD$'s for each are summed over all (or some subset of), and items $i = 1,2, \dots, I$, variable types $v = 1,2, \dots, V$, units of measurement $u = 1,2, \dots, U$, and regions $r = 1,2, \dots, R$.
Unsurprisingly, if $M^{adj} = M^{base}$ the fraction above equals 1. If $M^{RMSD} < 1$, one can safely assess the model adjustment improved the performance of GLOBIOM with regards to FAOSTAT data over the baseline version and vice versa, $M^{RMSD} > 1$ indicates worsening performance.

The following ***Figure 33*** shows the results of an exercise of applying the M^{RMSD} measure to GLOBIOM. The setup of this exercise is as follows:

- Draw 99 times each of the $maxcrop_{r,c}$ parameters estimated in section 4.2 from uniform distributions with boundaries of $\pm\frac{2}{3}$ times and from the respective GLOBIOM baseline values for each supranational EU region.
- In addition, the baseline values are included for a total sample of 100 iterations of the $maxcrop_{r,c}$ parameters under consideration.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

- With this sample, the GLOBIOM model is run 100 times for each respective iteration, and their corresponding outputs are subsequently passed over to the validation script.

Plotted in Figure 35 are the natural logarithm of the resulting $M^{RMSD}s$ for each EU GLOBIOM region and all available items, variable types, and unit of measurement combinations. In the notation of equation (5), this means per EU region r [16]: the number of items I is equal to the number of available items, number of variable types V as well as units U. In total, the available count of unique combinations for comparison between three dimensions ranges between 95 (EU_Baltic) and 118 (EU_South). Lastly, the first plot in Figure 35 shows the resulting $M^{RMSD}s$ measures for the whole EU.

Applying the natural logarithm to M^{RMSD} eases the comparison between values indicating the same magnitude of improving and declining performance. For example, if $\ln(M^{RMSD})$ equates to positive (negative) 1, the numerator M^{adj} is ~ 2.7 times larger (smaller) than the denominator M^{base}.

[16] Essentially, omitting the summation over R in equation (5).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

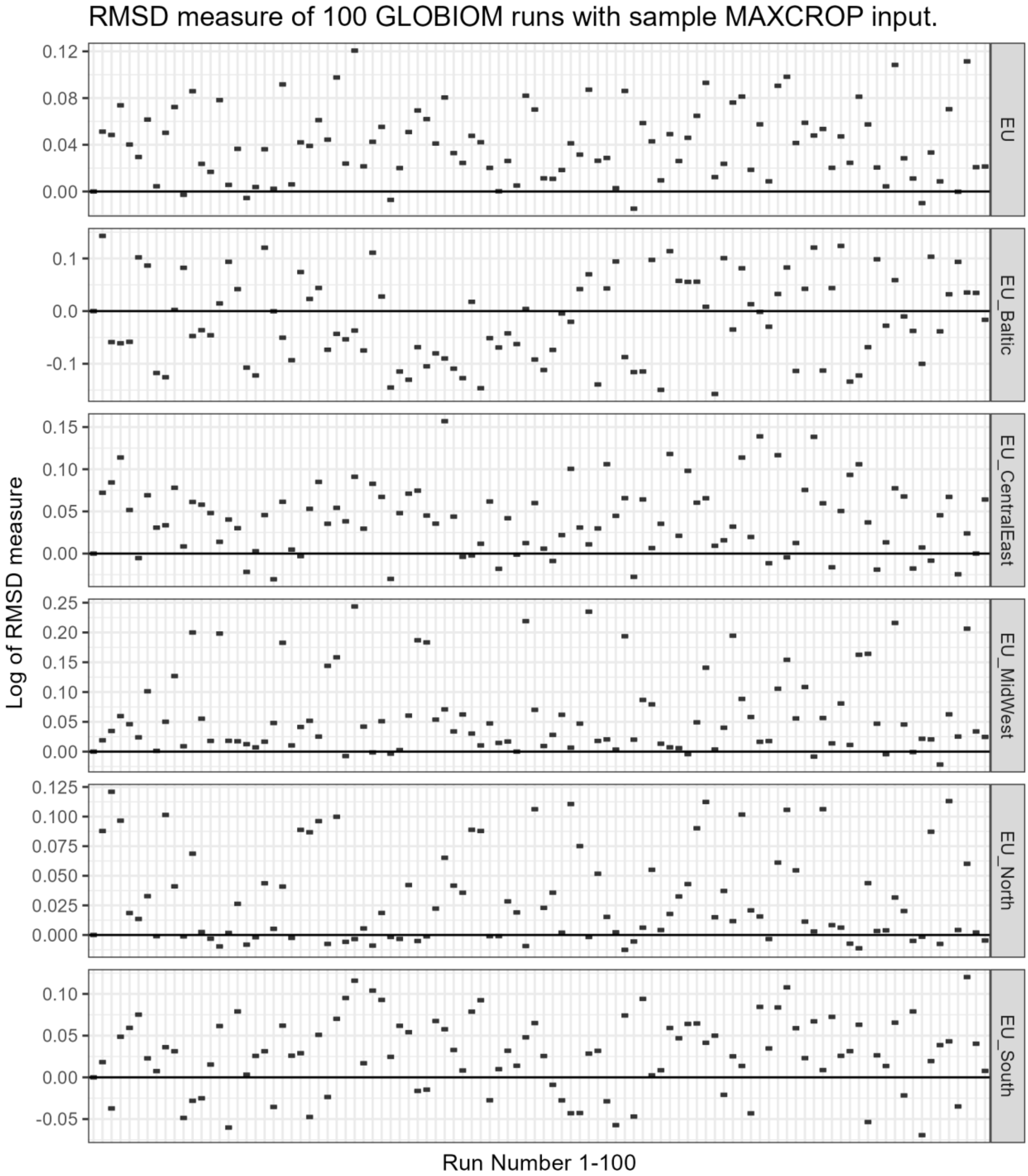


Figure 33 RMSD measure of 100 GLOBIOM runs with sample $\boldsymbol{maxcrop_{r,c}}$–input. *Y-axes depict the natural logarithm of M^{RMSD}, x-axes from left to right are 100 sample runs of M^{adj}, with run 1 being the baseline. Results are for the whole EU region (first plot) as well as for each EU GLOBIOM subregion (following plots).*

In general, the plots for each EU region paint an expected picture. While some iterations of randomly drawn $maxcrop_{r,c}$ parameter values lead to improved performance (negative values), others indicate deteriorating performance (positive values). However, the distribution between positive and negative

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

values varies between regions. In particular, the Baltic and Southern European regions are responding with improved performance to variations in the $maxcrop_{r,c}$ parameter, while in the other regions, the results are less impressive. Exemplary here is the GLOBIOM region EU_MidWest, which lacks noteworthy performance gains against FAOSTAT data with almost no runs leading to a performance measure M^{RMSD} of less than 1.

Focusing on the aggregate results for the EU (first plot), it becomes apparent that improving performance in one region does not necessarily translate to improved performance over the aggregate. This means the results of each region tend to offset each other when taken together. It is vital to understand here that in GLOBIOM, each region interacts with each other via trade linkages, and while some regions are responding well to changes to the $maxcrop_{r,c}$ parameter in terms of optimizing the relative performance gains to the baseline. This could also lead to decreased performance in other regions. For instance, GLOBIOM might decide with one parameter iteration to allocate the production of food products more efficiently in the Baltic region, matching FAOSTAT data along this dimension more closely. At the same time, aggregate demand in consumption, e.g., in EU_MidWest, is served by exports from the Baltic region to a larger degree, and domestic production in EU_MidWest is reduced. Moreover, for similar reasons, improved performance in one region might not correlate with the $maxcrop_{r,c}$ parameter iteration in the same region, but parameter values somewhere else.

The next section outlines an approach to disentangle the complex interaction effects of GLOBIOM in this regard. Ultimately, this effort could lead to a computationally more efficient way to search the parameter space in GLOBIOM to calibrate it to match official datasets more precisely without running the computationally intensive simulation of GLOBIOM.

4.4 A prototype calibration method of the macro-level model GLOBIOM to micro-econometric estimates

In this subtask, a prototype workflow for calibrating GLOBIOM is presented, where a machine learning approach is employed to approximate the functional form of GLOBIOM. The machine learning model utilized is the so-called Bayesian Additive Regression Trees (BART) model.

Since first introduced by Chipman et al. (2010), the BART model has been a staple in the machine learning literature due to its remarkable ability to approximate unknown functions f, relative ease of use, and flexibility. In principle, similar to other ensemble models, BART is a sum-of-tree model, where each tree partitions the input space in order to explain only part of the output. Prone to overfitting, regularization priors ensure that these decision trees remain simple in their structure, i.e., representing only a limited subset of relationships between covariates and the output variable. In the literature, these *shallow* regression trees are referred to as weak learners, and by summing over many of these so-called weak learners, BART excels single complex models, e.g., multivariate regression methods, in their predictive performance.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

In detail, the BART model is defined as approximating the unknown function f of an input X to predict a response y as follows:

$$y = \bar{f}(X) + \varepsilon = \sum_{s=1}^{S} v(X|T^s, \mu^s) + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2) \tag{6}$$

where v denotes a tree function that takes an $N \times K$-matrix X as input and outputs according to a tree structure T^s and b^s terminal nodes in the set $\mu^s = \{\mu_1^s, \dots, \mu_{b^s}^s\}$. Each tree structure T^s is a set of splitting rules, i.e., internal nodes, of the form $x_j \leq c_i$ or $x_j > c_i$ – with x_j denoting the j^{th} column in X and c_i being a threshold parameter.

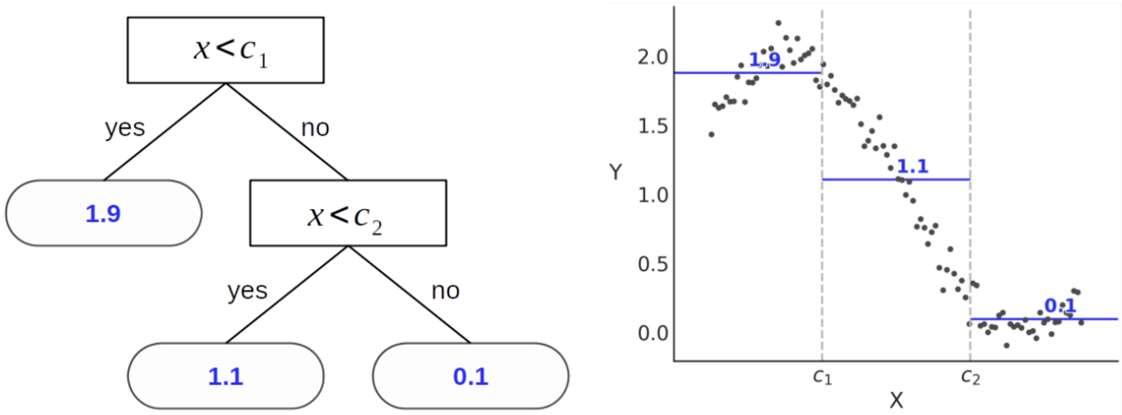


Figure 36 Example of a single tree function. *The left-hand side shows an example decision tree structure T^s, with $i = 1{,}2$, and the right-hand side depicts the corresponding partitioning of the input space of a single x_j to explain a part of y.*

Figure 30 illustrates the behaviour of such a tree function. The left-hand plot gives an example of how sequences of splitting rules lead to terminal nodes, and the tree function returns their corresponding terminal node parameter value. The tree structure begins with the first splitting rule $x \leq c_1$, if its condition is met, the sequence either ends in the terminal node $\mu_1 = 1.9$ or moves on to the next splitting rule and ends in terminal nodes $\mu_2 = 1.1$ or $\mu_3 = 0.1$ depending on $x \leq c_2$. The right-hand side illustrates the manner, such as splitting rules to partition the input space and explain part of the response.

While a single tree function in itself is able to represent complex interaction effects between elements in X, summing over many tree functions easily incorporates additive effects and thus equips BART with exceptional representational flexibility – and increasingly so in the number

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

of trees S[17]. However, increased flexibility also implies proneness to over-fitting, which limits the designed capability of BART to approximate unknown functions. In this regard, one major feature of concern is precisely the potential depth, i.e., the number of consecutive splitting rules that each tree function may develop in its structure by introducing spurious multivariate combinations as well as dominating the total sum of terminal node parameters. Given the illustration in Figure 30, it is easy to think about a tree structure that partitions each single data point in x to one response value. Consequently, regularization priors on the tree structure T^S ensure that each tree remains simple in its form.

Treating GLOBIOM as an unknown function of its inputs, e.g., the parameters discussed in the exercises above, to its output variables and utilizing data generated in lieu of a simulation setup, BART is applied to approximate its form. The simulation setup implies running the GLOBIOM model N – times with variation over K parameters. More specifically, the data generated is an $N \times K$ input matrix and N – vectors y of GLOBIOM output variables. The BART model is trained on the sampled parameter values as covariates in X to explain the variation in a single response y of GLOBIOM.

On the one hand, the BART framework then allows for the analysis of the effects of covariates in X on the outcome. However, due to the nature of BART as a non-parametric or black-box model, such inference cannot be drawn directly but must be retrieved via, for example, Friedman's partial dependence function (Friedman, 2001), which summarizes the marginal effect a covariate or subset of covariates has on the response. In this fashion, the influence of each parameter on the chosen response can be assessed, conditional on the remaining set of covariates.

On the other hand, the BART model allows for searching the input space of K – parameters to efficiently calibrate these parameters to some desired level of a given performance measure, e.g., the RMSD measure presented in subtask. One key advantage is that a trained machine learning model is more efficient in terms of computing time than searching the parameter space directly via running GLOBIOM for a large sample of potential parameters to calibrate.

In detail, the calibration procedure is then setup as follows:

(1) Sample $N \times K$ matrix X of GLOBIOM parameter values from selected and sensible distributions, where one row in X carries values corresponding to the baseline setting of GLOBIOM.

[17] In most applications, the number of trees $S=200$ has proven to be a robust choice with performance deteriorating with larger values of S.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

(2) Run GLOBIOM N – times with the sample input from (1) and obtain N output values c over L comparison variables documented in subtask 4.3, i.e., $c \in C = \{c_{1,} \dots c_L\}$
(3) Run C through the validation procedure presented in subtask 4.3 to obtain N – times comparison measure M^{RMSD} and obtain $y = \{M_1^{RMSD}, \dots, M_N^{RMSD}\}$.
(4) Train the BART model on input $\boldsymbol{X}$ from (1) and response $\boldsymbol{y}$ from (3).
(5) Sample a large number of parameters from the same distributions as in (1).
(6) Use the trained BART model from (4) to predict the response variable $\overline{y}$ based on the new input sample from (5).
(7) Select from $\overline{y}$ the lowest predicted values and corresponding parameter values.

To assess the quality of the predicted selection of M^{RMSD} from (7), and thus, the fit of the BART model and its ableness to calibrate GLOBIOM, their corresponding parameter values can then be run through the actual GLOBIOM model and the resulting validation measures compared to the predicted selection.

As a proof-of-concept exercise, Figure ? reports the results of calibrating GLOBIOM by variation over the *maxcropsys*-parameter. Given the detailed description of the calibration procedure above, the exercise is setup as follows: (1) sample 500-times values of the *maxcropsys*-parameter per European GLOBIOM region & management system from uniform distributions between 1.001 and 5, plus one baseline specification, (2) & (3) run GLOBIOM 501-times and obtain log RMSD measure over all available comparison variables L, (4) train the BART model on training sample from (1) & (3), (5) sample 500000-times *maxcropsys*-parameter values as in (1), (6) predict log RMSD measure with trained BART model from (4) and sample input from (5), (7) select 10 iterations with the lowest predicted mean of the log RMSD measure.

To validate the predictive performance, the 10 sets of *maxcropsys*-parameter values leading to the lowest predicted mean of the log RMSD measure are replugged into GLOBIOM and run to obtain their actual log RMSD measure. Figure 37 then shows the predicted mean and 99% confidence set as well as the actual log RMSD measure of these 10 sample runs.
In practice, the BART R package (Sparapani et al., 2021) has been employed for training the model and predicting the responses $\overline{y}$.

The figure shows on the one hand the mean as well as the 99% confidence set of the predicted log M^{RMSD} measure (black dots & error bars) and the actual log M^{RMSD} as resulting from running GLOBIOM with the same set of parameter values (green triangles). Out of the 10 sampled iterations with the lowest predicted mean 7 actual values of the performance measure are within the 99% confidence set of the predictive distribution of the trained BART model. This indicates that the BART model reasonably well approximates the data generating

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

process of GLOBIOM to the log M^{RMSD} measure with regards to variation in *maxcropsys*-parameters per European GLOBIOM region. Although 3 actual values are outside the lower tail of the predictive density, their values indicate a better comparative performance than predicted. While these outliers are somewhat unsatisfactory from a pure forecasting perspective, given the relatively small amount of training data (with $N = 501$) and some indication of an upward bias in the BART-predictions (9 out of 10 actual values are well below their predicted mean counterparts) these results remain promising to further explore the capabilities of the BART model (or other machine learning methods) to calibrate GLOBIOM with respect to certain exogeneous parameter assumptions.

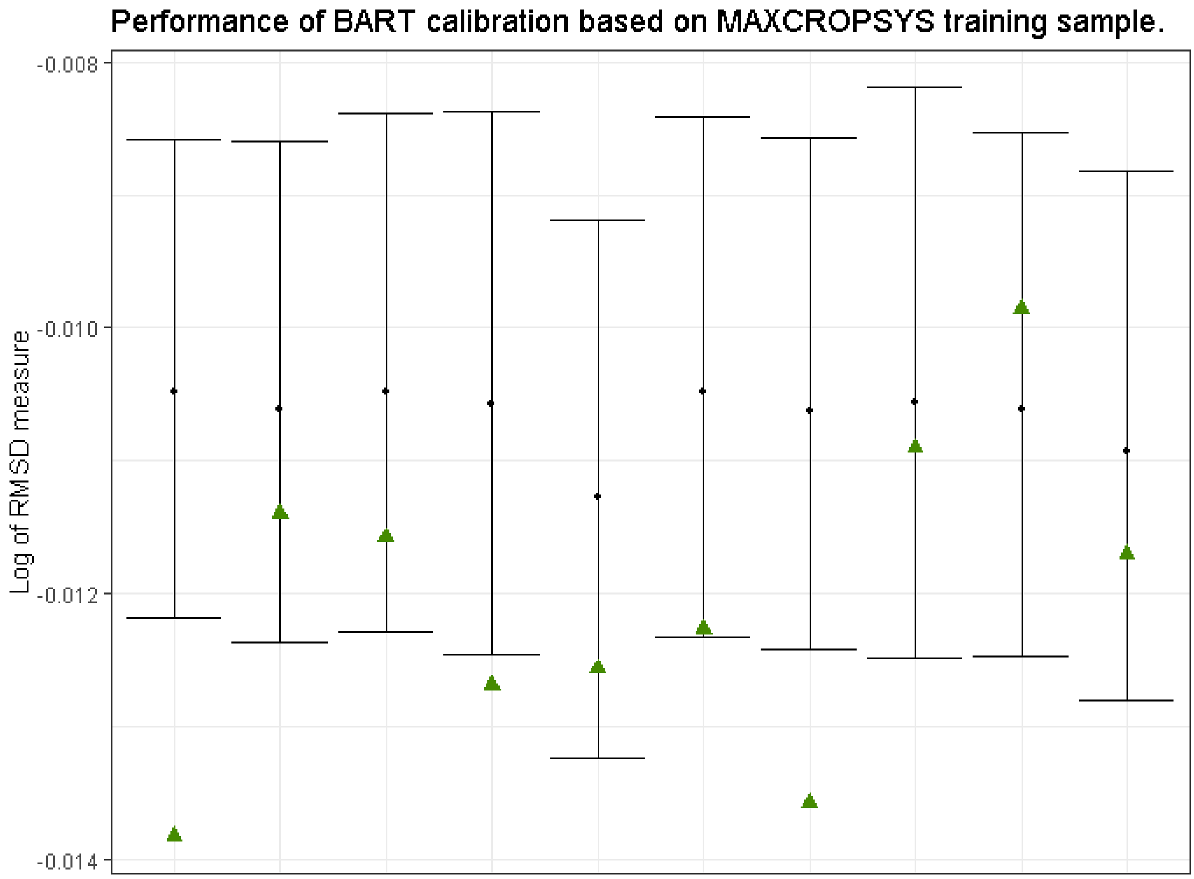


Figure 37 Results of BART calibration exercise based on sample $maxcropsys_{r,c}$–input. Black dots indicate the mean & error bars the 99% confidence set of the predicted log RMSD measure ($\bar{y}$), green triangles indicate the actual log RMSD measure from GLOBIOM runs with the same parameter values.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

5 IMPROVED ELASTICITIES OF TRANSFORMATION / IMPACTS ON PRODUCTIVITY COEFFICIENT

5.1 Structural change representation in current models

IFM-CAP:

Structural change is defined as (Reimund et al., 1981): *„a significant change in the ownership, control, and organizational characteristics of resources used in the production of a commodity or within a subsector."* Structural change applies to the whole sector or subsectors and is about the changes in one or more of the following distributions (further elaborated in Chavas, 2001):

1. Farm size (and economies of scale)
2. Specialization (many outputs or one)
3. Technology and farm organization

IFM-CAP does not explicitly deal with structural change. All of the above characteristics of the farm are considered fixed across scenarios, so their distribution across farms does not change.

Several authors highlight the relevance of incorporating structural change into policy evaluation models. Reidsma et al. (2015) say that structural change will influence the impacts and adaptation of the sector, and thus excluding it will possibly overestimate the effects of climate change. Espinosa et al. (2016) say that information about farm structural change is of great interest to policymakers and stakeholders and provides the basis for policy analysis. More specifically, she highlights that the new CAP design interacts with investment decisions and enter/leave decisions CAP. Zimmermann et al. (2009) also support that within the integrated impact assessment context, structural change is necessary to be included. It may significantly improve the validity of the social, economic, and environmental indicators.

For this, including structural change in IFM-CAP will improve the model's capabilities. In order to do so, we will apply a simple statistical land market mechanism to redistribute land. The available land for redistribution is provided by econometric exit estimations from WP4.

5.2 Linkages to WP4

In WP4, deliverable D4.2, a logit model is used to represent the binary decision of the farmer to exit the sector. The German Farm Structure Survey (FSS) survey is used and includes information on the farms that exited agricultural activity between 2010 and 2020.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Given a set of explanatory parameters (x_i), the effect on the probability to exit is estimated (vector of coefficients β):

$$\log\left(\frac{p(exit_i = 1|x_i, \beta)}{1 - p(exit_i = 1|x_i, \beta)}\right) = x_i'\beta + \varepsilon_i \tag{7}$$

One complication is that the set of explanatory variables in the FSS (including the neighbouring farms) is not always present in the IFM-CAP model. Further, some variables might be slightly differently defined. For instance, in IFM-CAP, the standard gross margins are derived with more costs than the standard gross margins used in the exit model. Finally, we use the following subset of common variables:

Table 10 WP4 subset of variables used to estimate the exit probability with the IFM-CAP data.

VARIABLE	CODING IN EXIT MODEL	TYPE OF VARIABLE
Farm Type	TiT15, …, TiT84	Categorical
Organic farm	organic1, organic3	Categorical
NUTS2	C0010UG5xxx	Categorical
Total agricultural land used (hectare)	C0240	Continuous
Total agricultural land used squared (hectare)	C0240_sq	Continuous
Livestock units	C3391	Continuous
Standard gross margin dedicated to general cropping per activity per hectare	P1_sgm_Basis_ratio	Continuous
Standard gross margin dedicated to horticulture per activity per hectare	P2_sgm_Basis_ratio	Continuous
Standard gross margin dedicated to permanent crops per activity per hectare	P3_sgm_Basis_ratio	Continuous
Standard gross margin dedicated to grazing livestock and forage per activity per head	P4_sgm_Basis_ratio	Continuous
Standard gross margin dedicated to granivores per activity per head	P5_sgm_Basis_ratio	Continuous

Source: Own compilation.

The estimations of the categorical variables shift the estimation intercept. The estimations of the continuous variables are multiplied with the corresponding IFM-CAP data to estimate the marginal effect on the probability to exit.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

5.3 The simulation of land markets

Direct land exchange between the FADN farms is not a good way to represent the exchange of land between the farms that exit and the farms that stay. It is very unlikely that the FADN farms are neighbouring farms; additionally, the weights of the farms cannot be used.

For this, we will simulate the land market as a random process where the land a staying farm will receive depends on related farm characteristics.

We select the farm's gross margin as the characteristic that will determine how much land is allocated to the farm. In the future implementation, a better characteristic is the shadow price of land, possibly complemented with other farm properties. That requires running the model parametrically with a stepwise increase of the available land and recording the new gross margin. Alternatively, given sufficient data sources, an econometric model could provide information on the distribution of the land that a farm receives conditional on its farm characteristics.

Nevertheless, we proceed with the farm gross margin as the characteristic that determines the allocation of land to farms. More specifically, we assume that the distribution of the share of land that a farm will receive follows the same distribution of the gross margins of the farm. We further assume that both distributions follow the same exponential distribution. Thus, for each NUTS2 area, we estimate the λ parameter of the exponential distribution. Figure 29 shows an example of the gross margin distribution and the fitted exponential probability. We then allocate the share of land according to the estimated density function. This works because the sum of the density function equals 1.

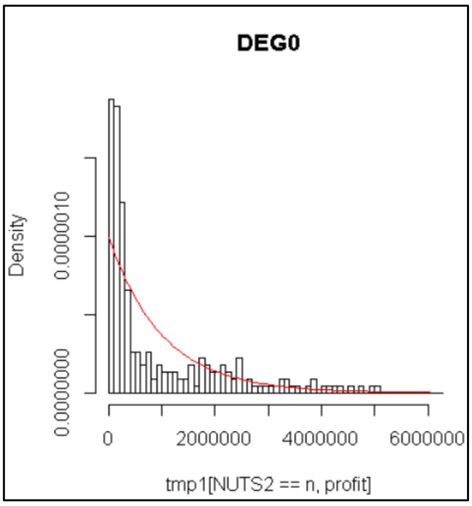


Figure 34 The distribution of the gross profit across farms for NUTS2=DEG0 (histogram) and the related fitted exponential distribution (red line). *Source: Own compilation. Based on IFM-CAP FADN data.*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

5.4 Results

The cumulative distribution of the probability to exit is given in **Figure *35***. Almost 25% of the farms have a 50% probability of exiting.

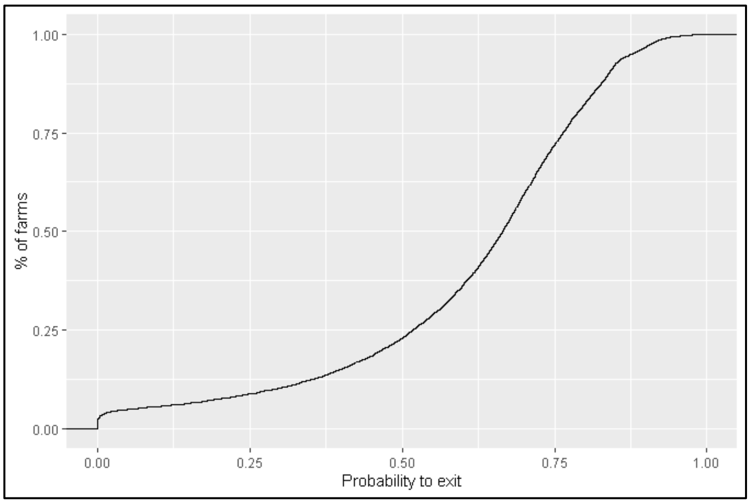


Figure 35 Cumulative distribution of the probability to exit. *Source: Own compilation. Based on IFM-CAP FADN data.*

Assuming that 23% of the farms will exit, we choose the 23% of the farms with the highest exit probability.[18] The land freed from the farms per NUTS2 is as follows (given that the land is multiplied by the FADN weight):

Table 11 Land to redistribute (in hectares) after the farms that will exit were estimated.

NUTS2	ALL UAA	TO LAND MARKET	%	NUTS2	ALL UAA	TO LAND MARKET	%
DE11	532,320	95,217	18%	**DE92**	352,067	66,904	19%
DE12	168,060	13,326	8%	**DE93**	1,019,909	27,867	3%
DE13	82,740	3,887	5%	**DE94**	749,990	88,565	12%
DE14	463,787	37,924	8%	**DEA1**	221,439	29,820	13%
DE21	467,887	10,472	2%	**DEA2**	189,043	34,268	18%
DE22	454,196	30,525	7%	**DEA3**	372,043	20,470	6%
DE23	391,434	22,403	6%	**DEA4**	379,864	35,122	9%
DE24	344,462	37,773	11%	**DEA5**	226,804	15,298	7%

[18] The average probability of a farm in 2010 to exit until 2020 is 23% (deliverable D4.2).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

DE25	405,499	50,189	12%	**DEB1**	201,753	17,010	8%
DE26	457,227	68,568	15%	**DEB2**	121,096	8,970	7%
DE27	380,419	69,861	18%	**DEB3**	320,974	76,915	24%
DE40	1,403,232	3,877	0%	**DEC0**	66,878	7,584	11%
DE60	1,932	1,932	100%	**DED2**	365,758	90,072	25%
DE71	187,826	28,410	15%	**DED4**	372,126	60,846	16%
DE72	178,333	16,924	9%	**DED5**	200,249	28,388	14%
DE73	351,530	55,953	16%	**DEE0**	1,299,145	76,781	6%
DE80	1,436,422	60,518	4%	**DEF0**	918,261	481,848	52%
DE91	265,523	31,401	12%	**DEG0**	845,390	551	0%

Source: Own compilation. Based on IFM-CAP FADN data.

Table 11 presents, in total agricultural land use (UAA), the amount of freed land from exiting farms and the share of freed land to total agricultural land. One can see that the share of land from the exiting farms is heterogeneous between the NUTS2 regions. For instance, among the larger NUTS2 regions in terms of total agricultural land, DEF0 frees almost 50% of the agricultural land, whereas the largest NUTS2 region (DE40) has only negligible values. In DE60, the smallest NUTS2 region, all farms exit the sector.

Table 12 Gini coefficient of the distribution of land before and after farm exit.

NUTS2	BEFORE EXIT	AFTER EXIT	NUTS2	BEFORE EXIT	AFTER EXIT
DEF0	0.382	0.315	**DE27**	0.281	0.285
DEA3	0.281	0.275	**DE22**	0.288	0.285
DEA2	0.249	0.248	**DE21**	0.310	0.308
DEA4	0.304	0.294	**DE24**	0.212	0.221
DEA1	0.345	0.271	**DE11**	0.411	0.296
DEA5	0.343	0.324	**DE93**	0.377	0.326
DE94	0.369	0.341	**DE92**	0.341	0.312
DEB3	0.521	0.281	**DE91**	0.292	0.268
DEB2	0.308	0.251	**DEG0**	0.545	0.527
DEB1	0.384	0.298	**DE71**	0.293	0.288
DEC0	0.266	0.257	**DE26**	0.397	0.299
DEE0	0.558	0.518	**DED2**	0.525	0.414

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

DE80	0.509	0.488	**DED5**	0.553	0.459
DE40	0.418	0.411	**DED4**	0.532	0.470
DE72	0.296	0.287	**DE13**	0.424	0.319
DE73	0.284	0.273	**DE12**	0.485	0.273
DE25	0.287	0.243	**DE14**	0.372	0.322
DE23	0.221	0.218			

Source: Own compilation. Based on IFM-CAP FADN data.

Table 12 shows the distribution of land before and after exit. In almost all NUTS2 regions, we observed that the land is more equally distributed after the exit situation. This is due to the case that we distribute the freed land according to the empirical exponential distribution.

Table 13 Change in land use due to the exchange of land (Land use after the exit of farms minus land use before).

NUTS2	ARABLE		FODDER		PERMANENT		VEGETABLES	
	UAA before	Change	UAA before	Change	UAA before	Change	UAA before	Change
DE11	271,458	2.9%	226,327	3.7%	29,926	-53.4%	4,610	-45.6%
DE12	92,171	1.9%	69,648	-1.5%	2,115	-53.1%	4,126	-63.8%
DE13	36,687	2.7%	43,586	1.2%	2,069	-69.8%	399	-23.4%
DE14	181,487	1.5%	269,399	1.5%	12,443	-75.8%	457	-82.5%
DE21	197,667	-0.8%	269,632	0.3%	367	6.8%	221	5.5%
DE22	243,756	-0.2%	205,232	-0.2%	37	-100.0%	5,170	-7.5%
DE23	194,972	-2.2%	196,374	2.2%			87	-45.7%
DE24	174,647	-3.4%	169,425	3.5%	388	-72.4%	2	10.7%
DE25	186,007	-0.9%	213,957	2.9%	555	-36.0%	4,980	-93.9%
DE26	300,073	-2.5%	150,497	5.9%	6,367	-33.0%	291	-4.1%
DE27	112,147	9.2%	266,636	-3.6%	784	-80.8%	852	-4.3%
DE40	840,607	0.1%	555,821	-0.4%	1,089	-25.3%	5,715	0.6%
DE60			1,749	-100.0%			183	-100.0%
DE71	113,404	-5.0%	65,626	2.6%	408	46.4%	8,388	35.7%
DE72	80,221	-0.1%	98,091	-1.8%			21	9.7%
DE73	197,447	-4.7%	153,066	6.1%	237	-100.0%	780	15.7%
DE80	1,017,129	0.8%	418,856	-2.4%	11	3.5%	426	-82.4%
DE91	238,464	-0.4%	26,817	-3.8%			241	-19.6%
DE92	234,350	-1.8%	114,522	2.9%			3,195	-8.4%
DE93	451,260	-0.3%	553,641	2.1%	10,556	-91.1%	4,452	-12.3%

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

DE94	285,989	-5.0%	460,519	2.4%	2,454	-65.2%	1,028	-63.7%
DEA1	96,033	-5.5%	106,576	6.5%	857	-96.9%	17,973	-9.6%
DEA2	117,347	-9.4%	64,323	25.1%	660	-100.0%	6,714	-77.1%
DEA3	176,839	0.5%	193,463	-0.3%	53	-100.0%	1,687	-37.4%
DEA4	267,671	-0.9%	110,937	2.5%	188	47.3%	1,070	-58.0%
DEA5	89,727	4.0%	136,853	-2.7%			224	22.9%
DEB1	115,031	0.9%	78,854	2.5%	7,830	-41.5%	39	-100.0%
DEB2	30,073	0.5%	89,364	1.6%	1,659	-99.6%		
DEB3	180,060	13.1%	75,433	18.2%	54,462	-70.4%	11,020	8.8%
DEC0	27,943	-2.4%	38,932	1.5%	4	23.3%		
DED2	217,328	1.9%	142,714	-3.6%	1,194	-2.5%	4,522	-19.0%
DED4	218,220	1.8%	152,167	-2.7%	1,594	-97.2%	145	-41.9%
DED5	162,727	-3.3%	36,415	7.0%	87	-100.0%	1,019	-100.0%
DEE0	965,992	-2.0%	328,281	6.0%	530	-62.0%	4,343	6.3%
DEF0	423,416	-11.9%	490,025	7.2%	733	-100.0%	4,087	-100.0%
DEG0	560,370	-0.2%	279,927	-0.1%	3,615	-3.4%	1,478	-10.0%

Source: Own compilation. Based on IFM-CAP FADN data.

Table 13 shows the change in the distribution of arable, fodder, permanent, and horticulture land use. Permanent and horticulture land use decreased much more than arable and fodder land. The descriptive statistics and estimation models show much higher average exit rates for permanent and horticulture farm types. The distribution process of freed land increased the land use of the surviving farms. Hence, the surveyed farms do not change their productive orientation and do not overtake permanent or horticulture production activities. In reality, farms with similar production orientations are more likely to take over freed land from exiting farms. First, if this were not the case, there would be incentives to do so as prices might increase due to lower supply from exiting farms. Second, farms with similar production have lower entry barriers regarding managerial capabilities and other productive requirements already in place.

Further, the estimation models are done with German FSS data. The distribution of farms with respect to their land use is very different between FSS and FADN farms. The farms selected in FADN are truncated with respect to their standard output at the farm level. This means only farms over a certain threshold are sampled in FADN. Hence, there is a selection bias at play, which makes it likely that the estimated coefficients of the exit model do not exactly fit the farms in FADN. It also has to be noted that the variable "age of the farm holder," which is of major importance, could not be used to calculate exit probabilities. The distribution would likely be different from what we show here.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

5.5 Conclusion

From the estimated exit model from deliverable D4.2, coefficients have been transferred to estimate exit probabilities of farms in IFM-CAP. After calculating exit probabilities, the freed land has been distributed according to an empirical distribution of observed land use. With this, no competition about land took place. It is unknown where the FADN farms are located, so they cannot be distributed according to nearby surveying farms from freed land of exiting farms. Further, a closer look at the new distribution of productive land use was made. Permanent and horticulture production decreased most relative to arable and fodder land use. This is mostly explained by the distribution process of freed land from exiting farms and due to the selection bias of farms sampled in FADN and observed in the German FSS, from which the exit model is estimated. Although many estimated coefficients from the exit model could be used to model farm exit in IFM-CAP, the most important and predictive one – the age of the farm holder – could not be applied. The results will likely differ according to the distribution of age across FADN farms.

Further research should consider the underlying sample selection of FADN farms compared to the farms observed in FSS data. Further, the distribution process of freed land from the exiting farms to the surveying farms should be simulated by considering shadow values of land, for instance. Additionally, more regionally differentiated exit models could also be estimated for their coefficients with respect to farm characteristics. In the applied model, only the average exit probability is shifted across NUTS2 regions, but the coefficients for the continuous variables are the same for all farms.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

6 IMPROVED RISK REPRESENTATION

6.1 Introduction

The EU's reduced intervention in agricultural markets, together with the increased variability in yields due to climate change, have led to increasingly volatile output prices and more income uncertainty. However, for an individual producer, increased output price volatility does not necessarily imply changes in the level and variance of income because income also depends on input costs, yields, and the correlation between them (Pennings et al., 2010). More specifically, a producer faces different kinds of uncertainty: i) production uncertainty due to uncontrollable elements such as weather; ii) price uncertainty because the output price is unknown at the time decisions must be made; iii) technological uncertainty; and iv) policy uncertainty (Moschini and Hennessy, 2001). Depending on the correlation between different kinds of uncertainty, the increased price volatility may result in more overall uncertainty for producers. The resulting uncertainty in producers' incomes leads to rising income risk. However, the increased risk perceived does not only depend on current activities but is also relative to other activities. In selecting potential alternative land uses, it may be of importance whether these land uses are substitutes or complements compared with current land-use activities. Hence, the likelihood of land-use change depends on the degree to which the producer is risk-averse and whether the crops are complements or substitutes.

Climate change and extreme weather events can also increase the intensity and likelihood of short-term variability and shocks to agricultural supply. Food supply shocks due to crop losses inside Europe may lead to farmers adjusting their land use or management decisions as well as to changes in consumption patterns. Crop losses may become of such a magnitude and frequency that farms structurally experience that their costs are larger than their benefits of production. In case this happens, several adaptation options may be possible. Extreme droughts may eliminate the possibility of rain-fed agriculture, leading to a shift in crop management from rain-fed to irrigated agriculture. It may also be that irrigation is not possible due to the available water or not the most profitable option in the specific location. In this case, farmers may stop growing the crop at the location and turn to a more profitable crop that is more resistant to extreme weather events. If these adaptation options are no longer viable, producers may be forced to leave a certain area, leading to farms ceasing to exist and land abandonment.

Eventually, these adjustments may lead to significant macroeconomic effects. It is therefore important to think conceptually about how to link farmer behaviour from individual households, such as modelled using farm models, to market-level models to analyze the

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

implications of changes in behaviour as a consequence of climate or policy changes to macro-economic market impacts.

In Task 4.4, microeconomic models are developed that analyze producers' choices. These models can inform the behaviour of equilibrium models when faced with uncertain events, such as climate-induced production shocks that may lead to farm structural change. The main objective of this sub-task is to think conceptually about the use of the output of Task 4.4 for including risk behaviour in models such as GLOBIOM. A methodological framework with the aim to investigate the impacts of crop-specific insurance on optimal management decisions on a farm-household level, considering income and risks in crop production, and subsequently upscale this to consider changes in crop area allocation, prices, and trade in Europe is developed. The conceptual method, therefore, serves as a proof of concept for future research. For IIASA, GLOBIOM has been further adjusted to be run in a non-stationary fashion with the aim to assess the impact of extremes such as climate-induced yield shocks on producer behaviour and their aggregate effects on, e.g., agricultural markets and land use. Using the best available climate data and crop model outputs from estimations by EPIC-IIASA, we assess the impacts of future extreme yield. The remainder of this task is organized as follows: in subsection 6.2, we develop a method to adapt GLOBIOM to analyze extreme events. In subsection 6.3, we provide an overview for including yield shocks in GLOBIOM. In subsection 6.4, we go into the need for risk management. In subsection 6.5, we develop an approach to incorporate risk in GLOBIOM and the possibility of hedging against insurance. In subsection 6.6, we develop a stylized farm household modelling approach to parameterize risk premiums in GLOBIOM. We end with a conclusion and discussion section.

6.2 Adapting GLOBIOM for the analysis of extreme events

GLOBIOM can be enhanced to deal with shocks in prices and yields in a static-comparative fashion. To allow for the analysis of these events, a "short run" response to yield shocks is implemented by limiting the possible production response to the shock. These limitations to the production responses include the restriction of land reallocation per sector for all land use sectors to reflect short-term adjustments and the reduction of possibilities for substitution between land and other inputs for crops.

GLOBIOM's objective function is defined as the sum of global consumer and producer surplus. GLOBIOM defines this as the integral under the demand functions minus the sum of all production, resource, and trading costs (Havlík et al., 2011).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

$$
\begin{aligned}
&MaxOBJ_t = \\
&\sum_{r,y}\left[\int \varphi^{dem}_{r,t,y}\left(D_{r,t,y}\right)d(.)\right]-\sum_{r}\left[\int \varphi^{splw}_{r,t}\left(W_{r,t}\right)d(.)\right]-\sum_{r,m}\left(\tau^{proc}_{r,m}\cdot P_{r,t,m}\right) \\
&-\sum_{r,l,\tilde{l}}\left[\int \varphi^{lucc}_{r,l,\tilde{l},t}\left(\sum_{c,g} Q_{r,t,c,g,l,\tilde{l}}\right)d(.)\right]-\sum_{r,c,g,l,s,m}\left(\tau^{land}_{c,g,l,s,m}\cdot A_{r,t,c,g,l,s,m}\right) \\
&-\sum_{r,c,g,l,s,m}\left(\tau^{calib}_{c,g,l,s,m}\cdot A_{r,t,c,g,l,s,m}\right)-\sum_{r,c,g,a,m}\left(\tau^{calib}_{c,g,a,m}\cdot B_{r,t,c,g,a,m}\right) \\
&-\sum_{r,\tilde{r},y}\left[\int \varphi^{trade}_{r,\tilde{r},t,y}\left(T_{r,\tilde{r},t,y}\right)d(.)\right]
\end{aligned}
\tag{8}
$$

where MaxOBJ represents the sum of consumers' and producers’ surplus, ϕ^{dem} the constant elasticity demand function, d the final demand, ϕ^{splw} represents the constant elasticity water supply function, W represents the water use, τ^{proc}: is the processing cost by a unit of the primary product, P the processed quantity, ϕ^{lucc} the land use/cover change cost function with rising marginal costs, Q the amount of land use/cover change, τ land the management cost per hectare of land use (except for water), A the land use activities, τ^{calib}: the calibrated production cost per hectare of land use activities or livestock unit, B the livestock numbers, ϕ^{trade} the constant elasticity international trade cost function, T the international shipments. The indices r represent the region, t the period, c the country, g the spatial grid, l the land use type, s the primary product, a the animal type, y the final product, and m the management system.

For a producer, the resulting shadow prices of land derived from solving Eq.(8) represent the land's marginal contribution to profit. If a producer has no constraints on land use, profit maximization occurs at the point where shadow prices are equal among all alternative land uses. However, the equality of shadow prices among land uses only accounts for expected output prices because producers do not know output prices at the time they choose their production activities and must base their expectations on past experience. This causes uncertainty for the producer about the difference between the actual and expected output price, which may differ per activity and through time. To accommodate for the differences between allocation decisions based on expected prices and the outcomes of these decisions, we solve Eq. (8) first by replacing the part of the constant elasticity demand function belonging to crop production in Eq. (8) with the expected revenues obtained from crop production:

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

$$
\begin{aligned}
& MaxPOBJ_t = \\
& \sum_{r,a}\left[\int \varphi^{dem}_{r,t,a}\left(D_{r,t,a}\right)d(.)\right] + \sum_{r,c,g,l,i,m}\left(p^{*}_{r,t,i}\cdot A_{r,t,c,g,l,i,m}\right) \\
& -\sum_{r}\left[\int \varphi^{splw}_{r,t}\left(W_{r,t}\right)d(.)\right] - \sum_{r,m}\left(\tau^{proc}_{r,m}\cdot P_{r,t,m}\right) \\
& -\sum_{r,l,\tilde{l}}\left[\int \varphi^{lucc}_{r,l,\tilde{l},t}\left(\sum_{c,g} Q_{r,t,c,g,l,\tilde{l}}\right)d(.)\right] - \sum_{r,c,g,l,s,m}\left(\tau^{land}_{c,g,l,s,m}\cdot A_{r,t,c,g,l,s,m}\right) \\
& -\sum_{r,c,g,l,s,m}\left(\tau^{calib}_{c,g,l,s,m}\cdot A_{r,t,c,g,l,s,m}\right) - \sum_{r,c,g,a,m}\left(\tau^{calib}_{c,g,a,m}\cdot B_{r,t,c,g,a,m}\right) \\
& -\sum_{r,\tilde{r},y}\left[\int \varphi^{trade}_{r,\tilde{r},t,y}\left(T_{r,\tilde{r},t,y}\right)d(.)\right]
\end{aligned}
\tag{9}
$$

where *MaxPOBJ* represents the producers' surplus based on expected prices of crop production and the consumers' surplus of animal and forest products, p^* represents the expected price of crop production, and the index i represents crop products.

In GLOBIOM, production can be altered along the supply curve in order to meet expected demand. In the long run, the supply curve may be altered via, e.g., technological change and farm structural change, and the demand curve can be altered through, e.g., GDP and population changes, leading to a new equilibrium price. For inter-annual changes, however, producers cannot change the production quantities of a certain crop anymore, and the adaptive capacity of changing production quantities must come from consumption or trade instead of altering land allocation or changing management styles.

We first solve *MaxPOBJ* as depicted in Eq. (9), where producers maximize their expected revenues based on expected prices of crop production. Upon solving Eq. (9), we fix the allocation of $A_{r,t,c,g,l,i,m}$. After the producer's land allocation and management decision based on expected prices has taken place, production has an upper bound: it is defined as the goods harvested based on the land allocation and the outcome of the yields. With the fixed allocation, we solve MaxOBJ in Eq. (8). This two-step system implies that within an agricultural season, an unanticipated change in yields will lead to a change in the supply of products, which will lead to a change in the corresponding prices and demand of the product. Only in the next period will a change in resource costs allow producers to shift the supply and reconsider their crop allocation decisions.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

6.3 Climate impact estimation

Climate change has the potential to affect the agriculture, forestry, and fisheries sectors, both negatively (e.g., from more extreme storms, lower rainfall, increasing variability, extreme heat) and positively (e.g., from CO_2 fertilization, extended seasons). These effects will arise from gradual climate change and extreme events that will affect production, but also from indirect effects, e.g., changes in the prevalence of pests and diseases. To identify events in the future that influence producers' risk attitude, impacts of gradual climate change are extreme weather events are selected under future climate conditions.

The impacts of gradual climate change and extreme events on yields come from the EPIC-IIASA. Regarding gradual climate change impacts, annual EPIC-IIASA output is converted to the decadal GLOBIOM resolution by using 30-year moving average values – i.e., 15 years before and 15 years after - over the time horizon of the model (Eq. (10). The historical (base) yields ($Y_{c,base}$) are calibrated using the FAO yields for 2000, while the gradual climatic effects of the year 2050 (λ^{c}_{2050}) are calculated by taking the average effect between 2035-2065.

$$\lambda^{cc}_{c,T,i,RCP} = \frac{1}{Y_{c,base,i,RCP}} \sum_{t=T-15}^{T+15} \frac{Y_{c,t,i,RCP}}{30} = \frac{\bar{Y}_{c,T,i,RCP}}{Y_{c,base,i,RCP}} \tag{10}$$

where λ^{cc} is the climatic impact on crop yields at each decadal timestep (T) for each grid cell (i) under each degree of warming (RCP). $Y_{c,base}$ is the base year crop yield.

To analyze the impacts of the extreme weather event, a supplementary factor (λ^{var}), which reflects the extreme event modelled by the hybrid model, is added to Eq. (10) after the producer has made their decisions based on gradual climate change impacts. The value of this supplementary factor is selected as the largest production loss given GLOBIOM's baseline 2050 area allocation and the yield deviations predicted by the hybrid model (pX) in the 30-year time window, here, 2035-2065.

$$Y^{p}_{soybean,T,i,RCP,,pX} = Y_{soybean,base,i} \times \lambda^{cc}_{soybean,T,i,RCP} \times \lambda^{se}_{T,i} \times \lambda^{var}_{soybean,T,i,RCP,pX} \tag{11}$$

$$\lambda^{var}_{soybean,T,i,RCP,pX} = \frac{Y_{soybean,T,i,RCP,pX}}{\frac{1}{30}\sum_{T-15}^{T+15} Y_{soybean,t,i,RCP}} = \frac{Y_{soybean,T,i,RCP,pX}}{\bar{Y}_{soybean,T,i,RCP}} \tag{12}$$

In GLOBIOM, the combined impacts of extreme weather event-related yield losses and gradual climate change are implemented as factor changes and multiplied with the baseline yields.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

For the major crops grown in Europe (rapeseed, rye, rice, soybeans, sugar beet, sunflower, corn, potato, winter wheat, and barley), EPIC-IIASA model outputs based on Euro-Cordex climate data were produced for the GCM-RCP climate scenarios. All runs consider simulations with explicit accounting for CO_2 fertilization. For each of the 30-year time slices, we compare the difference between the annual yield and the mean yield level of that time slice. For an aggregation of impacts of the shocks across individual crops, the yields are computed as weighted averages of all crops weighted by their area.

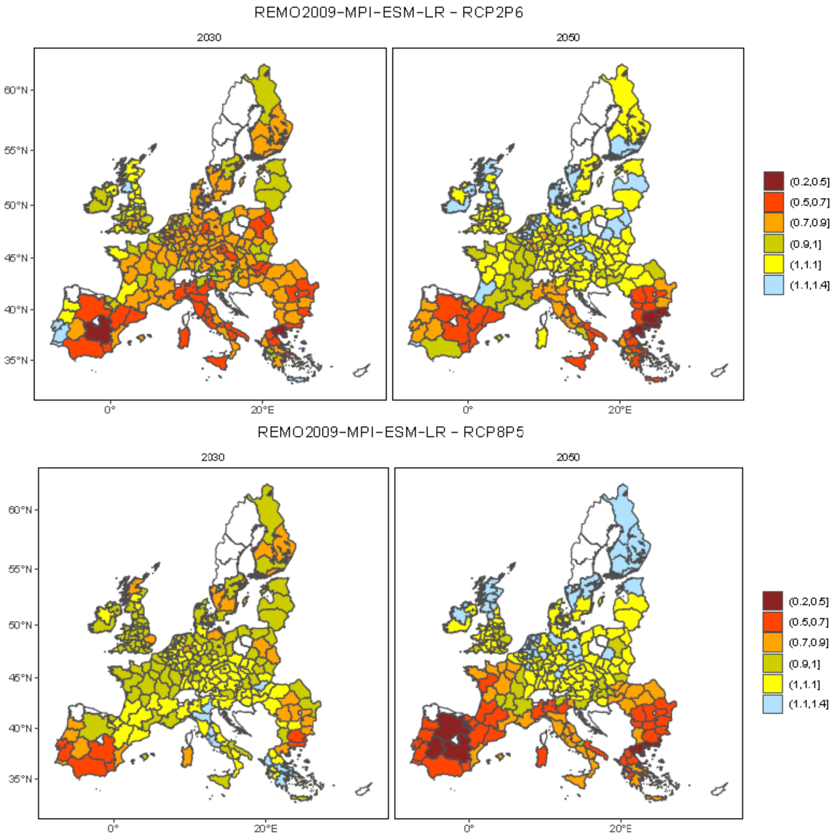


Figure 36 EPIC IIASA model outputs.

Both the climate-induced yield impact of gradual change as well as the yield impact induced by weather variability can be implemented in GLOBIOM.

6.4 The need for risk management

Producers are generally considered risk averse, meaning they will give up some level of expected income to reduce the possibility of a negative outcome (Arrow, 1996a). The most common way for them to do so is by altering their production plan. This is why, upon analyzing land allocation decisions, producers' preferences have often been characterized using an

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

expected utility function (J.-P. Chavas and Pope, 1985; Coyle, 1999; Lansink, 2008; Sckokai and Moro, 2006). Although there has been quite some critique on the approach of an expected utility function (see, e.g., Buschena and Zilberman, 1994), it is still one of the leading frameworks to describe producers' economic choices.

The increased instability of agricultural incomes strengthens the need for risk management. Risk management is used to control the possible adverse consequences of uncertainty that may arise from production decisions. A producer may adopt several measures to decrease rising income risk, such as crop diversification and forward and future contracts. Government policies are also aimed at reducing production risk. Government intervention is necessary to shift risk away from producers due to failures in the ideal competitive market for risk-shifting (Arrow, 1996b). This is especially the case for catastrophic events, such as floods and droughts, which are characterized by systemic risk, meaning that there is a large geographical correlation between farms (Glauber, 2004; Meuwissen et al., 2003; Miranda and Glauber, 1997).

A well-known measure supported by governments to assist in risk management is the possibility for farmers to insure (part of the) farm operations. These may protect against the risk of losing (part of the) income due to catastrophic events (such as livestock diseases) or common fluctuations (such as whole-farm insurance). Programs reducing income variability entail both a wealth and an insurance effect that may lead to different land allocation decisions (Adams et al., 2001; J.-P. Chavas and Holt, 1996; Hennessy, 1998). The recent spikes in agricultural prices caused an increased appeal for financial safety nets among member states.

6.5 Inclusion of risk and insurance in GLOBIOM

In this section, we discuss the implementation of risk aversion and the possibility of adopting insurance in GLOBIOM. GLOBIOM's objective function is defined as the sum of global consumer and producer surplus. Prices and trade are endogenous to the model and adjust based on changes in demand (exogenously driven by population and GDP constraints) and supply. Because of the deterministic nature of the model, in combination with the equilibrium structure where the optimum between supply and demand is sought without explicitly representing agents, the influence of risk in area allocation would naturally enter the model through a change in the cost or a change in the revenues. This added cost component that acts on the consumer surplus would have to be parameterized through a more farm-level decision-making model that could quantify the risk in terms of costs. This cost component would enter GLOBIOM directly in the objective function and be specific to the agricultural activity employed.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

GLOBIOM's objective function is defined as the integral under the demand functions minus the sum of all production, resource, and trading costs, as shown in Eq. (13). The uncertainty for the producer about the difference between the actual and expected output prices may cause them to prefer a situation where they give up part of their revenue to get a certain income. To accommodate for the differences between allocation decisions based on preferred revenues (i.e., expected revenues including a cost component to quantify risk aversion) and the outcomes of these decisions, we solve Eq. (8) first by replacing the part of the constant elasticity demand function belonging to crop production in Eq. (8) by the expected revenues based on risk preferences related to crop production:

$$
\begin{aligned}
\mathrm{MaxOBJt} = & \sum_{r,y}\left[\int \varphi_{r,t,y}^{dem}(D_{r,t,y})d(.)\right] \sum_{r,c,g,l,i,m}\left(p_{r,t,i}^{*}\cdot A_{r,t,c,g,l,i,m} - C_{r,c,l,s}\right) \\
& - \sum_{r}\left[\int \varphi_{r,t}^{splw}(W_{r,t})d(.)\right] - \sum_{r,m}\left(\tau_{r,m}^{proc}\cdot P_{r,t,m}\right) \\
& - \sum_{r,l,l^{*}}\left[\int \varphi_{r,l,l^{*},t}^{lucc}\left(\sum_{c,g} Q_{r,t,c,g,l,l^{*}}\right)d(.)\right] \\
& - \sum_{r,c,g,l,s,m}\left(\tau_{c,g,l,s,m}^{land}\cdot A_{r,t,c,g,l,s,m}\right) \\
& - \sum_{r,c,g,l,s,m}\left(\tau_{c,g,l,s,m}^{calib}\cdot A_{r,t,c,g,l,s,m}\right) \\
& - \sum_{r,c,g,a,m}\left(\tau_{c,g,a,m}^{calib}\cdot B_{r,t,c,g,a,m}\right) \\
& - \sum_{r,r^{*},y}\left[\int \varphi_{r,r^{*},t,y}^{trade}(T_{r,r^{*},t,y})d(.)\right] - \sum_{r,y}\left(\beta_{c}^{p*}\cdot S_{c}^{p*}\right) \\
& + \sum_{r}\left(\beta_{c,r,y}^{d*}\cdot S_{c,r,y}^{d*}\right)
\end{aligned}
\tag{13}
$$

where *MaxPOBJ* represents the producers' surplus based on expected revenues, including risk preference of crop production and the consumers' surplus of animal and forest products, p^{*} * *A* - C represents the expected revenue of crop production minus risk aversion coefficient *C*, and the index i represents crop products.

$$
S_{c,r,y} = \begin{cases} and1 \text{ if } \sum_{c=1}^{C} p_{r,t,i}^{*}\cdot A_{r,t,c,g,l,i,m} - C_{r,c,l,s} < S_{c,r,y}^{*} \quad \text{(insurance adoption)} \\ and0 \text{ if } \sum_{c=1}^{C} p_{r,t,i}^{*}\cdot A_{r,t,c,g,l,i,m} - C_{r,c,l,s} \geq S_{c,r,y}^{*} \quad \text{(no insurance adoption)} \end{cases}
\tag{14}
$$

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

where s^* represents the revenue obtained from potential payout – premium. If this is higher than the expected revenue minus the cost of the risk aversion coefficient, then there is adoption of the insurance. If this is lower than the expected revenue minus the cost of the risk aversion coefficient, then there is no adoption of the insurance. The cost of the risk aversion coefficient is defined by agricultural product and would come either from FarmDyn or are determined as described further below.

After the producer's land allocation and management decision based on expected revenues, including risk preference and the possibility for insurance, has taken place, production has an upper bound: it is defined as the goods harvested based on the land allocation and the outcome of the yields. With the fixed allocation, we solve MaxOBJ in Eq. (8), with the indemnity and payout of adopted insurance now directly included:

$$\begin{aligned}
\mathrm{MaxOBJt} = & \sum_{r,y}\left[\int \varphi_{r,t,y}^{dem}(D_{r,t,y})d(.)\right] - \sum_{r}\left[\int \varphi_{r,t}^{splw}(W_{r,t})d(.)\right] \\
& - \sum_{r,m}\left(\tau_{r,m}^{proc} \cdot P_{r,t,m}\right) - \sum_{r,l,l^*}\left[\int \varphi_{r,l,l^*,t}^{lucc}\left(\sum_{c,g} Q_{r,t,c,g,l,l^*}\right)d(.)\right] \\
& - \sum_{r,c,g,l,s,m}\left(\tau_{c,g,l,s,m}^{land} \cdot A_{r,t,c,g,l,s,m}\right) \\
& - \sum_{r,c,g,l,s,m}\left(\tau_{c,g,l,s,m}^{calib} \cdot A_{r,t,c,g,l,s,m}\right) \\
& - \sum_{r,c,g,a,m}\left(\tau_{c,g,a,m}^{calib} \cdot B_{r,t,c,g,a,m}\right) \\
& - \sum_{r,r^*,y}\left[\int \varphi_{r,r^*,t,y}^{trade}(T_{r,r^*,t,y})d(.)\right] - \sum_{r,y}\left(\beta_c^{p*} \cdot S_c^{p*}\right) \\
& + \sum_{r}\left(\beta_{c,r,y}^{d*} \cdot S_{c,r,y}^{d*}\right)
\end{aligned} \tag{15}$$

Where $\mathrm{MaxOBJ_t}$ represents the sum of consumers' and producers' surplus, ${S^{p}}^*{}_c$ the indemnities paid in case insurance is chosen, ${S^{d}}^*{}_{r,c,y}$ the payout in case insurance is chosen and revenues drop below threshold X. $\beta_{r,y}^{p*}$ and $\beta_{r,y}^{d*}$ represent the cost for indemnities and the payouts, respectively.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

6.6 Farm household level model to calibrate parameters for GLOBIOM

To assess the impact of increased yield volatility on farmers' production decisions, maximizing expected revenues minus risk aversion, we need to estimate the crop-specific risk aversion coefficient to be implemented as a cost component in market-level models such as GLOBIOM. To approximate this cost component, we can either use existing farm-level models such as FarmDyn or establish stylized farm household models. An example of such a stylized farm household model is given below.

We assume producers maximize income while accounting for risk in their production decisions. Representative arable farmers with fixed amounts of land and facing exogenous input and output prices aim to maximize expected utility from total revenues by allocating land to various crops. Currently, producers receive a direct payment per hectare that varies by crop based on historic entitlements. However, a flat-rate payment was introduced with the 2015 crop year; it provides the same payment regardless of the crops planted by the producer and is referred to as the single farm payment (SFP).

To analyze the crop allocation decision, we develop the following model:

$$\text{Maximize } U = \sum_{k=1}^{K} E[R_k] - \tfrac{1}{2}\,\varphi\,\sigma^2 \tag{16}$$

Subject to:

$$R_{k,t} = [p_{k,t}\, y_{k,t} - c_k(w) + SPS_k]\, x_k,\ \forall\, k \tag{17}$$

$$\sigma^2 = \sum_{k=1}^{K}\sum_{i=1}^{K}\left[x_k \times CV(R_k, R_i) \times x_i\right] \tag{18}$$

$$CV(R_k, R_i) = \frac{1}{T}\sum_{t=1}^{T}\left(R_{k,t} - E[R_k]\right)\left(R_{i,t} - E[R_i]\right)\ \forall\, k,i \tag{19}$$

$$E[R_k] = \frac{1}{T}\sum_{t=1}^{T} R_{k,t}\ \ \forall\, k \tag{20}$$

$$\sum_{k=1}^{K} x_k \le \overline{X} \tag{21}$$

U represents the producer’s utility; $\sum E[R_k]$ is the expected total revenue minus variable costs from crop production; φ is the risk aversion coefficient that takes the form $-\dfrac{U''(I)}{U'(I)}$, where *I*

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

refers to the farm household's income;[19] σ^2 is the variance associated with the total crop portfolio; $p_{k,t}$ and $y_{k,t}$ represent the respective output price and yield for crop k in period t; $c_k(w)$ is the per unit-area variable cost of producing crop k as a function of exogenously-determined input prices w; and *SPS* is the flat-rate payment based on historic entitlements (€/ha). Further, $CV(R_k,R_i)$ refers to the covariance matrix, where R_i and R_k are the respective realized gross margin to crops i and k, and $\mathrm{E}[R_k]$ is the farmer's expected gross margin (€/ha) from planting crop k; x_k denotes the number of hectares allocated to produce crop k; and $\overline{X}$ represents the total area (ha) the farmer has available to allocate to crops. There are K crops that can be planted in any given period, and there are T periods.

Equation (17) calculates the farmer's gross margin accruing to each crop in each period given the allocation of land to crops, which is endogenously chosen in the model. SPS is included in Eq. (17), but the fixed production cost is not because fixed costs are part of the PMP term (as explained next). Equation (18) specifies the risk associated with the total crop portfolio, while Eq. (19) provides the variance-covariance matrix. Equation (20) calculates the expected gross margin that accrues to each crop over all periods (simulations). Finally, the constraint in Eq. (21) indicates that the farmer's cultivated area does not exceed the available area. In each period, the producer must decide how to allocate her $\overline{X}$ hectares among the K different crops so as to maximize utility over the total set of crops.

6.7 Discussion and conclusion

The main objective of this section is to think conceptually about the use of microeconomic models to inform dealing with risk and uncertainty in producer's behaviour in market-level models. Macro-level models currently have limited capabilities to consider changes in the volatility of commodity prices. Therefore, this task develops a methodology to add risk premia to commodity prices reflecting commodity-specific and country-specific farmer risk aversion. A methodological framework with the aim to investigate the impacts of crop-specific insurance on optimal management decisions, considering income and risks in crop production, and subsequently upscale this to consider changes in crop area allocation, prices, and trade in Europe is developed. We show how market-level models such as GLOBIOM can be adapted to deal with increased yield volatility as a consequence of climate change; how crop models such as EPIC-IIASA can be used to assess the impacts of future crop yield volatility; how risk in agricultural decision-making can be included in market-level models, and how this risk can be estimated using stylized farm household modelling. Together, this serves as a proof of concept for future research.

There is still debate about how the risk, as estimated by farm household models such as FarmDyn, can best be transferred to market-level models. Task 4.4 developed the curvature of the value function on risk preference and statistically determined the risk preference of farmers. However, it has not been possible to translate the outputs of task 4.4 to a risk premium that can be incorporated into GLOBIOM. Generating changes in risk premiums in a farm(household) model with risk preferences is not straightforward. The changes in the risk premiums are in the dual domain (a kind of “shadow price” change), while we observe changes in the cropping pattern in the simulations. To estimate the risk parameters, information on the variability of the prices and yields can be obtained from EPIC-IIASA, as well as costing from FADN. A second issue exists around translating a farm-specific risk premium to a per-crop and per-hectare risk premium. Further research could analyze whether an econometric approach could be better suited. Using a revealed preferences approach, one could econometrically estimate country average risk aversion coefficients based on FADN data and explore possibilities to integrate these into GLOBIOM to assess impacts on production, consumption, trade, and agricultural markets.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

7 IMPROVED REPRESENTATION/ ADOPTION OF MITIGATION TECHNOLOGIES

7.1 Introduction

The European Green Deal foresees achieving climate neutrality by 2050 and sets the objective via the European Climate Law of reducing greenhouse gas (GHG) emissions by at least 55% until 2030. In this context, the agricultural sector is covered by the EU's Effort Sharing Decision (ESD) and Effort Sharing Regulation (ESR) together with the sectors of transport, buildings, and waste. Jointly, they aim to reduce GHG emissions by 30% until 2030 compared to the base year 2005. Given that GHG emissions from the agricultural sector declined by only 2% from 2005 to 2020 (EEA, 2022), more strenuous endeavours to reduce GHG emissions are necessary to achieve the given targets.

Given the urgency of this topic, policy assessments in the domain of climate change mitigation are one of the most frequent applications of current economic models by the European Commission (EC) and an ongoing research topic of high relevance in micro- and macro-economic models covering the agricultural sector (Barreiro-Hurle et al., 2021; Frank et al., 2021; Huber et al., 2023; Kokemohr et al., 2022; van Meijl et al., 2006). The application of models on multiple scales is key, as different types of questions require different modelling approaches. Micro-models, such as single-farm level models, can be used to assess the impact of specific mitigation measures while accounting for farm heterogeneity and interaction effects between measures and other farm activities (Huber et al., 2023b; Lengers et al., 2014). This allows us to identify the most promising GHG mitigation measures and construct marginal abatement cost curves (MACCs), which are critical tools to provide policymakers and macro-models with information on the cost-effectiveness of mitigation measures. In contrast, macro-models, such as partial equilibrium models (PE) and computable general equilibrium models (CGE), lack the detail provided by micro-models due to their more aggregated character. However, they give the advantage of factoring in market feedback, land-use change, structural changes in the agricultural sector, and linkages across sectors through factor markets and substitution effects (Frank et al., 2019). Considering these model characteristics, macro models allow us to find the most cost-efficient mitigation potential for the agricultural sector for specific regions and on a global level.

A challenge in macro-models is often to develop a consistent and regional-specific database for abatement costs of mitigation measures, as the availability of cost estimates is scarce and often based on expert opinion for a specific country, region, or production system (US EPA, 2013). To complete the database for mitigation measures on a global or even regional level, assumptions have to be made to extrapolate the values to other countries and production

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement N° 817566.

systems. This can also lead to the omission of various mitigation measures as no reliable information is available. Moreover, these databases typically lack information regarding the adoption rate of mitigation measures by farmers. This absence of data in the construction of MACCs leads to overestimating the mitigation potential in their application within macro-models. Here, single farm-level models, such as FarmDyn, can produce country and farm-type specific data for mitigation measures due to their ability to simulate the enforced use of mitigation measures and the endogenous decision to adopt a mitigation measure under specific policy constraints, such as a carbon tax. However, this model feature also depends on the availability of farm-level data.

This sub-task addresses these shortcomings of the representation of mitigation measures in macro-models based on previous work in Task 3.3 on farmers' adoption behaviour of mitigation measures and through the linkage of the single farm level model FarmDyn with the macro models GLOBIOM and MAGNET from the MINDSTEP model toolbox. Specifically, we aim to demonstrate conceptually, using the case of dairy farms, the following potential advantages of the model linkages:

- We want to show how the single-farm level model FarmDyn can be used to extend the available mitigation measures in the macro-models by adding and parameterizing novel mitigation measures in GLOBIOM and through integrating the new measures in the MACCs used by MAGNET. The chosen mitigation measures align with the findings of adoption behaviour in Task 3.3.
- In the linkage to MAGNET, we want to apply the mitigation measures to all EU member states using single farm-level data from the FADN database to highlight the impact of country specifics expressed in farm heterogeneity.
- In the linkage with GLOBIOM, the objective is to illustrate the influence of country-specific environmental accounting schemes and the intensity level of the farm on the abatement potential and costs.

The subtask is structured as follows. First, we introduce the conceptual framework of the model linkage between FarmDyn and the two macro-models GLOBIOM and MAGNET. Second, we introduce each model with respect to model descriptions, their current representation of mitigation measures, and their technical implementation in the models. Third, we introduce the farm-level data used for each specific model linkage. Eventually, we present the modelling results for (1) FarmDyn representing the input data for the macro-models, (2) GLOBIOM with respect to the used values for the mitigation measures as well as the impact on their MACC curves in the simulation, (3) MAGNET with respect to the MACC curves and their impact on

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement N° 817566.

total emissions and other key variables. Lastly, the results are discussed and put into perspective in the concluding remarks.

7.2 Conceptual framework of model linkage

This section introduces the conceptual framework and model linkages of the micro-model FarmDyn and the two macro-models GLOBIOM and MAGNET. It covers the data preparation and implementation step for FarmDyn, the model simulation setup of Farmdyn, and the description of the interface between the models, explicitly covering the input/output and data conversion step. The workflow of the model linkages follows the structure presented in **Figure *37***.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

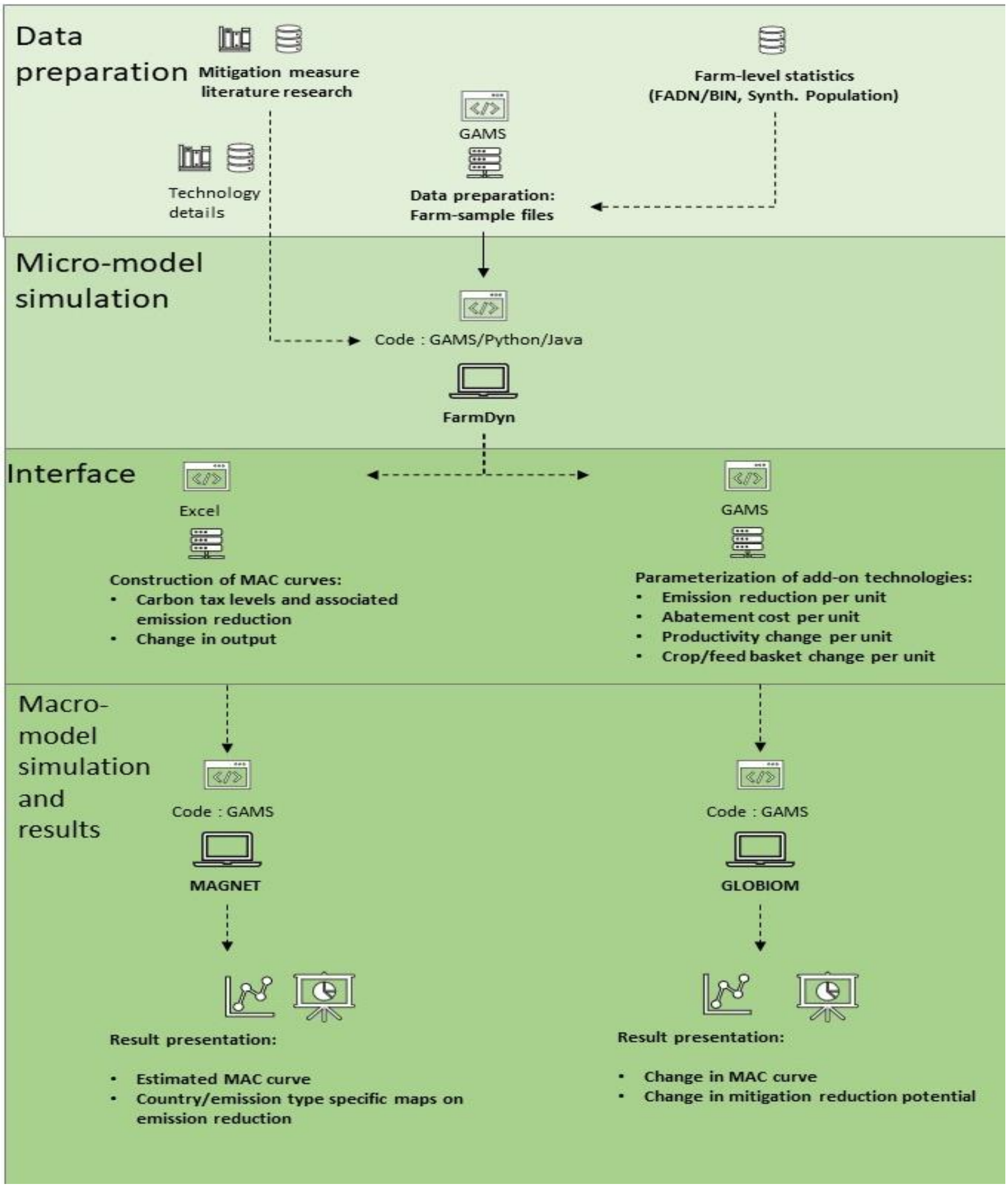


Figure 37 Workflow and model linkage.

7.2.1 Modelling setup and data preparation step

To construct both the marginal abatement cost curves for MAGNET and parameterize the novel mitigation measures, called add-on technologies, in GLOBIOM, the new mitigation measures had to be implemented in FarmDyn. The choice of mitigation measures is based on previous work of Task 3.3 on farmers' adoption behaviour and encompasses the use of feed additives, feed concentrates, and herd management.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

In addition, FarmDyn requires constructing a farm sample file that contains all relevant information on the different dairy farms used in each of the exercises based on the farm-level statistics described in section 7.4. As our work in this exercise is a proof of concept, we apply two different farm samples for GLOBIOM and MAGNET with two different foci to explore the linkage potential based on their distinct model features.

GLOBIOM differentiates in their bovine livestock system between extensive and intensive farms based on the grassland share of the production system. To match the extensive and intensive livestock system, we use two typical German and Dutch farms characterized as extensive and intensive dairy farms. Thus, we can leverage the versatility of FarmDyn to model specific farm types with different intensity levels and to show the impact of the livestock system-specific add-on technologies.

MAGNET has a raw milk sector equivalent to the dairy farm type in FarmDyn. However, it does not differentiate between intensities. In the linkage to MAGNET, we want to showcase the ability of Farmdyn to provide data for marginal abatement cost curves, taking farm heterogeneity between country-specific average farms into account. Even though the underlying parameterization of FarmDyn for technology coefficients and cost structures is based on the German default version, we can show how country-specific typical farm endowments affect the construction of country-specific MAC curves.

7.2.2 FarmDyn simulation setup

The two macro-models, GLOBIOM and MAGNET, have two inherently different implementations of mitigation measures, namely add-on technologies and technology-based marginal abatement cost curves. Based on their implicit and explicit characteristics, the simulation setup for FarmDyn has, on the one hand, to produce parameters that can be used to transfer to a specific add-on technology, and on the other hand, it must provide data for a marginal abatement cost curve given different levels of a carbon tax. Practically, this implies that for GLOBIOM, we run for each of the implemented mitigation measures and country-specific intensive and extensive farm types one instance where the mitigation measure is exogenously enforced. The results are then used in the subsequent data processing step to populate the new add-on technologies in GLOBIOM. Given that the farm sample is different for MAGNET, we run for each EU country the average farm in Farmdyn with an enforced feed additive and endogenous mitigation measures (see section 7.3.1 for an explanation of endogenous measures) with three different carbon tax levels. The first tax level is zero, giving us the baseline. The second tax level is 65 euros per CO_2-eq., covering the cost of the enforced mitigation measures. The third one is 130 euros per CO_2-eq., which triggers additional endogenous mitigation measures such as extended lactation or changes in the feeding regime.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

7.2.3 Micro – Macro model interface

The interfaces between the micro-model FarmDyn and the macro-models MAGNET and GLOBIOM describe the input/output relationship in the data processing. In the interface to GLOBIOM, FarmDyn provides data on the farm level, which is country-specific (Dutch or German) and technology-specific, i.e., the exogenous mitigation measures. The data includes information on global warming potential (GWP) differentiated by source, profits, and livestock unit of cows and heifers. The data is converted to the parameter structure of the add-on technology by calculating the relative emission changes for each mitigation technology considering the emission source. These relative changes are applied to the GLOBIOM management dataset to calculate the absolute emission reduction levels. The costs are calculated using the difference in profit between the farm outcome with and without the technology. FarmDyn provides MAGNET data for each EU member state based on an average dairy farm for each EU-28 country. The data includes the different carbon tax levels and the corresponding total GWP emissions, which can be used to construct the technology-based marginal abatement costs.

7.2.4 Macro-model simulation and results

The impact of novel mitigation measures in the portfolio of add-on technologies in GLOBIOM and the implementation in MAGNET's MACCs are presented in the result section.
For GLOBIOM, we use the SSP2 with nine GHG price trajectories for 2030 to show MACCs as a simulation result with and without the new technologies, considering the results from the German dairy farms and those of the Dutch dairy farms, respectively. Further, it is highlighted which mitigation measures impact various abatement sectors, such as technical, structural, and activity-based options. In addition, regionalized EU results with emission reductions are presented. MAGNET uses the same SSP2 economic and yield growth trajectory for 2040, but results are given only for a carbon tax of 50 €/tCO2eq for EU-28 and globally. The presented results assess the production, import, export, prices, as well as emission levels of the raw milk sector.

7.3 Model descriptions

In this section, we describe the micro-model FarmDyn and the macro-models GLOBIOM and MAGNET from the MIND STEP model toolbox, emphasizing the different implementations of the GHG mitigation technologies. The first section briefly introduces FarmDyn and presents the most relevant model features. This includes the GHG emission accounting for Germany and the Netherlands, the explicit mitigation technologies, and a description of mitigation strategies on-farm based on changes in farm management. Second, the partial equilibrium model GLOBIOM is presented, highlighting the most important features with respect to mitigation technologies and the relevant parameters which are extended by FarmDyn. Third,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

we introduce the computable general equilibrium model MAGNET, focusing on the most relevant sectors and the implemented marginal abatement cost curves (MACCs).

7.3.1 FarmDyn

FarmDyn is a highly detailed bio-economic farm scale optimization model based on mixed-integer programming. It simulates farmers' decisions on farm management, agricultural production, and investments in a comparative setting. The model contains detailed information on bio-physical and economic processes linked to farming activities. This bio-economic model setup allows us to determine the trade-offs between economic and environmental indicators considering the production of both agricultural outputs and environmental externalities (Janssen and van Ittersum, 2007).

FarmDyn has multiple country-specific adjustments[20]. In this exercise, we use the German and Dutch versions that differ in input data and model equations to capture different cost structures, technology coefficients, agronomic characteristics, and statuary provisions. This includes country-specific environmental accounting calculations based on national guidelines. In the context of non-CO2 emissions, this impacts the choice of the methodology based on different tier levels (Penman et al., 2006), divergent manure excretion levels per cow and their detail, and different feeding options with more detail in the Dutch version.

7.3.1.1 Exogenous and endogenous non-CO_2 mitigation measures

Farmdyn distinguishes between exogenous and endogenous non-CO_2 mitigation measures. Endogenous mitigation measures describe on-farm management adaptations as a response to an external shock, such as a carbon price policy or an emission ceiling scenario. Exogenous mitigation measures are activated by the FarmDyn user and assess one mitigation measure at a time or multiple enforced mitigation measures simultaneously. In the MIND STEP Deliverable 3.3, an extensive literature review on mitigation measures was done to assess the most suitable candidates to be added to the already existing portfolio of mitigation measures within FarmDyn. The mitigation options chosen in that process were based on the survey of Dutch dairy farmers, looking not only at economic but also behavioural aspects (Task 3.3) and their potential impact with respect to total mitigation and associated costs in the linkage to the macro-models. Further, not all mitigation measures for the agricultural sector found in the literature research are implementable in FarmDyn due to its features as a supply-side farm-

[20] For more extensive information on the parameterization of Farmdyn and its model structure, you can refer to its documentation: https://farmdyn.github.io/documentation/

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

level model. In the following section, we will describe the chosen exogenous and endogenous measures in FarmDyn in more detail.

7.3.1.2 Exogenous measures in FarmDyn

This section introduces the exogenous measures in FarmDyn covering feed additives, herd management options, and concentrates differentiated by their methane-producing potential. FarmDyn differentiates two possible feed additives, namely vegetable oil and Bovaer®. Both feed additives are mutually exclusive as no data is available for their combined use. Activating one of the feed additives forces it into the feeding ration while reducing the methane emission stemming from the enteric fermentation. Depending on the feed additive, it requires either 6% of the total DM intake for vegetable oil or 0.06% of the DM intake in the case of Bovaer®. The associated reduction of methane from enteric fermentation is 20% (vegetable oil) and 30% (Bovaer®), respectively. The prices for the feed additives are taken from literature for standard feed oil and information from experts in the case of Bovaer®[21].

The next mitigation option is available as an exogenous and endogenous measure depending on the model setup, namely the extension of the lactation period of dairy cows. By extending the lactation period, less young stock is required on the farm to replace the herd, reducing the number of animals and hence the associated emissions. In general, this measure is controversial as it is contrary to the general long-term breeding goal of many farms. The current length of the average lactation period of a herd is predominantly determined by the objective to increase one of the selected traits, e.g., milk yield, fat, and or protein content, which translates into a high turnover of cows in the herd (De Vries, 2017). Extending the lactation period of cows reduces the turnover within the herd and could slow down the increase in, e.g., the average milk yield of the herd. In a comparative setting, i.e., a myopic one-year view in our case, the extension would result in an immediate cost reduction due to lower fodder cost for the sold young stock linked to the emission reduction, resulting in a win-win situation. Whereas in a long-term view, the average milk yield could decrease, the emission per milk yield could be lower. Despite its limitations, we see this option as a valid mitigation measure to be assessed in this task and implemented by extending the average lactation period of a cow by 1.5 years in the German version and 0.5 in the Dutch version and adding an extra cost of 40 Euro per cow.

The last mitigation measure, the use of emission-reduced concentrate feed, is also available as an endogenous and exogenous option; however, only in the Dutch version. Due to its feed emission accounting methodology based on Tier 3, the Dutch version provides the option to feed concentrate, which has a lower enteric fermentation methane emission factor than

[21]Confidential expert knowledge - Interview by Pieter Willem Blokeland (WEcR).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

conventional feed. The potential methane emission reduction is 5% and 10% depending on the concentrates used, and the costs of the concentrate are based on Šebek et al. (2016). **Table 14** gives an overview of the used exogenous mitigation measures.

Table 14 Mitigation measures implemented in FarmDyn

Mitigation measure	Mean of mitigation and assumed emission reduction	Assumed costs	References
Feed additive – Vegetable oil **(DE, NL)**	Vegetable oil (e.g., linseed oil) reduces the methane emission from the enteric fermentation step by 20%	The associated costs are based on the quantity given to the cows and the cost per unit of linseed oil. Further, the impact on the feeding regime is expected as the oil contains a lot of NEL without other macronutrients. The required feed ration based on the dry matter intake is 0.6%. The price is set to 500 Euro/ton.	(Doreau et al., 2018; Vargas et al., 2020)
Feed additive – Bovaer **(DE, NL)**	Bovaer reduces in the enteric fermentation step the emitted methane emission by 20%	The assumed costs are solely based on the quantity given to the dairy cows and the cost per unit of Bovaer. The quantity given to the cow accounts for 0.06% of the dry matter intake. The price of Bovaer is ca. 50 Euro per cow.	(van Gastelen et al., 2022), DSM (2022)[22]
Increased number of lactations – Cow longevity **(DE, NL)**	Decreases the number of replacements/heifers on the farm, thereby reducing their associated emissions. There is no precise emission level per remonte as it is determined by the feeding and other farm parameters. Hence, the emission reduction differs between farms.	To improve/maintain the health of cows (e.g., mastitis issues), the variable costs are increased by 40 Euros per cow to cover veterinary costs. At the same time, there are no further costs for feeding the sold young stock, reducing the variable costs for feeding, which can result in negative variable costs for the farm.	(Dallago et al., 2021; Grandl et al., 2019)
Methane-reducing concentrate (NL)	Concentrates with a lower methane emission factor from enteric fermentation compared to conventional concentrates reduce methane emissions. The low-emission concentrates differ in composition compared to the conventional concentrates.	Additional costs are relative to the conventional concentrates and range from 0.3-3.8% for the concentrates with a 5% methane reduction and 3.6-11.9% for the concentrates with a 10% methane reduction.	(Šebek et al., 2016)

[22] Based on expert knowledge: Confidential information - Interview by Pieter Willem Blokland.

7.3.1.3 Endogenous measures in FarmDyn

FarmDyn provides a range of endogenous measures covering feeding options, variation in crop mix, crop intensity levels, and adaptation of herd size. Endogenous measures are solely a reaction to an external shock, such as a carbon price, a subsidy to reduce the on-farm carbon emissions, or a carbon emission ceiling based on carbon emission levels in the baseline. As described above, some of the external measures can also be activated to be endogenous and will, therefore, not be elaborated again.

Based on animal type and their respective output level, the model defines a certain set of feeding requirements with respect to, for example, net energy for lactation (NEL), dry matter (DM), and raw protein (XP). Each feeding requirement can be met by a certain optimized feeding ration that considers the prices and feed attributes of each feedstuff. For example, this optimized feeding ration could contain more NEL needed for the cow to meet the required DM and XP quantities. In the German version, the CH_4 from the enteric fermentation is determined by the amount of NEL fed. It gives the model options to shift the feeding ration towards a feed composition where the NEL meets the required level to reduce CH4 emissions. In the Dutch version, the CH_4 from the enteric fermentation is determined by a feed-specific methane emission factor (van Dijk et al., 2020). It allows the model to shift the feeding ration towards lower enteric fermentation methane levels.

Related to the feeding adaptation, the model can adjust the crop mix on the farm to account for crops with less non-CO_2 emissions as they require, e.g., less fertilizer from animal excrement or chemical fertilizer. A change in crop mix can also be triggered by a change in the feeding composition described above, leading to different emission levels from fields. This can result in either higher or lower non-CO2 emissions coming from the arable section of the model. Another crop-related farm management option to reduce emissions is the change in intensity level, defined by the amount of nitrogen fertilizer used to achieve a certain yield level. The relationship between the N-fertilizer applied, and the yield is implemented as a linearized N-response curve in the German (Heyn and Olfs, 2018) and Dutch versions (same as the German version).

The "ultima ratio" measure to reduce emissions on farms is the reduction of the size of the herd. This entails both the reduction of the active dairy cows and the reduction of the required young stock for the replacements. The likelihood of this option being triggered is based on each cow's profit margin, which highly depends on the farm setup. Farms with high variable costs for the purchase of roughage and for exporting manure to other farms have a low profit margin, which is more sensitive to increasing carbon prices than farms that can produce the fodder relatively cheaply and have enough land to distribute their manure.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

7.3.1.4 Non-CO_2 emission database

For this task, FarmDyn considers only on-farm non-CO_2 emissions to delineate the emission boundaries clearly from emission positions in the macro-models. This way, we avoid double-accounting. For example, imported feedstuff such as soybeans or derivates coming from South America with related land-use changes are covered by the macro-models. Hence, the emissions sources on farms include methane (CH_4) from enteric fermentation and manure storage, nitrous oxide (N_2O) emissions from the application of manure and mineral fertilizer, as well as other nitrogen compounds resulting in N_2O emissions. In calculating emissions and emission factors, we follow the tier level used for the respective national inventory. In general, a higher tier level is associated with greater detail in the calculation of the related emission. The relevant references for accounting methodology and emission factors are shown country-specific in **Table 15**.

Table 15 References for accounting methodology and emission factors.

Emission	Source of emission	Methodology applied (Year; Tier level)		Emission factor (Year; Tier level)	
		German version	Dutch version	German version	Dutch version
CH_4	Enteric fermentation	(IPCC, 2019; Tier 2)	IPCC (2019; Tier 3)	Haenel et al. (2020)	van der Van der Zee et al. (2021))
CH_4	Stable, storage, and pasture	IPCC (2019; Tier 2)	IPCC (2019; Tier 2)	Haenel et al. (2020)	van der Zee et al. (2021)
NH_3	Emissions from stable and storage	EMEP/EEA (2016; Tier 2)	EMEP/EEA (2016; Tier 2)	Haenel et al. (2020)	van der Zee et al. (2021)
NH_3	Manure application	EMEP/EEA (2016; Tier 2)	EMEP/EEA (2016; Tier 2)	Haenel et al. (2020)	van der Zee et al. (2021)
NH_3	Excreta from pasture	EMEP/EEA (2016; Tier 2)	EMEP/EEA (2016; Tier 2)	Haenel et al. (2020)	van der Zee et al. (2021)
N_2O, NO_x, N_2	Emissions from stable and storage	EMEP/EEA (2016; Tier 2)	IPCC (2019; Tier 1)	Haenel et al. (2020)	van der Zee et al. (2021)
N_2O, NO_x, N_2	Emissions from manure application	IPCC (2019; Tier 1)	IPCC (2019; Tier 2)	Haenel et al. (2020)	van der Zee et al. (2021)
N_2O, NO_x, N_2	Emissions from excreta from pastures	IPCC (2019; Tier 1)	IPCC (2019; Tier 2	Haenel et al. (2020)	van der Zee et al. (2021)
NH_3, N_2O, NO_x, N_2	Emissions from mineral fertilizer application	IPCC (2019; Tier 1)	IPCC (2019; Tier 2)	Haenel et al. (2020)	van der Zee et al. (2021)
N_2O	Indirect N2O emissions from prior	IPCC (2019; Tier 1)	IPCC (2019; Tier 1)	IPCC (2006)	van der Zee et al. (2021)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

	NOx, NH3 and NO3 emissions

Note: A more detailed explanation of the environmental accounting in the Dutch Version can be found in the MIND STEP Deliverable 3.3 and for the German version on the FarmDyn documentation website under (https://farmdyn.github.io/documentation/FarmDynDocumentation/ModelDescription/EnvironmentalAccounting/environmental_accounting/).

To illustrate the impact on the total emissions from the different emission factors and methodologies following the national emission inventory guidelines, we can see Table 16, where FarmDyn results for the German and Dutch versions are compared. The table shows the non-CO_2 emissions differentiated by emission source, i.e., enteric fermentation, field, mineral fertilizer application, animal manure application, and stable and storage. The table shows that the primary source of emissions in both cases is enteric fermentation. However, the German version has considerably higher emissions due to its less detailed tier level. In contrast, the Dutch version exhibits higher emissions from the stable and storage parts and field parts of the farm.

It should be noted that besides differences in GHG emission accounting, the Dutch and German versions of FarmDyn also differ regarding the system of feed requirements, the number of grassland options, and nutrient excretion per animal, which might impact the emission results. Table 16 shows that GHG mitigation technologies focusing on enteric fermentation will have a lower impact in the Dutch version, given the applied tier level. GHG mitigation technologies focussing on emissions from stable and storage will be less effective if the German version of GHG emission accounting is applied.

Table 16 GHG emission by source on an average dairy farm in Germany and the Netherlands (kg CO2-eq per kg FPCM) and index-based comparison between the German and Dutch farms.

Emission source	Emission type	German version	Dutch version	Index (German version = 100)
Enteric fermentation	CH_4	0.73	0.56	0.77
Field (indirect, crop residues, and leaching)	N_2O_{ind}	0.01	0.04	2.79
Mineral fertilizer (application mineral fertilizer)	N_2O, N_2O_{ind}	0.03	0.05	1.46
Pasture (excreta on pasture)	CH_4, N_2O, N_2O_{ind}	0.04	0.04	0.99
Animal manure (application animal manure)	N_2O, N_2O_{ind}	0.04	0.02	0.57
Stable and storage (stable and storage)	CH_4, N_2O	0.04	0.16	4.26
Total	CO2-eq.	0.89	0.87	0.98

Source: own calculations.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

7.3.2 GLOBIOM

The Global Biosphere Management Model (GLOBIOM) Havlík et al. (2014) is a partial equilibrium model that covers the global agricultural and forestry sectors, including the bioenergy sector. Commodity markets and international trade are represented in 59 economic regions here. Prices are endogenously determined at the regional level to establish market equilibrium to reconcile demand, domestic supply, and international trade. The spatial resolution of the supply side relies on the concept of Simulation Units, which are aggregates of 5 to 30 arcmin pixels belonging to the same altitude, slope, and soil class and the same country (Skalský et al., 2008). For crops, livestock, and forest products, spatially explicit Leontief production functions covering alternative production systems are parameterized using biophysical models like EPIC (Environmental Policy Integrated Model) (Williams, 1995), G4M (Global Forest Model) (Gusti, 2010; Kindermann et al., 2008), or the RUMINANT model (Herrero et al., 2013). For the present study, the supply side spatial resolution was aggregated to 2 degrees (about 200 x 200 km at the equator). Land and other resources are allocated to the different production and processing activities to maximize a social welfare function, which consists of the sum of producer and consumer surplus. The model includes six land cover types: cropland, grassland, short rotation plantations, managed forests, unmanaged forests, and other natural vegetation lands. The model can switch from one land cover type to another depending on the relative profitability of primary, by-, and final product production activities. Spatially explicit land conversion over the simulation period is endogenously determined within the available land resources and conversion costs considered in the producer optimization behaviour. Land conversion possibilities are further restricted through biophysical land suitability and production potentials and through a matrix of potential land cover transitions.

GLOBIOM covers major GHG emissions from agricultural production, forestry, and other land use, including CO_2 emissions from above- and belowground biomass changes, N_2O from the application of synthetic fertilizer and manure to soils, N_2O from manure dropped on pastures, CH_4 from rice cultivation, N_2O and CH_4 from manure management, and CH_4 from enteric fermentation. For this study, only results for non-CO_2 emissions were reported. The model explicitly covers different mitigation options for the agricultural sector: technical mitigation options such as anaerobic digesters, livestock feed supplements, nitrogen inhibitors, etc., are based on Beach et al. (2015), and structural adjustments are represented through a comprehensive set of crop and livestock management systems parameterized using bio-physical models, i.e., transition in management systems, reallocation of production within and across regions (Havlík et al., 2014), and consumers' response to market signals (Valin et al., 2014). The objective of task 5.2.5 was to improve the default representation of the technical

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

dairy mitigation options in GLOBIOM by extending the dairy-related mitigation option coverage using FarmDyn simulations.

7.3.2.1 Explicit representation of mitigation measures in add-on technologies

Technological agricultural non-CO_2 mitigation options, such as anaerobic digesters and animal feed supplements, are based on the default set-up on the EPA mitigation option database (Beach et al., 2015a). Emission reduction potentials (% emission savings), costs (annual costs, i.e., direct costs and labour costs, change in input costs, and investment costs, i.e., for anaerobic digesters), and potential impacts on productivities (% increase/decrease) were taken from the EPA mitigation options database. Relative emission savings and productivity changes were then applied to the different management systems in the GLOBIOM model to calculate absolute changes in GHG emissions and product output. Mitigation options (characterized by GHG reduction, productivity changes, and economic costs) are implemented in the model as additional management activities which can be applied on top of a production system. Mitigation options are adopted if the economic benefit, i.e., through avoided carbon tax payments and potential productivity changes, exceeds the cost of an option. Detailed information on the parameterization of the different mitigation options for the agricultural sector is presented in (Frank et al., 2018).

7.3.2.2 Emission database for the add-on technologies

Parameters for the representation of agricultural non-CO_2 mitigation options in GLOBIOM, as presented in **Table 17**, have been based for the EU in the past on the global EPA mitigation options database (Beach et al., 2015a).

Table 17 Global average GHG reduction, impact on productivities, and costs for technical mitigation options for the livestock sector taken from Frank et al. (2018). Ranges across regions are presented in brackets.

Mitigation option	Non-CO_2 reduction [% change]	Productivity changes [% change]	Annual costs [$ /TLU]
Antibiotics[a]	-2 (-6 to 0)	+5	6 (5 to 10)
Bovine somatotropin (bST)[b]	+5 (0 to +10)	+12 (11 – 13)	110 (100 to 240)
Propionate precursors	-13 (-10 to -19)	+5	41 (35 to 60)
Anti-methanogen vaccination	-10	+5	9 (5 to 20)
Intensive grazing	-14 (-13 to -15)	-11	6 (5 to 20)
Large-scale complete-mix digesters	-85	-	25 (5 to 55)
Large-scale covered lagoon	-85	-	34 (10 to 70)
Large-scale fixed-film digester	-85	-	34 (10 to 60)
Large-scale plug-flow digesters	-85	-	38 (10 to 75)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Small-scale digester	-50	-	7 (5 to 15)
Centralized digester[c]	-90	-	8 (5 – 45)

TLU: livestock unit, an animal of 250 kg live weight. [a] Antibiotics: No application in Europe and Taiwan (Maron et al., 2013)[b] bST: No application in Australia, Canada, Europe, Japan, or New Zealand (Dervilly-Pinel et al., 2014); [c] Centralized digesters are only applied in Europe.

7.3.3 MAGNET

MAGNET is a recursive dynamic multi-sector, multi-region computable general equilibrium (CGE) model. It covers the global economy comprehensively and utilizes the Global Trade Analysis Project (GTAP) database developed at Purdue University (Hertel and Tsigas, 1997). One key advantage of MAGNET in the context of GHG mitigation policies, compared to other models discussed, is its ability to capture intra-sectoral relationships within the agricultural sector and inter-sectoral linkages between the agricultural sector and other sectors. Due to its comprehensive nature, MAGNET not only simulates the flow of costs and benefits to other industrial sectors but also considers the impact on governments, consumers, and other producers.

MAGNET encompasses important features, which are required to link them to highly detailed farm-level models such as FarmDyn. First, MAGNET covers 14 agricultural production systems, including distinct sectors for ruminants, non-ruminants, and the raw milk sector. This breakdown of livestock systems facilitates the interface with farm-level models that align with corresponding farm types. For instance, the MAGNET raw milk sector can be matched to the dairy branch in FarmDyn. Second, Magnet uses the comprehensive US EPA non-CO2 database (US EPA, 2013), encompassing methane (CH4) and nitrous oxide (N2O). These emissions from the livestock sectors are tied to the output variables and can be lowered based on implicit mitigation technologies in marginal abatement cost curves (MACCs). This disaggregation of GHG emission types and the use of MACCs enables an evaluation of emission reduction potential through various mitigation technologies, considering their effectiveness in reducing specific types of emissions.

Tasks 5.2.5 aims to improve the existing MACCs in MAGNET twofold. First, the linkage of MAGNET and FarmDyn allows moving from two European MACC zones (see **Figure** 38) to country-specific MACCs in the EU for a better perception of country-level dynamics. This enables a better assessment of production and trade decisions on the European and country levels. Second, it assesses technology change by extending the underlying mitigation measures used to develop the MACCs.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

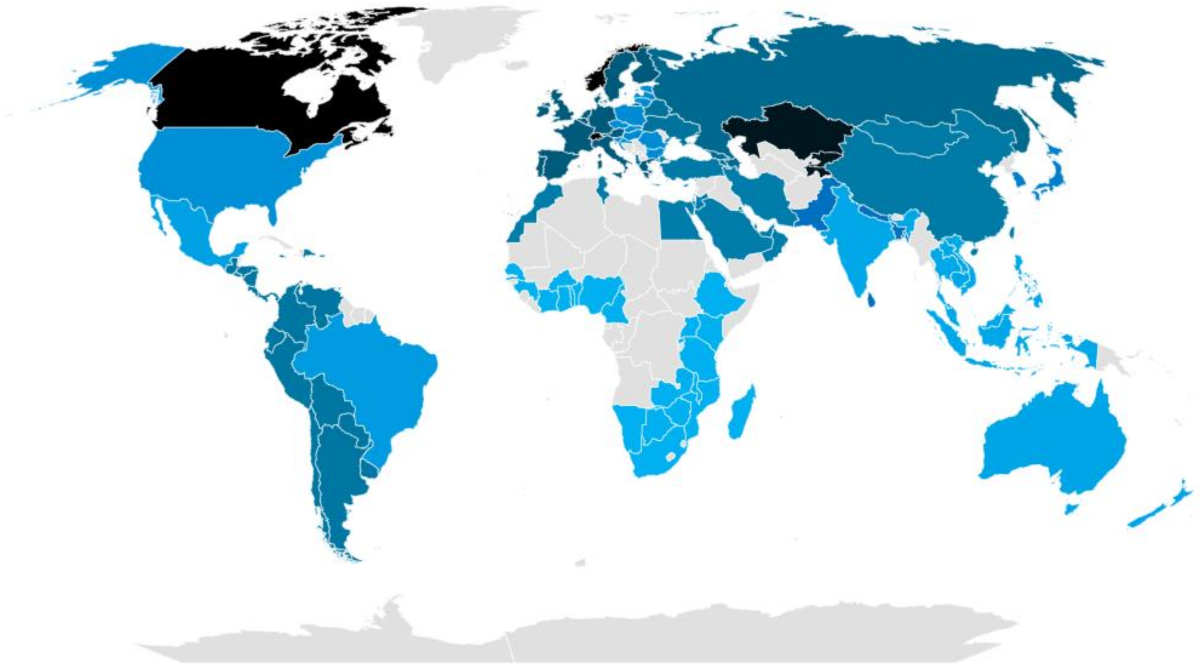


Figure 38 Previous Aggregation of MACC data.

7.3.3.1 Implicit representation of mitigation measures in MACCs

This subsection describes the Marginal Abatement Curve (MAC) mechanism, its aim and implementation in MAGNET, and the refinement introduced through MINDSTEP. The Marginal Abatement Curves are an instrument that allows a more detailed perception of the changes in emissions intensity derived from the taxation of emissions: i) to determine the costs of implementation of new technology and ii) to study policies alternative to the carbon taxes (e.g., reimbursement for green technologies adoption). The MAC relies on the idea that any sectorial production is related to a certain level of emission, which contributes to the overall emission level depending on the quantity produced. As such, any production technology has a certain emission intensity. The starting point is to calculate the ad valorem equivalent tax equal to the revenue to ensure the targeted emission level. This revenue depends on the emission amount weighted for its indexed price divided over the value added of the relative emitting sector (the price of output multiplied by the quantity of output), multiplied by the emission tax rate. Conceptually speaking, this implies introducing a linear relationship between carbon price/tax and the change in emission intensity (**Figure *39***).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

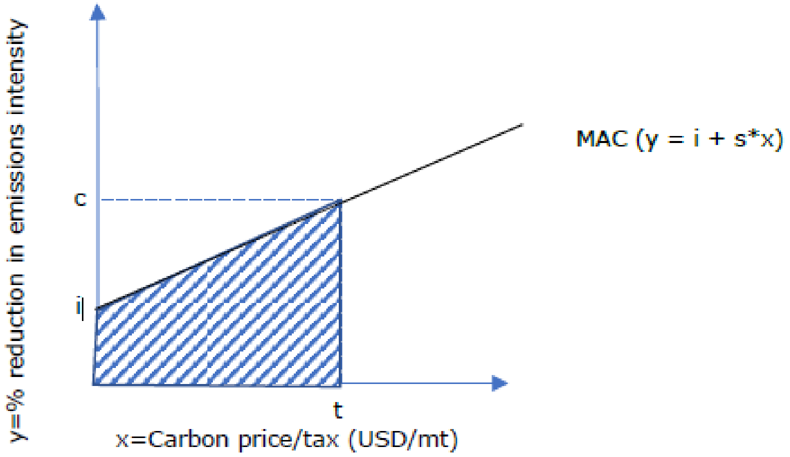


Figure 39 Conceptual Mac Curve

Thus, the fundamental concept is emission intensity, i.e., emissions over production. Its linear relationship with the carbon tax/price is determined over an intercept and a slope of the linear function, which are the factors determining the overall response behaviour of the model. Even though MAGNET's code is generic and allows it to accommodate all sectors, the current data availability is rather limited, which is the reason for the implementation of the link with FarmDyn, which provides detailed data on different greenhouse gasses. To be noted, MAGNET requires imposing a restriction on the intercept, i.e., to be non-negative. This ensures that we do not get an increase in emissions intensity for some small initial levels of carbon price.

7.3.3.2 Database and underlying mitigation measures

MAGNET uses GTAP 10 database with the base year 2014 (Aguiar et al., 2019) and provides long-term projections spanning 2040 and beyond. The projections take into account yield and economic growth assumptions aligned with the Shared Economic Pathway (SSP2) (Fricko et al., 2017). Additionally, the model integrates emissions data from the US EPA database (US EPA, 2013), encompassing methane (CH_4) and nitrous oxide (N_2O) emissions. Furthermore, CO_2 emissions from the GTAP Energy-Environmental database (GTAP-E) are included to provide a comprehensive coverage of carbon dioxide emissions within the model.

The database utilized to develop the Marginal Abatement Cost Curves (MACCs) includes information on mitigation technologies and greenhouse gas (GHG) reduction practices in farming sourced from the US EPA (2013). This database adopts an engineering approach, providing cost estimates and associated abatement quantities for various mitigation technologies ranked based on their relative magnitude. The specific set of mitigation technologies represented in the MACCs for a given region and production system depends on factors such as their availability and applicability. This includes considerations such as

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

technological restrictions and approvals that determine which mitigation technologies can be incorporated into the MACCs.

7.4 Farm sample

For each of the macro models, a distinct farm-level sample is developed. For GLOBIOM, a typical extensive and intensive dairy farm is chosen based on national farm-level data. Results from these typical farms are then assumed to be able to parameterize add-on technologies for all EU countries. For constructing the MACCs in MAGNET, data on farms for each EU country are used with the German version of the Farmdyn model.

7.4.1.1 Farm sample based on typical farm approach

This section describes the source of farm-level data for the German and Dutch farm samples used in the linkage to GLOBIOM. The farm population for the Dutch version is derived from the Farm Accountancy Data Network (FADN), which provides economic information on farmers from a sample of the entire farm population. It covers all member states of the European Union (EU) and is used to evaluate new and existing policy measures. The data provided is based on harmonized bookkeeping principles and covers only agricultural holdings which can be considered commercial. For the Dutch version, a sub-sample of the Dutch FADN version called “Bedrijveninformatienet” (BIN) containing data covering roughly 1500 agricultural and horticultural enterprises is used.

A synthetic farm population (Pahmeyer et al., 2021) is used for the German version, developed based on the German Farm Structure Survey (2016)[23]. In this farm population, each farm is characterized based on its farm type, its agricultural land in hectares differentiating between arable and grassland, and their animal numbers in livestock units differentiating between animal types. The farm type used is based on the main farming activities of a farm and their relative contribution to the standard output of those activities following the EU typology of 2008 (European Commission, 2008). Using public sources, the synthetic farm population is developed for the federal state of North-Rhine Westphalia (NRW). For this specific task, we are using the farm sample developed for the “Rheinische Revier” population. Key farm data for both the German and Dutch farms are given in **Table *18***.

Table 18 Country and intensity-specific key farm characteristics used in FarmDyn

	Intensive		Extensive	
	Dutch	German	Dutch	German
Number of cows [LU]	117	220	98	34

[23] This dataset is available here

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

Arable Land [ha]	11	160	9	8
Grassland [ha]	44	10	54	18
Share of grassland [%]	80	5.6	86	69
Milk Yield [‘00 kg]	87	80	87	75
Number of farms [n]	121	1	91	1

In the simulation scenarios, input and output prices are set to the default values of the corresponding country-specific FarmDyn version. This covers, among other things, prices for milk, crops, livestock, machinery, and hired workers. Technology coefficients such as labour and machinery requirements per on-farm operation and activity are also country-specific.

7.4.1.2 EU-wide farm-level database

The farm accountancy data network (FADN) (European Commission, n.d.) monitors farms’ income and business activities in the EU Member States. FADN follows harmonized bookkeeping principles and is based on national surveys. It covers agricultural holdings that are considered commercial, based on size criteria, and aims to provide representative data within the category's region, economic size, and farm type. Across all Member States, the size of the FADN sample was above 83000 farms in 2019. FADN comprises information on farm endowments like labour force, area, herd size, and depreciation on machinery and buildings, to name a few. Further, financial accounting data for the whole farm are available: expenditures for variable inputs like fertilizer, pesticides, or purchased animal feeds.

For the construction of the database for the EU-wide version of FarmDyn to generate MAC curves for the MAGNET model, a sub-sample of dairy farms (farm type number “TF45”) with at least five dairy cows, and a milk yield over a reasonable range (>0 and <=12000 kg/cow/year), was selected for the year 2019, resulting in more than 11000 individual farms.

While it is technically possible to execute FarmDyn for all individual farms, this is not always practical for such large samples. Apart from long computation times, the main problem is that FADN provides information on farm endowments and output coefficients but not on input coefficients by production activity. This information can usually be derived from handbooks on standard farming practices or, in some cases, from farm surveys but is generally not available for individual farms in FADN. Therefore, the modelled farms would not differ in their cost structure, resulting in the repeated execution of very similar model instances for farms with comparable endowments and productivity. For this reason, individual farms are often grouped to generate typical or average farms with comparable characteristics, depending on certain projects or research questions.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

In the case of this report, representative farms for each NUTS2 region in the FADN were created by extracting the relevant variables necessary for running the FarmDyn model and aggregating them at the NUTS2 level using the mean, weighted with the SYS02 weights. **Table *19*** shows an overview of relevant farm structural variables extracted from the FADN.

Table 19 Weighted mean of the variables of the FADN used in FarmDyn

NUTS0	Number of Cows [LU]	Arable land [ha]	Grassland [ha]	Milk Yield ['00 kg/cow/year]	Number of Calves [count]	Number of Heifers [count]	Share of Grassland [%]	n
AT	21.35	4.78	21.31	67.27	12.18	3.04	0.81	669
BE	82.43	20.88	38.26	78.23	33.97	11.67	0.60	205
BG	33.25	8.63	10.85	44.95	13.66	3.05	0.30	45
CZ	139.40	161.28	152.79	68.28	86.16	22.80	0.55	110
DE	72.44	35.83	40.76	71.97	39.62	10.91	0.60	2530
DK	179.57	104.34	66.33	92.27	97.87	9.66	0.40	391
EE	116.02	109.68	180.79	72.67	55.79	13.84	0.81	98
ES	59.98	8.30	21.52	75.77	19.14	9.73	0.72	766
FI	42.40	23.42	51.39	87.99	18.52	1.30	0.72	229
FR	65.38	40.42	57.06	67.78	31.77	14.61	0.60	847
HR	20.96	14.05	10.44	52.25	9.96	1.78	0.39	131
HU	118.98	88.79	39.93	62.20	64.15	11.38	0.26	67
IE	83.88	1.50	62.90	57.67	51.36	10.91	0.98	298
IT	57.59	12.95	14.14	65.71	26.19	9.60	0.47	613
LT	21.95	13.02	37.42	54.90	9.83	2.14	0.75	219
LU	81.74	36.72	66.77	75.93	46.62	19.31	0.64	193
LV	25.08	13.22	47.85	56.82	11.68	2.39	0.82	242
MT	72.72	3.82	0.00	69.10	43.65	4.54	0.00	71
NL	101.60	9.42	49.23	85.74	29.17	4.17	0.85	355
PL	21.98	13.96	11.21	57.24	12.19	2.15	0.44	2082
PT	36.06	7.17	9.58	68.82	20.94	4.60	0.36	239
RO	12.10	6.67	5.77	43.87	7.45	0.38	0.39	180
SE	89.88	46.39	115.14	84.97	28.61	16.45	0.72	320
SI	20.87	4.45	14.00	53.81	10.14	2.86	0.75	138
SK	292.99	374.56	557.32	65.57	146.52	32.41	0.58	34
UK	147.43	17.24	106.64	72.53	68.72	25.82	0.90	444

In addition to farm specific data relating to specialist dairy farms, yield data was aggregated from all farms from the FADN to get more precise yield information since using only dairy

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

farms would have yielded wrong parameters due to outliers or small sample sizes. The yields were first calculated per farm by dividing the production quantity of each crop over their corresponding area. Then, the yields were aggregated for each NUTS level. At the NUTS0 level, missing values were imputed using the EU means, and at subsequent levels, missing values were imputed with the values of the higher NUTS level. However, grassland yields for the different management practices are not readily available from the FADN database, so data was taken from the CAPRI model on the national grassland yields for each country. Then, knowing the default yields for Germany as presented in the FADN, the rest of the grassland production for each country was divided by the German national production to get scaling factors that were multiplied by the default yields in the FADN. **Table 20** presents the weighted mean of the calculated yields for the arable and grass crops from FADN data and the CAPRI database.

Table 20 Weighted mean of the calculated yields [t] for arable crops in the FADN and mean grassland management yields scaled using the default values in FarmDyn and data on total yields in Europe from CAPRI grassland data.

NUTS0	CM	SM	SC	SBS	WB	SB	WR	WW	PT	gra1	gra2	gra3	gra4
AT	10.4	30.7	6.1	1.7	5.0	70.7	2.9	5.2	22.0	4.1	4.8	4.1	5.8
BE	8.8	17.8	6.1	2.6	7.7	79.4	3.8	8.2	22.0	7.3	8.6	7.3	10.4
BG	6.9	22.7	2.6	1.4	3.9	61.5	2.5	4.5	22.0	2.0	2.4	2.0	2.9
CZ	6.3	32.1	5.5	2.5	4.5	58.8	3.4	5.2	21.2	3.4	4.0	3.4	4.8
DE	8.5	28.5	6.6	3.0	5.9	64.6	3.1	6.6	22.0	8.5	10.0	8.5	12.0
DK	7.5	9.5	5.0	2.0	4.1	57.4	3.2	5.7	21.0	7.2	8.4	7.2	10.1
EE	8.7	30.0	2.4	1.7	2.4	61.5	1.5	2.7	15.5	3.6	4.2	3.6	5.1
ES	13.1	30.9	2.8	1.7	3.1	97.8	2.5	4.0	27.0	2.8	3.4	2.8	4.0
FI	8.7	21.6	3.1	1.9	3.1	35.7	1.4	2.6	11.3	5.1	6.0	5.1	7.2
FR	7.8	30.7	4.9	2.8	5.7	83.4	3.0	6.2	27.3	4.1	4.9	4.1	5.8
HR	8.7	41.3	4.7	2.6	4.1	52.8	2.8	5.0	22.0	7.3	8.6	7.3	10.4
HU	7.9	34.3	3.6	1.9	4.2	64.2	3.2	4.8	22.0	3.5	4.1	3.5	4.9
IE	8.7	30.7	5.7	3.0	6.0	61.5	4.5	8.3	22.0	5.4	6.4	5.4	7.7
IT	10.5	47.7	3.7	2.5	3.8	56.2	2.6	5.2	22.2	3.1	3.7	3.1	4.5
LT	4.4	27.7	3.0	2.1	2.8	51.7	2.3	3.3	22.0	4.3	5.1	4.3	6.1
LU	8.7	30.7	7.4	1.3	5.4	61.5	3.2	5.8	22.0	7.3	8.6	7.3	10.4
LV	8.7	11.0	2.6	2.0	2.2	61.5	1.8	2.6	22.0	4.8	5.7	4.8	6.9
MT	8.7	30.7	4.2	2.3	4.3	61.5	2.8	5.0	22.0	2.6	3.1	2.6	3.7
NL	8.2	38.8	4.0	2.9	6.5	75.1	2.8	7.9	35.1	8.9	10.5	8.9	12.6
PL	8.6	36.0	5.0	1.7	3.6	59.6	2.8	4.4	22.0	3.4	4.0	3.4	4.8
PT	4.9	34.0	1.7	1.9	5.5	61.5	3.3	3.5	12.9	4.7	5.5	4.7	6.6
RO	6.4	21.5	3.9	2.0	3.9	31.5	2.5	4.4	22.0	2.6	3.0	2.6	3.7
SE	2.9	30.3	3.5	1.8	3.3	55.7	2.1	4.1	18.2	5.1	6.0	5.1	7.3

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

SI	9.3	30.7	4.0	1.9	4.1	41.5	2.8	4.2	22.0	1.5	1.8	1.5	2.2
SK	8.3	34.5	3.9	2.1	3.4	57.5	2.9	4.3	16.6	3.2	3.8	3.2	4.6
UK	20.3	36.0	5.3	2.8	5.7	68.7	3.4	7.8	36.2	5.4	6.4	5.4	7.7

CM –Corn maize; SM – Silage maize; SC – Summer cereals; SBS – Sugar beans; WB – Winter barley; SB- Sugar beet; WR – Winter rape; WW – Winter wheat; PT – Potatoe; gra1-4 – gras types differing in yield and number of cuts

In the simulation scenarios, prices were assumed to be the same as the default prices in FarmDyn, corresponding to German prices. This includes the milk price, output prices for crops and livestock, manure export and import, and prices for machinery and hired workers. Labour requirements per each type of operation are also considered to be the same for all farms, taking the default values for Germany in FarmDyn. Since we assume the same carbon tax levels for all farms, this corresponds to an indexation of tax rates to German farms under different farm structures across the EU. Applying the same tax rate to all countries might affect different farms differently if they have different cost structures. Perhaps the average farm in some countries may or may not afford the tax, whereas in other countries, the tax may be too low, so assuming equal prices everywhere means that the applied tax shares the same effect that it would on a German farm that has the same farm structure (number of cows, area of arable land, grassland, milk yield, among others). This could also be interpreted as the effect of a carbon tax in different countries that would have the same effect per farm as a carbon tax in Germany. Overall, since EU countries differ in their farm structure from the German case, we expect that the general effect will be different than in Germany.

7.5 Results for improved parameterization of macro-models

7.5.1 Scenario overview

Before presenting the results for each of the linkages between FarmDyn and the macro-models GLOBIOM and MAGNET, a summary of the scenario in the macro-models and the delivered information from FarmDyn is given. The following **Table *21*** shows each of the most important scenario information.

Table 21 Key assumptions in scenario setup

		GLOBIOM	MAGNET
	Economic Projection	SSP2	SSP2
	Base year	2000	2014
	Projection year	2030	2040

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

	GHG price trajectory	0, 10, 25, 50, ..., 200 [USD_{2000}/tCO_2-eq.][24]	50 [USD_{2014}/tCO_2-eq.] in Europe and global implementation
	Mitigation technology representation	Explicit (add-on technology)	Implicit (MACC)
Derived from FarmDyn simulation setup	Mitigation measures	Bovaer, vegetable oil, extended lactation, methane-reducing concentrate	Bovaer, all other endogenous measures (section 7.3.1.3)
	Underlying emission accounting	National inventory: Germany The Netherlands	German national inventory
	Farm type – Production system – Sector	Dairy farm to bovine livestock system	Dairy farm to the raw milk sector
	Farm sample approach	Typical farm for the region (Rheinische-Revier, Germany) and country (Netherlands)	Average (representative) farm at NUTS2 level for all EU member states
	Intensity of farm-level	Intensive and extensive	Not differentiated

Both macro-models use the same yield and economic growth projection aligned with the Shared Economic Pathway (SSP2). The base year for GLOBIOM is 2000, whereas MAGNET's base year is 2014, with the projection year of 2030 for the former model and 2040 for the latter. Two different GHG price trajectories are chosen. This is based on the fact that, in the parameterization of the add-on technologies with FarmDyn data, no specific carbon tax simulation runs had to be made, leaving the GHG price trajectories only used in the simulation with GLOBIOM. In contrast, FarmDyn had to be run with different carbon price levels to populate the MACC curves of 0, 65, and 130 EUR/tCO_2-eq. Since the MACC curves are linear, only a limited number of carbon price levels were required to obtain information about the intercept and the slope of the functional form. In the simulation with MAGNET, as stated in the table above, only one carbon price was chosen to assess the impact of the new mitigation technologies, namely 50 USD/tCO2eq. The representation of mitigation technology in both macro-models differs as GLOBIOM has an explicit one, whereas MAGNET has an implicit one.

In addition to the simulation scenario setup in the macro-models, the simulation setup with FarmDyn for the linkage with the respective model differed. This is not only to accommodate differences in the macro-models but also to use and explore the versatility of FarmDyn to provide a wide range of information to improve macro-models. This includes the representation of two or more intensity levels (FarmDyn to GLOBIOM), the use of distinct

[24] GHG prices of 50/100 USD_{2000}/tCO_2eq correspond approximately to 65/130 $Euro_{2020}/tCO_2eq$

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

emission accounting schemes (FarmDyn to GLOBIOM), and the extension of EU-28 member state-specific MACC results (FarmDyn to MAGNET).

In the macro-model simulation, GLOBIOM compares the impact on the GHG emission reduction potential and the abatement costs with and without the extended portfolio of mitigation measures illustrated at MACCs and for different European regions. MAGNET instead is used to assess the role of the (improved) MACC (regional detail and technological implementation) under a 50 USD/tCO2eq carbon tax, both when the tax is applied only in Europe and in Europe and the Rest of the World to compare the trade, production and macroeconomic implication of adopting this measure only in the EU.

7.5.2 Farmdyn to GLOBIOM

7.5.2.1 FarmDyn results for add-on technologies

We run simulations for each country, i.e., Germany and the Netherlands, and one typical intensive and extensive dairy farm, respectively. For each of the country and intensity combinations, we provide farm-level results for the baseline and for each add-on technology (Bovaer®, extended lactation (ExtLact), vegetable oil additive (VegOil), and methane-reducing concentrate (Conc_10). Table 22 below shows the most relevant variables used in the parameterization step of the add-on technologies in GLOBIOM. Profit is used to determine the related abatement costs based on the difference in profit between the baseline and the add-on technology. Global warming potential (GWP) and global warming potential from enteric fermentation (entGWP) are used to determine the reduction in emissions from the add-on technology. The number of cows is provided to determine the relative costs and emissions based on the livestock unit level.

Table *22* Interface variables in the linkage between FarmDyn and MAGNET

		Intensive		Extensive	
		Dutch	German	Dutch	German
GWP [t CO2-eq.]	Baseline	909	1640	791	258
	Bovaer®	729	1270	639	198
	ExtLact	895	1561	779	247
	VegOil	735	1287	656	220
	Conc_10	897	-	780	-
Profit ['000 Eur 2020]	Baseline	146	327	167	41
	Bovaer®	139	314	161	39
	ExtLact	144	328	162	38
	VegOil	136	310	146	36
	Conc_10	144	-	165	-
	Baseline	601	1232	506	201

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

entGWP [t CO2-eq.]	Bovaer®	421	863	354	140
	ExtLact	591	1158	499	191
	VegOil	427	878	371	161
	Conc_10	589	-	495	-
Cows [LU]	Baseline	117	220	98	34
	Bovaer®	117	220	98	34
	ExtLact	117	220	98	34
	VegOil	117	219	98	34
	Conc_10	117	-	98	-
Heifers [LU]	Baseline	20	48	17	7
	Bovaer®	20	48	17	7
	ExtLact	20	31	17	5
	VegOil	17	48	15	7
	Conc_10	20	-	17	-

LU – livestock unit; GWP – global warming potential; entGWP – GWP stemming from enteric fermentation

The means of reducing the GHG emissions on dairy farms primarily target emissions stemming from enteric fermentation either directly with Bovaer® or vegetable oil additives or indirectly through reducing heifers based on extended lactation. The results show the expected direction for all country and intensity combinations, i.e., a decrease in profits and a reduction in GWP and entGWP. As we show only exemplary farm-level results provided to GLOBIOM, we cannot make a meaningful comparison between the different intensities and countries based on the differences in initial endowments, especially total acreages and type of land, as well as the differences in the national GHG accounting schemes in the Netherlands and Germany.

7.5.2.2 Intensity parameterized add-on technologies in GLOBIOM

Two datasets were provided by FarmDyn (Germany, Netherlands) containing key parameters for the representation of new dairy addon technologies (Bovaer®, vegetable oils, extended lactation time, concentrates) for an extensive and intensive livestock system in GLOBIOM. This dataset included information on changes in GHG emissions, productivities, feed composition, and farm profits in response to the adoption of a mitigation technology.

GHG reduction efficiencies for each FarmDyn mitigation technology and management system were calculated by comparing a mitigation scenario with the baseline values for CH_4 and N_2O emissions from enteric fermentation, stable and storage, manure application, and pastures and mapped to the equivalent emissions accounts from livestock in GLOBIOM. Multiplying these technologies and management-system-specific GHG reduction efficiencies (%) with the

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

default GHG emission factors for dairy production systems in GLOBIOM yielded the absolute GHG abatement (tCO_2eq per livestock unit (LU)) per technology in GLOBIOM.

The costs for each mitigation technology were calculated using information on marginal abatement costs from FarmDyn. Therefore, first, the change in farm profits in response to the adoption of a specific technology was calculated and converted from $Euros_{2020}$ (FarmDyn) to USD_{2000} (GLOBIOM). The change in profits was then divided by the GHG emission savings for each technology and interpreted as a proxy for the adoption costs of a certain technology in GLOBIOM (USD_{2000}/tCO_2eq emission reduction). Multiplying these costs with the total emission savings per technology (tCO_2eq/LU) yielded the total costs of a given technology in GLOBIOM (USD_{2000}/LU).

Next to the FarmDyn information on GHG emission reduction coefficients and costs, changes in the livestock feed baskets (for wheat, corn, and soya) were reflected in GLOBIOM for each technology (where relevant). For example, vegetable oils as feed additives would require additional demand for soya in livestock feeds that would need to be supplied.

The parameters for the extensive FarmDyn system were mapped to the more grass-based and other dairy production systems (LGH, LGA, LGT, OTHER) in GLOBIOM while the parameters for the intensive FarmDyn system were mapped to the mixed-cereal feeding and urban dairy production system (MRH, MRA, MRT, URBAN). Results for GHG reduction efficiency and costs of each mitigation measure are presented in intensity and country-specific in **Table** 23.

Table *23* Converted key FarmDyn variables for the linkage with GLOBIOM

		Intensive		Extensive	
		Dutch	German	Dutch	German
GHG reduction efficiency [%]	Bovaer	-21%	-25%	-21%	-25%
	ExtLact	-2%	-6%	-2%	-5%
	VegOil	-21%	-24%	-19%	-17%
	Conc_10	-1%	-	-2%	-
Costs [USD_{2000}/tCO_2e]	Bovaer	29	26	29	25
	ExtLact	85	-8	271	183
	VegOil	43	34	112	93
	Conc_10	137	-	135	-

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

7.5.2.3 New MAC curves in GLOBIOM

Nine GHG price trajectories were included in the baseline SSP2 scenario to derive marginal abatement cost curve (MACC) for agricultural non-CO_2 emissions with- and without representation of new FarmDyn mitigation technologies in GLOBIOM. GHG prices (10, 25, 50, 75, 100, 125, 150, 175, and 200 USD/tCO_2eq) were implemented on EU27 agricultural non-CO_2 emissions (CH_4 from enteric fermentation, manure management, and rice cultivation, N_2O from fertilizers, manure applied and dropped on pastures, and manure management) in 2030. By contrasting results from the GHG price scenarios to the baseline without mitigation efforts in 2030, the mitigation potentials and associated costs in the form of a MACC were derived.

Both parameterizations of the new mitigation options, as quantified by FarmDyn for Germany (UBO) and the Netherlands (WR), yield consistent results in terms of additional GHG abatement once implemented GLOBIOM. In both set-ups, agricultural non-CO_2 mitigation potentials increase by 27-30 MtCO_2eq/year in 2030 at 100 USD/tCO_2eq (~130 Euros/tCO_2eq), as shown in **Figure** 40. Hence, the adoption of new mitigation technologies can deliver an additional 5% of GHG abatement in EU agriculture as emissions reductions relative to the baseline levels increase from 33% to 38% at 100 USD/tCO_2eq in 2030. Especially the application of Bovaer (15-16 MtCO_2eq/year) and enhanced vegetable oils as livestock feed (11-12 MtCO_2eq/year) are responsible for the additional abatement potentials. In contrast, enhanced lactation period or increased concentrate feeds seem to play only a minor role and are less cost-effective (**Figure** 40). New FarmDyn technologies are cost-effective at GHG prices above 25 USD/tCO2eq, and most of the potential is already realized with GHG prices below 100 USD/tCO_2eq.

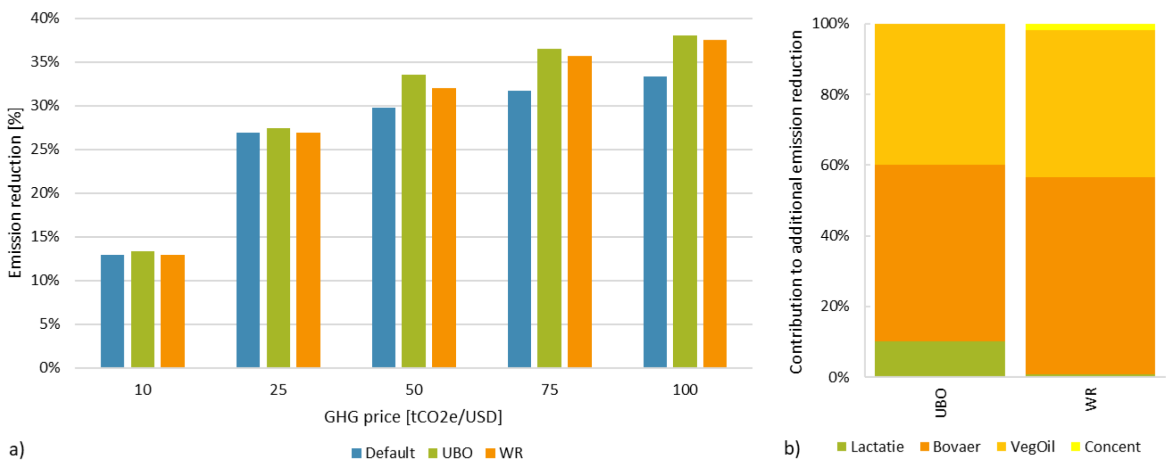


Figure *40* **Panel a) shows the total agricultural non-CO_2 mitigation potential (% change to baseline emissions) for EU agriculture in 2030.** *Default – no new FarmDyn technologies, UBO -FarmDyn technologies from Germany, WR – FarmDyn technologies from the Netherlands. Panel b) shows the contribution of each*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

new technology to the increased emission reduction potential compared to the default set-up at 100 USD/tCO$_2$eq in 2030.

Across EU regions, our results suggest that the new mitigation technologies contribute additional GHG mitigation at 100 USD/tCO$_2$eq primarily in Middle and Western EU member states (14-15 MtCO$_2$eq/year), followed by Southern (~5 MtCO$_2$e/year) and Eastern (~5 MtCO$_2$e/year) EU countries (**Figure** 41). In relative terms, again, Middle and Western EU member states can at most increase their non-CO$_2$ emission reduction compared to the default MACC at 100 USD/tCO$_2$eq (+ 8-9%), followed by Northern (+ 6-7%) and Southern (+ 5-6%) EU countries likely due to different shares of intensive/extensive livestock production systems with altering FarmDyn mitigation option parameterization.

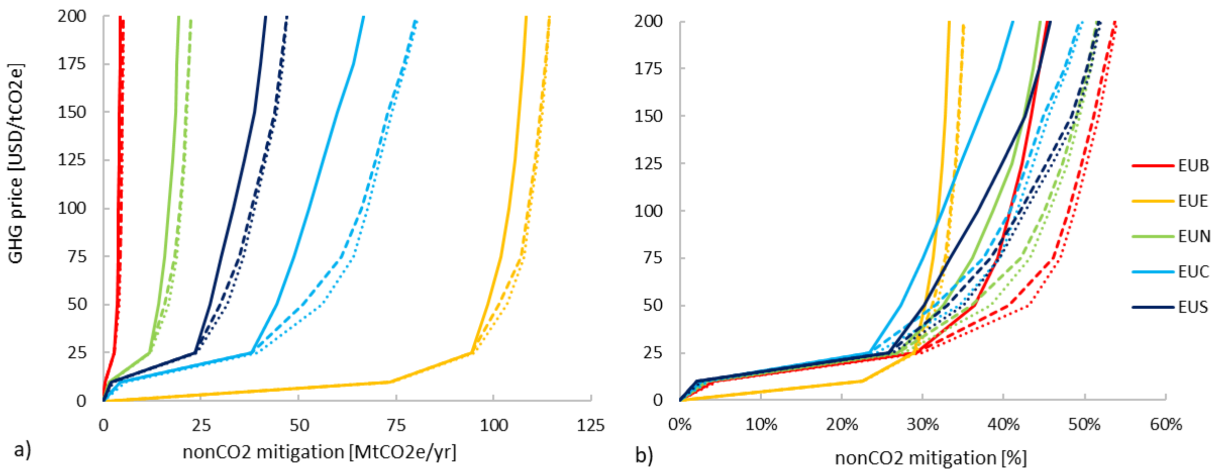


Figure *41* **EU agricultural non-CO2 mitigation potentials (Panel a – absolute mitigation potentials, Panel b – relative changes compared to the baseline) across EU regions. EUB – Baltics member states, EUE – Eastern member states, EUN – Northern member states, EUC – Middle and Western member states, EUS – Southern member states. Solid lines represent the default MACC in GLOBIOM without new FarmDyn technologies, pointed lines – MACC including FarmDyn technologies from Germany (UBO), dashed lines – MACC including FarmDyn technologies from the Netherlands (WR).**

7.5.3 FarmDyn to MAGNET

7.5.3.1 Relevant FarmDyn results for MACCs

To parameterize the MACCs in MAGNET, FarmDyn provides information on the relative change in total GWP at a given carbon tax for all EU member states for all endogenous measures in FarmDyn and with the additional exogenous abatement options Bovaer® and extended lactation. We show exemplary results for the relative change in total GWP at given carbon prices in **Figure** 42 for all farms at the NUTS2 level. We can see that for the scenario with solely endogenous measures, a reduction of total on-farm GWP of roughly 3% at a carbon

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

tax of 65 EUR/CO2-eq can be seen, with an average reduction of 7% at a carbon tax of 130 EUR/CO2-eq. Including Bovaer® and extended lactation as an abatement option increases the average relative reduction of total on-farm GWP to 23 and 25% for a carbon price of 65 and 130 EUR/CO2-eq, respectively.

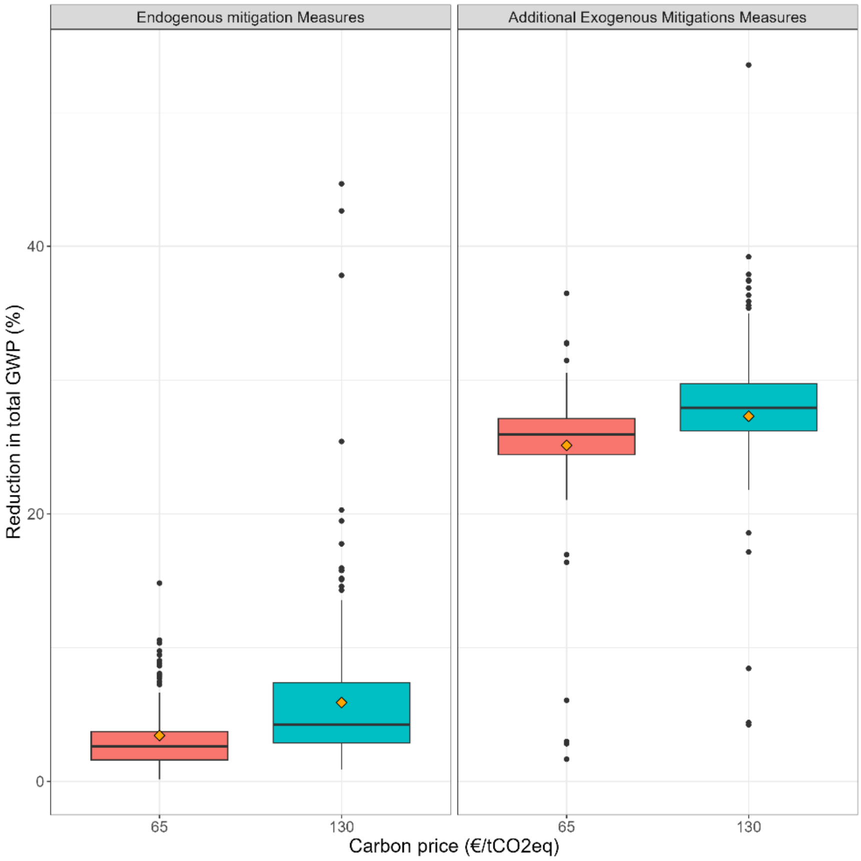


Figure 42: Box-Plot of single farm level results of FarmDyn for each average NUTS2 farm for all member states once with limited abatement options in FarmDyn and with the additional abatement option Bovaer Dots – single farm results from FarmDyn; Diamond - weighted mean

Figure 43 provides a graphical illustration for all EU member states for the given scenarios with only endogenous options and the additional abatement options for different carbon price levels. As indicated by the box plots above, our results show an overall reduction in global warming potential, which becomes more uniform once we add Bovaer® and extended lactations into the mix. The only exception is Lithuania since the average farms in this country cannot afford Bovaer, and because the rest of the countries could, most of the reduction in GWP seen is due to a reduction in methane stemming from enteric fermentation.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

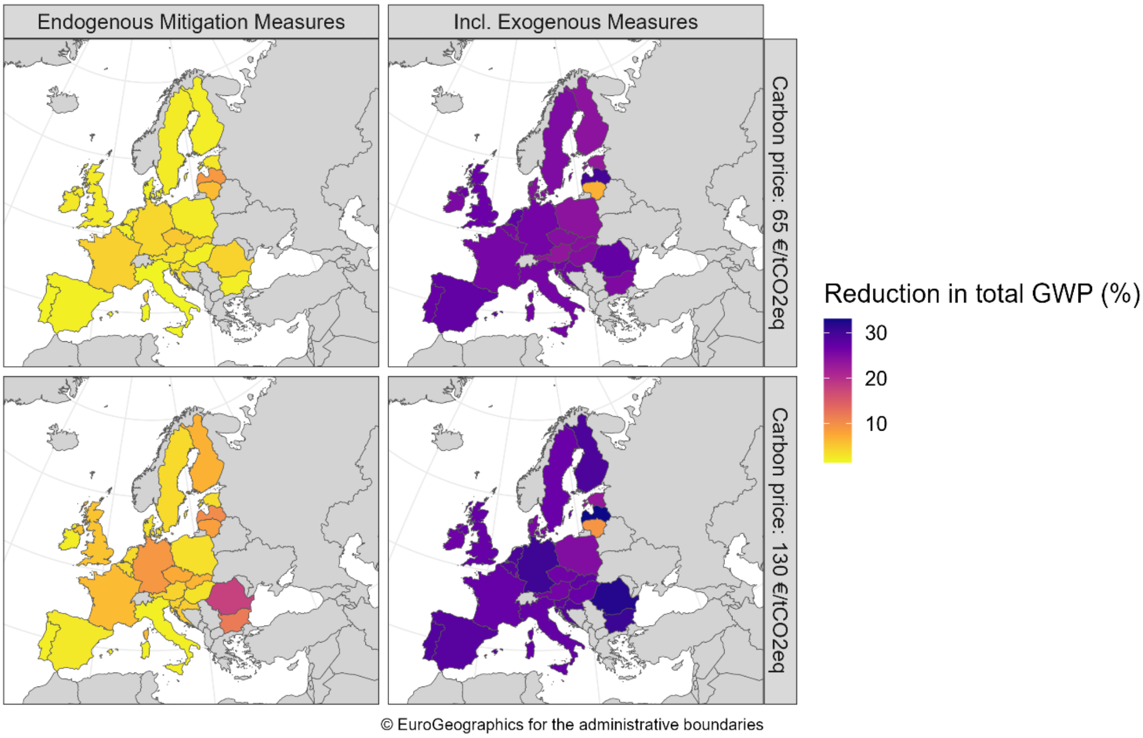


Figure 43 Reduction of GWP per country in the EU-28 given carbon taxes of 65 and 130 EUR/t CO2eq with endogenous mitigation measures and additional mitigation measures in some countries (Bovaer® and extended lactation)

The endogenous measures in FarmDyn include, as described in section 7.3.1.3, the reduction of herd size, which ultimately is expressed in a reduction of milk output in FarmDyn. Based on our results and the given carbon tax, the milk output remains practically unchanged except at a carbon tax of 130 EUR/t CO2eq in a few countries, as seen in **Figure *44***. Bulgaria and Romania reduce their milk output by about 10 – 15% with a carbon tax of 130 EUR/t CO2eq, but this reduction is ameliorated when including additional mitigation measures. The United Kingdom also reduces milk output at 130 EUR/t CO2eq by about 5%. However, this effect is lost when including additional mitigation measures.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

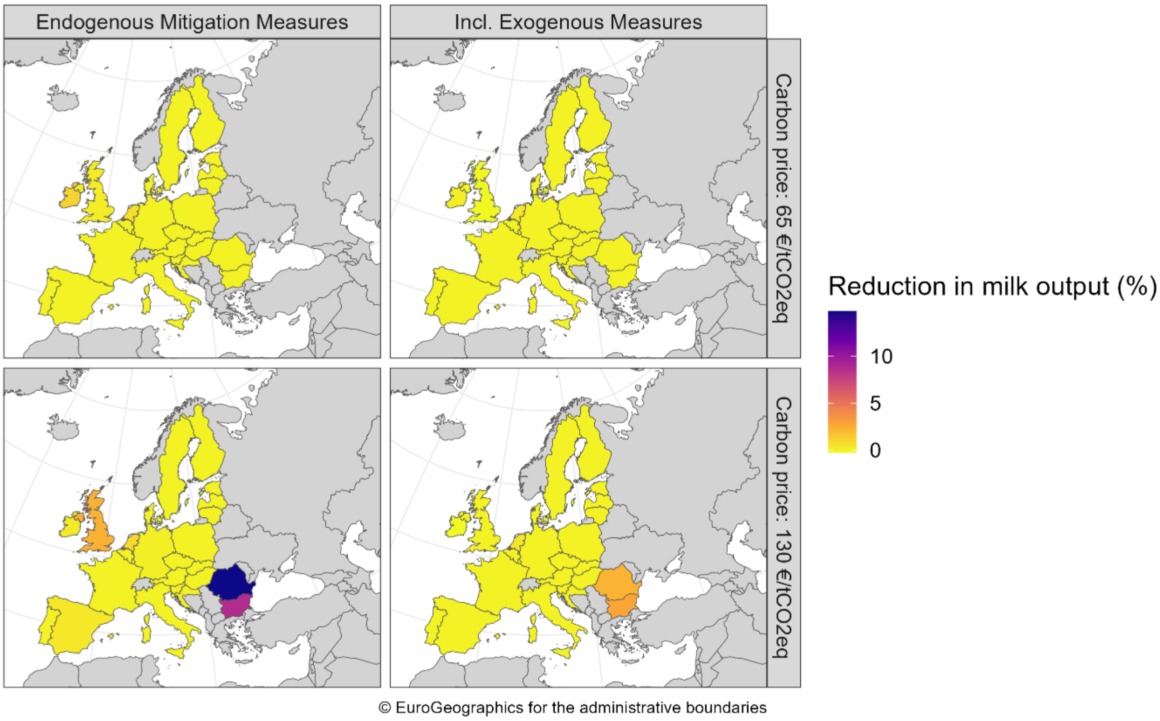


Figure 44 Reduction of milk output per country in the EU-28 given carbon taxes of 65 and 130 EUR/t CO2eq with endogenous mitigation measures and additional mitigation measures in some countries (Bovaer® and extended lactation)

7.5.3.2 MACCs for the raw milk sector

The data from the FarmDyn simulation runs are the basis for constructing the country-specific MACCs for two different emissions: i) methane (CH4) and ii) nitrous oxide (N2O). It is important to note that the intercept for the linear MACC curve is imposed to be non-negative, regardless of the values FarmDyn provides, to avoid issues of increasing emission intensity at small initial levels of carbon prices in MAGNET.

7.5.3.3 Emission intensity reduction for non-CO_2 emissions

Figure 45 shows significant differences both in slope and intercept between European countries, which signals a different emissions reduction sensitivity for the same carbon tax between countries based on the heterogeneity present in the farm sample data. Further, the implementation of MAC curves developed with FarmDyn data for endogenous measures without novel technologies (new) shows a similar reduction range compared to the old MACCs used in MAGNET.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

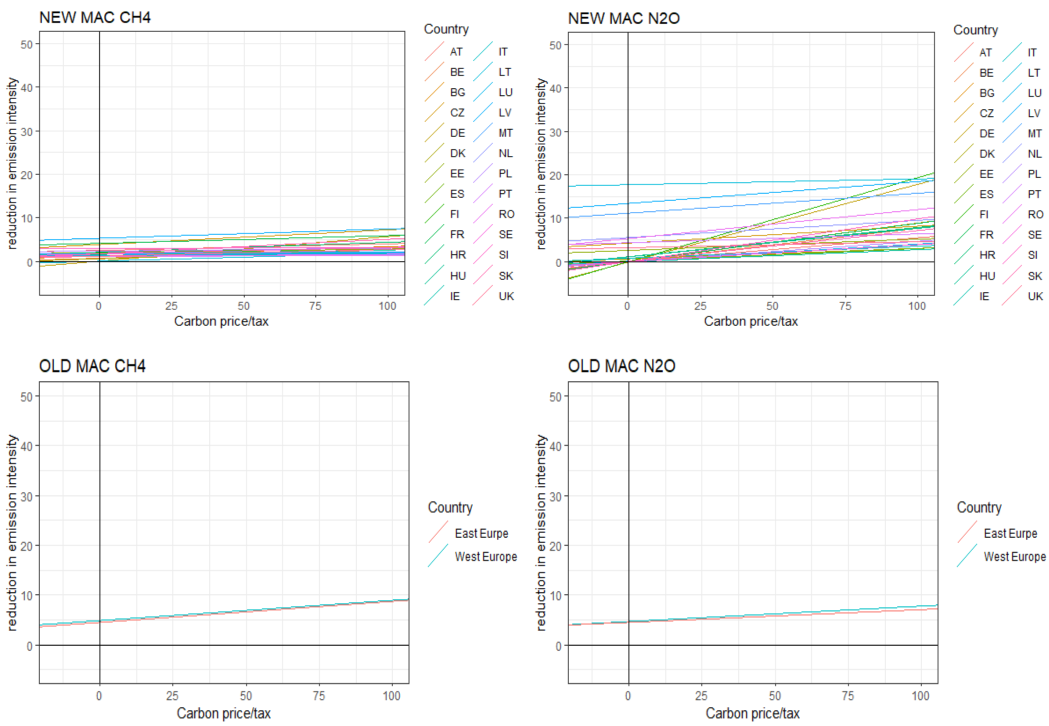


Figure 45 Upper left and right – Marginal abatement cost curve for CH4 and N2O with new FarmDyn MACCs without novel technologies for each EU-28 member state; Lower left and right – Marginal abatement cost curve for CH4 and N2O for two European regions (east and west) used previously in MAGNET

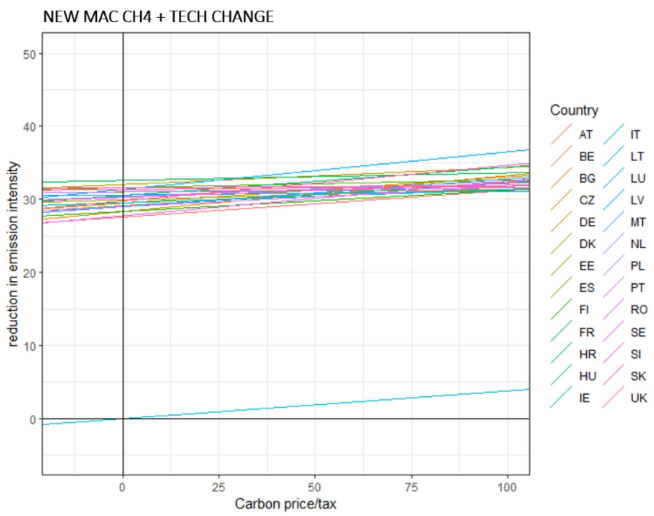


Figure 46 **Marginal Abatement Cost Curve for CH4 with novel technologies (new+tech) for all EU-28 member states**

Based on the results of **Figure** 46, we can see the impact of Bovaer® and extended lactation on the emissions from the enteric fermentation increase the reduction potential for CH_4, strongly differentiating the MACC structure for CH4, even with respect to the updated N_2O

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

curve, which is almost equal in the case of the previously used MACCs in MAGNET. This suggests the strong potential of technological shifts in the MACC curves.

7.5.3.4 Impact of new MACC implementation in MAGNET

Table 24 shows the impacts in Europe of a global tax of 50$ per tonne of C02 by 2040. It shows that the previous MACC calibration, based on a general regional aggregation in Eastern and Western Europe, was leading to an overestimation of the power of the global carbon tax. Table 24 shows that a $50 carbon tax initially resulted in about -15% CO2 equivalent emission reduction. The FarmDYN parametrized MAC curves provide a slightly lower reaction on the aggregate EU28 level (about -10.4%). Despite these (rather small) differences, it can be concluded that the FarmDyn calibrated MAC curves provide a solid improvement of the MAGNET model as the results are based on bottom-up regionally differentiated farm abatement possibilities. **Table 24** also shows the potential of technological change, specifically the Bovaer® and extended lactation implementation**,** in terms of CH4 emissions and overall impacts (new + tech). Indeed, when allowing for technological change, which has been calibrated with FarmDyn results, we see that a lower loss in European milk production is associated with a sensitively lower emission level in both CH4 and CO2 equivalent emissions at the European level – emission decline is up to -44.3% instead of -10.41%. One of the biggest differences between the old and the new implementation is the ability to observe trends at the country level instead of only at the European regional level.

Table 24 Relative change of key variables for milk for old, new, and new+tech mitigation measures for EU-28 before and after implementation of a global tax of 50 USD/t CO2eq., compared to the baseline.

	Old	New	New + Tech
Production Volume	-0,80	-1,59	-0,73
Producer Market Price	8,7	15,9	13,24
Exports Volume	24,4	80,3	108,4
Imports Volume	-62,8	-43,3	-48,2
CH4 Emissions	-15,6	-9,53	-55,2
CO2 emissions	-0,5	-1,32	1,48
N2O Emissions	-14,8	-13,79	-12,7
CO2 Eq emissions	-15,2	-10,41	-44,3

Note: "Old" refers to results under original MAC curves in MAGNET, "New" refers to results used with MAC curves parametrized from FarmDyn under constant technology, and "New+tech" refers to FarmDyn-based MAC curves allowing for technology changes

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Hereafter, two sets of implications can be derived from **Table 25** and **Table 26**. The first concerns the difference in policy implementation. When the carbon tax is implemented only in Europe and not in the other global regions, the European response to the policy is more homogeneous and has stronger intensity. As only EU milk production is “penalized” by additional costs, the reductions in milk production are indeed more substantial than in the global tax case. Being normally an exporting region, Europe starts to rely strongly on milk imports, acquiring the product from the regions in which the price is not inflated by the additional carbon tax. Indeed, it can be noted that the Rest of Europe (REU), which is unaffected by tax imposition, has diverging trends from the rest of the countries, not having a sensitive spike in import dependency and increasing production and exports (but also emissions).

The differences in the absolute percentage changes in production and overall CO2 equivalent emissions between the two scenarios, i.e., imposing the tax only in Europe or also at the global level, are significant but relatively low. The effects are relatively similar because the EU region bears the same tax burden in the two cases. Nevertheless, when the carbon tax is applied to the whole world, the equally distributed taxation burden leads to different specialization choices based on specific country production and economic incentives. For example, without considering the implementation of technological change, Belgium finds it convenient to increase substantially (in relation to the other countries) its milk production, which also implies an increase in its emissions, resulting in it being the only country with a net increase in its CH4 and CO2 equivalent emissions. Nevertheless, this side effect in terms of emissions is mitigated by the implementation of the new technology, as this trend does not appear in Table 26, where Belgium can increase its milk production by the same amount without the side effect of increasing emissions.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

Table 25 **a) Relative change of production volume, producer market price, export and import volume of milk for EU-28 and rest of Europe at a 50 USD/tCo2eq price in EU only (EU 50) and globally (WORLD 50) with new MACs without novel technologies. b) Relative change of CH4, CO2, N2O, and CO2eq emissions for EU-28 and rest of Europe at a 50 USD/tCo2eq price in EU only (EU_50) and globally (WORLD_50) with new MACs without novel technologies.**

a)

Region	Production Volume		Producer Market Price		Exports Volume		Imports Volume	
	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC
EU28	-1,59	-3,15	15,90	11,18	80,30	-45,80	-43,30	44,80
REU	-1,25	0,64	14,99	1,77	79,40	6,30	-57,00	4,40
AUT	-1,97	-3,45	15,74	12,26	70,10	-45,40	-33,10	34,40
BLX	6,26	-2,21	19,11	15,59	41,40	-57,80	-39,10	127,20
BGR	-4,63	-5,37	22,74	18,56	13,80	-64,50	-13,50	53,10
HRV	-7,59	-8,38	36,39	33,76	-47,60	-84,60	8,10	80,30
CZE	-1,14	-3,00	10,95	8,00	135,60	-28,40	-39,60	21,30
DNK	0,93	-1,66	12,97	7,75	94,10	-27,90	-36,90	6,70
EST	-3,37	-3,76	19,61	17,75	38,80	-62,80	-32,40	60,60
FIN	0,73	-1,51	12,65	9,30	125,00	-37,00	-36,30	26,50
FRA	-1,09	-2,64	18,20	14,26	44,30	-50,60	-27,40	46,40
DEU	-2,64	-4,10	14,30	10,93	87,60	-42,70	-34,50	28,00
HUN	-1,62	-3,18	17,17	13,59	54,00	-50,60	-25,90	42,00
IRL	-21,13	-24,82	25,04	20,71	-4,90	-70,10	-8,50	14,60
ITA	0,50	-1,13	16,29	14,09	62,40	-53,00	-29,60	43,20
LVA	-0,71	-1,99	18,88	13,22	46,40	-50,00	-30,60	43,80
LTU	-2,18	-3,17	26,60	23,17	-5,10	-72,90	-11,70	80,10
NLD	0,79	-3,79	14,24	9,51	91,20	-32,70	-34,70	21,20
POL	-2,50	-3,65	16,34	13,28	64,60	-50,00	-29,80	42,20
PRT	2,65	-0,15	15,15	10,73	82,70	-40,20	-31,30	32,80
ROU	-4,04	-3,61	16,71	12,22	58,90	-46,10	-32,60	40,40
SVK	0,92	0,11	15,81	11,12	72,30	-40,30	-29,80	34,00
SVN	-5,40	-6,65	25,57	22,07	-3,40	-69,70	-17,90	76,90
ESP	0,96	-0,42	11,94	9,28	121,50	-34,40	-38,80	25,00
SWE	-0,69	-2,41	14,80	10,83	69,50	-44,10	-31,10	31,50

b)

	CH4 Emissions		CO2 emissions		N2O Emissions		CO2 Eq emissions	
Region	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC
EU28	-9,53	-9,88	-1,32	-3,04	-13,79	-14,17	-10,41	-10,79
REU	-13,38	0,64	-1,21	0,41	-12,82	0,63	-13,07	0,63
AUT	-10,20	-11,56	-0,65	-2,14	-8,46	-9,84	-9,72	-11,08
BLX	2,25	-5,91	6,47	-2,02	-0,90	-8,81	1,78	-6,35
BGR	-9,81	-10,51	-4,40	-5,10	-9,93	-10,63	-9,80	-10,49
HRV	-14,85	-15,58	-6,96	-7,72	-15,09	-15,81	-14,32	-15,04
CZE	-14,38	-15,99	-0,69	-2,53	-19,20	-20,72	-15,21	-16,81
DNK	-2,74	-5,23	2,28	-0,22	-3,98	-6,44	-2,94	-5,42
EST	-9,55	-9,92	-2,97	-3,37	-12,73	-13,08	-10,56	-10,92
FIN	-5,79	-7,88	1,83	-0,47	-17,17	-19,02	-9,15	-11,18
FRA	-13,78	-15,13	-0,64	-2,14	-6,67	-8,13	-12,06	-13,44
DEU	-7,78	-9,16	-2,41	-3,84	-17,91	-19,15	-10,32	-11,67
HUN	-7,21	-8,68	-1,44	-2,99	-6,09	-7,58	-6,95	-8,42
IRL	-25,12	-28,63	-21,09	-24,80	-22,34	-25,97	-24,21	-27,76
ITA	-3,89	-5,44	0,81	-0,81	-5,41	-6,94	-4,07	-5,62
LVA	-16,69	-17,76	1,55	0,32	-37,22	-38,03	-24,04	-25,02
LTU	-3,97	-4,94	-1,08	-2,03	-42,42	-43,00	-16,63	-17,48
NLD	-2,92	-7,34	2,38	-2,30	-16,19	-20,01	-6,37	-10,63
POL	-9,61	-10,67	-2,01	-3,12	-7,02	-8,11	-8,69	-9,77
PRT	-1,00	-3,70	2,88	0,12	-12,30	-14,70	-3,19	-5,83
ROU	-7,30	-6,88	-3,75	-3,23	-31,25	-30,93	-11,72	-11,32
SVK	-7,13	-7,88	1,21	0,42	-4,87	-5,63	-6,66	-7,41
SVN	-13,24	-14,39	-4,89	-6,14	-13,96	-15,10	-13,06	-14,21
ESP	-3,28	-4,61	1,69	0,33	-12,46	-13,66	-5,08	-6,37
SWE	-6,73	-8,34	-0,56	-2,25	-5,37	-7,01	-6,30	-7,92

Table 26: a) Relative change of production volume, producer market price, export and import volume of milk for EU-28 and rest of Europe at a 50 USD/tCo2eq price in EU only (EU 50) and globally (WORLD 50) with new MACs with novel technologies. b) Relative change of CH4, CO2, N2O, and CO2eq

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

emissions for EU-28 and the Rest of Europe at a 50 USD/tCo2eq price in EU only (EU 50) and globally (WORLD 50) with new MACs with novel technologies.

a)

Region	Production Volume		Producer Market Price		Exports Volume		Imports Volume	
	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC
EU28	-0,73	-2,287	13,24	8,46	108,4	-38,1	-48,2	31,9
REU	-1,489	0,401	14,87	1,65	74,9	2,7	-55,8	4,5
AUT	-0,913	-2,417	12,99	9,45	93,4	-37,8	-36,1	26,1
BLX	6,995	-0,973	14,69	11,23	79	-46,3	-49,7	82,4
BGR	-3,273	-4,106	17,97	13,63	46,1	-53,7	-20,8	38
HRV	-5,285	-6,173	28,03	25,29	-20,9	-76,4	-2,2	57
CZE	-0,444	-2,334	9,14	6,13	154,4	-22,7	-41,1	16,1
DNK	1,763	-0,827	10,82	5,48	114,5	-19,4	-39,3	1,3
EST	-2,552	-3,002	16,04	14,1	66,7	-55	-37,6	46,7
FIN	1,358	-0,914	10,57	7,15	149,7	-30	-38,6	20
FRA	-0,366	-1,94	15,1	11,05	66,9	-43,2	-32,2	35
DEU	-1,607	-3,04	11,66	8,2	114,5	-34,3	-37,5	20,4
HUN	-0,845	-2,441	13,81	10,13	82,2	-41	-30,2	30,7
IRL	-15,623	-19,41	19,49	14,96	28,2	-58,7	-12,5	10,8
ITA	1,045	-0,612	12,74	10,48	95,7	-43,1	-34,8	30,7
LVA	-0,71	-1,899	17,96	12,04	49,5	-48,3	-31,2	39,8
LTU	-2,744	-3,765	26,03	22,58	-5,5	-73,2	-11,7	77,2
NLD	2,314	-2,336	11,44	6,56	118,8	-23	-38	13,1
POL	-1,57	-2,719	13,05	9,9	94,7	-40,5	-34,7	30,8
PRT	3,125	0,274	12,6	8,02	106	-32	-34,8	23,8
ROU	-3,128	-2,66	13,54	8,95	86	-36,4	-36,7	28,8
SVK	0,689	-0,094	13,63	8,83	88,1	-34,2	-32	26,2
SVN	-3,925	-5,136	20,98	17,28	20,2	-61,7	-24,1	60,2
ESP	1,244	-0,176	9,49	6,77	149,3	-26,2	-42,1	17
SWE	-0,157	-1,877	12,67	8,62	88,5	-37,4	-33,7	24,8

b)

Region	CH4 Emissions		CO2 emissions		N2O Emissions		CO2 Eq emissions	
	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC
EU28	-55,2	-54,6	1,487	-0,241	-12,7	-13,08	-44,3	-44
REU	-13,6	0,4	-1,456	0,173	-13,04	0,4	-13,3	0,4
AUT	-57,2	-57,8	2,064	0,533	-5,59	-7,02	-45,6	-46,4
BLX	-55,7	-59	9,508	1,419	-0,98	-8,36	-42,1	-46,4
BGR	-59,7	-60,1	-0,457	-1,213	-11,35	-12,11	-50,1	-50,6
HRV	-62,6	-63	-1,22	-2,068	-14,23	-15,03	-48,7	-49,2
CZE	-61,8	-62,5	1,452	-0,429	-15,46	-17,07	-52,6	-53,5
DNK	-58,1	-59,2	4,978	2,35	-1,73	-4,23	-45	-46,4
EST	-60,7	-60,9	0,097	-0,352	-12,01	-12,42	-41,4	-41,7
FIN	-56,9	-57,9	3,433	1,106	-15,67	-17,56	-40,1	-41,5
FRA	-61,9	-62,5	1,906	0,395	-8,67	-10,11	-49,6	-50,4
DEU	-59,8	-60,4	0,696	-0,696	-17,36	-18,57	-49,2	-49,9
HUN	-58,9	-59,5	1,02	-0,559	-10,08	-11,53	-48,8	-49,6
IRL	-65	-66,6	-12,415	-16,273	-18,04	-21,72	-49,8	-52,1
ITA	-59,2	-59,9	3,202	1,542	-4,09	-5,66	-46,6	-47,5
LVA	-62,2	-62,7	3,97	2,872	-35,9	-36,67	-52,7	-53,2
LTU	-6,3	-7,2	-1,604	-2,577	-42,5	-43,1	-18,2	-19
NLD	-58,7	-60,6	5,635	0,861	-16,14	-19,96	-47,1	-49,5
POL	-60,4	-60,9	1,142	0,036	-6,21	-7,31	-45,7	-46,3
PRT	-57	-58,2	5,172	2,366	-10,71	-13,18	-46,9	-48,4
ROU	-58,9	-58,7	-1,21	-0,605	-22,42	-22,05	-52	-51,8
SVK	-59,7	-60	2,918	2,187	-5,91	-6,65	-49,4	-49,8
SVN	-61,9	-62,4	-0,524	-1,718	-12,75	-13,85	-49,3	-50
ESP	-60,1	-60,7	3,336	1,938	-1,96	-3,34	-47,7	-48,5
SWE	-59,4	-60,1	1,398	-0,285	-3,95	-5,6	-42,1	-43,1

7.5.3.5 Technological Change Impact

Calibrated on FarmDyn simulations output, shifts in the MACC composition (i.e., increase in the potential country-specific mitigation power) are demonstrated to have a significant impact. Indeed, as shown in Table 27, all the European countries show economic

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

improvements due to the implementation of the new technology. While in the rest of Europe, where the new technology is not implemented, production and exports decrease, and import dependency increase, all the European countries, with the notable exception of Lithuania, successfully achieve an additional 50% reduction of both CH4 and CO2 equivalent emissions relative to milk production.

Table 27 **a) Relative change of production volume, producer market price, export and import volume of milk for EU-28 and rest of Europe at a 50 USD/tCo2eq price for Europe only (EU 50) and globally (WORLD 50) with new MACs with novel technologies. b) Relative change of CH4, CO2, N2O, and CO2eq emissions for EU-28 and the Rest of Europe at a 50 USD/tCo2eq price for Europe only (EU 50) and globally (WORLD 50) with new MACs with novel technologies**.

a)

	Production Volume		Producer Market Price		Exports Volume		Imports Volume	
	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC
EU28	0,88	0,89	-2,30	-2,45	15,58	14,23	-8,71	-8,87
REU	-0,24	-0,23	-0,10	-0,12	-2,51	-3,44	2,74	0,02
AUT	1,08	1,07	-2,37	-2,50	13,69	13,95	-4,58	-6,18
BLX	0,69	1,27	-3,71	-3,77	26,54	27,29	-17,36	-19,73
BGR	1,42	1,33	-3,89	-4,16	28,44	30,45	-8,44	-9,86
HRV	2,50	2,40	-6,13	-6,33	50,98	53,39	-9,57	-12,94
CZE	0,71	0,69	-1,63	-1,73	7,98	8,01	-2,46	-4,27
DNK	0,83	0,85	-1,91	-2,11	10,48	11,78	-3,80	-5,07
EST	0,85	0,79	-2,98	-3,10	20,09	20,81	-7,68	-8,64
FIN	0,62	0,60	-1,84	-1,97	11,00	11,13	-3,60	-5,18
FRA	0,73	0,72	-2,62	-2,81	15,67	15,06	-6,53	-7,76
DEU	1,06	1,10	-2,31	-2,46	14,39	14,54	-4,62	-5,93
HUN	0,79	0,76	-2,87	-3,04	18,29	19,30	-5,77	-7,91
IRL	6,98	7,20	-4,44	-4,76	34,78	37,93	-4,37	-3,35
ITA	0,55	0,52	-3,06	-3,16	20,55	20,87	-7,45	-8,72
LVA	0,00	0,09	-0,77	-1,04	2,15	3,33	-0,87	-2,83
LTU	-0,57	-0,61	-0,45	-0,48	-0,36	-1,20	-0,08	-1,64
NLD	1,51	1,51	-2,46	-2,70	14,42	14,34	-5,02	-6,75
POL	0,96	0,97	-2,83	-2,98	18,30	19,17	-6,93	-8,05
PRT	0,46	0,43	-2,22	-2,45	12,78	13,78	-4,98	-6,79
ROU	0,95	0,98	-2,71	-2,91	17,06	17,98	-6,02	-8,27
SVK	-0,23	-0,20	-1,88	-2,07	9,17	10,22	-3,14	-5,80
SVN	1,56	1,62	-3,66	-3,92	24,39	26,32	-7,53	-9,43
ESP	0,28	0,24	-2,19	-2,29	12,58	12,56	-5,47	-6,42
SWE	0,54	0,55	-1,86	-1,99	11,25	11,94	-3,86	-5,07

b)

	CH4 Emissions		CO2 emissions		N2O Emissions		CO2 Eq emissions	
	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC	WORLD_50_MAC	EU_50_MAC
EU28	-50,50	-49,60	2,84	2,89	1,27	1,27	-37,80	-37,20
REU	-0,20	-0,20	-0,25	-0,23	-0,24	-0,23	-0,20	-0,20
AUT	-52,30	-52,30	2,73	2,73	3,14	3,13	-39,70	-39,70
BLX	-56,70	-56,40	2,85	3,51	-0,08	0,,494	-43,10	-42,80
BGR	-55,40	-55,40	4,13	4,10	-1,58	-1,66	-44,70	-44,80
HRV	-56,10	-56,10	6,17	6,12	1,01	0,92	-40,10	-40,20
CZE	-55,40	-55,40	2,15	2,16	4,63	4,61	-44,10	-44,20
DNK	-56,90	-56,90	2,63	2,57	2,35	2,36	-43,30	-43,30
EST	-56,50	-56,60	3,17	3,13	0,82	0,76	-34,50	-34,50
FIN	-54,30	-54,30	1,57	1,59	1,81	1,79	-34,10	-34,10
FRA	-55,80	-55,80	2,57	2,59	-2,15	-2,16	-42,70	-42,70

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

DEU	-56,50	-56,40	3,19	3,27	0,67	0,71	-43,30	-43,30
HUN	-55,70	-55,70	2,50	2,50	-4,25	-4,28	-44,90	-45,00
IRL	-53,30	-53,20	10,99	11,33	5,54	5,75	-33,80	-33,60
ITA	-57,60	-57,60	2,38	2,38	1,40	1,38	-44,30	-44,30
LVA	-54,60	-54,60	2,38	2,54	2,11	2,20	-37,70	-37,60
LTU	-2,40	-2,40	-0,53	-0,56	-0,14	-0,18	-1,90	-1,90
NLD	-57,40	-57,50	3,18	3,23	0,06	0,05	-43,50	-43,50
POL	-56,20	-56,20	3,22	3,26	0,87	0,88	-40,50	-40,50
PRT	-56,50	-56,60	2,23	2,24	1,82	1,79	-45,20	-45,20
ROU	-55,60	-55,60	2,64	2,71	1,28	12,87	-45,60	-45,60
SVK	-56,60	-56,60	1,68	1,76	-1,10	-1,07	-45,80	-45,80
SVN	-56,10	-56,00	4,59	4,71	1,41	1,47	-41,70	-41,70
ESP	-58,80	-58,80	1,62	1,61	12,00	11,96	-44,90	-45,00
SWE	-56,50	-56,50	1,97	2,01	1,51	1,52	-38,20	-38,20

Remark: The emissions changes due to new technology implementations (lower half of the table) have inverted colours (green for negative values and red for positive) as lowering emissions with respect to the no-tech scenario is considered a positive impact.

7.5.3.6 Strengths and Weaknesses of FarmDyn/Magnet Coupling

Several challenges emerged in updating the MAC curves with FarmDyn data, specifically considering the technology change. In FarmDyn, technological shifts are the preferential response to the introduction of a carbon tax, i.e., if a tax is implemented, farmers try to avoid paying it as much as they can, shifting to different input and/or more emission-efficient production techniques if available. This is not the case in MAGNET. The model is built by default to increase the product price by a tax, leading to an equivalent abatement/reduction in emission intensity. Technological changes can only be handled if exogenous data are available, varying the intercept and slope of the (linear) MAC curve, which defines the behaviour of the abatement reaction for each carbon tax, as it was performed in the case of Bovaer® and extended lactation implementation in this deliverable. This relates to evident challenges in implementing FarmDyn inputs in MAGNET, as they require further elaboration from the basic standard response to match (at least in the baseline) the MAGNET characteristic (only tax impacts). The spatial resolution of the model FarmDyn is the single farm with a dataset for farms at the European level, while MAGNET is global. This introduces a series of issues since, in FarmDyn, responses to tax outside Europe and import/export decisions are not relevant, while trade is one of the main driving forces in MAGNET. Significant differences emerge due to international specialization decisions and substantial changes in the implication of the same carbon tax in Europe if the tax is also applied (or not) to the rest of the world, see **Table 25**, **Table 26**, and **Table 27**.

Nevertheless, the soft link with Farm-Dyn provides the possibility to have more sub-regional detail at the European level (which is critical in highlighting sub-regional production and mitigation choices) and the possibility to evaluate the impacts of new technologies implementation as the Bovaer® and extended lactation implementation that was tested in this case study. The coupling of this model, though it carries challenges, has proven to be a significant effort since it expands the realism, precision, and scenario possibility (i.e., the

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

introduction of technologies, absent in the beginning) that the macroeconomic model can perform.

7.6 Discussion and concluding remarks

The primary objective of this section is to explore options to improve the representation of mitigation measures in macroeconomic models using the single-farm level model FarmDyn. Based on the findings of farmers' adoption behaviour of mitigation measures in Task 3.3, this task assesses the impact of the mitigation measure portfolio extension in the explicit representation (single add-on technologies) in GLOBIOM and the implicit representation (MAC curves) in MAGNET, respectively. Rooted in the modular structure idea of an IDM (Task 3.2), the versatility of FarmDyn allows it to deal with various kinds of requirements posed by the linkage to different kinds of macro-models, such as the partial equilibrium model GLOBIOM and the computable general equilibrium MAGNET. Derived from these model features, this task further investigates the potential application of mitigation measures accounting for farm intensity and country-specific GHG emission accounting (GLOBIOM), as well as accounting for EU-wide farm heterogeneity in the construction of MAC curves (MAGNET).

The results for the linkage of FarmDyn to GLOBIOM show that given the national GHG accounting schemes of the Dutch and German versions, the GHG emission reduction for the mitigation technologies differs slightly. The results based on the differentiation between intensive and extensive between the two countries highlight that heterogenous assumptions about national GHG accounting and intensity levels can have a huge impact on both GHG reduction potential as well as the implied costs, especially when farm interactions and farm management options, such as vegetable oil feed or extended lactation are considered. Mitigation options with limited impact on the farm (management and other interactions), such as Bovaer®, show a more consistent reduction potential and costs across intensities and environmental accounting schemes, making them more suitable for extensions in the macro-models. Considering that this section only looked at dairy farms, the results for both intensities and GHG accounting schemes show a significant reduction potential with Bovaer® and vegetable oil, with additional emission reductions in Europe between 5-9% for the entire agricultural sector compared to the baseline.

Our results show that FarmDyn can produce data with similar mitigation reduction potential and costs compared to the initial MACCs in MAGNET for each of the EU-28 countries based on NUTS2-specific average dairy farms. Adding novel mitigation technologies to the construction of the MACs corresponds to a technology shock in MAGNET with major implications on production, trade, and emissions in the raw milk sector. We see that the reduction in the application with MACCs covering implicitly novel technologies reduces the GHG emissions in the EU-28 raw milk sector significantly with more than 35% compared to the baseline, which

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

is in the range of the reduction levels in GLOBIOMs EU-28 results. However, the additional reduction potential for MAGNET comparing old and new MACCs is substantially higher than in GLOBIOM. The scenario assessment emphasizes the importance of defining practical boundaries and policies during the setup phase to evaluate the effects of new technologies. Specifically, it involves determining the suitable regions for implementing these technologies and whether a carbon price should be imposed on all regions or only a select few.

In conclusion, this section offers valuable insights into the potential to extend the portfolio of mitigation measures implicitly and explicitly in macro-scale models using single-farm level models. Foremost, the wide range of simulation options in single-farm level models allows to establish loose linkages to multiple macro-economic models such as partial equilibrium models and computable general equilibrium models. This proof of concept allowed us to extend the initial differentiation of mitigation technologies by farm heterogeneity, farm intensity, and nationally specific GHG accounting schemes. However, it should be noted that this linkage also highlights the challenge posed by limited data availability, which hampers the accurate representation of diverse cost structures and marginal abatement costs within the single-farm level model. Eventually, further research is warranted to increase the coverage of single-farm level models to provide macroeconomic models with a wider range of spatial coverage to produce more robust policy assessments of mitigation potential in the agricultural sector.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

8 IMPROVED MARKET POWER PARAMETERS AND PRICE TRANSMISSION ELASTICITIES

As stated in MIND STEP Deliverable 4.4, the potential impact of organizations of producers and/or contractual agreements are not adequately represented in traditional New Industrial Organization (NEIO) models. Indeed, the majority of the theoretical and empirical literature on market power and price transmission currently adopts the assumption of perfect competition within markets. This statement is also valid in the context of Computable General Equilibrium (CGE) models. Indeed, even if some features mimicking aspects of market imperfections have been already introduced for a very long time (Harris, 1984; Harrison et al., 1997) and there is a substantial sub-strand of the CGE literature addressing this issue, inspired by Melitz's theoretical framework (Melitz, 2003), CGEs, in general, are mostly still using the defaults sets of assumptions, i.e., perfect competition, price-taking stakeholders, no costs of entry/exit from markets, market clearing and zero profit for firms. In particular, a standard assumption is the Armington assumption (Armington, 1969), which postulates that goods produced in different countries are imperfect substitutes, meaning that goods in the same region are more easily substituted with each other than imported ones. Imperfect competition of domestic vs. foreign is already accounted for standardly. Lifting the assumption of perfect competition can be fundamental for a more realistic assessment of policies and properly quantifying their effective macroeconomic and trade impacts. The data required for implementing Imperfect competition in CGE concerns assumptions about strategic behaviour, expectations and limits to market entry, price discrimination, product differentiations, and computation of the perceived demand elasticities in mark-up equations (Roson, 2006). In particular, the following modifications are required, depending on the choice of an explicit or implicit integration:

A. **Implicit**: The effect of heterogeneity is implicitly represented by shifts in the Armington taste (elasticity) parameters while maintaining the CES-based Armington structure (Zhai, 2008). Indeed, there are papers, e.g. (Dixon et al., 2016), which state that it is not required to implement a Melitz model in CGEs since Armington models can replicate their trade impacts by adjusting the usual elasticities of substitution. As such, different approaches have been applied to achieve a more realistic representation of overall trade effects, also driven by real-life firm heterogeneity, without explicitly implementing heterogeneous firms in the models. For example, Dixon and Rimmer (2002) uses a calibration on the Armington based on historical data, while Kuiper and Van Tongeren (2006) shift the Armington taste parameters exogenously based on estimated econometric gravity equations.
B. **Explicit**: First, this choice requires data inputs on firms' unitary profits or firm-specific mark-ups, the number of firms and the respective production level, industry elasticity

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

values, and data on economies of scale. Nevertheless, the minimum assumptions necessary to implement imperfect competition are the following[25]:

Data on the firm value added/production level and resource use to split the original representing firm into its heterogeneous component.

Choices on the Perceived Price Elasticities. In the mainstream setting, demand and perceived price elasticity (PPE) coincide. This follows the assumption that if only one firm exists (and there is perfect competition and no return to scale), the price is set up to be equivalent to the marginal cost, which is also equivalent to the average costs. Being just one firm available, a price change entails a variation embodied in the percentage change in demand induced by the price change in the object. In imperfect competition, the price is not necessarily equivalent to the marginal costs, but their relationship is weighted by the PPE. As such, the PPE embodies the competitor's reaction to a price change of the price-setting firm, which can inflate or deflate the final impact on the competitors' prices. This is the minimum to define the heterogenous' firms' behaviour.

One option is to calibrate this elasticity, as Jafari and Britz (2018) suggested. In this context, heterogeneity in firms is introduced based on a parameter λ (share parameter) representing some preference weights calibrated on the variety of production in the single regions. This allows for a differentiation between products by origin, as in the Armington, adding the love of variety effect. Since the quantity equation is modified, the price equation also needs to be adapted. Applying the share to the price computation for all the varieties results in the computation of the average price variety per firm, which is then reaggregated in the total variety price change. Furthermore, this technique is applied to estimate the demand for specific shares of production as intermediate inputs in each sector as part of the model functioning. In summary, they use some empirical weights to split the original production into different variety subsets. Nevertheless, different perceived elasticities calibration can vary under different assumptions, e.g., oligopolistic interaction (Willenbockel, 2004).

Definition of market. In general, CGEs are based on two criteria: origin (domestic, foreign) and level (intermediate or final consumption). In particular, the relationship in the first category is determined by Armington's assumption. On this basis, implementing imperfect competition requires adaptation of these dimensions to perceive multiple firms. There are two ways to do

[25] Indeed, there are also other parameters such as assumption on the entry/exit market costs and economies of scale, though while they can be influenced by the presence of the explicit representation of firm heterogeneity in the model, are not condictio sine qua non to implement it (Roson, 2006).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

this. The first is to assume that the role of imperfect competitors is relevant only in the domestic context (meaning that within all the single regions, the firms compete as different products). This means just adding another layer to the (domestic) demand structure. The second is to relax the Armington standard assumption, allowing for all products of all firms to compete (e.g., Akgul et al., 2016; Swaminathan and Hertel, 1997).

As such, the most challenging issue in introducing heterogeneity in a CGE resides in estimating the difference between firm prices and marginal costs, which is assumed to be zero in the standard model. From the literature, it emerges that this can be done by splitting by heterogeneous firm values and then calibrating through PPE estimates. Therefore, we expect to adopt the methodology described in Deliverable 4.4 as an empirical basis for estimating the price differentiation factor to introduce heterogeneity in the model in the future.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

9 CONCLUSIONS

In conclusion, this deliverable (D5.2) highlights the technical advancements made in the MIND STEP modelling toolbox. The focus is on improving existing EU-wide and global models used by the European Commission, with an emphasis on harmonizing production systems, enhancing the representation of farm types, calibrating behavioural parameters, incorporating structural changes, improving risk representation, assessing greenhouse gas emissions, and enhancing market power parameters and price transmission elasticities. These improvements aim to provide more accurate and comprehensive assessments of European agricultural production systems and their responses to various factors.

The deliverable outlines the work within the main subtasks of the project, showcasing the specific enhancements made in each section. Notable achievements include the harmonization of production systems and farm typologies, the calibration of behavioural parameters in macro-level models, the representation of structural changes in current models, the integration of risk representation in GLOBIOM, the assessment of greenhouse gas emissions using micro and macro-level models, and the enhancement of market power parameters and price transmission elasticities in CAPRI and MAGNET models. These advancements pave the way for improved policy evaluation and scenario assessments, providing valuable insights for decision-makers in the agricultural sector.

10 ACKNOWLEDGEMENTS

This Report is part of the H2020 MIND STEP project, which received funding from the European Union's Horizon 2020 research and innovation program under grant agreement N° 817566

11 REFERENCES

Adams, G., Westhoff, P., Willott, B., and Young, R. E. (2001). Do "Decoupled" Payments Affect U.S. Crop Area? Preliminary Evidence from 1997–2000. *American Journal of Agricultural Economics*, *83*(5), 1190–1195. https://doi.org/10.1111/0002-9092.00266

Aguiar, A., Chepeliev, M., Corong, E. L., McDougall, R., and van der Mensbrugghe, D. (2019). The GTAP Data Base: Version 10. *Journal of Global Economic Analysis*, *4*(1), 1–27. https://doi.org/10.21642/JGEA.040101AF

Akgul, Z., Villoria, N. B., and Hertel, T. W. (2016). GTAP-HET: Introducing firm heterogeneity into the GTAP model. *Journal of Global Economic Analysis*, *1*(1), 111–180. https://doi.org/10.21642/JGEA.010102AF

Armington, P. S. (1969). A Theory of Demand for Products Distinguished by Place of Production. *IMF Staff Papers*, *16*(1), 159–178. http://www.palgrave-journals.com/imfsp/journal/v16/n1/full/imfsp19697a.html%5Cnhttp://www.palgrave-journals.com/imfsp/journal/v16/n1/pdf/imfsp19697a.pdf

Arrow, K. J. (1996a). The theory of risk-bearing: Small and great risks. *Journal of Risk and Uncertainty*, *12*(2–3), 103–111. https://doi.org/10.1007/BF00055788

Arrow, K. J. (1996b). The theory of risk-bearing: Small and great risks. *Journal of Risk and Uncertainty*, *12*(2–3), 103–111. https://doi.org/10.1007/BF00055788

BAB. (n.d.). *BAB online calculator for Austrian conventional agriculture (field crops)*. https://idb.agrarforschung.at/default.html

Bahta, S. T., Berner, A., and Offermann, F. (2011). Estimation of Commodity Specific Production Costs Using German Farm Accountancy Data. *2011 International Congress, August 30-September 2, 2011, Zurich, Switzerland*. http://ideas.repec.org/p/ags/eaae11/114233.html

Barreiro-Hurle, J., Bogonos, M., and Himics, M. (2021). *Modelling environmental and climatic ambition in the agricultural sector with the CAPRI model – Exploring the potential effects of selected farm to fork and biodiversity strategies targets in the framework of the 2030 climate targets and the post 2020 Com*. https://data.europa.eu/doi/10.2760/98160

Beach, R. H., Creason, J., Ohrel, S. B., Ragnauth, S., Ogle, S., Li, C., Ingraham, P., and Salas, W. (2015a). Global mitigation potential and costs of reducing agricultural non-CO 2 greenhouse gas emissions through 2030. *Journal of Integrative Environmental Sciences*, *12*(sup1), 87–105. https://doi.org/10.1080/1943815X.2015.1110183

Beach, R. H., Creason, J., Ohrel, S. B., Ragnauth, S., Ogle, S., Li, C., Ingraham, P., and Salas, W. (2015b). Global mitigation potential and costs of reducing agricultural non-CO 2 greenhouse gas emissions through 2030. *Journal of Integrative Environmental Sciences*, *12*(sup1), 87–105. https://doi.org/10.1080/1943815X.2015.1110183

Billor, N., Hadi, A. S., and Velleman, P. F. (2000). BACON: blocked adaptive computationally efficient outlier nominators. In *Computational Statistics and Data Analysis* (Vol. 34). www.elsevier.com/locate/csda

Buschena, D. E., and Zilberman, D. (1994). What Do We Know About Decision Making Under Risk and Where Do We Go from Here? *Journal of Agricultural and Resource Economics*, *19*(2), 425–445. https://onlinelibrary.wiley.com/doi/abs/10.1111/0002-9092.00266

Cesaro, L., Marongiu, S., Zanoli, A., Donati, M., Arfini, F., and Paris, Q. (2013). *The use of RICA to estimate the cost of production in agriculture: application of econometric and mathematical programming methodologies* (L. Cesaro and S. Marongiu (eds.)). INEA.

Chavas, J.-P., and Holt, M. T. (1996). A Joint Analysis of Risk Preferences and Technology. *The Review of Economics and Statistics*, *78*(2), 329–335. http://www.jstor.org/stable/2109935

Chavas, J.-P., and Pope, R. (1985). Price uncertainty and competitive firm behavior: Testable hypotheses from expected utility maximization. *Journal of Economics and Business*, *37*(3), 223–235. https://doi.org/10.1016/0148-6195(85)90019-0

Chavas, J. (2001). Structural change in agricultural production: economics, technology and policy. In *Handbook of agricultural economics* (Vol. 1, pp. 263–285).

Chipman, H. A., George, E. I., and McCulloch, R. E. (2010). BART: Bayesian additive regression trees. *The Annals of Applied Statistics*, *4*(1), 266–298. https://doi.org/10.1214/09-AOAS285

Coyle, B. T. (1999). Risk Aversion and Yield Uncertainty in Duality Models of Production: A Mean-Variance Approach. *American Journal of Agricultural Economics*, *81*(3), 553–567. https://doi.org/10.2307/1244015

Dallago, G. M., Wade, K. M., Cue, R. I., McClure, J. T., Lacroix, R., Pellerin, D., and Vasseur, E. (2021). Keeping Dairy Cows for Longer: A Critical Literature Review on Dairy Cow Longevity in High Milk-Producing Countries. *Animals*, *11*(3), 808. https://doi.org/10.3390/ani11030808

De Vries, A. (2017). Economic trade-offs between genetic improvement and longevity in dairy cattle. *Journal of Dairy Science*, *100*(5), 4184–4192. https://doi.org/10.3168/jds.2016-11847

Dixon, P. B., and Rimmer, M. T. (2002). *Dynamic general equilibrium modelling for forecasting and policy. A practical guide and documentation of Monash*. Elsevier.

Dixon, P., Jerie, M., and Rimmer, M. (2016). Modern Trade Theory for CGE Modelling: The Armington, Krugman and Melitz Models. *Journal of Global Economic Analysis*, *1*(1), 1–110. https://doi.org/10.21642/jgea.010101sm1f

Doreau, M., Arbre, M., Popova, M., Rochette, Y., and Martin, C. (2018). Linseed plus nitrate in the diet for fattening bulls: effects on methane emission, animal health and residues in offal. *Animal*, *12*(3), 501–507. https://doi.org/10.1017/S1751731117002014

EEA. (2022). *Greenhouse gas emissions from agriculture in Europe*. European Environment Agency. https://www.eea.europa.eu/ims/greenhouse-gas-emissions-from-agriculture

EMEP/EEA. (2016). *EMEP/EEA air pollutant emission inventory guidebook 2016: Technical guidance to prepare national emission inventories. European Environment Agency.* (Issue EEA Report No 21/2016).

Espinosa, M., Gocht, A., Heckelei, T., and Paloma, S. G. y. (2016). Incorporating farm structural change in models assessing the Common Agricultural Policy: An application in the CAPRI farm type model. *Journal of Policy Modeling*, *38*(6), 1040–1059. https://doi.org/10.1016/j.jpolmod.2016.03.005

European Commission. (n.d.). *Farm accountancy data network*. https://agriculture.ec.europa.eu/data-and-analysis/farm-structures-and-economics/fadn_en

European Commission. (2008). Commission Regulation (EC) No 1242/2008 of 8 December 2008 establishing a Community typology for agricultural holdings. *Official Journal of the European Union*, *L 335/3*.

European Commission. (2022). *Factsheet on 2014–2020 Rural Development Programme for Romania* (Issue September).

Frank, S., Beach, R., Havlík, P., Valin, H., Herrero, M., Mosnier, A., Hasegawa, T., Creason, J., Ragnauth, S., and Obersteiner, M. (2018). Structural change as a key component for agricultural non-CO2 mitigation efforts. *Nature Communications*, *9*(1), 1060. https://doi.org/10.1038/s41467-018-03489-1

Frank, S., Havlík, P., Stehfest, E., van Meijl, H., Witzke, P., Pérez-Domínguez, I., van Dijk, M., Doelman, J. C., Fellmann, T., Koopman, J. F. L., Tabeau, A., and Valin, H. (2019). Agricultural non-CO2 emission reduction potential in the context of the 1.5 °C target. *Nature Climate Change*, *9*(1), 66–72. https://doi.org/10.1038/s41558-018-0358-8

Frank, S., Havlík, P., Tabeau, A., Witzke, P., Boere, E., Bogonos, M., Deppermann, A., van Dijk, M., Höglund-Isaksson, L., Janssens, C., Kesting, M., van Meijl, H., Pérez-Domínguez, I., and Valin, H. (2021). How much multilateralism do we need? Effectiveness of unilateral agricultural mitigation efforts in the global context. *Environmental Research Letters*, *16*(10), 104038. https://doi.org/10.1088/1748-9326/ac2967

Fricko, O., Havlik, P., Rogelj, J., Klimont, Z., Gusti, M., Johnson, N., Kolp, P., Strubegger, M., Valin, H., Amann, M., Ermolieva, T., Forsell, N., Herrero, M., Heyes, C., Kindermann, G., Krey, V., McCollum, D. L., Obersteiner, M., Pachauri, S., … Riahi, K. (2017). The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century. *Global Environmental Change*, *42*, 251–267. https://doi.org/10.1016/j.gloenvcha.2016.06.004

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, *29*(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

Glauber, J. W. (2004). Crop nsurance econsidered. *Agricultural Economics*, *86*(5), 1179–1195.

Grandl, F., Furger, M., Kreuzer, M., and Zehetmeier, M. (2019). Impact of longevity on greenhouse gas emissions and profitability of individual dairy cows analysed with different system boundaries. *Animal*, *13*(1), 198–208. https://doi.org/10.1017/S175173111800112X

Gusti, M. (2010). An algorithm for simulation of forest management decisions in the global forest model. *Artificial Intelligence*, *N4*, 45–49.

Haenel, H.-D., Rösemann, C., Dämmgen, U., Döring, U., Wulf, S., Eurich-Menden, B., ... and, and Fuß, R. (2020). Calculations of gaseous and particulate emissions from German agriculture 1990 - 2018: Report on methods and data (RMD) Submission 2020. *Thünen Report*, *No. 77*. https://doi.org/https://doi.org/10.3220/REP1584363708000

Hallam, D., Bailey, A., Jones, P., and Errington, A. (1999). Estimating Input Use and Production Costs from Farm Survey Panel Data. *Journal of Agricultural Economics*, *50*(3), 440–449. https://doi.org/10.1111/j.1477-9552.1999.tb00892.x

Harris, R. (1984). Applied general equilibrium analysis of small open economies with scale economies and imperfect competition. *The American Economic Review*, *74*(5), 1016–1032.

Harrison, G. W., Rutherford, T. F., and Tarr, D. G. (1997). Quantifying the Uruguay Round. *The Economic Journal*, *107*(444), 1405–1430. https://doi.org/10.1111/j.1468-0297.1997.tb00055.x

Havlík, P., Schneider, U. A., Schmid, E., Böttcher, H., Fritz, S., Skalský, R., Aoki, K., Cara, S. De, Kindermann, G., Kraxner, F., Leduc, S., McCallum, I., Mosnier, A., Sauer, T., and Obersteiner, M. (2011). Global land-use implications of first and second generation biofuel targets. In *Energy Policy* (Vol. 39, Issue 10, pp. 5690–5702). https://doi.org/10.1016/j.enpol.2010.03.030

Havlík, P., Valin, H., Herrero, M., Obersteiner, M., Schmid, E., Rufino, M. C., Mosnier, A., Thornton, P. K., Böttcher, H., Conant, R. T., Frank, S., Fritz, S., Fuss, S., Kraxner, F., and Notenbaert, A. (2014). Climate change mitigation through livestock system transitions. *Proceedings of the National Academy of Sciences*, *111*(10), 3709–3714. https://doi.org/10.1073/pnas.1308044111

Hennessy, D. A. (1998). The Production Effects of Agricultural Income Support Policies under Uncertainty. *American Journal of Agricultural Economics*, *80*(1), 46–57. https://doi.org/10.2307/3180267

Herrero, M., Havlík, P., Valin, H., Notenbaert, A., Rufino, M. C., Thornton, P. K., Blümmel, M., Weiss, F., Grace, D., and Obersteiner, M. (2013). Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. *Proceedings of the National Academy of Sciences*, *110*(52), 20888–20893. https://doi.org/10.1073/pnas.1308149110

Hertel, T. W., and Tsigas, M. E. (1997). Structure of GTAP. In T. W. Hertel (Ed.), *Global Trade Analysis: Modeling and Applications* (pp. 9–71). Cambridge University Press. https://doi.org/10.1627/jpi1958.9.890

Heyn, J., and Olfs, H.-W. (2018). *Wirkungen reduzierter N-Düngung auf Produktivität, Bodenfruchtbarkeit und N-Austragsgefährdung - Beurteilung anhand mehrjähriger Feldversuche*.

Huber, R., Tarruella, M., Schäfer, D., and Finger, R. (2023a). Marginal climate change abatement costs in Swiss dairy production considering farm heterogeneity and interaction effects. *Agricultural Systems*, *207*, 103639. https://doi.org/10.1016/j.agsy.2023.103639

Huber, R., Tarruella, M., Schäfer, D., and Finger, R. (2023b). Marginal climate change abatement costs in Swiss dairy production considering farm heterogeneity and interaction effects. *Agricultural Systems*, *207*, 103639. https://doi.org/10.1016/j.agsy.2023.103639

IAEI. (2018). *Costs of Agricultural Products*. http://www.iaei.cz/costs-of-agricultural-products/

IIASA/FAO. (2012). Global Agro-ecological Zones (GAEZ v3.0). In *IIASA and FAO*.

IPCC. (2019). *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories* (E. Calvo Buendia, K. Tanabe, A. Kranjc, J. Baasansuren, M. Fukuda, S. Ngarize, A. Osako, Y. Pyrozhenko, P. Shermanau, and S. Federici (eds.)). IPCC, Switzerland.

Janssen, S., and van Ittersum, M. K. (2007). Assessing farm innovations and responses to policies: A review of bio-economic farm models. *Agricultural Systems*, *94*(3), 622–636. https://doi.org/10.1016/j.agsy.2007.03.001

Just, R. E., Zilberman, D., Hochman, E., and Bar-Shira, Z. (1990). Input Allocation in Multicrop Systems. *American Journal of Agricultural Economics*, *72*(1), 200–209. https://doi.org/10.2307/1243159

Kindermann, G., McCallum, I., Fritz, S., and Obersteiner, M. (2008). A global forest growing stock, biomass and carbon map based on FAO statistics. *Silva Fennica*, *42*(3). https://doi.org/10.14214/sf.244

Kokemohr, L., Escobar, N., Mertens, A., Mosnier, C., Pirlo, G., Veysset, P., and Kuhn, T. (2022). Life Cycle Sustainability Assessment of European beef production systems based on a farm-level optimization model. *Journal of Cleaner Production*, *379*, 134552. https://doi.org/10.1016/j.jclepro.2022.134552

KTBL. (n.d.). *Standard gross margins*. https://daten.ktbl.de/sdb/welcome.do?lang=en

Kuiper, M., and Van Tongeren, F. (2006). Using gravity to move Armington An empirical approach to the small initial trade share problem in general equilibrium models. *9th Annual Conference on*

Global Economic Analysis.

Lansink, A. O. (2008). Area Allocation Under Price Uncertainty on Dutch Arable Farms. *Journal of Agricultural Economics*, *50*(1), 93–105. https://doi.org/10.1111/j.1477-9552.1999.tb00797.x

Lengers, B., Britz, W., and Holm-Müller, K. (2014). What Drives Marginal Abatement Costs of Greenhouse Gases on Dairy Farms? A Meta-modelling Approach. *Journal of Agricultural Economics*, *65*(3), 579–599. https://doi.org/10.1111/1477-9552.12057

MAGRAMA. (2013). *Resultados técnico-económicos de Cultivos Herbáceos 2010*.

MAPA. (2020). *Resultados técnico-económicos de Cultivos Herbá-ceos 2016*.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, *71*(6), 1695–1725. https://doi.org/10.1111/1468-0262.00467

Meuwissen, M. P. M., Huirne, R. B. M., and Skees, J. R. (2003). Income Insurance in European Agriculture. *EuroChoices*, *2*(1), 12–17. https://doi.org/10.1111/j.1746-692X.2003.tb00037.x

Miranda, M. J., and Glauber, J. W. (1997). Systemic Risk, Reinsurance, and the Failure of Crop Insurance Markets. *American Journal of Agricultural Economics*, *79*(1), 206–215. https://doi.org/10.2307/1243954

Moschini, G., and Hennessy, D. A. (2001). Uncertainty, risk aversion, and risk management for agriculture producers. Volume 1, Part A. In B. Gardner and G. Rausser (Eds.), *Handbook of Agricultural Economics* (Vol. 1, pp. 88–153). Elsevier Science B.V. http://www.sciencedirect.com/science/article/pii/S1574007201100058

Penman, J., Gytarsky, M., Hiraishi, T., Irving, W., and Krug, T. (2006). 2006 IPCC - Guidelines for National Greenhouse Gas Inventories. In *Directrices para los inventarios nacionales GEI*. https://projecteuclid.org/journals/annals-of-applied-statistics/volume-4/issue-1/BART-Bayesian-additive-regression-trees/10.1214/09-AOAS285.full

Pennings, J. M. E., Garcia, P., and Oskam., A. J. (2010). Private Market and Price Stabilization Methods. In *EU Policy for Agriculture, Food and Rural Areas* (pp. 183–190). Wageningen Academic Publishers.

Reidsma, P., Wolf, J., Kanellopoulos, A., B.F., S., Mandryk, M., Verhagen, J., and Van Ittersum, M. K. (2015). Climate change impact and adaptation research requires integrated assessment and farming systems analysis : a case study in the Netherlands. *Environmental Research Letters*. https://doi.org/10.1088/1748-9326/10/4/045004

Reimund, D. A., Martin, R. J., and Moore, C. V. (1981). *Structural Change in Agriculture: The experience for Broilers, Fed Cattle, and Processing Vegetables*.

Roson, R. (2006). Introducing imperfect competition in CGE models: Technical aspects and implications: with an illustration about trade liberalization in agriculture. *Computational Economics*, *28*(1), 29–49. https://doi.org/10.1007/s10614-006-9034-6

Sckokai, P., and Moro, D. (2006). Modeling the Reforms of the Common Agricultural Policy for Arable Crops under Uncertainty. *American Journal of Agricultural Economics*, *88*(1), 43–56. https://doi.org/10.1111/j.1467-8276.2006.00857.x

Šebek, L. B., Mosquera, J., and Bannink, A. (2016). *Rekenregels voor de enterische methaan-emissie op het melkveebedrijf en reductie van de methaan-emissie via mesthandling, het handelings-perspectief van het voerspoor inzichtelijk maken met de Kringloopwijzer*. https://doi.org/10.18174/391726

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Skalský, R., Tarasovičová, Z., Balkovič, J., Schmid, E., Fuchs, M., Moltchanova, E., Kindermann, G., and Scholtz, P. (2008). *GEO-BENE global database for bio-physical modeling v. 1.0 - concepts, methodologies and data. The GEO-BENE database report*.

Sparapani, R., Spanbauer, C., and McCulloch, R. (2021). Nonparametric Machine Learning and Efficient Computation with Bayesian Additive Regression Trees: The BART R Package. *Journal of Statistical Software*, *97*(1), 1–66. https://doi.org/10.18637/jss.v097.i01

Surry, Y., Desbois, D., and Butault, J. P. (2013). *General cost of production model : conceptual framework , econometric specifications and estimation procedures*.

Swaminathan, P., and Hertel, T. (1997). *Introducing monopolistic competition into the GTAP model.* (GTAP Technical Paper No. 6.).

US EPA. (2013). *Global mitigation of non-CO2 greenhouse gases: 2010-2030*.

Valin, H., Sands, R. D., van der Mensbrugghe, D., Nelson, G. C., Ahammad, H., Blanc, E., Bodirsky, B., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Mason-D'Croz, D., Paltsev, S., Rolinski, S., Tabeau, A., van Meijl, H., von Lampe, M., and Willenbockel, D. (2014). The future of food demand: understanding differences in global economic models. *Agricultural Economics*, *45*(1), 51–67. https://doi.org/10.1111/agec.12089

van der Zee, T., Bannink, A., van Bruggen, C., Groenestein, K., Huijsmans, J., van der Kolk, J., Lagerwerf, L., Luesink, H., Velthof, G., and Vonk, J. (2021). *Methodology for estimating emissions from agriculture in the Netherlands. Calculations for CH4, NH3, N2O, NOx, NMVOC, PM10, PM2.5 and CO2 using the National Emission Model for Agriculture (NEMA) – Update 2021*. http://library.wur.nl/WebQuery/wurpubs/504907

van Dijk, W., de Boer, J., de Haan, M. H. A., Mostert, P., Oenema, J., and Verloop, J. (2020). *Rekenregels van de KringloopWijzer 2020 : Achtergronden van BEX, BEA, BEN, BEP en BEC: actualisatie van de 2019-versie*. https://doi.org/10.18174/533882

van Gastelen, S., Dijkstra, J., Heck, J. M. L., Kindermann, M., Klop, A., de Mol, R., Rijnders, D., Walker, N., and Bannink, A. (2022). Methane mitigation potential of 3-nitrooxypropanol in lactating cows is influenced by basal diet composition. *Journal of Dairy Science*, *105*(5), 4064–4082. https://doi.org/10.3168/jds.2021-20782

Van Meijl, H., Van Rheenen, T., Tabeau, A., and Eickhout, B. (2006). The impact of different policy environments on agricultural land use in Europe. *Agriculture, Ecosystems and Environment*, *114*(1), 21–38. https://doi.org/10.1016/j.agee.2005.11.006

Vargas, J. E., Andrés, S., López-Ferreras, L., Snelling, T. J., Yáñez-Ruíz, D. R., García-Estrada, C., and López, S. (2020). Dietary supplemental plant oils reduce methanogenesis from anaerobic microbial fermentation in the rumen. *Scientific Reports*, *10*(1), 1613. https://doi.org/10.1038/s41598-020-58401-z

Willenbockel, D. (2004). Specification choice and robustness in CGE trade policy analysis with imperfect competition. *Economic Modelling*, *21*(6), 1065–1099. https://doi.org/10.1016/j.econmod.2004.03.003

Williams, J. R. (1995). The EPIC Model. In V. P. Singh (Ed.), *Computer Models of Watershed Hydrology* (pp. 909–1000). Water Resources Publications, Highlands Ranch.

Wood-Sichra, U., Joglekar, A. B., and You, L. (2016). Spatial Production Allocation Model (SPAM) 2005: Technical Documentation. *Harvest Choice*, 1–87. http://mapspam.info

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

You, L., and Wood, S. (2006). An entropy approach to spatial disaggregation of agricultural production. *Agricultural Systems*, *90*(1–3), 329–347. https://doi.org/10.1016/j.agsy.2006.01.008

You, L., Wood, S., Wood-Sichra, U., and Wu, W. (2014). Generating global crop distribution maps: From census to grid. *Agricultural Systems*, *127*, 53–60. https://doi.org/10.1016/j.agsy.2014.01.002

Zhai, F. (2008). Armington meets Melitz: Introducing firm heterogeneity in a global CGE model of trade. *Journal of Economic Integration*, 575–604.

Zimmermann, A., Heckelei, T., and Domínguez, I. P. (2009). Modelling farm structural change for integrated ex-ante assessment: review of methods and determinants. *Environmental Science and Policy*, *12*(5), 601–618. https://doi.org/10.1016/j.envsci.2009.01.014

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 817566.

12 ANNEX

Table A1 Mapping between GLOBIOM Land use classification and CLC level 3 classification.

GLOBIOM Land use classification	CLC level 3 classification
Urban	Continuous urban fabric
Urban	Discontinuous urban fabric
Urban	Industrial or commercial units
Urban	Road and rail networks and associated land
Urban	Port areas
Urban	Airports
Urban	Mineral extraction sites
Urban	Dump sites
Urban	Construction sites
Urban	Green urban areas
Urban	Sports and leisure facilities
CrpLnd	Non-irrigated arable land
CrpLnd	Permanently irrigated land
CrpLnd	Rice fields
OthAgri	Vineyards
OthAgri	Fruit trees and berry plantations
OthAgri	Olive groves
GrsLnd	Pastures
OthAgri	Annual crops associated with permanent crops
OthAgri	Complex cultivation patterns
OthAgri	Land principally occupied by agriculture with significant areas of natural vegetation
OthAgri	Agro-forestry areas
Forest	Broad-leaved forest
Forest	Coniferous forest
Forest	Mixed forest
OthNatLnd	Natural grasslands
OthNatLnd	Moors and heathland
OthNatLnd	Sclerophyllous vegetation
OthNatLnd	Transitional woodland-shrub
NotRel	Beaches dunes sands
NotRel	Bare rocks
NotRel	Sparsely vegetated areas
NotRel	Burnt areas

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

NotRel	Glaciers and perpetual snow
NotRel	Inland marshes
NotRel	Peat bogs
NotRel	Salt marshes
NotRel	Salines
NotRel	Intertidal flats
NotRel	Water courses
NotRel	Water bodies
NotRel	Coastal lagoons
NotRel	Estuaries
NotRel	Sea and ocean
NotRel	NO DATA

Table A2 GLOBIOM's FAOSTAT derived data over items, variables, and units.

Item	Variable	Unit
Barley (BARL) Corn (CORN) Wheat (WHEA) Rapeseed (RAPE) Rice (RICE) Soya (SOYA) Sunflower Seed (SUNF) Sugar Cane (SUGC) Oil Palm (OPAL) Bovine Meat (BVMEAT) Pig Meat (PGMEAT) Poultry Meat (PTMEAT) Sheep and Goat Meat (SGMEAT) Almond Milk (ALMILK) Poultry Eggs (PTEGGS)	Export (EXPO) Feed (FEED) Food (FOOD) Import (IMPO) Net Import (NETT) Other use (OTHU) Production (PROD) Price in US dollar per ton (XPRP USD 2000) Yield (YILD)	1000 ha 1000 t Per ton fm t/ha
Cropland (CRPLND)	Land area (LAND)	1000 ha

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Table A3: Mapping between GLOBIOM regions and countries

GLOBIOM region	Country
Argentina	Argentina
Australia	Australia
Brazil	Brazil
Canada	Canada
China	China
Congo Basin	The Gabon Equatorial Guinea Republic of the Congo Democratic Republic of the Congo Cameroon Central African Republic
Eastern Africa	Tanzania Kenya Ethiopia Uganda Burundi Rwanda
EU Baltic	Latvia Lithuania Estonia
EU Central-East	Poland CzechRep Slovakia Hungary Slovenia Croatia Romania Bulgaria

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

EU Mid-West	France Belgium Netherlands Luxembourg Germany Austria
EU North	UK Denmark Sweden Finland Ireland
EU South	Spain Portugal Italy Greece Cyprus Malta
Former USSR	Belarus Kazakhstan Azerbaijan Turkmenistan Uzbekistan Moldova Georgia Armenia Tajikistan Kyrgyzstan
India	India
Indonesia	Indonesia
Japan	Japan
Malaysia	Malaysia
Mexico	Mexico

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Middle East	Iraq Yemen Saudi Arabia Kuwait Iran Qatar United Arab Emirates Oman Israel Lebanon Jordan Syria Bahrain
New Zealand	New Zealand
Northern Africa	West Sahara Morocco Algeria Tunisia Libya Egypt
Pacific Islands	Samoa Papua New Guinea Solomon Islands New Caledonia Vanuatu Fiji-I ands

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Rest of Central America	El Salvador Costa Rica Panama Guatemala Belize Honduras Nicaragua Cuba Bahamas Jamaica Haiti Dominican Republic Guadeloupe Trinidad and Tobago
Rest of Central Europe (RCEU)	Bosnia and Herzegovina Serbia Montenegro Albania Macedonia
Rest of Western Europe (ROWE)	Iceland Norway Switzerland Greenland

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Rest of South America	Ecuador Peru Chile Bolivia Guyana Suriname Paraguay Uruguay French Guiana Colombia Venezuela Falkland Islands
Rest of South Asia	Pakistan Sri Lanka Nepal Bangladesh Bhutan
Rest of South East Asia	Thailand Philippines Myanmar Brunei Darussalam Timor-Leste Singapore Vietnam Laos Cambodia DPR Korea Mongolia
Russia	Russian Federation
South Africa	South Africa

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Rest of Southern Africa	Angola
	Namibia
	Zimbabwe
	Mozambique
	Madagascar
	Swaziland
	Malawi
	Mauritius
	Reunion
	Comoros
	Zambia
	Botswana
	Lesotho
South Korea	South Korea
Turkey	Turkey
Ukraine	Ukraine
USA Region	USA
	Puerto Rico

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.

Western Africa	Mauritania Senegal Mali CotedIvoire BurkinaFaso Ghana Niger Benin Nigeria Chad Sudan Somalia Djibouti CapeVerde Gambia GuineaBissau Guinea SierraLeone Liberia Togo Eritrea

i

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 817566.