MODELLING INDIVIDUAL DECISIONS TO SUPPORT THE EUROPEAN POLICIES RELATED TO AGRICULTURE

Deliverable D4.2: Report on modelling structural change and farm interaction on land markets and interfaces with the MIND STEP model toolbox (M36+4)

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ACRONYMS

AWU	Annual Working Unit
CAP	Common Agricultural Policy
CAPRI	Common Agricultural Policy Regionalised Impact analysis model
CET	Constant Elasticity Transformation
CGE	Computable General Equilibrium
CLC	Corine Land Cover
EU	European Union
FADN	Farm Accountancy Data Network
FDZ	Forschungsdatenzentrum (see RDC)
FSS	Farm Structure Survey
FSU	Farm Spatial Unit
HSU	Homogenous Spatial Unit
IDM	Individual Decision Making
IFM-CAP	Individual Farm Model for CAP Analysis
JRC	Joint Research Centre
KTBL	Kuratorium für Technik und Bauwesen in der Landwirtschaft
LFA	Less Favoured Areas
LU	Livestock Units
MINDSTEP	Project acronym
NUTS	Nomenclature of Territorial Units
PE	Partial Equilibrium
RDC	Research Data Centre
SGM	Standard Gross Margin
SO	Standard Output
UAA	Utilized Agricultural Area

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EXECUTIVE SUMMARY

In Section 2, an analysis to farm exit in the German agriculture was undertake. The German agricultural sector has experienced significant changes in recent decades, including a decrease in the number of farms and an increase in farm size. Factors contributing to these changes include lower profitability of smaller farms, farmers age, lack of successors, and socio-economic drivers. A logit model was used to analyze the decision of farmers to exit the farming sector between 2010 and 2020 using data from the German Farm Structure Survey. The data set was augmented by systematic incorporation of spatial and farm interaction effects (Herfindahl-Hirschman-Index of agricultural land used – a proxy for the distribution agricultural land), specific regional characteristics (economic indicators at NUTS 3 regional level) as well as detailed georeferenced biophysical data (incorporation of soil-climate regions) capturing local production conditions. Results showed that farm-level variables, such as the farmer's age, agricultural land use, profitability, and farm type, had a greater impact on the exit decision compared to neighborhood and regional variables. The most predictive variable was the farmer's age. The results indicate that various factors contribute to the exit of farms from the agricultural sector and should be interpreted with caution, as they are observational and cannot establish causality. The use of the results is foreseen in sub-task 5.2.3.

Section 3 presents farm exit estimations in the broader framework of structural change analysis in Norway. This section examines the factors driving changes in the structure of Norwegian agriculture, using farm census data and a Multiplicative Competitive Interaction (MCI) model. The MCI framework was extended to account for absolute farm numbers and exit decisions, and to consider the effect of neighboring farms on farm structure. The analysis covers the period 1996 to 2015 and considers four production specializations and seven size classes, resulting in 15 farm groups, including an exit group and a residual group. Results show that the relative importance of variables is similar to previous findings, but farm manager age and population density were not selected as significant variables. The extension to include the neighboring farms improved the explanatory power of the model, and simulations indicate that larger farm groups are expected to increase their share in 2025, while a declining farm density negatively impacts most farm groups. Limitations include the absence of farm income data and the effects of regional heterogeneity and other missing variables. The model's extension towards absolute farm numbers and exit groups can now be used for policy impact analysis using mathematical programming models.

In Section 4, the Agrispace model is applied to farm structure survey data in Norway. The EU (CAP) and Norway are using agricultural policies with different payment rates for production activities and farms at the regional level and for different farm sizes, which creates challenges for agricultural sector models that assume uniform payment rates. This research investigates the impact of these farm-specific payment rates on supply and farm structure using the Agrispace model in Norway. Norway was selected as a case study due to its diverse agricultural policies with payment rates that vary by region and farm size. The simulation results indicate that the level of per unit payments for agricultural products within a region, referred to as payment farm-specificity, plays a significant role in shaping the supply of these products. This is because payment farm-specificity affects both the number of farms and the level of activity (i.e., number of animals and farmed area) within a region. The impact of changing payment farm-specificity varies among payment recipients and more research is required to understand the relationship between recipient characteristics and impact. The findings suggest that incorporating payment farm-specificity into agricultural sector models, such as the CAPRI model, which do not currently account for farm structure and structural change, will be important. This work will be carried out in the MIND-STEP subtask 5.2.3.

Section 5 presents the improvement of an existing land market model prototype of IFM-CAP. In land market research, various models are used to simulate land supply, allocation, and markets. These

models range from abstract Computable General Equilibrium (CGE) models to more detailed Agent Based Models. CGE models use Constant-Elasticity of Transformation functions and some include land supply and transformation functions. Partial Equilibrium (PE) models use a CGE structure and CET functions. Non-economic land cover models use actual land cover maps and Spatial Land Cover Change models use transition probabilities. Agent Based Models combine spatial competition and land cover change algorithms. The IFM-CAP land market model incorporates elements of general and partial equilibrium models and is spatially scalable, allowing for more detailed farm location information to be used. The current land market model does not yet account for a new delineation. The implementation using the farm spatial unit (FSU) delineation for at least ten selected regions in Germany compatible with the farm exit estimations from section one will be conducted in WP Task 5.2.3. „Subtask 5.2.3 Structural change representation in current models“. The target is to build cluster of FSU with similar homogenous factors for land and to account for the pressure on the land market from intensive animal production. The delineation will be based on a cluster of the presented for parameters on income per AWU in Euro, milk yield in tones per cow, stocking density in LU/ha and wheat yield in quintals/per in Germany. The cluster is then the new cell to run the IFM-CAP farm inside the cells which are located in the cluster together with the land market model.

1. BACKGROUND

Drivers for structural change are manifold and include technology and productivity growth, farm-household and path dependency, input and output prices and macroeconomic conditions. A comprehensive theoretical framework accounting for the known drivers of structural adjustment in agriculture does not exist. However, in the field of econometric methods, there are applications of certain aspects of farm structural change, e.g., farm exit and growth, or applications that analyse structural change with a Markov transition probability model.

Recent progress in the availability of detailed individual farm data has broadened the potential for policy impact analysis on the strategic behaviour of farmers. This Task conducts **farm exit estimations for Germany** (Section 2) and **Norway for which single-farm data** at census level are available (Section 3 and 4). The Norwegian case is considered because the available data include the geolocation of the farm address. This provides an interesting case to explore possibilities that can be transferred to EU members once such data is available there as well (in Germany farm location are currently available at a 5x5 km grid level). These new methods capture well non-linear relationships (including thresholds) and complex dynamics over time.

Further innovations compared to the literature on farm exit estimations are the systematic incorporation of spatial, farm interaction effects, specific regional characteristics as well as detailed georeferenced biophysical data (climate and soil, see WP2) capturing local production conditions. The new delineation approach is presented in Section 5.

2. FARM EXIT ESTIMATIONS WITH GERMAN FARM STRUCTURE SURVEY / CENSUS DATA

2.1. Introduction and related literature

The agricultural sector of the European Union (EU) has experienced significant changes in recent decades. One of the most evident developments is the decline in the number of farms, an increase in farm size, and a change in production specialization. For instance, the number of farms in the EU fell by about 37% (an average of 2.1% per year) between 2005 and 2020, which corresponds to a decrease of about 5.3 million farms. Average farm size in total utilized agricultural area grew by 60% (3.1% per year) during the same period (Eurostat, 2022). As farm size increases, farms tend to specialize in cereal cropping and grazing livestock, moving away from permanent crops, granivores, and mixed farming (European Commission, 2013b). Understanding the drivers of these changes can help predict future developments and inform policy decisions, as one of the key goals of the Common Agricultural Policy (CAP) is to promote rural development (European Commission, 2013a) and prevent the abandonment of agricultural production in certain areas (European Commission, 2003).

The German agricultural sector showed the same pattern regarding declining number of farms and increasing farm size. In particular, in Germany the number of farms declined by 12% from about 299,000 in 2010 to roughly 236,500 in 2020. In the same time, the average size in total utilized agricultural area of a farm increased by about 13% from 56 to 63 hectares (Statistisches Bundesamt, 2021b).

There are several factors that contributed to structural change in agriculture that use either macro or micro data. Macro-level studies use information on farm structure at the regional or national level to analyze its dynamics and drivers over time (Goetz and Debertin, 2001; Breustedt and Glauben, 2007; Neuenfeldt *et al.*, 2019, 2021; Ramsey, Ghosh and Sonoda, 2019). Micro-level studies, on the other hand, use data on individual farms to explain structural changes, often using farm size growth models (Sumner and Leiby, 1987; Weiss, 1999; Bremmer *et al.*, 2002) or exit models (Mishra, Raggi and Viaggi, 2010; Landi *et al.*, 2016; Saint-Cyr *et al.*, 2019; Paroissien, Latruffe and Piet, 2021; Thiermann, Breustedt and Rosenau, 2021; Zorn and Zimmert, 2022). For example, the impact of various socio-economic drivers on changes in farm specialization were analyzed using farm-level data (Neuenfeldt *et al.*, 2014; Röder *et al.*, 2014). Some other studies have also combined micro and macro data to better identify drivers and predict structural change (Storm et al., 2015a, 2016).

Several determinants to explain structural change have been found in the literature. Most prominently technology (economies of scale, productivity growth, farm household and path dependency), input and output prices and macroeconomic conditions (e.g. unemployment rate), regional characteristics, agricultural policies, off-farm opportunities and competitive pressures from non-agricultural sectors for resources (e.g. (Cochrane, 1958; Boehlje, 1992; Harrington, Reinsel and Harrington, 1995; Balmann *et al.*, 2006; Alvarez-Cuadrado and Poschke, 2011; Zimmermann and Heckelei, 2012; Arfa *et al.*, 2015; Neuenfeldt *et al.*, 2019, 2021; Neuss, 2019)). Further important determinants of agricultural specialization across regions are natural and climate conditions. For example, growing degree days or altitude are related to land-use changes (Fezzi and Bateman, 2011) or elevation and steepness (Müller and Zeller, 2002). Mandryk et al. (Mandryk, Reidsma and van Ittersum, 2012) present literature that indicated climate change as a cause of structural changes. Climate change induces changes in climatic conditions or climate variability that affect crop productivity, yields, farmer income and land use (Olesen and Bindi, 2002; Bradshaw, Dolan and Smit, 2004; Berry *et al.*, 2006; Reidsma *et al.*, 2008; Bindi and Olesen, 2011; Agovino *et al.*, 2019).

Incorporating spatial patterns or neighboring effects has shown to be important in recent years. Storm et al. (Storm, Mittenzwei and Heckelei, 2015) showed how direct payments and of farm size affect structural change in Norway, and emphasized the importance of farm interaction for strategic farm decisions due to the competition over land causing regional specific patterns and spatial dependencies. Recent work using a spatial framework has also highlighted the spill-over effects in farm specialization activities and the role of cooperation and competition between farms in influencing the adoption of diversification activities (Vroege *et al.*, 2020) in Europe. They also draw the conclusion of dependence of spatially proximate farms to each other and that different degrees of proximity matter. Similarly, Saint-Cyr et al. emphasized that with respect to neighboring effects and spatial patterns there is substantial variation between farm types in Brittany (Saint-Cyr *et al.*, 2019). Heterogenous rather than homogenous effects of own and neighboring characteristics like farm size, age and profit have been shown to be of relevance for early exit of younger farmers in France (Paroissien, Latruffe and Piet, 2021). Neighboring effects have often been analyzed based on farm characteristics of farmer decisions (Case, 1992; Holloway, Shankar and Rahman, 2002; Läpple *et al.*, 2017). Adoption decisions as social norms and attitudes (Läpple and Kelley, 2015) and access to information – direct and through the neighborhood – and social conformity show the importance of farmers' interactions (Wollni and Andersson, 2014). Transactions between farm households also rely on their local economies (Roberts, Majewski and Sulewski, 2013). While it is difficult to quantify farm activity diversification related to off-farm or non-agricultural activities using available statistics, some research on this topic has also incorporated spatial patterns and neighboring effects. For example, a case study in Eastern Germany found that diversification through touristic development is more common in rural areas, and that the likelihood of farms continuing operations increases with closer proximity to urban consumer markets (Lange *et al.*, 2013). Such income diversification strategies seem to be a future path for farms as a survival strategy (Weltin *et al.*, 2017). Focusing on efficiency, Schneider et al. (Schneider, Skevas and Lansink, 2021) and Skevas and Lansink (Skevas and Lansink, 2020) also indicate the existence of neighboring effects on arable and dairy farms in Dutch agriculture.

Studies focused on relevant determinants for exit decisions have shown that smaller farms with respect to area cultivated or herd sizes (Hoppe and Korb, 2006; Breustedt and Glauben, 2007; Landi *et al.*, 2016; Paroissien, Latruffe and Piet, 2021; Zorn and Zimmert, 2022), lower profitability (Bragg and Dalton, 2004; Piet *et al.*, 2012; Dong *et al.*, 2016; Landi *et al.*, 2016; Ramsey, Ghosh and Sonoda, 2019; Saint-Cyr *et al.*, 2019; Paroissien, Latruffe and Piet, 2021; Zorn and Zimmert, 2022) and older farmers or farms with no successor are associated with a higher likelihood of exit (Weiss, 1999; Gale, 2003; Pietola, Väre and Lansink, 2003; Hoppe and Korb, 2006; Mishra, El-Osta and Shaik, 2010; Piet *et al.*, 2012; Dong *et al.*, 2016; Landi *et al.*, 2016; Ramsey, Ghosh and Sonoda, 2019; Saint-Cyr *et al.*, 2019; Corsi, Frontuto and Novelli, 2021; Zorn and Zimmert, 2022), as are spatial effects. Contrary to most studies, higher exit rates for smaller farms are not observed for dairy and sow farms in Germany measured in terms of herd size (Thiermann, Breustedt and Rosenau, 2021). In addition, a high population density can either increase (Goetz and Debertin, 2001; Landi *et al.*, 2016) or decrease (Foltz, 2004; Glauben, Tietje and Weiss, 2006) the exit rates of farmers. Decoupling of subsidies from production seems to intensify the exit of farms with livestock production and speeding up exit of farms already in in motion of leaving the sector (Kazukauskas *et al.*, 2013). Recent research also emphasizes the fact that exit rates seem to differ for farm size or farm holder's age with respect to different farm types (Saint-Cyr *et al.*, 2019). It is also argued that farms' profitability is increased by farm support and this reduces farm exit (Goetz and Debertin, 2001; Breustedt and Glauben, 2007). Higher unemployment rates (Harrington, Reinsel and Harrington, 1995; Weiss, 1999; Foltz, 2004; Ramsey, Ghosh and Sonoda, 2019; Saint-Cyr *et al.*, 2019; Zorn and Zimmert, 2022) and lower lending rates (Foltz, 2004) or lower access to loans (Kitenge, 2022) are also related to lower exit rates. Off-farm employment opportunities are often proxied by part-time farming and showed mixed results regarding the exit rates, as it can be a stabilizing factor (in particular for small farms) or an indicator for smoother change of occupation (Hallam, 1991; Goddard *et al.*, 1993; Harrington, Reinsel and Harrington, 1995; Gebremedhin and Christy, 1996; Weiss, 1997; Goetz and Debertin, 2001; Glauben, Tietje and Weiss, 2006), like by off-farm income (Boehlje, 1992; Goddard *et al.*, 1993; Glauben, Tietje and Weiss, 2006). To complement to the list of determinants, Swiss dairy farms showed a higher probability of exiting with higher number of employees, the degree of specialization, for specific regions (regarding benefits from protected designation of origin and difficulty of production) and off-farm opportunity costs of labor. Thereby, the probability of leaving the sector decrease with higher number of family workers, quality, animal welfare programs (organic, BTS, RAUS) as well as direct payments (Zorn and Zimmert, 2022).

A further strand of studies that is related to exit decisions is the process of succession or generational renewal and refers to the fact that the farm is not leaving the sector but instead continued by a family or outside successor. Succession or renewal is not the focus of the analysis in this paper and the reader is referred to some of the related literature (Kimhi, 1994; Kimhi and Lopez, 1999; Kimhi and Nachlieli, 2001; Glauben *et al.*, 2009; Mishra, El-Osta and Shaik, 2010; Duesberg, Bogue and Renwick, 2017; Cavicchioli, Bertoni and Pretolani, 2018; Nordin and Lovén, 2020; Coopmans *et al.*, 2021)

2.2. Data and empirical implementation

2.2.1. Estimation model and empirical implementation

We implement a logit model to represent the binary decision of the farmer to exit the sector. This model can be seen as a latent utility model in which the utility of staying or exiting the farm business is represented by the latent variable. The utility of the farmer may be altered by own characteristics, by that of neighboring farms or regional variables. Let $exit_i^*$ be the latent variable of interest which determines the farmer's decision to exit the business from 2010 to 2020. Therefore, the exit variable is defined:

$$\begin{aligned} exit_i &= 1 \;\; if \; exit_i^* > 0, \\ exit_i &= 0 \;\; if \; exit_i^* \leq 0, \end{aligned} \tag{1}$$

Where $exit_i$ is the observed outcome of farm i and $exit_i = 1$ means the farm is exiting the sector whereas $exit_i = 0$ it stays in business.

In general, the conditional probability of exit is denoted by:

$$P(exit_i = 1|x_i, \beta) = \sigma(x_i'\beta) = \frac{\exp\,(x_i'\beta)}{1 + \exp\,(x_i'\beta)} \tag{2}$$

Where σ is the standard logistic function.

This can be written as the logarithm of the odds (log odds):

$$\log\left(\frac{P(exit_i = 1|x_i, \beta)}{1 - P(exit_i = 1|x_i, \beta)}\right) = x_i'\beta + \epsilon_i \tag{3}$$

Where β is estimated in a linear regression on log odds of the probability of exiting the business over staying in business and ϵ_i is the error term.

In this analysis we observe the exit or stay in business decision of the farmer between the year 2010 and 2020. This means, that our analysis is a cross-sectional regression and the estimated coefficients must be interpreted as between farms and not within. Even though there are more years available in the German FSS, some of the variables that are of particular interest for the analysis, are only surveyed comprehensively for all the farms in 2010 and 2020. [1] This is especially the case for the variable age of the farm holder. Additionally, consistent spatial information through a raster identifier is given from 2010 onwards and hence, limits the analysis and use of spatial information to the years taken here.

In the German FSS each farm gets a unique identifier. In what follows, we suppose that if this identifier is not observed in 2020, the farmer exits the sector between 2010 and 2020 and the variable “exit” equals one. Contrary, if the identifier is observed in 2020, the farmer stays in business. However, there might be other reasons why the identifier is not observed in 2020. First, the farm is merged with one or more other farms and hence, only one of these farms keeps the identifier. Second, it is also possible, that a farm is dissolved after 2010, but is re-founded before 2020. This might be no real exit from the sector, but we cannot control for that and in our case, we define those farms as exiting. Third, a farm might be so small that it is near the lower thresholds of being covered in the survey. Hence, it might be the case that a farm observed in 2010 falls below the minimum requirements in the years until 2020 and is therefore not surveyed, even though it is still in business.

To capture all relevant and available characteristics or other variables to correlate with the decision to exit the sector, we set our focus on data in or around 2010. Most of all variables at farm level are captured in 2010. Some regional variables or other external information which are used to derive explanatory variables might be an average of values around 2010. We will provide more information on that in a later chapter.

As our point of start is 2010, we do not explore the structure of farms that entered the sector after 2010 and before 2020.

In this first analysis, we consider neighboring effects. Here, only one variable is used to capture neighboring effects. The distribution of total agricultural land used across neighboring farms (Herfindahl-Hirschman-Index) in the same raster. It is foreseen, to extend the use of spatial variables.

A raster is an area of generally 5 times 5 kilometers and is provided for the German FSS beginning in 2010. Figure 1 describes this spatial structure. The point in the middle is the hypothesized farmstead.[2] All farms belonging to a raster are located at the same point in the midpoint of the raster. The square around this midpoint is the raster. The nine green squares locate the neighboring farms based on the Queen contiguity. The blue radius describes an area of about 12 kilometers and the red squares describes neighboring farms within the green squares and additionally Queen contiguity around the green squares. For example, in the German federal state of Brandenburg between 2006 and 2018, 90% of the farms have their newly acquired farm plots within 12 kilometers and 65% within 5 kilometers (Plogmann *et al.*, 2022). In Bavaria, approximately 90% of the farms have their plots within 5 kilometers (Machl *et al.*, 2018). Both examples can be considered as cases from the lower and upper part of the distribution of average distances from the farmstead to the cultivated fields. The average farm size in terms of total agricultural land in 2020 of Brandenburg (242 hectares) is almost 6 times larger than that of Bavaria (37 hectares) (Statistisches Bundesamt, 2021a). We think it is very likely that larger farms have also larger distances between their farmstead and their fields. Therefore, we

[1] Throughout the paper we call the German agricultural data FSS, which stands for farm structure survey. The years 2003, 2007 and 2016 are full population surveys, but some variables are surveyed only for sample farms. They are called “farm structure surveys” (“Agrarstrukturerhebung”). 1999, like 2010 and 2020, is an “agricultural census”, generally capturing more variables for all farms.

[2] In the German FSS, there is no information regarding plots or even their location. Each information is bound to the farmstead. For our analysis, we can only make use of the farm location by using the midpoint of the municipality or raster. Therefore, each farm of the same area (municipality or raster) has the same location.

suggest that farms within the 5x5 kilometers raster as well as farms in the adjoining raster squares can be considered as relevant in terms of influences from neighboring farms.

This means, we expect that most effects of what neighbors can have should be measurable within the raster or in the adjoining raster squares (green area).

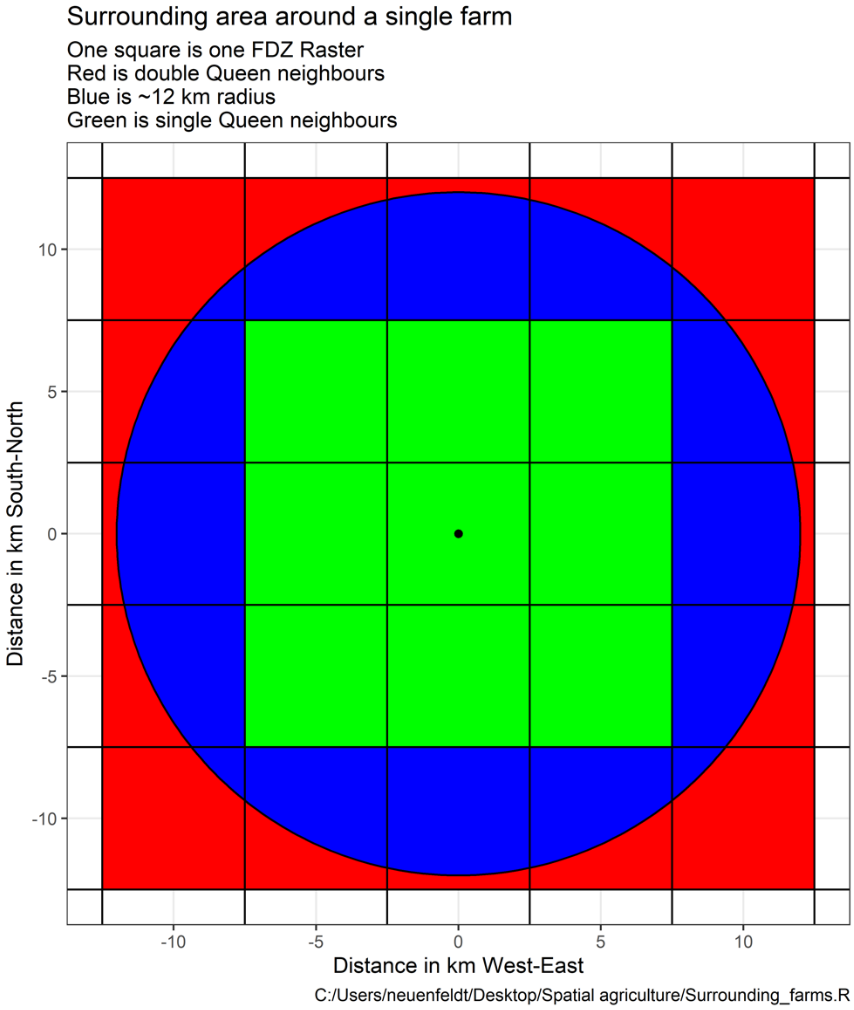

Figure 1. Scheme of neighboring areas around the hypothesized farmstead of a farm

2.2.2. Data descriptive statistics

In this chapter we present the data used in the estimation of the farmer's decision to exit the business. In Table 1 the descriptive statistics of numeric variables differentiated for farms that stay in business and exiting farms are presented. Additionally, the mean differences between these two groups is provided . We differentiate three groups of continues variables, one is at farm level, the other two at regional level, whereas one is defined as a neighboring variable of the raster and the other is at NUTS 3 level, which is usually at a larger scale than that of a raster. The age of the farmer (and the square of it), the average growth rate of agricultural land used and livestock units in the years before 2010, land rental payments per hectare for different land categories, livestock units, ratio of rented land and total agricultural land (and the square of it) are directly derived from the survey. The standard gross margins dedicated to general cropping activity, horticulture, permanent crops, grazing livestock and forage, as well as granivores are derived from the corresponding activity levels from the survey and the average standard gross margin values from a KTBL database.[3] The remaining variables are the Herfindahl-Hirschman-Index for total agricultural land in the raster, which depicts how the agricultural land is distributed between neighboring farms. The variables at NUTS 3 regions are compensation of payments and disposable income per head, population density and the unemployment rate.

Most notable differences between staying and leaving farms are: Exiting farms tend to have older farm holders, have degrowth in terms of land and livestock use, pay less for rented land, have smaller farms in terms of land and livestock use and have a much lower gap between their total standard gross margin and their land rental payments. They are also facing more uneven distributed land around them and have a higher population density in their NUTS 3 region.

Table 1. Descriptive statistics of numeric variables differentiated for farms that stay in business and exiting farms (2008-2018 averages)[4]

Explanatory variable	Farms that stay in business		Farms that exit business		Mean Difference – exit minus stay	P-value
	Mean	Standard deviation	Mean	Standard deviation		
Farm level data						
Age of the farm holder	48.43	9.52	52.76	11.25	4.32	0.00
Age of the farm holder squared	2436.55	932.70	2909.80	1184.76	473.26	0.00
Average growth rate of agricultural land use	2.58	21.13	-0.87	11.68	-3.46	0.00
Average growth rate of livestock units	0.75	22.75	-2.09	22.17	-2.83	0.00
Land rental payments for arable land per hectare	127.01	206.07	77.18	182.14	-49.83	0.00
Land rental payments for grass land per hectare	69.04	104.10	41.11	88.16	-27.94	0.00
Land rental payments for other land per hectare	63.30	543.88	66.38	937.00	3.08	0.20
Land rental payments for total agricultural land per hectare	193.76	544.18	163.45	1012.15	-30.31	0.00
Livestock units	50.91	116.96	18.80	89.90	-32.11	0.00
Ratio of rented land on total agricultural land	37.95	31.96	26.79	33.63	-11.16	0.00

[3] We took the average between 2008 and 2018. The standard gross margins are made available up to NUTS 2 regions.

[4] The summary statistics of variables at NUTS 3 level are calculated from the distribution of number of farms in farm structure survey.

Standard gross margin dedicated to general cropping per activity	575.67	589.49	463.81	603.52	-111.86	0.00
Standard gross margin dedicated to granivores per activity	135.72	292.47	124.65	290.05	-11.07	0.00
Standard gross margin dedicated to grazing livestock and forage per activity	421.55	482.91	289.17	598.62	-132.38	0.00
Standard gross margin dedicated to horticulture per activity	3472.70	26399.39	7985.24	44183.31	4512.55	0.00
Standard gross margin dedicated to permanent crops per activity	1273.72	3745.33	1793.07	4449.64	519.35	0.00
Standard gross margin minus land rental payments (€)	97399.67	238189.07	42268.17	129555.00	-55131.51	0.05
Total agricultural land used (hectare)	65.34	168.00	24.61	55.88	-40.74	0.00
Total agricultural land used squared (hectare)	32495.21	431574.97	3728.28	50972.30	-28766.93	0.31
Neighboring variable						
Herfindahl-Hirschman-Index for total agricultural land in the raster	0.04	0.05	0.04	0.06	0.01	0.00
Regional variable at Nuts 3						
Compensation of employees (1,000 €) - Manufacturing sector	31.58	3.29	31.58	3.54	-0.01	0.37
Compensation of employees (1,000 €) - Service sector	44.16	6.97	44.18	7.22	0.02	0.27
Disposable income of private households (€)	21082.35	1959.42	20971.82	1880.93	-110.53	0.00
Population density per square kilometer	214.88	273.82	247.80	374.02	32.92	0.00
Unemployment rate	4.61	2.06	4.78	2.08	0.17	0.00

Source: Own compilation. See data sources section.

In Table 2 the distribution of farms staying in or exiting business across soil-climate-regions are depicted. An explanation of the soil-climate regions can be found in Roßberg et al. (Roßberg *et al.*, 2007). Most notably, the distribution of exiting farms spans from 12.7% to 35.1% but is on average relative evenly distributed between the regions. The lowest exit rate is found in the Alps region (199: lower temperatures, higher rainfall, high altitude, and steepness), the largest in the north of Lower-Saxony (151: low soils quality).

Table 2. Distribution of farms staying in or exiting business across soil-climate-regions

Soil-climate-region	Farms that stay in business	Farms that exit business	Soil-climate-region	Farms that stay in business	Farms that exit business
101	1,795 (73.3%)	655 (26.7%)	134	6,059 (77.5%)	1,759 (22.5%)
102	2,264 (74.7%)	766 (25.3%)	141	2,312 (76.4%)	713 (23.6%)
104	3,959 (75.6%)	1,280 (24.4%)	142	8,168 (75.4%)	2,669 (24.6%)
105	222 (67.1%)	109 (32.9%)	143	3,694 (77.2%)	1,089 (22.8%)
106	148 (78.7%)	40 (21.3%)	145	3,889 (77.1%)	1,156 (22.9%)
107	2,167 (77.8%)	617 (22.2%)	146	6,981 (75.3%)	2,288 (24.7%)
108	3,442 (78.6%)	938 (21.4%)	147	5,227 (73.2%)	1,916 (26.8%)
109	1,441 (75.1%)	479 (24.9%)	148	10,364 (76.4%)	3,195 (23.6%)
111	4,538 (77.7%)	1,305 (22.3%)	150	5,195 (72.5%)	1,966 (27.5%)
112	10,186 (80.0%)	2,550 (20.0%)	151	3,784 (64.9%)	2,047 (35.1%)
113	12,436 (74.8%)	4,195 (25.2%)	152	3,652 (76.2%)	1,142 (23.8%)
114	15,606 (78.7%)	4,223 (21.3%)	153	3,722 (72.8%)	1,392 (27.2%)
115	17,599 (80.6%)	4,223 (19.4%)	154	2,131 (73.9%)	752 (26.1%)
116	9,582 (80.4%)	2,343 (19.6%)	155	1,218 (73.2%)	446 (26.8%)
117	14,990 (82.9%)	3,086 (17.1%)	156	1,533 (74.1%)	536 (25.9%)

120	2,091 (76.3%)	648 (23.7%)	157	757 (73.1%)	278 (26.9%)
121	16,310 (71.0%)	6,676 (29.0%)	158	937 (70.2%)	397 (29.8%)
122	4,331 (81.5%)	984 (18.5%)	191	818 (73.8%)	290 (26.2%)
123	4,797 (76.0%)	1,517 (24.0%)	192	252 (79.7%)	64 (20.3%)
127	3,870 (72.0%)	1,506 (28.0%)	193	852 (78.7%)	231 (21.3%)
128	2,913 (73.2%)	1,065 (26.8%)	194	110 (82.1%)	24 (17.9%)
129	2,183 (74.7%)	741 (25.3%)	195	356 (75.9%)	113 (24.1%)
130	1,775 (78.2%)	496 (21.8%)	196	1,382 (81.6%)	311 (18.4%)
132	3,183 (74.8%)	1,073 (25.2%)	198	5,935 (81.8%)	1,321 (18.2%)
133	4,968 (74.6%)	1,689 (25.4%)	199	3,240 (87.3%)	471 (12.7%)

Source: Own compilation.

Table 3 shows distribution of farms staying in or exiting business across NUTS 2 regions. Most notably, the distribution of exiting farms ranges from 16.3% in Oberbayern (091: south of Bavaria) to 30.8% in Rheinhessen-Pfalz (073: south-west of Germany). On average, the exit rate is relatively evenly distributed between the regions.

Table 3. Distribution of farms staying in or exiting business across NUTS 2 regions

Nuts 2 Region	Farms that stay in business	Farms that exit business	Nuts 2 Region	Farms that stay in business	Farms that exit business
010	10,365 (69.6%)	4,534 (30.4%)	083	10,475 (77.0%)	3,136 (23.0%)
031	3,579 (76.4%)	1,103 (23.6%)	084	9,322 (80.5%)	2,252 (19.5%)
032	5,357 (74.9%)	1,792 (25.1%)	091	21,142 (83.7%)	4,104 (16.3%)
033	8,761 (75.6%)	2,822 (24.4%)	092	13,208 (79.2%)	3,466 (20.8%)
034	13,676 (74.0%)	4,801 (26.0%)	093	9,909 (80.7%)	2,373 (19.3%)

051	4,037 (74.9%)	1,351 (25.1%)	094	6,657 (76.5%)	2,045 (23.5%)
053	4,374 (75.7%)	1,401 (24.3%)	095	7,663 (77.1%)	2,275 (22.9%)
055	8,242 (77.3%)	2,420 (22.7%)	096	6,885 (74.9%)	2,310 (25.1%)
057	5,867 (75.3%)	1,921 (24.7%)	097	12,667 (80.0%)	3,169 (20.0%)
059	4,828 (78.7%)	1,309 (21.3%)	100	930 (70.5%)	389 (29.5%)
064	4,378 (75.7%)	1,402 (24.3%)	120	4,267 (75.8%)	1,365 (24.2%)
065	3,343 (75.0%)	1,113 (25.0%)	130	3,356 (71.0%)	1,369 (29.0%)
066	5,684 (75.1%)	1,885 (24.9%)	145	2,129 (78.3%)	591 (21.7%)
071	4,689 (73.2%)	1,717 (26.8%)	146	1,872 (78.5%)	513 (21.5%)
072	3,714 (71.3%)	1,494 (28.7%)	147	920 (77.8%)	262 (22.2%)
073	6,196 (69.2%)	2,754 (30.8%)	150	3,281 (77.8%)	938 (22.2%)
081	10,965 (76.2%)	3,432 (23.8%)	160	2,828 (77.3%)	830 (22.7%)
082	3,798 (77.0%)	1,132 (23.0%)			

Source: Own compilation. Based on AFiD-panel farm structure data 2010.

Table 4 shows the distribution of farms staying in or exiting business across socioeconomic / legal farm type, farming systems and type of farming. For socioeconomic / legal farm type, full and part time farming is only surveyed for sole proprietorship farms, the remaining farms are corporate and partnership farms. Part time farms (30%) tend to exit the business more often than full time and corporate/partnership farms (18% vs. 15.6%). Organic farms exit less often than conventional farms. Regarding type of farming, horticulture and permanent crops farm (34% to 42%) exit the sector more often than the remaining farm types (14% to 30%).

Table 4. Distribution of farms staying in or exiting business across socioeconomic farm type, farming systems and type of farming.

Categories	Levels of categories	Farms that stay in business	Farms that exit business
Socioeconomic / legal farm type	Full time - Sole proprietorship	111,045 (82.0%)	24,367 (18.0%)

	Part time - Sole proprietorship	96,296 (70.0%)	41,322 (30.0%)
	Corporate and partnership farms	22,023 (84.4%)	4,081 (15.6%)
Farming system	Organic	13,960 (84.4%)	2,572 (15.6%)
	Conventional	215,404 (76.2%)	67,198 (23.8%)
Type of farming	Specialist cereals, oilseeds and protein crops	25,294 (71.0%)	10,307 (29.0%)
	General field cropping	26,822 (71.1%)	10,881 (28.9%)
	Specialist horticulture	4,746 (57.8%)	3,471 (42.2%)
	Specialist vineyards	10,228 (65.7%)	5,346 (34.3%)
	Other specialist permanent crops	4,857 (62.1%)	2,960 (37.9%)
	Specialist dairying	57,010 (86.1%)	9,170 (13.9%)
	Specialist cattle - rearing and fattening	17,306 (75.7%)	5,569 (24.3%)
	Cattle - dairying, rearing and fattening combined	8,287 (83.7%)	1,610 (16.3%)
	Sheep, goats and other grazing livestock	22,602 (70.5%)	9,453 (29.5%)
	Specialist pigs	13,379 (81.6%)	3,010 (18.4%)
	Specialist poultry and various granivores combined	2,391 (80.9%)	565 (19.1%)
	Mixed cropping	3,106 (81.3%)	715 (18.7%)
	Mixed livestock holdings	9,015 (84.8%)	1,614 (15.2%)
	Field crops - grazing livestock combined	14,636 (83.1%)	2,975 (16.9%)
	Various crops and livestock combined	9,685 (82.0%)	2,124 (18.0%)

Source: Own compilation. Based on AFiD-panel farm structure data 2010.

2.2.1. Data sources

The farm structure survey data used in the analysis:

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/41121.2007.00.01.1.1.0; AFiD-Panel farm structure 1999/2001/2003/2005/2007, On-Site-Access.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/41121.2020.00.01.1.1.0; AFiD-Panel farm structure 2010/2013/2016/2020, On-Site-Access.

Standard gross margins are derived from an API which can be found online at: https://www.ktbl.de/webanwendungen/standarddeckungsbeitraege.

Unemployment rate, table AI002-1 at: https://statistik.arbeitsagentur.de/SiteGlobals/Forms/Suche/Einzelheftsuche_Formular.html?nn=1610104&topic_f=gem-jz.

Compensation of employees, at: https://www.statistikportal.de/de/vgrdl/ergebnisse-kreisebene/einkommen-kreise - vgrdl_r2b2_bs2020.xlsx.

Disposable income, at: https://www.statistikportal.de/de/vgrdl/ergebnisse-kreisebene/einkommen-kreise - vgrdl_r2b3_bs2020.xlsx.

2.3. Results

Table 5 presents the estimated coefficients of the model and also provides a Wald confidence interval and the metric of variable importance.[5]

Table 5. Estimated coefficients of the model

Category	Variable	Estimate	Wald confidence interval	Variable importance
	Intercept	3.2029	[2.802; 3.604112]	NA
Farm level	Total agricultural land used (hectare)	-0.0080	[-0.008; -0.007608]	42.27
	Total agricultural land used squared (hectare)	0.0000	[0; 0]	38.19
	Livestock units	-0.0025	[-0.003; -0.002108]	13.69
	Age of the farm holder	-0.1062	[-0.112; -0.099928]	32.82
	Age of the farm holder squared	0.0014	[0.001; 0.0014]	45.02
	Land rental payments for total agricultural land per hectare	0.0002	[0; 0.0002]	5.95
	Land rental payments for arable land per hectare	-0.0007	[-0.001; -0.0007]	14.45
	Land rental payments for grass land per hectare	-0.0010	[-0.001; -0.000804]	15.99
	Land rental payments for other land per hectare	-0.0003	[0; -0.0003]	6.96
	Ratio of rented land on total agricultural land	-0.0022	[-0.003; -0.001808]	12.73
	Standard gross margin dedicated to general cropping per activity	-0.0001	[0; -0.0001]	13.71
	Standard gross margin dedicated to horticulture per activity	0.0000	[0; 0]	0.11

[5] The higher the metric of variable importance, the more variation in the dependent variable is induced due to a change in the respective explanatory variable.

	Standard gross margin dedicated to permanent crops per activity	-0.0000	[0; 0]	11.20
	Standard gross margin dedicated to grazing livestock and forage per activity	-0.0000	[0; 0]	2.68
	Standard gross margin dedicated to granivores per activity	-0.0001	[0; -0.0001]	3.84
	Standard gross margin minus land rental payments (€)	-0.0000	[0; 0]	18.03
	Average growth rate of agricultural land use	-0.0127	[-0.014; -0.01172]	23.44
	Average growth rate of livestock units	-0.0048	[-0.006; -0.00382]	9.81
Neighbouring variable	Herfindahl-Hirschman-Index for total agricultural land in the raster	1.6675	[1.427; 1.907796]	13.60
Regional variable at Nuts 3	Compensation of employees (1,000 €) - Service sector	-0.0021	[-0.004; 0.000056]	1.94
	Compensation of employees (1,000 €) - Manufacturing sector	-0.0045	[-0.01; 0.000792]	1.65
	Unemployment rate	-0.0283	[-0.041; -0.015952]	4.52
	Population density per square kilometre	0.0001	[0; 0.0001]	3.86
	Disposable income of private households (€)	-0.0000	[0; 0]	7.26

Source: Own compilation.

Rather than going into detail of each explanatory variable, we stick to some selected variables. Here, we are going to have a closer look at some of the explanatory variables that are most important in explaining variance of the dependent variable "exit". These variables are age of the farm holder (and squared), total agricultural land used (and squared) (hectare), standard gross margin minus land rental payments (€), average growth rate of agricultural land use and Herfindahl-Hirschman-Index of total agricultural land use in the raster.

As the estimated coefficients do not show directly how the explanatory variables relate to the predicted value in magnitude, we show figures in which each explanatory variable is evenly drawn between the one and 99 percent quantile of its distribution. From each value, the prediction of exiting is calculated given the estimated model, in which all other variables are held at their mean values. For the categorical variables, we estimate each combination and give each predicted probability a pseudo weighting value, which considers how many observations each level of the categorical variables has. The weighted average of these predicted probabilities for each selected explanatory variable gives our final estimates. The thick lines are the predicted values, the gray ribbons below and above the curve show the uncertainty of the prediction and is calculated with the use of the variance-covariance matrix of the estimated coefficients.

Do not considering any explanatory variables, from 2010 to 2020 around 23% exit the sector.[6] The predicted probabilities must be analysed in relation to the average exit rate of 23%.

Figure 2 shows the predicted probability of exiting for the average farm for different values of age, ranging from about 26 to 77 years. The average probability of exit ranges from around 13%-18% (~-10pp to -5pp compared to average exit rate) for younger farm holders up to 60% (~+37pp compared to average exit rate) for older ones. These probabilities are deviating a lot from the average exit rate, showing the importance of age in predicting exit. The rather strong curvature is because, that the estimated coefficients content a linear and quadratic term. It can be seen, that on average, the lowest probability is between 32 and 42 years. The older the farm holder, the more likely the farm holder exits the sector. This is not a surprise, as older farmers will retire at ages over 65.

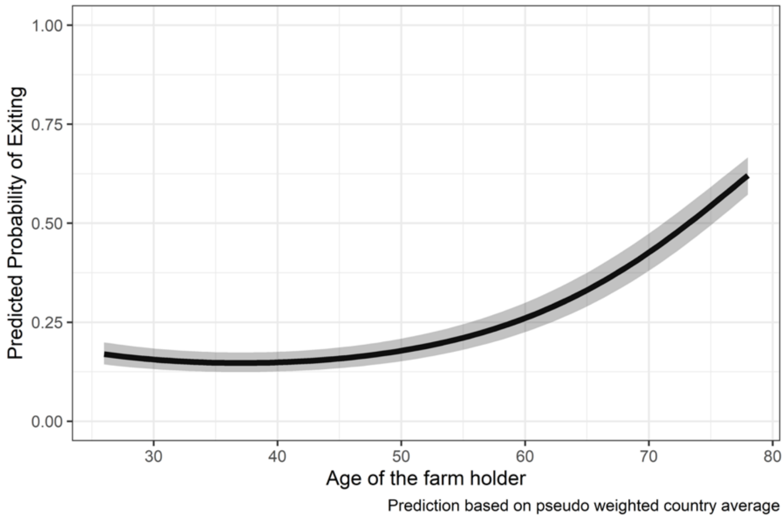

Figure 2. Predicted probability of exit over the distribution of the age of the farm holder

Figure 3 shows the predicted probability of exiting for the average farm for different values of total agricultural land use, ranging from about 0 to 700 hectares. The average probability of exit ranges from around 25% (~+2pp) for smaller farms down to almost 0% (~-23pp) for the largest ones. As in the above example, the rather strong curvature is due to the estimated linear and quadratic term. It can be seen, that rather smaller farms are more likely to exit the sector.

[6] As there are also entries in the farm survey in 2020, the number of farms in the sector decreased by about 13%.

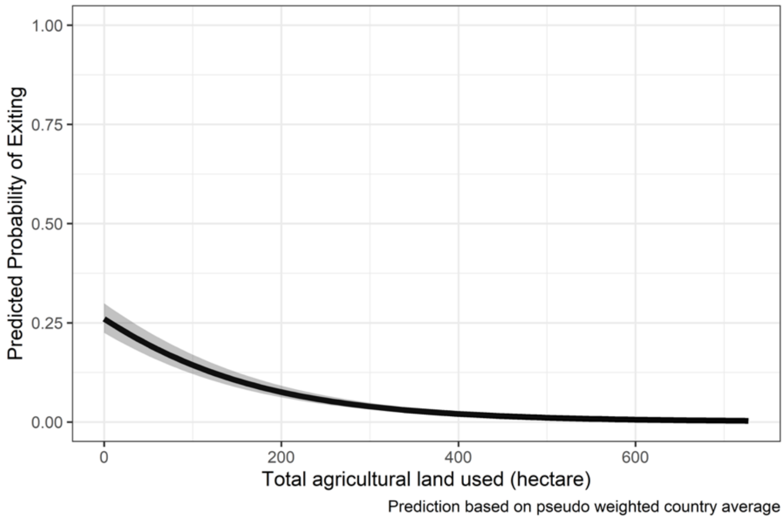

Figure 3. Predicted probability of exit over the distribution of the total agricultural land used

Figure 4 shows the predicted probability of exiting for the average farm for different values of standard gross margin minus land rental payments, ranging from about 0 to over 750,000€. The average probability of exit ranges from around 25% (~+2pp) for farms that have only small amounts of standard gross margin over rental payments down to 6% (~-17pp) for much more profitable farms. It can be seen, that with increasing standard gross margin over land rental payments, farms are less likely to exit the sector.

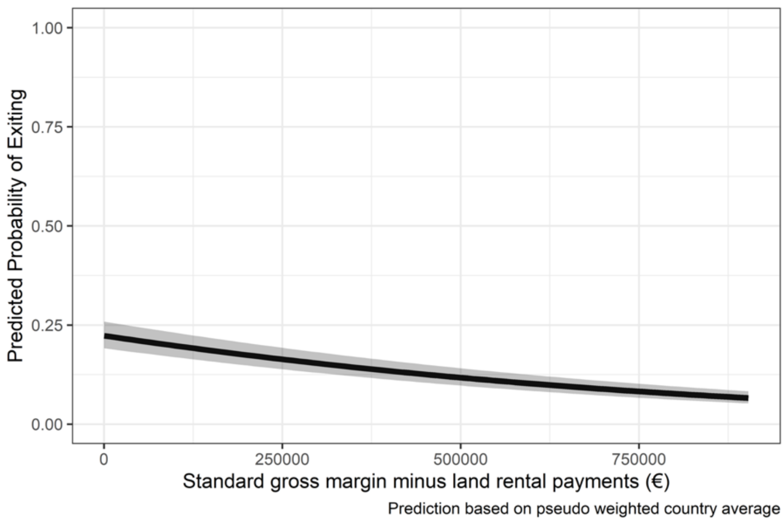

Figure 4. Predicted probability of exit over the distribution of the standard gross margin minus land rental payments

Figure 5 shows the predicted probability of exiting for the average farm for different values of the average growth rate of agricultural land use, ranging from about -25 to almost 50 hectares. The average probability of exit ranges from around 26% (~+3pp) for farms that decreased in size, to about 21% (~-2pp) for farms that did not declined or increased in size, down to 12% for most increasing farms. It can be seen, that farms that grew in the years before are less likely to exit the sector.

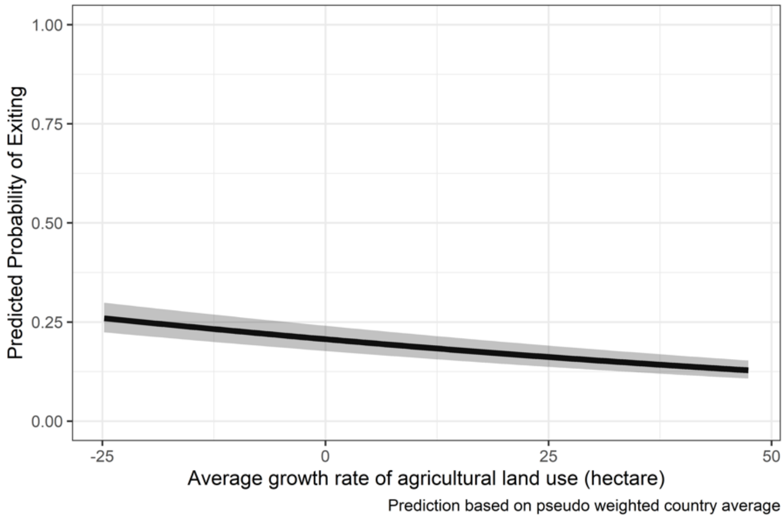

Figure 5. Predicted probability of exit over the distribution of the average growth rate of agricultural land use

Figure 6 shows the predicted probability of exiting for the average farm for different values of the Herfindahl-Hirschman-Index of total agricultural land use in the raster, ranging from slightly about 0 to almost 0.3. The average probability of exit ranges from around 20% (~-3pp) for farms that face rather evenly distributed agricultural land between neighboring farms up to 27% (~+4pp) for farms that have neighbors owning a larger share of agricultural land compared to their neighbors. It can be seen, that farms that are located in regions with more unevenly distributed land are more likely to exit the sector.

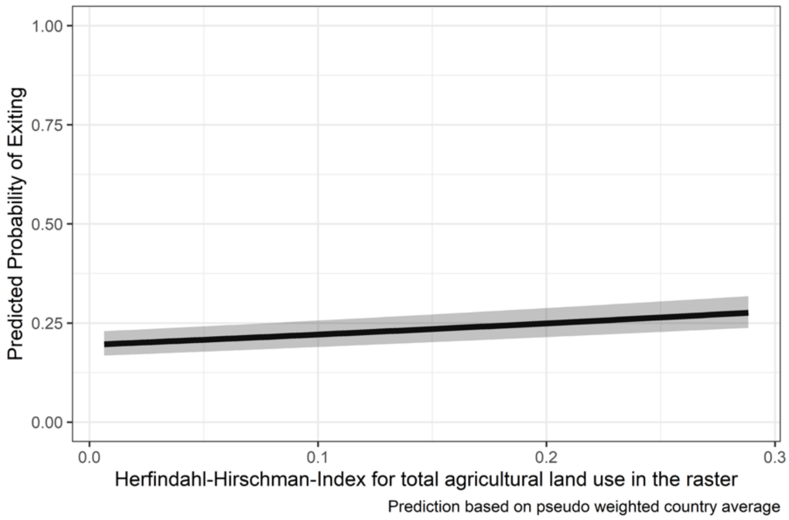

Figure 6. Predicted probability of exit over the distribution of the Herfindahl-Hirschman-Index

2.4. Transferability to IDM models

In Subtask 5.2.3 it is foreseen to use the results in the IFM-CAP model. In order to do this, variables that are part of the IFM-CAP model must be also part of the exit estimations.

2.4.1. List of variables used for matching

First examinations with team of IFM-CAP revealed the following list that might be used to match the estimated coefficients to the model and predict exit probabilities (Table 6). For the continues variables one can predict the exit probability and the estimates from categorical variables shift the probability given the values of the continues variables.

Table 6. Variables that can be matched between IFM-CAP model and Farm Exit model

Variable	Variable in Exit model[7]	Type of variable	Comments
Farm type	TiT15, …, TiT84	Categorical	Shifts the exit probability w.r.t. the sign of the coefficient
Farm size (lu, uaa, etc.)	C0240, C0240_sq, C3391	Continues	Conditional exit probability w.r.t. values of the variable
Crop (ha) and animal (heads or lu) activities	NA	Continues	Not used so far in exit estimation model
Family work	NA	Categorical	Not used so far in exit estimation model
Organic farm (true/false)	organic	Categorical	Shifts the exit probability w.r.t. the sign of the coefficient
Standard gross margins	P1_sgm_Basis_ratio P2_sgm_Basis_ratio P3_sgm_Basis_ratio P4_sgm_Basis_ratio P5_sgm_Basis_ratio sdb_farm_vs_C0421	Continues	Conditional exit probability w.r.t. values of the variable
Area payments / rented area	C0421_ha C0422_ha C0423_ha C0424_ha C0411_ratio	Continues	Conditional exit probability w.r.t. values of the variable
Regional dummies	C0010UG5	Categorical	Shifts the exit probability w.r.t. the sign of the coefficient
Legal form	C0045	Categorical	Shifts the exit probability w.r.t. the sign of the coefficient

Source: Own compilation.

[7] Full overview of abbreviations and the full name of each variable can be found in the annex.

In the farm exit model, there are two variables estimated and might be matched based on IFM-CAP model data: value_diff_mean_C0240 and value_diff_mean_C3391. The growth rate of the total agricultural land use and livestock units. As both variables need data from former years, it has to be checked if this is possible within the IFM-CAP model data. These variables promise good usability to alter exit probabilities.

The list of the following variables cannot be matched: HHI_C0240_RasterID, Alter, Alter_sq, AE_mean_1.3, AE_mean_1.4, ALO_Gesamt_value_mean, EW_qkm_value_mean, VE_2.4_value_mean and bkr***. These variables are not part of IFM-CAP and cannot be matched directly. But we have to take them into account for the prediction of the exit probabilities which is explained in the next section.

2.4.2. Empirical implementation

The implementation of exit probabilities in IFM-CAP is very much straightforward. It contents two parts of a multiplication of explanatory variables with their coefficients and the transformation of this into probabilities. One part of the explanatory variables are those that are perfectly matched between the IFM-CAP and the farm exit model (X_{obs}). These are matched at farm level. The remaining explanatory variables are provided from the summary statistics of the farm exit model and are taken at their mean value ($\bar{X}$). We need all variables from the exit estimation model to properly calculate the exit probabilities:

$$\widehat{Exit} = \frac{\epsilon^{X\beta}}{1 + \epsilon^{X\beta}} \tag{4}$$

Where $X \cup \{X_{obs}; \bar{X}\}$, $X\beta$ are the log-odds of the multiplication of the matrix of explanatory variables X of the farms with their coefficients β and $\widehat{Exit}$ is the vector of predicted farm exit probabilities.

So far this seems to be a clear way to go and the probabilities will be distributed to be within zero and one. But what farms have to be considered as exiting the sector? We suggest to do the following:

1. What is the average probability of exiting the sector? --> we know that are about 23%
2. We order the predicted probabilities beginning from the highest to the lowest
3. We take the 23% farms with highest probability to exit as $exit = 1$ and the remaining as $exit = 0$

When we assume, that the results from the exit model are also transferable to the farms from the IFM-CAP model, we are predicting the exit probability of IFM-CAP farms in 10 years. Because our farm exit estimation model estimated the exit probability of a farm in 2010 that exited the sector in 2020.

2.5. Conclusions and Outlook

In this paper we estimated the exit probability of a German farm observed in the farm census between 2010 and 2020. We augmented the data from the farm census with further data that has been shown of importance in the literature. More conclusions are drawn when the extended models are implemented.

The foreseen implementation of the estimated results of the exit estimation model into the IFM-CAP model is a straightforward way. Final implementation of more extended models will enrich this section or will be reported in deliverable D5.2.

The whole approach will be extended in the coming months. Therefore, the farm exit models are estimated with additional explanatory variables and more neighbouring effects are considered.

2.6. Appendix

Table 7. Description of continues variables

Abbreviation	Resolution	Full name
C0240	Farm level	Total agricultural land used (hectare)
C0240_sq	Farm level	Total agricultural land used squared (hectare)
C3391	Farm level	Livestock units
Alter	Farm level	Age of the farm holder
Alter_sq	Farm level	Age of the farm holder squared
C0421_ha	Farm level	Land rental payments for total agricultural land per hectare
C0422_ha	Farm level	Land rental payments for arable land per hectare
C0423_ha	Farm level	Land rental payments for grass land per hectare
C0424_ha	Farm level	Land rental payments for other land per hectare
C0411_ratio	Farm level	Ratio of rented land on total agricultural land
P1_sgm_Basis_ratio	Farm level	Standard gross margin dedicated to general cropping per activity
P2_sgm_Basis_ratio	Farm level	Standard gross margin dedicated to horticulture per activity
P3_sgm_Basis_ratio	Farm level	Standard gross margin dedicated to permanent crops per activity
P4_sgm_Basis_ratio	Farm level	Standard gross margin dedicated to grazing livestock and forage per activity
P5_sgm_Basis_ratio	Farm level	Standard gross margin dedicated to granivores per activity
sdb_farm_vs_C0421	Farm level	Standard gross margin minus land rental payments (€)
value_diff_mean_C0240	Farm level	Average growth rate of agricultural land use
value_diff_mean_C3391	Farm level	Average growth rate of livestock units
HHI_C0240_RasterID	Neighbouring variable	Herfindahl-Hirschman-Index for total agricultural land in the raster
AE_mean_1.3	Regional variable at Nuts 3	Compensation of employees (1,000 €) - Service sector
AE_mean_1.4	Regional variable at Nuts 3	Compensation of employees (1,000 €) - Manufacturing sector

ALO_Gesamt_value_mean	Regional variable at Nuts 3	Unemployment rate
EW_qkm_value_mean	Regional variable at Nuts 3	Population density per square kilometer
VE_2.4_value_mean	Regional variable at Nuts 3	Disposable income of private households (€)

Source: Own compilation.

Table 8. Description of categorical variables

Abbreviation	Categories	Extended abbreviation	Description	Full name
C0045	1	C00451	Socioeconomic / legal farm type	Full time - Sole proprietorship
C0045	2	C00452	Socioeconomic / legal farm type	Part time - Sole proprietorship
C0045	3	C00453	Socioeconomic / legal farm type	Corporate and partnership farms
organic	1	organic1	Farming system	Organic
organic	3	organic3	Farming system	Conventional
TiT	15	TiT15	Type of farming	Specialist cereals, oilseeds and protein crops
TiT	16	TiT16	Type of farming	General field cropping
TiT	2	TiT2	Type of farming	Specialist horticulture
TiT	35	TiT35	Type of farming	Specialist vineyards
TiT	36_38	TiT36_38	Type of farming	Other specialist permanent crops
TiT	45	TiT45	Type of farming	Specialist dairying
TiT	46	TiT46	Type of farming	Specialist cattle - rearing and fattening
TiT	47	TiT47	Type of farming	Cattle - dairying, rearing and fattening combined
TiT	48	TiT48	Type of farming	Sheep, goats and other grazing livestock
TiT	51	TiT51	Type of farming	Specialist pigs
TiT	52_53	TiT52_53	Type of farming	Specialist poultry and various granivores combined
TiT	6	TiT6	Type of farming	Mixed cropping
TiT	7	TiT7	Type of farming	Mixed livestock holdings

TiT	83	TiT83	Type of farming	Field crops - grazing livestock combined
TiT	84	TiT84	Type of farming	Various crops and livestock combined
C0010UG5	010, …, 160	C0010UG5101, …, C0010UG5160	NUTS 2 regions	
bkr	101, …, 199	bkr101, …, bkr199	Soil-climate-areas	

Source: Own compilation.

2.7. References

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3. FARM EXIT ESTIMATIONS FOR NORWAY USING SINGLE-FARM DATA AT CENSUS LEVEL

3.1. Introduction

Cooper and Nakanishi (1997) defined the MCI as market share models that explain the market shares of brands or products and investigated how they are affected by firms' own actions (e.g., marketing instruments and management choices), the actions of competitors and other factors such as general economic development or policy changes. The MCI model analyses market shares in a competitive environment where the market is divided into submarkets of brands, groups of customers, time periods or geographical regions. The approach can also be found in publications for sectors such as hospital services and the financial sector. The underlying hypothesis is that the determinant of market share is the attraction (or utility) that consumers feel towards alternative submarkets or brands when making a purchasing choice given the available options.

Based on this framework, Röder et al. (2014) applied the first time MCI to the context of farm structure. This approach explained whether an individual farm has developed over time in a certain direction of specialization. In this context, we tried to answer whether MCI outperforms the oft-applied Markov approach. Using an artificially generated time series of production branches with known parameters, the Markov and the MCI both recovered the pattern without problems. They concluded that for the underlying data set, both approaches seem appropriate. However, the advantage of a change in methodology arises from other considerations. First, using Markov implies defining classes to obtain transitions, which can blur farm branch adjustments within the class. Second, MCI significantly reduces the parameter dimensionality problem inherent in Markov transitions. The MCI model reduces the number of parameters to be estimated but still allows for the identification of determinants and prediction of shares.

Röder et al. (2014) show that data constraints arise from exclusive use of FADN data, and their share of production branches can be omitted by using farm-type shares at the regional level. Farm-type changes at the regional level are likely to be smaller and less erratic and hence better to estimate.

For an application of the MCI, we identify a minimum set of assumptions regarding farmers' behavior. First, the farm-type production programs and decisions about structural investments were made by utility maximization at the farm-household. Second, the production specialization and size class encompassed groups with similar socioeconomic and production characteristics. Third, the percentage or share, rather than the absolute number, better reflects the distribution at the regional level. Finally, market signals such as prices, subsidies and other relevant factors exist at the aggregated farm-type level and are consistent with those that drive individual farmers.

Neuenfeldt et al., 2019 analyzed farm structural change in the EU using farm-type shares from FADN observations in all NUTS2 regions in the EU over the period from 1989 to 2013 with the MCI model. We faced several challenges: on the one hand, the methodology that classified the FADN farms according to their production orientation was changed in the FADN. Fortunately, there was a transition period that could be used to map the typology, which allowed us to consider time series before 2004. On the other hand, the explanatory variables had to be merged into the farm groups. The different spatial and temporal resolutions were not always compatible.

They discussed in the paper the theoretical justification for analyzing farm structural change in the MCI context. To support our argument, it was necessary to analytically relate farm-type shares in the population to the distribution of farm production choices and show that this relationship is equivalent to the MCI model formulation that assumes utility maximation. Such a derivation is not straightforward because the model formulation is highly discontinuous. For this reason, they illustrated the consistency of the theoretical concept numerically using a simulation of a synthetic farm population. The numerical experiment assumed the profit maximization of farms. The farm models were parameterized by randomly drawing prices, yields and land endowments for each farm. The results indicated that the MCI was capable of explaining well the profit-maximizing behavior of single farms at the aggregated farm-type level.

The results of the estimation in the paper showed that the largest share of the variance in farm-type shares across regions and time is explained by past farm-type shares, indicating the importance of historic specializations. New Member States tend to have a more dynamic farm structure; past farm-group shares explain almost 52% of farm structural change in old MS, while in the EU-12, its contribution is approximately 19%. The paper presented a detailed discussion of the drivers. The results are of course subject to several limitations, which we discussed in the paper, but it might be relevant to point at one specific issue. In this paper, we focused on farm structural change related to farm-type shares. They did not analyze the number of farms (total and for each type), which is a key element of farm structural change. This lack of analysis could be either remedied by making a separate prediction of the total number of farms and then combining this with MCI shares or as further developed in this project by considering a farm type that depicts the share of exiting (inactive) farms.

The paper developed during the **MIND STEP** project under this task contributed to two developments. On the one hand, we showed how helpful it is to use information from the farm structural survey, which also allows very precise accounting for the number of farms. Unfortunately, these data are thus far not available in the EU, even upon request. Instead, we used data from Norway, which were publicly available, from 1996 to 2015. Furthermore, we used an artificial group of so-called “inactive farms” (those that have dropped out over time) within the MCI framework to predict, in addition to the farm shares, the corresponding total number of farms in accordance with its significant explanatory variables. The proposed extension of the MCI was an important step in applying the concept to quantitative simulation models and in accounting for farm structural change.

In more detail in this section we extend the analysis of farm structural change with respect to farm specialisation, size and exit in Norway (Neuenfeldt *et al.*, 2019) by, first, explicitly incorporating the location information of farms generating a number of neighbouring farms within a certain range, and, second, by predicting farm numbers in addition to farm group shares, which allows for consideration of the exit farm group. We use Norwegian single-farm full census data for the period 1996–2015. Four production specialisations and seven size classes represent farm groups, as well as a residual and an exit farm group at the regional level. Compared to those of Neuenfeldt et al. (Neuenfeldt *et al.*, 2019), the estimates indicate the explanatory power and importance of aggregated farm location information in the model. Simulation analysis shows that the farm groups develop differently, given a change in number of neighbouring farms with respect to farm numbers and farm group shares.

Norway, as did many other industrialised countries, went through substantial structural changes in the agricultural sector, reflected in the declining number of farms, farm size growth and production re-specialisation over time. A better understanding of the drivers of (Saint-Cyr *et al.*, 2019)these past structural changes, particularly of the farmers’ exit decisions, will help in projecting future developments and has significant policy implications on the national and international levels.

Today, agriculture in Norway is dominated by grass-based dairy farming, beef and sheep production and, to some extent, spring and winter cereals for bread or animal feed, mainly in the southern regions (Mittenzwei *et al.*, 2017). The agricultural structure is rather small-scale, with a total number of 42.018 farms in 2015, with an average farm size of 23.5 ha (Statistics Norway, 2019). The total agricultural area in 2015 was 0.986 million hectares, which corresponds to 2.7% of the country’s total land area. Norwegian agriculture is hence dominated by very small farms, compared to the rest of Europe where farming has been rationalised into much larger units, improving the structural efficiency of agriculture.

This structural development partly results from one of the most strongly state regulated agricultural sectors in Europe (Forbord, Bjørkhaug and Burton, 2014). Compared to other countries, the Norwegian farming sector is heavily dependent on governmental support measures, as more than the half of farm income is related to market price support and subsidies (*Agricultural Policy Monitoring and Evaluation 2014: OECD Countries*, no date). Agricultural policy measures are negotiated between the Norwegian government and the farmers' organisations on a yearly basis. Therefore, the payment rates that differ by region and farm size can change every year, potentially affecting the structure of the Norwegian agricultural sector over time (Mittenzwei *et al.*, 2017).

The literature offers a multitude of additional determinants to explain structural change in Norway, which are also in line with findings in other countries, including technology (economies of scale, productivity growth, farm household and path dependency), input and output prices and macroeconomic conditions (e.g. unemployment rate), regional characteristics, agricultural policies and competitive pressures from non-agricultural sectors for resources (e.g. (Cochrane, 1958; Harrington, Reinsel and Harrington, 1995; Balmann *et al.*, 2006; Alvarez-Cuadrado and Poschke, 2011; Zimmermann and Heckelei, 2012; Arfa *et al.*, 2015; Neuss, 2019)). Natural and climate conditions are important determinants of agricultural specialisation across regions. For instance, growing degree days or altitude are related to land-use changes (Fezzi and Bateman, 2011) or elevation and steepness (Müller and Zeller, 2002). Mandryk et al. (Mandryk, Reidsma and van Ittersum, 2012) give a short overview of literature that indicated climate change as a cause of structural changes. Climate change refers to changes in climatic conditions or climate variability that affect crop productivity, yields, farmer income and land use (Olesen and Bindi, 2002; Bradshaw, Dolan and Smit, 2004; Berry *et al.*, 2006; Reidsma *et al.*, 2008; Bindi and Olesen, 2011; Agovino *et al.*, 2019).

Important drivers in Norway include techno-economic development (economies of scale) and a reduced compensation to smaller farmers since the 1990s (Forbord, Bjørkhaug and Burton, 2014), as well as the fact that farm types are differently affected, such that farms with breeding stock, primarily sheep and dairy cattle, are more likely to continue farming (Stokstad, 2010).

The importance of incorporating spatial patterns or neighbouring effects has become apparent in recent years. Storm et al. (Storm, Mittenzwei and Heckelei, 2015) showed the importance of direct payments and of farm size for structural change in Norway, and highlighted the importance of farm interaction for strategic farm decisions due to the competition over land causing regional specific patterns and spatial dependencies. Additional recent work using a spatial framework highlighted the spill-over effects in farm specification activities and indicated cooperation and competition between farms that affect the adoption of diversification activities (Vroege *et al.*, 2020) in Europe. Vroege et al. [24] also conclude that spatially proximate farms are not independent of each other, and different degrees of proximity matter. Similarly, Saint-Cyr et al. (Saint-Cyr *et al.*, 2019) highlight the substantial variation between farm types with respect to neighbouring effects and spatial patterns in Brittany. Neighbouring effects have often been analysed based on farm characteristics of farmer decisions (Case, 1992; Holloway, Shankar and Rahman, 2002; Läpple *et al.*, 2017). Adoption decisions as social norms and attitudes (Läpple and Kelley, 2015) and access to information – direct and through the neighbourhood – and social conformity (Wollni and Andersson, 2014) show the importance of farmers' interactions. Roberts et al. (Roberts, Majewski and Sulewski, 2013) show that transactions between farm households also depend on their local economies. Even though farm activity diversification related to off-farm or non-agricultural activities is difficult to quantify with available statistics, some work on this topic has also incorporated spatial patterns and neighbouring effects. Among others, a case study in Eastern Germany revealed that diversification in terms of touristic development is more prone to farms in rural areas, and continuation of farming increased with closer proximity to urban consumer markets (Lange *et al.*, 2013). Such income diversification strategies seem to be a possible way to go for farms in the future as a survival strategy (Weltin *et al.*, 2017). Focusing on efficiency, Schneider et al. (Schneider, Skevas and Lansink, 2021) and Skevas and Lansink (Skevas and Lansink, 2020) also indicate the existence of neighbouring effects on arable and dairy farms in Dutch agriculture.

Studies focused on relevant determinants for exit decisions have shown that smaller farms (Breustedt and Glauben, 2007; Landi *et al.*, 2016; Hoppe, no date; Thiermann, Breustedt and Rosenau, no date), lower profitability (Bragg and Dalton, 2004; Dong *et al.*, 2016) and older farmers or farms with no successor are associated with a higher likelihood of exit (Weiss, 1999; Gale, 2003; Pietola, Väre and Lansink, 2003; Mishra, El-Osta and Shaik, 2010; Dong *et al.*, 2016; Corsi, Frontuto and Novelli, 2021; Hoppe, no date), as are spatial effects. In addition, a high population density can either increase (Landi *et al.*, 2016) or decrease (Glauben, Tietje and Weiss, 2006) the exit rates for farmers. Decoupling of subsidies from production seems to accelerate the exit of livestock production farms and of farms that were already in the process of leaving the sector (Kazukauskas *et al.*, 2013). Recent research also highlights the fact that exit rates seem to be differently influenced by farm size or farm holder's age with regard to different farm types (Saint-Cyr *et al.*, 2019). Breustedt and Glauben (Breustedt and Glauben, 2007) and Goetz and Debertin (Goetz and Debertin, 2001) argue that farms' profitability is increased by farm support and this reduces farm exit. Among other determinants, Foltz (Foltz, 2004) has shown for the Connecticut dairy industry that higher prices, lower lending rates, higher unemployment and lower population density increased the probability to stay in business.

Rather than being a result, structural change (i.e. change in the type of farming) is also seen as a driver that influences farm income distribution (Piet and Desjeux, 2021).

Most of the studies thus far reviewed have focused either on a subpopulation of farms or on a specific set of determinants to explain structural change. A comprehensive theoretical framework accounting for all major drivers of structural adjustment in agriculture, including farmers' exit decisions and accounting for all specialisation and spill-over effects between the farm population, was not considered.

A promising strand of analysing farm structural change has been developed by using Multiplicative Competitive Interaction (MCI) models, which analyse the heterogeneous economic and social behaviour of farm groups at the regional level (Neuenfeldt *et al.*, 2019). The models have been applied to the farm accountancy data network (FADN) in Europe to analyse structural change with respect to the development of farm group shares, i.e., farm specialisations and size classes as farm typology, over time at the NUTS2 regional level.[8] This farm typology was representative of the FADN regions, usually in a similar manner to that of the NUTS2 regions in the EU. The approach has major drawbacks, which make direct use of the results for policy assessment on determinants of structural change and the use for EU impact assessment models, such as CAPRI (Gocht and Britz, 2011) or IFM-CAP (Louhichi *et al.*, 2018), difficult. The evolution of the total number of farms, required to identify the actual number of farms in a farm group, affected by structural change is missing. The MCI approach operates on shares of farm groups over time and does not provide estimates on the total farm number of each group. In addition, an exit group (share of inactive farmers over time) was not considered, as this would also require knowing the evolution of the total active farm population over time. Although the missing total numbers of farms can be solved by using additional observations from regional farm structure survey (FSS) time to capture the general trend of total farm numbers in a region, it would result into two different approaches and hence is prone to inconsistencies.

The disadvantage of this work was mainly the missing incorporation of the absolute number of farms and, consequently, the missing exit class. In addition, the data quality of the regional representative

8 'The NUTS classification subdivides the economic territory of the EU Member States into territorial units (regions) […]. The classification is made up of three hierarchical levels: each Member State is divided into so-called NUTS 1 regions, which in turn are subdivided into NUTS 2 regions and then divided further into NUTS 3 regions'. (European Union, 2015: 4–5)

farm groups over time was of concern when using FADN. Changes in the methodology, due to a change in the sampling plan, or a change in the classification scheme, i.e., standard gross margin (SGM) versus standard output (SO), seriously affected the data quality and hence the estimation results.

Given this background, the aim of this paper is twofold. First, we extend the approach of Neuenfeldt et al. (Neuenfeldt *et al.*, 2019) such that it accounts for entering and exiting farms in the MCI framework, which allows for quantification of the absolute numbers of all active and inactive groups. The proposed extension of the MCI is an important step in applying the concept for quantitative simulation models and in accounting endogenously for farm structural change. The second aim of the paper is to make use of spatial information by fully exploiting the location information of the Norwegian dataset, i.e., to estimate neighbouring effects, indicated recently in the literature as an important driver for structural change.

Our paper therefore contributes to the existing literature on farm structural change in several ways. First, we apply and extend the MCI approach by using FSS data to incorporate farm entry/exit decisions, and, second, we explicitly incorporate the location information of farms by using indicators to account for the number of neighbouring farms within a certain radius, which has not previously been used in this strand of analysis. We investigate whether and how a farm group is affected by the density of neighbouring farms. In other words, we analyse which farm group and region shrink due to competition effects or which grow due to positive externalities deriving from agglomeration economies.

The paper is structured as follows. The next section introduces the MCI approach with a short explanation and relevant references. In the third section, we explain the construction of farm groups at the regional level, including the definition of the exit class, and the choice of explanatory variables is justified. In section four, the model results are presented. A simulation experiment with the incorporated locational variable is presented in section five. The final section concludes the research described in the paper.

3.2. Methods

We use the Multiplicative Competitive Interaction (MCI) proposed by Neuenfeldt et al. (Neuenfeldt *et al.*, 2019) for explaining farm structural change, which is originally based on the theoretical framework developed for the estimation of market share attractions in the marketing literature (Cooper and Nakanishi, 1997)[9].

This theoretical framework has been extended to agricultural farm groups distinguished by production specialisation and farm size. According to Gocht et al. (Gocht *et al.*, 2012) and Neuenfeldt et al. (Neuenfeldt *et al.*, 2019), the farmers' choices on production activities determine the share of different farm groups in a region. Analogous to the market share hypotheses of Cooper and Nakanishi (Cooper and Nakanishi, 1997), in which brands and products compete for shares of a limited market, the different farm groups compete for their share over limited agricultural resources (e.g. land, labour).

9 Generally, MCI are also applied in the marketing literature to explain market shares of brands or products to investigate how they are affected by firm's own actions (e.g. marketing instruments, management choices), actions of competitors, and other factors such general economic development or policy changes (Cooper and Nakanishi, 1997; Fok, Hans and Paap, 2002). They rely on two fundamental hypotheses: (i) the market share of a brand or product is proportional to the marketing effort applied by the firm (Kotler, 1984) and (ii) consumers are attracted to different brands/products and the most attractive one gains the largest market share (Bell, Keeney and Little, 1975). The MCI approach is also applied in other fields than marketing like hospital services (Erickson and Finkler, 1985) and the financial sector (Banker and Kauffman, 1988; Banker *et al.*, 2010; Bod'a, 2017).

Hence, each farm group share depends on the resources allocated and their efficient use in the production process.

According to Neuenfeldt et al. (Neuenfeldt *et al.*, 2019) the model does not need to impose constraints on parameters to ensure that the shares sum up to one, because subsequent normalisation accounts for this. A further advantage is that farm group specific sets of explanatory variables can be used to specify the estimation equations. This is particularly important in the presence of heterogeneous farm groups, because farm group shares (e.g. dairy farms versus cereal farms) may be affected by different drivers. For example, payments coupled to production activities are specifically relevant only for certain farm groups.

The observed farm group shares can be seen as the result of utility-maximising behaviour of each farm, given all the information and circumstances it faces. Depending on the production decisions, a farm represents a specific farm group. Therefore, the farm group share in a region is defined by the aggregated utility generated from farming activities by the farm group relative to the total utility obtained by all farm groups:

$$s_{i,t} = \frac{U_{i,t}}{\sum_{j=1}^{I} U_{j,t}}, \tag{1}$$

where i and j are farm group indices, t is time, $U_{i,t}$ is the utility of farm group i in t, $s_{i,t}$ is the share of farm group i in all farm groups in t, and I is the number of farm groups considered at the regional level.

The utility of specific farm activities is formulated as a multiplicative function:

$$U_{i,t} = e^{\alpha_i} \prod_{k=1}^{K} f_k(X_{k,i,t})^{\beta_{k,i}} \epsilon_{i,t}\ , \tag{2}$$

where K is the number of explanatory variables, $X_{k,i,t}$ is the k-th explanatory variable explaining the utility of farm group i in t, $\beta_{k,i}$ is the coefficient measuring the influence of the k-th explanatory variable on the utility of farm group i in t, α_i is a farm group-specific parameter, f_k is the positive, monotone transformation of $X_{k,i,t}$ and $\epsilon_{i,t}$ is the error term.

Each farm group is estimated separately and the variables with the most predictive power are selected via a forward selection based on the Bayesian information criterion. The estimation equation for each farm group *i* across the regions reads as follows:[10]

$$\log(s_{i,t}) = \alpha_i + \sum_{k=1}^{K}\sum_{r=0}^{R} \beta_{\text{k,i,r}}\, log(X_{\text{k,i,t-r}}) + \varepsilon_{\text{i,t}}, \quad s_{k,i,t-r} \in X_{\text{k,i,t-r}} \quad and \quad i = 1,2,\ldots,I\ , \tag{3}$$

where variable $s_{i,t}$ is the share of farm group i in year t for I farm groups. α_i is the farm group specific intercept, $\beta_{k,I,r}$ is the farm group specific coefficient for each explanatory variable of all explanatory variables K, and r is the lag which can be 0 for time-independent variables or between 1 and 4 for time-dependent variables. $X_{k,i,t}$ is the k-th explanatory variable explaining the farm group share i in t for different lags r, and the lagged farm group shares of group i are also part of the set of explanatory variables.

To ensure that the estimated farm group shares are summing up to 1, the shares of the farm groups are calculated by using the normalisation procedure (Nakanishi and Cooper, 1982). This means that,

10 Why this model is useful and applicable to the estimation of farm group shares is comprehensively derived in Neuenfeldt (Neuenfeldt *et al.*, 2019).

if $\hat{y}_{i,t}$ is the estimate of the dependent variable in the equation above, the estimated farm group share, $\hat{s}_{i,t}$, is given as follows:

$$\hat{s}_{i,t} = \frac{\exp\,(\hat{y}_{i,t})}{\sum_{j=1}^{I} \exp\,(\hat{y}_{i,t)}}, \tag{4}$$

where farm group share i is calculated as the ratio of the inverse logarithm of the estimate divided by the sum of all the inverse logarithm estimates of the dependent variable over all farm groups.

We refrain from presenting all the estimated coefficients for each farm group and rather report some statistics of the fit of the estimated regressions and the summary of the decomposition results of the drivers of farm structural change, and compare them with Neuenfeldt et al. (Neuenfeldt *et al.*, 2019).

To elaborate the fit of the estimated regressions, we take a closer look at the coefficient of determination for each estimated regression. The farm group-specific coefficient of determination is calculated as follows:

$$R_i^2 = 1 - \frac{\sum_{t=5}^{T}\left(s_{i,t} - \hat{s}_{i,t}\right)^2}{\sum_{t=5}^{T}\left(s_{i,t} - \bar{s}_{i,t}\right)^2}, \tag{5}$$

where $\bar{s}_{i,t}$ is the average farm group share of farm group i at time t, and T is the total number of available years.

3.3. Data

3.3.1. Farm group construction

We follow the farm typology of the European Union to construct farm groups.[11] This typology is also applied to FSS and FADN. The advantage is that later we can compare our results with the findings of Neuenfeldt et al. (Neuenfeldt *et al.*, 2019), who use the same rules of constructing farm groups. Official European data, as FSS or FADN, classifies farms by production specialisation (principal type of farming) and farm size (economic size class). Each farm group in our paper is a combination of farm specialisation and size class. We consider four farm specialisations and seven size classes, as provided in Table 9. Specialist cereals oilseeds and protein crops, various field crops combined, specialist dairying and sheep, goats and other grazing livestock farm are the farm types of our choice. We further define size classes ranging from below 4,000 standard output (SO[12]), between 4,000 SO and 8,000 SO, up to above 100,000 SO, as depicted in Table 9. For the crop activities, only the smaller size classes are considered; for animal grazing activities, the larger size classes are considered. The principal type of farming (farm specialisation) is defined in terms of dominant farm activity of the farm calculated as the relative share of SO of the dominant activity in the total farm SO (European Commission, 2010). The selected farm groups are chosen based on their relative importance in terms of SO for Norwegian agriculture. For our analysis we further group the remaining farms into the residual farm group (all remaining combinations of farm specialisation and size class) when they are still active. Finally, and to contribute to another part of structural change – entry or exit – we construct an exit farm group, which

[11] See Commission Regulation (EC) No 1242/2008 of 8 December 2008 establishing a Community typology for agricultural holdings: https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A32008R1242-.

12 "The standard output of an agricultural product (crop or livestock), abbreviated as SO, is the average monetary value of the agricultural output at farm-gate price, in euro per hectare or per head of livestock." (see http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Standard_output_(SO))

is derived as the difference of the maximum number of active farms over the whole period deducted by the active farms in each period.

Table 9: Selected stratification of farm type and size class

Farm group	Farm specialisation	Farm size
Specialist cereals (4K - 8K SO)	Specialist cereals oilseeds and protein crops	4K - 8K SO
Specialist cereals (8K - 15K SO)		8K - 15K SO
Specialist cereals (15K - 25K SO)		15K - 25K SO
Specialist cereals (25K - 50K SO)		25K - 50K SO
Crops combined (- 4K SO)	Various field crops combined	Up to 4K SO
Crops combined (4K - 8K SO)		4K < 8K SO
Crops combined (8K - 15K SO)		8K - 15K SO
Crops combined (15K - 25K SO)		15K - 25K SO
Crops combined (25K - 50K SO)		25K - 50K SO
Specialist dairying (25K - 50K SO)	Grazing (Specialist dairying)	25K - 50K SO
Specialist dairying (50K - 100K SO)		50K - 100K SO
Specialist dairying (100K SO)		100K SO and above
Other grazing livestock (25K - 50K SO)	Sheep, goats and other grazing livestock	25K - 50K SO
Residual farm group	All other farm specialisations and sizes	
Inactive farms (exit farm group)	Not applicable	

Source: Own contribution.

3.3.2. Model variable construction

For the whole dataset over the period from 1996 to 2015 we have 84,901 unique farms. After deselecting regions with low numbers of farms, our dataset still has 82,641 unique farms in 51 regions. After the selection procedure is done and the relevant regions and farm groups are chosen, the farm group shares ($s_{i,t}$) are calculated in the following form:

$$s_{i,t} = \frac{n_{i,t}}{N_t}, \tag{6}$$

with $n_{i,t}$ being the number of farms belonging to farm group i in year t, and N_t being the total number of farms in year t. The construction of the exit farm group is achieved by finding the year with the maximum number of farms (N_{max}) for the whole dataset and setting the number of farms in this group as the difference of all active farms and the maximum number of farms, as follows:

$$n_{\text{exit\_exit},t} = N_{max} - N_{t\ i,t} \tag{7}$$

Figure 7 presents the development of the farm group shares from 2000 to 2015. There were roughly 69,000 farms in 1996, declining to roughly 38,000 farms in 2015 (-45%). Grazing and various field crops activities are predominant in Norway in terms of SO. It is also apparent that the larger-size class farms of specialist cereals oilseeds and protein crops, various field crops combined, and specialist dairying farms are increasing, whereas the smaller-size classes are decreasing over time. The exit farm group is increasing over time, but at a diminishing rate.

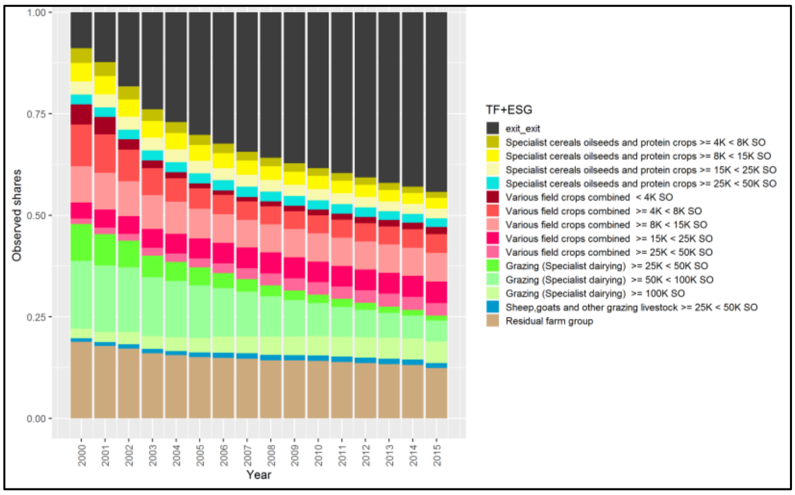
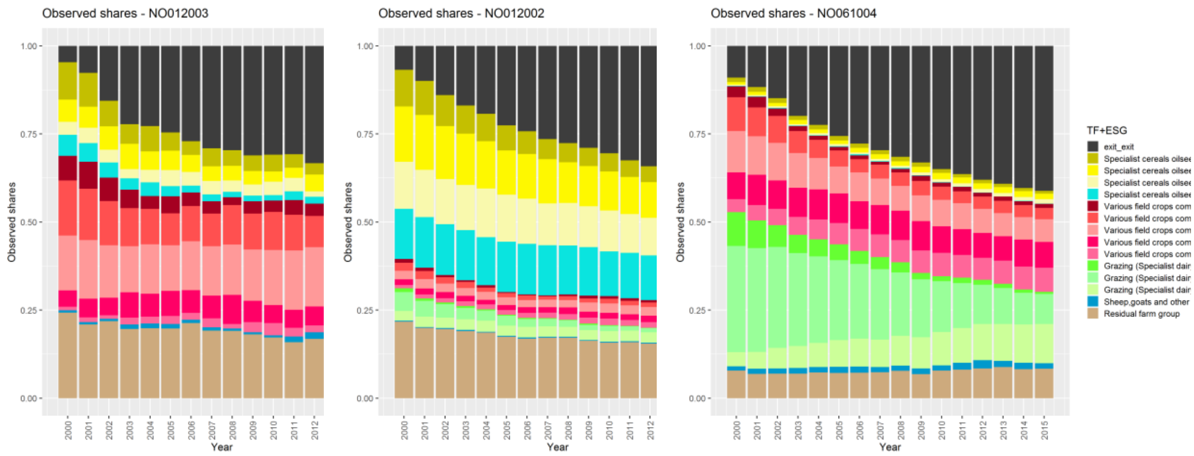


Figure 7. Development of the chosen farm typology in Norway.

Source: Own contribution.

The following three figures show the evolution of the farm groups of three regions: NO012003, which is the intersection of NUTS3 region NO012 and the agricultural region 3; NO012002, which is the intersection of NUTS3 region NO012 and the agricultural region 2; and, finally, NO012003, which is the intersection of NUTS3 region NO061 and the agricultural region 4. All regions contain different farm groups, and the data suggest that the inactive farm group is increasing.



(a) (b) (c)

Figure 8. Development of the chosen farm typology in example regions (a) NO012003, (b) NO012002 and (c) NO061004.

Source: Own contribution.

3.3.3. Choice of explanatory variables

We use six sets of explanatory variables (see Table 10), $X_{k,i,t}$ in our analysis, which have been used thoroughly in the literature to analyse farm structural change in terms of farm entry or exit, and change in farm specialisation and size: (i) prices (input and output prices), (ii) population and age, (iii) subsidies, (iv) macroeconomic variables, (v) natural conditions and (vi) locational information. Variables containing information about the location of farms are discussed below in more detail. Table 10 provides mean, standard deviation and median as well as the spatial and temporal resolution. The sources of the explanatory variables are Norwegian census farm data (subsidies, age of the farm holder, number of neighbouring farms), EUROSTAT (interest rate, unemployment rate), the World Bank (GDP growth rate), CAPRI (prices), and CORINE land cover (arable land, artificial surface, heterogeneous agricultural areas, pastures and permanent crops) and EUGIS (slope and elevation), as well as CRU TS 4.01 database[13] (temperature, precipitation and potential evapotranspiration to calculate mean and standard deviation for growing degree days and vegetation period for threshold 5 and 10 degrees Celsius).

The farm group specific explanatory variables for the exit farm group are constructed in two ways. First, country and regional data are the same as for the active farm groups. Second, the farm group specific variables are constructed by averaging over all active farm groups in each region. For instance, the price of cereals is the same for all inactive and active farm groups regardless of the regions. The regional level variables, such as population density, are the same in each region for all farm groups. The variables that are farm group-specific at the regional level are different for each active farm group and region. This means that, for the inactive (exit) farm group, these variables are calculated as the regional average over all active farm groups. For instance, total subsidies are farm group- and region-specific for each active farm group, and thus for the exit farm group an average of the active farm group values is used.

Table 10: Summary statistics of explanatory variables in each variable category (2000-2015)

Variable category	Variable group and name	Mean	Standard deviation	Median	Spatio-temporal resolution
Macro-economic variables	Growth rate of GDP	3.73	1.56	3.67	Country level / annual
	Interest rate from EMU convergence criterion series	4.41	1.49	4.41	
	Unemployment rate (total, female)	3.37	0.62	3.34	
	Unemployment rate (total, male)	3.74	0.64	3.6	
	Unemployment rate (total, age above 25)	2.58	0.53	2.55	
	Unemployment rate (total, age under 25)	9.55	1.32	9.2	
	Unemployment rate (total)	3.57	0.6	3.48	
Population and Age	Age of farm holder	49.26	2.89	49.17	Farm group specific at regional level / annual
	Population density	22.91	28.6	12.2	Regional level / annual
Prices	Price of Beef	3746.25	3888.18	716.98	Country level / annual
	Price of Cereals	244.06	258.18	31.53	
	Price of Eggs	1481.61	1591.58	278.51	
	Price of Fruits	1857.81	2066.1	593.66	
	Price of Grass	25.94	25.72	1.84	
	Price of Oil seeds	320.56	312.12	51.68	
	Price of Other animals output	915.08	1051.8	283.25	
	Price of Other crops	1001.22	1055.98	114.8	
	Price of Pork meat	2946.53	2919.58	234.04	
	Price of Potatoes	231.02	256.76	58.34	
	Price of Poultry meat	1671.74	1766.23	271.73	

[13] See https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.01/ge/ for description.

	Price of Raw milk at dairy	446.19	476.38	83.86	
	Price of Renting of milk quota	859.34	823.17	144.9	
	Price of Seed	1010.7	1077.92	122.03	
	Price of Services input	1000	1005.94	131.84	
	Price of Sheep and goat meat	5658.93	5626.03	1398.65	
	Price of Vegetables	1044.68	1071.95	211.19	
	PC of ani. and cro. inp. prices	1000	1005.94	131.84	
	PC of ani. inp. prices	859.34	823.17	144.9	
	PC of cro. in. prices	1010.7	1077.92	122.03	
	PC of oth. cro. inp. prices	2657.45	2924.85	641.27	
Subsidies	Total subsidies averaged per farm	21078.22	18587.2	16260.6	Farm group specific at regional level / annual
	Total subsidies divided by utilised agricultural area	1041.02	615.29	942.58	
Natural conditions	Aridity index	2.45	0.93	2.25	Farm group specific at regional level / annual
	Arable land	0.11	0.13	0.05	Regional level / constant
	Artificial surfaces	0.03	0.04	0.01	
	Heterogeneous agricultural areas	0.09	0.06	0.07	
	Pastures	0.05	0.06	0.03	
	Permanent crops	0.74	0.19	0.81	
	Elevation derived from a 100 m raster	280.33	181.26	222.1	
	PC of CORINE 2000 data (ARAB)	0.31	0.27	0.2	
	PC of CORINE 2000 data (ARTI)	0.15	0.13	0.1	
	PC of CORINE 2000 data (HETE)	0.19	0.12	0.14	
	PC of CORINE 2000 data (PAST)	0.07	0.06	0.04	
	Slope derived from a 100 m raster	17.56	7.99	15.1	
	Vegetation period (mean) days over 10 °C	101.06	31.93	106.62	Farm group specific at regional level
	Vegetation period (stand. Dev.) days over 10 °C	11.4	9.41	8.48	
	Vegetation period (mean) days over 5 °C	172.09	33.62	171.93	
	Vegetation period (stand. Dev.) days over 5 °C	10.63	7.95	8.46	
	Mean of growing degree days with 10 °C threshold	860.13	347.34	880.16	
	Standard deviation of growing degree days with 10 °C threshold	120.49	79.55	107.98	
	Mean of growing degree days with 5 °C threshold	1025.58	324.05	1030.93	
	Standard deviation of growing degree days with 5 °C threshold	108.56	65.1	92.36	
Location information	Average number of neighbouring farms within 10km	118.53	92.13	94.46	Farm group specific at regional level / annual
	Average number of neighbouring farms within 20km	357.05	269.7	280.73	
	Average number of neighbouring farms within 50km	1629.53	1096.66	1395.85	

Source: Own contribution. For some farms with missing age of the farm holder a regional average was used. For some farms with missing location information a regional and or farm group average was used.
Note: PC = principal component.

We added three variables for location information (see Table 11), namely, the average number of neighbouring farms of a farm group. These annual variables are calculated at the regional level. For this, we are counting the number of farms within a 10, 20 or 50km radius of each farm in the data set. Afterwards, the farm level data was averaged to the regional level. With increasing farm size in terms of SO, the average number of neighbouring farms is increasing. On average, the farm specialisation, various field crops combined, and other grazing livestock face fewer neighbouring farms, whereas grazing and specialised cereals farms are surrounded by more neighbouring farms. For all farm groups, one can see that there is a huge variation over region and time for the number of neighbouring farms.

Existing literature distinguishes between two types of effects of neighbouring farms' size. First, neighbours are seen as competitors, especially regarding the acquisition of agricultural land (Weiss, 1999). In this case, a farmer who is surrounded by larger farms may stop farming if these larger farms introduce new technologies more quickly, as they are likely to have better access to information and financial resources (Goddard *et al.*, 1993). A higher willingness to pay for land of the neighbouring farms results in a negative impact on the probability to continue with the farm under consideration. Further, Storm et al. (Storm, Mittenzwei and Heckelei, 2015) showed the importance of farm interaction for strategic farm decisions due to the competition over land causing regional specific patterns and spatial dependencies. On the other hand, neighbours can be seen as a source of motivation and a model for the introduction of new technologies (Case, 1992; Holloway, Shankar and Rahman, 2002; Läpple *et al.*, 2017). In this case, the size of neighbouring farms has a positive effect on the survival of the farm concerned, as a farmer surrounded by larger farms is more likely to adopt the innovative technologies they use (Harrington, Reinsel and Harrington, 1995). Vroege et al. (Vroege *et al.*, 2020) suggested in their analysis that locally proximate farms seem rather to cooperate and that competitive effects may occur at higher spatial levels. As neighbouring effects can be very heterogenous between farm types (Saint-Cyr *et al.*, 2019), we try to reflect this by our farm group-specific analysis.

Table 11: Summary of number of neighbouring farms per farm group

Farm group	**Average number of neighbouring farms within**								
	10 km			**20 km**			**50 km**		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
Specialist cereals (4K - 8K SO)	148.5	13.0	590.0	439.9	39.0	1470.9	1959.7	311.0	4509.5
Specialist cereals (8K - 15K SO)	150.7	23.0	722.7	440.5	73.2	1763.0	1957.6	407.0	4563.4
Specialist cereals (15K - 25K SO)	167.0	26.0	835.7	481.0	57.0	1779.2	2089.6	458.2	4691.3
Specialist cereals (25K - 50K SO)	172.6	10.5	925.0	494.4	40.0	1842.0	2160.6	328.0	4669.6
Crops combined (- 4K SO)	102.1	2.0	488.4	316.2	5.2	1203.0	1512.4	31.8	4977.8
Crops combined (4K - 8K SO)	100.4	3.3	348.6	313.8	5.4	1131.2	1499.4	32.3	4989.6
Crops combined (8K - 15K SO)	103.4	3.5	368.3	319.0	6.1	1130.3	1499.1	25.5	4948.3
Crops combined (15K - 25K SO)	105.1	3.5	387.6	321.2	6.2	1207.9	1496.4	27.7	4700.6
Crops combined (25K - 50K SO)	109.7	4.0	442.6	330.5	6.5	1161.5	1529.6	32.1	4760.9
Specialist dairying (25K - 50K SO)	106.9	2.0	447.4	330.2	4.0	1239.2	1511.1	27.0	5111.4
Specialist dairying (50K - 100K SO)	115.8	4.0	554.7	347.3	6.9	1336.9	1548.4	32.6	4815.6

Specialist dairying (100K SO -)	125.0	4.1	667.2	368.2	7.8	1548.1	1587.2	38.1	5302.0
Other grazing livestock (25K - 50K SO)	99.3	2.0	387.4	313.6	5.0	1337.0	1528.7	34.0	5374.5
Residual farm group	114.3	5.6	542.2	341.5	8.8	1321.2	1546.6	38.0	4738.1

Source: Own contribution

As we estimate regional farm group models, the question arises how the aforementioned aspects of neighbouring effects, which are derived from farm level interaction, are transmitted and interpreted to our regional case. Therefore, we aim to analyse the farm structure (how the farm groups are evolving over time), given that there are different trends in the number of neighbouring farms within a certain range, and how these lead to different states of farm structure. Figure 9 presents the regional resolution chosen on which farm structural change is analysed. The borders of administrative zones (NUTS3) are in black, and the agricultural regions[14] are marked in 10 colours. For instance, in one NUTS3 region, there can be several agricultural regions. The intersection gives us the opportunity to capture heterogenous effects coming from administrative or natural units.

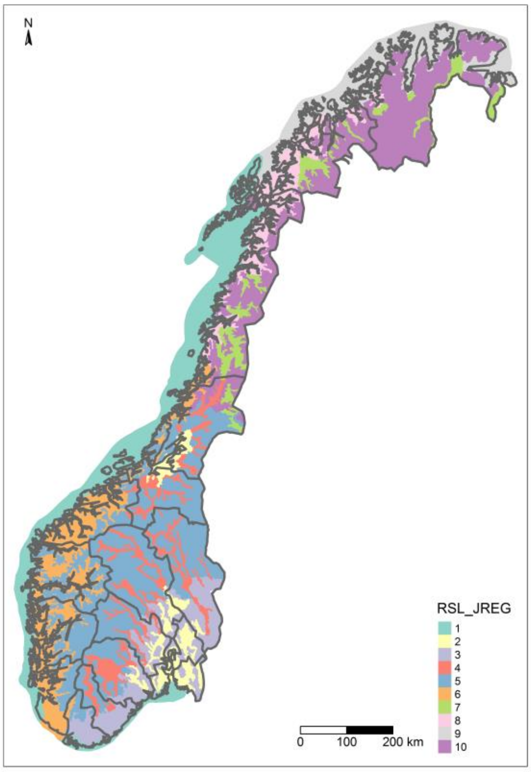


Figure 9. Regional aggregation of NUTS3 and agricultural regions in Norway.

Source: Own contribution.

[14] The geo reference file comes from https://kart8.nibio.no/uttak_Download/landskap/0000_32632_Jordbruksregioner_SHAPE.zip and the agricultural regions are made available from NIBIO https://kartkatalog.geonorge.no/metadata/landscape-agricultural-regions/ea46cdee-fbe8-4dd4-9017-c8f85ebe2253. Further information on the specific regions can be found at https://kart13.nibio.no/landskap/10_jordbruksregioner/Jordbruksregioner_kart/ and https://www.nibio.no/tema/landskap/landskapskart/nasjonalt-referansesystem-for-landskap/jordbruksregioner

3.4. Results

3.4.1. Coefficient of determination

The coefficient of determination of the estimated farm group equations ranges from 86.7% to 98.8% with a mean of 95.5%. This shows the overall high fit of the estimated models. The variable average number of neighbouring farms was selected to be a contributor to explain the shares of the smallest and largest specialist cereals, oilseeds and protein crops, the largest grazing and the exit farm group.

Three location information variables have been generated as an additional set of explanatory variables. After the forward selection, the 'average number of neighbouring farms within 10km' has been selected for four farm groups, as indicated in the last column in Table 4.

Table 12: Farm group-specific estimation results

Farm group	Coefficient of determination in %	Location information included
Specialist cereals (4K - 8K SO)	98.1	X
Specialist cereals (8K - 15K SO)	98.2	
Specialist cereals (15K - 25K SO)	98.5	
Specialist cereals (25K - 50K SO)	98.6	X
Crops combined (- 4K SO)	93.9	
Crops combined (4K - 8K SO)	96.2	
Crops combined (8K - 15K SO)	94.0	
Crops combined (15K - 25K SO)	93.1	
Crops combined (25K - 50K SO)	92.3	
Specialist dairying (25K - 50K SO)	96.1	
Specialist dairying (50K - 100K SO)	98.8	
Specialist dairying (100K SO -)	96.5	X
Other grazing livestock (25K - 50K SO)	86.7	
Residual farm group	96.0	
Inactive farms (exit farm group)	96.5	X

Source: Own contribution.

3.4.2. Comparison of observed and estimated shares

To further elaborate upon the fit of the estimated models, Figure 10 shows the absolute difference of the observed and estimated farm group shares aggregated for all regions at the country level. The Figure reveals that most of the differences are between -0.5 and 0.5 percentage points. The highest differences occur for the exit farm group in 2012, with 1.5 percentage points difference. Overall, errors are randomly distributed around a zero mean.

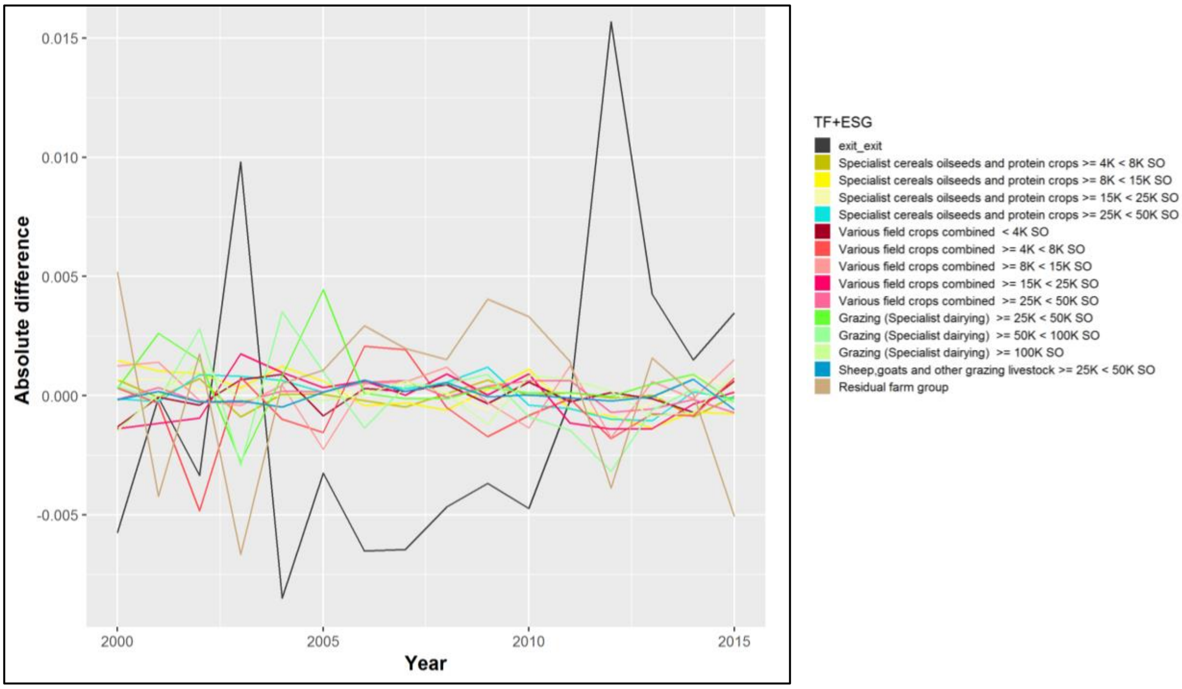


Figure 10. Absolute difference of observed and estimated farm group shares aggregated at country level[15]

Source: Own contribution.

3.4.3. Decomposition of the estimated effects

To better identify the importance of various drivers of farm structural change, we decompose the variance of the dependent variable—farm group shares—into relative contributions of each explanatory variable for all models (Fabbris, 1980; Grömping, 2015). The results are presented for the aforementioned variable sets and (past) farm structure (lags of dependent variables). Figure 11 presents the relative contribution of the explanatory variables to farm structural change in Norway. The past farm structure (the lagged farm group shares) itself explains most of the variance (87%), followed by natural conditions (4.1%) as well as subsidies (4.8%). The variables containing location information account for 2.6%; macro variables and prices have nearly no explanatory value.

[15] The share values in the data set are between 0 and 1. Therefore, absolute differences between observed and estimated shares are between -0.007 and 0.015 which translates into -0.7 and 1.5 percentage points. For better understanding, the observed and predicted values are presented in the annex aggregated for Norway.

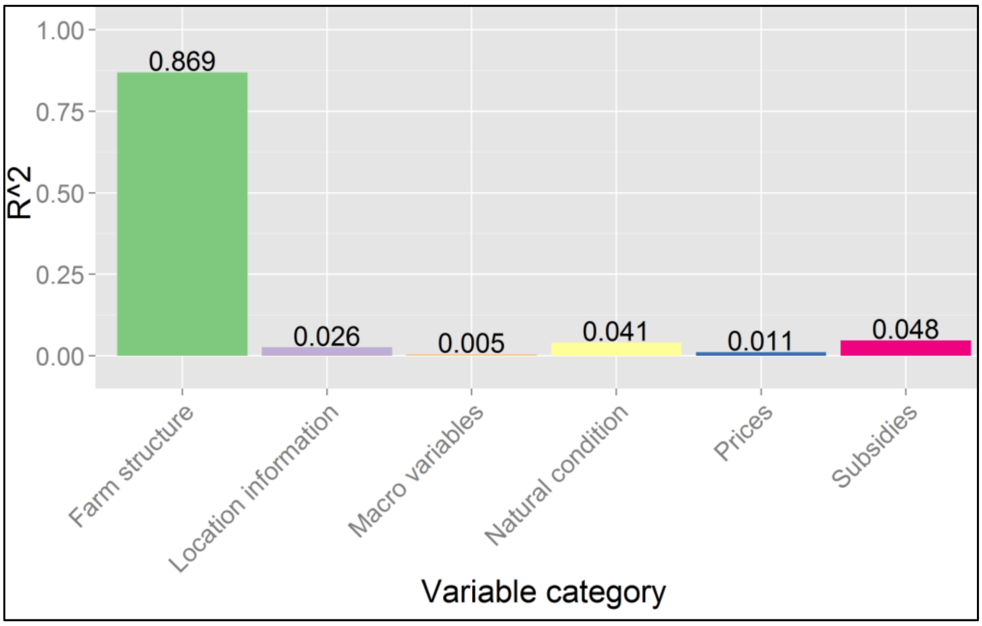


Figure 11. Relative contributions of the variable categories to farm structural change.[16]

Source: Own contribution.

When we look at the relative contributions of the variable categories across farm groups (see Figure 12), we can see that the historic farm structure contributes most to the explanatory power. Specifically, for the exit farm group, historic farm structure shows the lowest contribution (62.8%), whereas, for specialist cereals, oilseeds and protein crops (>=15k < 25k SO) it is highest (99.8%). Especially for the exit farm group (inactive farms), this low contribution seems to be reasonable, as this farm group is derived from exiting farms. It is of interest to note that subsidies show the highest contribution for the exit farm group (32%). Natural conditions explain most for the various field crops combined (>=15K < 25K SO), with 9.4%. The average number of farms explain most for the largest specialist cereals, oilseeds and protein crops, with 21.4%. Prices explain most for the largest grazing farm group (5.3%). The highest contribution from macro variables can be seen for the smallest various field crops combined farm group (2.4%). Most farm groups have more than two variable categories that contribute to the explanatory power, but no farm group contains all variable categories. These results contribute to the fact that several different determinants play a role in structural change, and these determinants correlate differently between farm specialisations and farm sizes.

[16] The variables from category “age and population” have not been selected in the forward selection based on the Bayesian information criterion.

Figure 12. Relative contribution of the variable categories to farm structural change across farm groups.

Source: Own contribution.

3.5. Sensitivity of location information

The sensitivity analysis focuses on the variable 'Average number of neighbouring farms within 10km' (nobs10km) in two ways. We test two different scenarios: an increase by 100% and a decrease by 50%. For this, we increased (decreased) sequentially per year the variable until 2025, which then reaches 200% (50%) of the value from 2015 (the last year of observation). The changes affect the variable at the farm group, at the region and in each year. The other explanatory variables in this sensitivity analysis stay constant to better eliminate the effect of the spatial location variable contribution to structural change. In **Table 5** the results are presented by the predicted farm group shares in comparison to the baseline scenario. The baseline scenario depicts the farm group shares that are predicted on a yearly basis until 2025 without changes.[17] The decreasing scenario may be understood as a continuation of increasing structural change (reducing the number of farms in a radius of 10 km), but at an increasing rate, whereas the increasing scenario may be seen as a change in the direction of the ongoing trend of the declining number of farms. We present the exit farm group, the smallest and largest specialist cereals farm group and the largest specialist dairying farm group, as they have the spatial location variable as explanatory in their farm group-specific estimation model. These farm

[17] Due to the dynamic model (lags of the farm group shares) there is still progress for the farm group shares – the importance of past farm structure comes into play.

groups have the strongest changes in their share, but, as all groups are linked in MCI to each other, the simulated variable also has an effect on the other farm groups.[18]

Table 13. Absolute no. of farms and percentage difference for an increase of 100% and a decrease of 50% of neighbouring farms within 10km compared to the baseline at country level.

No.	Farm group	Baseline			Scenario			
		No. farms 2015	2025		-50% decline in farm density		+100% increase in farm density	
		total	%	abs	%	abs	%	abs
1	Inactive farms (exit farm group) (*)	30,603	9	2,724	11	3,336	7	2,050
2	Specialist cereals (4K - 8K SO) (*)	1,028	-28	-288	-40	-407	-16	-159
3	Specialist cereals (8K - 15K SO)	1,801	-8	-144	-9	-157	-8	-148
4	Specialist cereals (15K - 25K SO)	1,655	-26	-430	-26	-430	-26	-430
5	Specialist cereals (25K - 50K SO) (*)	1,509	-2	-30	-21	-320	20	308
6	Crops combined (4K SO)	1,196	31	371	30	355	33	389
7	Crops combined (4K - 8K SO)	3,223	13	403	11	351	14	454
8	Crops combined (8K - 15K SO)	4,842	-6	-286	-7	-358	-5	-218
9	Crops combined (15K - 25K SO)	3,679	28	1,012	25	934	30	1,085
10	Crops combined (25K - 50K SO)	2,169	5	113	4	80	7	143
11	Specialist dairying (25K - 50K SO)	828	-71	-585	-71	-590	-70	-580
12	Specialist dairying (50K - 100K SO)	3,541	-59	-2,086	-60	-2,125	-56	-1,983
13	Specialist dairying (100K SO) (*)	3,679	10	357	15	541	5	177
14	O. grazing livestock (25K - 50K SO)	845	-23	-190	-24	-201	-21	-179
15	Residual farm group	8,566	-10	-814	-11	-899	-9	-737

Source: Own compilation.

Note: (*) depicts farm groups in which the variable 'average number of neighbouring farms within 10km' has been selected in the forward selection.

The Table reads as follows. If the number of neighbouring farms within 10km of specialist dairying (100K SO) (no. 13) is decreasing (increasing) by 50% (100%) until 2025, the relative percentage change is 15% (5%), which is 5 (5) percentage points higher/lower than the baseline with 10% relative change. The total number of farms is given in the third column for the year 2015. The absolute change in farm numbers is also presented.

Overall, a reduction in density of surrounding farms (declining scenario) leads in 12 active farm groups to a further reduction compared to the baseline, even if they increase from 2015 onwards (farm groups with a positive sign of the fourth and fifth column). As we are comparing to the baseline in which the trend of a declining number of farms continues, the decreasing scenario describes an even

[18] Inside the MCI framework the estimated farm group shares are constructed through normalization of the estimated.

higher exit of farms out of the sector. Please note that the effects presented are an aggregated picture over all 51 regions and the effects at the farm-group level might differ in a region. The sensitivity analysis reveals, however, that most farm groups are negatively affected (reducing the absolute and relative size), when the density of the surrounding farms declines, and spill-over effects and neighbouring cooperation become less possible (common use of machinery).

The analysis also reveals that the large farm groups, such as the farm group specialist dairying (100K SO), seems to be less dependent on agglomeration effects and can even further increase their importance by almost 200 farms in the declining scenario. It may be the result of a strong competition position of the large farms, e.g., on the land market (Storm, Mittenzwei and Heckelei, 2015), which may lead to lower profitability and thus to other smaller farm groups exiting the sector (Bragg and Dalton, 2004; Dong *et al.*, 2016). In contrast, the farm group specialist cereals (25K – 50K SO) (no. 5) is declining by about 290 farms, which is -21%.

For the scenario of increasing the density of surrounding farms, the results are almost mirrored. The increasing scenario describes the situation in which more farms have entered the farming sector compared to the baseline. This scenario can be interpreted as what would the farm structure look like if there would be more (neighbouring) farms. The ongoing trend of the declining number of farms in the sector is slowed down. In this case, farms entering the sector would choose those production activities that are associated with those farm groups that experience an acceleration in their shares compared to the baseline. There must have been relatively low entry barriers due to sufficient profits, lower land rents and growth of the most preferable farm groups. An increasing number of neighbouring farms is most likely a reasonable scenario in terms of farm division, because new entrants must take non-occupied agricultural land or lend from active farmers.

The inactive (exit) farm group (no. 1) must be considered differently. This farm group reflects the ongoing structural change in terms of declining active farm numbers and, hence, increasing inactive farms.

Structural change most often implies that smaller farms are exiting more frequently than larger farms. We predicted with the estimated model for the baseline development for most of the small farming groups a decline (specialist cereals (4K – 8K SO), crops combined (8K – 15K SO), specialist dairying (25K – 50K SO) and the residual farm group). Only the farm group crops combined could increase their shares for small size classes; this might be due to effects such as part-time farming or off-farm employment. The specialist cereals (25K – 50K SO) farm group (no. 5) is the only farm group that changes its baseline prediction from decreasing to increasing, probably observed since the decline in the baseline was rather moderate (-2%) and at the same time the effect of the two scenarios were very profound (-21%; +20%).

3.6. Discussion and conclusions

In this paper we analyse the drivers of farm structural change in Norwegian agriculture with farm census data. We adopt the Multiplicative Competitive Interaction (MCI) model. We extended the MCI framework, by accounting explicitly for the absolute farm numbers and hence a farm exit class, and, in addition, by considering farm locations with which to generate an aggregated variable—the number of neighbouring farms within a certain range. We apply this approach to Norwegian farm census data for the period 1996 to 2015. Overall, we consider four production specialisations and seven size classes generating 15 farm groups, including a residual and an exit farm group in a region. This allows us to simultaneously analyse farm structural change in terms of changing production orientation as well as exit decisions. A simulation experiment of a changing number of neighbouring farms gives us concrete advice as to how this variable influences the farm structure.

Results show that the relative importance of the different variable sets is comparable to that which is found by Neuenfeldt et al. (Neuenfeldt *et al.*, 2019). Differences exists, however, in particular with regard to the explanatories of farm manager age and population density, which have not been selected when applying the dimension reduction forward selection, which indicates insignificancy. The impact of population density on farm structures might be captured by spatial variables and by the regional units, stratified by agrarian and administrative zones. Further, at least for exit rates of farms, population density has mixed effects with respect to farm exits (Foltz, 2004; Glauben, Tietje and Weiss, 2006; Landi *et al.*, 2016). That the age of a farmer has not been selected as an explanatory variable can be explained due to its contrary effects (Vroege *et al.*, 2020) on farm exits. Farm managers who have been in the business for longer periods of time have more experience from which to react to changing conditions, but of course the probably increases when approaching retirement. To better account for this, farm succession is needed, but was not available in this study.

In the Appendix, Table A1 shows the heterogenous distribution of the farm groups among the agrarian zones in Norway. For clarity, we dropped the inactive and residual farm group from the Table. One can see that the specialist dairying farm groups and crops combined are almost always represented in all agrarian zones, whereas specialist cereals farms are mostly active in only a few agrarian zones. In correspondence to the high fit of the estimated farm group models, the strategy to intersect the administrative and agrarian zones in order to build the regional basis of the analysis shows the high interrelatedness between the development of farm groups among the regions and enables concentration of the analysis and discussion on farm groups.

Most of the structural change of the farms can be explained by the past farm structures and, to a smaller extent, by factors such as subsidies, natural conditions, macro variables and prices. This is not surprising, as Norwegian agriculture is highly subsidised and farm structural changes are less dynamic. This leads also to relatively stable shares for certain farm groups, and hence a higher explanatory contribution from past farm structures in the model, even though the total farm number is declining.

The extension by considering neighbouring effects gained additional explanatory power for the model. We tested three radius distances for deriving the spatial location indicator to describe the density of surrounding farms. The location variable with the radius of 10km was selected in a forward selection of being significant for explaining structural change for four farms groups. A larger radius seems to be less relevant.

When we use the model to project into the future of 2025 from 2015, we observe that larger farm groups (with respect to SO) are increasing their share relative to smaller ones, even if the number of total farms is declining. In the context of a sensitivity analysis with two scenarios, in varying the farm density, we found that most farm groups are negatively affected (reducing the absolute and relative size), when the density of the surrounding farms declines and spill-over effects and neighbouring cooperation become less possible. For the scenario of increasing the density of surrounding farms, the results are almost mirrored.

Our results face some limitations. Regarding the explanatory variables, one shortcoming is the missing information on farm income, as this is not collected in the census, and not available from other sources for long-time series, such as the census. Additionally, off-farm income, part-time farming or other gainful activities might increase the model quality to explain particular farm groups with a smaller farm size. As in Neuenfeldt et al. (Neuenfeldt *et al.*, 2019), our estimates may be affected by regional heterogeneity in social capital as well as formal and informal land market institutions, which we were not able to fully control in our estimations, partially also due to the unavailability of data. We could derive other variables that count the number of neighbouring farms, distinguishing between nearby farms that have similar and different demands to their surrounding area; or we could count not only the numbers of neighbouring farms within a certain range but also another farm as a neighbour, when this farm is located within a certain commuting range.

Due to the proposed extension in this paper towards absolute farm number and the exit group, we could now exploit the use of the estimated farm structural change model in the context of mathematical programming supply models for policy impact analyses, such as the Agrispace model (Mittenzwei and Britz, 2018).

3.7. Annex Data Availability Statement

The regionalised data set finally used for the MCI approach can be provided.

The single different data sources are obtained as follows.

The Norwegian farm structure survey data and deducted subsidy payments have been provided by Hugo Storm and Klaus Mittenzwei. Generally, the Norwegian farm structure survey data can be obtained from https://data.norge.no/datasets?opendata=true&theme=GOVE&losTheme=naring%2Flandbruk. Filter for Open data; Business – Agricultural sector; Government and public sector. The Norwegian name of the data sets is: 'Produksjons- og avløsertilskudd til jordbruksforetak – søknadsomgang'.

CAPRI database (2017). Database for prices—unit valued price (UVAP). COCO2: The Complete and Consistent Data Base (COCO) for the national scale. The finishing step estimates consumer prices, consumption losses, and some supplementary data for the feed sector (by-products used as feedstuffs, animal requirements on the MS level, contents and yields of roughage). Both tasks run simultaneously for all countries and build on intermediate results from the main (COCO1) part of COCO, such as human consumption and processing quantities. https://www.capri-model.org/dokuwiki_help/doku.php?id=getting_started_with_capri for data and https://www.capri-model.org/dokuwiki_help/doku.php?id=the_capri_data_base for explanation.

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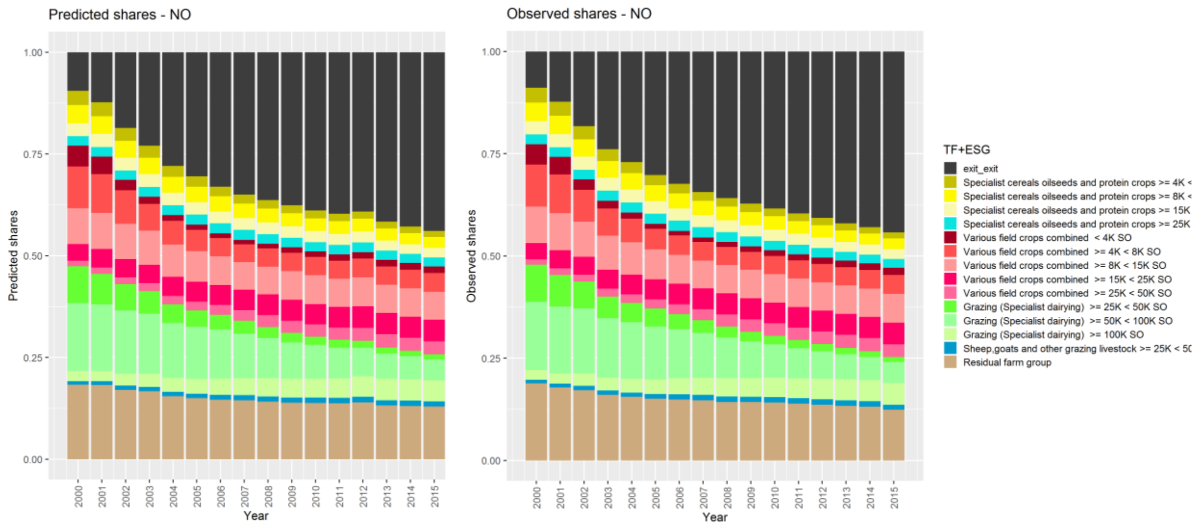
3.8. Appendix



(a) (b)

Figure A1. Predicted (a) and observed (b) farm group shares for Norway

Source: Own contribution.

Table A1. Average farm group shares for the agrarian zones in Norway.

	Agrarian zones							
Farm group	**1**	**2**	**3**	**4**	**6**	**7**	**8**	**9**
Specialist cereals (4K - 8K SO)	0.5	4.1	1.6	1.1	0	0	0	0
Specialist cereals (8K - 15K SO)	1.2	7.2	2.5	1.7	0.1	0	0	0
Specialist cereals (15K - 25K SO)	0.6	7.2	1.8	1.3	0.1	0	0	0
Specialist cereals (25K - 50K SO)	0.4	6.8	1.8	0.9	0	0	0	0
Crops combined (- 4K SO)	2.6	0.9	1.8	1.3	2.2	1.7	2.6	5.5
Crops combined (4K - 8K SO)	4.9	2.2	6.2	4.7	6.5	4.7	4.8	6.8
Crops combined (8K - 15K SO)	6.6	3.7	7.7	8	9.4	9.1	7.1	11
Crops combined (15K - 25K SO)	5.2	2.9	4.6	7.3	6.4	7.4	5.8	4.6
Crops combined (25K - 50K SO)	3.3	2	2.2	4.7	3.6	0	2.4	6.3
Specialist dairying (25K - 50K SO)	0.7	0.2	0.9	1.4	2.4	1.6	0.8	0
Specialist dairying (50K - 100K SO)	5.2	1.6	3.2	7.7	7.2	6.4	5.7	4.6
Specialist dairying (100K SO)	8.5	3.4	3.2	6.6	5.4	4.6	4	4.6
Other grazing livestock (25K - 50K SO)	1.3	0.5	1.5	1.3	1.9	0.3	1.1	0

Source: Own contribution.

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4. ESTIMATING THE IMPACT OF FARM-SPECIFIC PAYMENT RATES ON SUPPLY AND FARM STRUCTURAL CHANGE

4.1. Introduction

The agricultural policies of the EU (CAP) and Norway make increasingly use of agricultural policies that lead to heterogenous payment rates per eligible unit (e.g., animals, farmed land) for production activities and farms at the regional level. Such non-uniform payment rates are a challenge for many agricultural sector models as those models frequently assume regionally homogenous production activities, and hence regionally uniform payment rates. Hence, this research addresses the impact of farm-specific payment rates on supply (in the form of activity levels) and farm structural change.

We use the Agrispace model to address this research question as this model covers the full population of active farms in Norway. Norway is chosen as a case study as the countries' agricultural policies are characterized by a wide range of payments with payment rates that differ by region and by farm size making them heterogenous or farm-specific.

4.2. Model description of Agrispace

Agrispace is a recursive-dynamic and spatial multi-commodity model used for ex-ante policy analysis for the agricultural sector in Norway (Mittenzwei and Britz 2018). The model is based on the standard approach of competitive markets, profit maximizing producers and utility maximizing consumers. The agricultural sector is assumed to be small and open where prices for international food commodities and prices for inputs outside the sector are fixed. Markets for agricultural inputs and outputs are cleared resulting in regional prices and inter-regional trade flows.

The model distinguishes 32 regions that are homogenous with respect to payment rates and natural conditions to ensure very similar crop yields. Each region is divided into 4 to 16 clusters of individual farms which are modelled by aggregate production and factor supply functions. The farm clusters are derived by statistical analysis from the entire population of 42,180 farms applying for subsidies in the 2014 calendar year. The model differentiates 19 agricultural products and 6 input categories. Product-specific technology of each farm cluster is modelled by nested constant elasticity of substitution (CES) production functions. Production activities compete at the regional level for a composite commodity comprised of capital and labor, and three land categories. The farm cluster's total supply of capital and labor is modelled through a linear relationship that depends on average returns and on-farm and off-farm prices.

The regional land market consists of explicit land supply functions and implicit demand functions from the farm clusters. Land is distributed to the farm clusters implying that land markets are not perfect as returns between the cluster farms can vary. Feed demand differentiates various types of feed inputs such as soy cake, and cereals. Raw milk is processed into different dairy products such as fresh milk, cheese, butter, and milk powder with endogenous margins. For all other products, fixed processing margins apply.

Structural change happens through on and off-farm changes in labor and capital and competition in land markets between farm groups. Simulated changes in output quantities and land use at the farm cluster level are mapped in each year into each single farm. The mapping between the markets, farm clusters, and single farms ensures consistency between micro level and the partial equilibrium model results at the sectoral level. Farm exit depends on a farm size specific profit cut-off level and a stochastic component. The profit cutoff accounts for the observation that small farms and different production often receive lower returns on labor and capital. The model randomly disturbs the cut-off level for each farm to reflect non-economic impacts (e.g., accidents, illness or unexpected off-farm opportunities). Annual changes in profits enter the standard deviation of the stochastic term. A drop (or increase) in farm profit increases (or decreases) the standard deviation and thus increases (or decreases) the probability of a farm exit. In a final step, changes in production and land resulting from farm exit are mapped back to the cluster level.

Agrispace considers commodities as homogenous, such that price differences in space depend on transport margins and policy instruments. The model set-up reflects spatial arbitrage, i.e., price differences between two regions are restricted to the bi-lateral per unit transport and transaction costs. Semiflexible functional forms ensure global adherence to regularity conditions and allow consistent welfare analysis. A generalized Leontief (GL) expenditure system drives final demand. It has the advantage that curvature can be easily imposed globally. The GL system is based on indirect utility functions that depend on consumer prices and income, and it allows for own and cross-price effects. The model distinguishes the welfare of consumers, producers (including the food industry), owners of agricultural inputs (e.g., labor, land, and capital), and taxpayers. Farmers who own their land and capital are both producers and owners of agricultural inputs.

Agrispace is coded in GAMS (General Algebraic Modelling System). CONOPT is used for the Bayesian based parameter calibrations, while the market model is solved in PATH. A Graphical User Interface allows steering the model and results exploitation, which is implemented in GGIG (GAMS Graphical Interface Generator).

4.3. Proposed indexes to measure the heterogeneity of farm-specific payment rates

We propose two indexes for the heterogeneity or specificity of farm-specific payment rates for production activities and farm numbers at the regional level. These indexs are implemented and tested in Agrispace.

The two proposed indexes are defined as (1) the relative difference between the largest and the lowest per-unit payment for a given production activity in a given region, and (2) the standard deviation of the distribution of payment rates per activity and region. More technically, nine payment recipients are defined: cereals (GRCL), other arable crops (OACR), vegetables (VEGE), fruits (FRUT), gras (GRFD), cattle (COWS), sheep and goat (SHGT), pigs (PIGS) and poultry (PLTY).

```
set PaymRecep Main recipients of payments
 /
    GRCL   "Cereals"
    OACR   "Other arable crops"
    VEGE   "Vegetables"
    FRUT   "Fruits"
    GRFD   "Gras fodder"
    COWS   "Cattle"
    SHGT   "Sheep and goat"
    PIGS   "Pigs"
    PLTY   "Poultry"
```

Norwegian agriculture has a large variety of acreage payments, animal payments and output payments for horticulture, milk, meat, and eggs. The payment amounts for the various production activities are allocated to the respective payment recipient. For instance, payments for dairy cows (DCOW), suckler cows (SCOW), calves (CALV), cow's milk (CMLK) and beef (BEEF) are allocated to the payment recipient cattle (COWS). For each of the payment recipients, per unit payment rates are calculated at farm level by dividing the payment amount per payment recipient by the payment recipient level:

```
* Payments per farm and payment recipient
  p_result(rn,"",curFarm,"paym",PaymRecep,%1)
    = sum((paymtype,poact)$(payComb(paymType,poact,"") and PaymRecep_to_poact(PaymRecep,poact)),
          paymentPerType(rn,curFarm,paymtype,poact,%1));

* Payment recipient level
  p_result(rn,"",curFarm,"levl",PaymRecep,%1)
    = sum(poact$PaymRecep_to_poact(PaymRecep,poact), p_result(rn,"",curFarm,"levl",poact,%1));

* Per unit payment per farm and payment recipient
  p_result(rn,"",curFarm,"PerUnitPaym",PaymRecep,%1) $ p_result(rn,"",curFarm,"levl",PaymRecep,%1)
    = p_result(rn,"",curFarm,"paym",PaymRecep,%1) / p_result(rn,"",curFarm,"levl",PaymRecep,%1);
```

where $p\_result(rn,\text{""},curFarm,\text{"paym"},\text{PaymRecep},\%1)$ is the payment amount per payment recipient for the current farm, $p\_result(rn,\text{""},curFarm,\text{"levl"},\text{PaymRecep},\%1)$ is the payment recipient level for the current farm, and $p\_result(rn,\text{""},curFarm,\text{"PerUnitPaym"},\text{PaymRecep},\%1)$ is the per-unit payment per farm and payment recipient. The set *paymtype* contains the direct payments schemes available in Norwegian agricultural policies, *poact* is the set of production activities, and the set *payComb(paymType,poact)* links payment schemes and eligible production activities.

Based on the per unit payments per farm and payment recipient, a couple of parameters are calculated before the two indexes are derived.

```
* Payment degressivity index per region and payment recipient
  p_result(rn,"","","PDIMax",PaymRecep,%1)
    = smax(curFarm$rn_f(rn,curFarm), p_result(rn,"",curFarm,"PerUnitPaym",PaymRecep,%1));
  p_result(rn,"","","PDIMin",PaymRecep,%1)   '
    = smin(curFarm$(rn_f(rn,curFarm) $ (p_result(rn,"",curFarm,"PerUnitPaym",PaymRecep,%1) > 0)),
         p_result(rn,"",curFarm,"PerUnitPaym",PaymRecep,%1));
  p_result(rn,"","","PDICount",PaymRecep,%1)
    = sum(curFarm$(rn_f(rn,curFarm) $ p_result(rn,"",curFarm,"PerUnitPaym",PaymRecep,%1)), 1);
  p_result(rn,"","","PDIMean",PaymRecep,%1) $  p_result(rn,"","","PDICount",PaymRecep,%1)
    = sum(curFarm$rn_f(rn,curFarm), p_result(rn,"",curFarm,"PerUnitPaym",PaymRecep,%1))
                                 /  p_result(rn,"","","PDICount",PaymRecep,%1);
```

PDIMax (PDIMin) is the highest (lowest) per unit payment for a specific payment recipient *PaymRecep* in a given region *rn*. *PDICount* yields the number of farms in region *rn* with at least one unit of a given payment recipient *PaymRecep*. *PDIMean* calculates the mean *rn* for each payment recipient *PaymRecep* in region. These parameters allow for the calculation of the two indexes of the heterogeneity or specificity of payments rates:

```
* Payment degressivity index MaxMin per region and payment recipient
  p_result(rn,"","","PDIMaxMin",PaymRecep,%1) $ p_result(rn,"","","PDIMin",PaymRecep,%1)
    = p_result(rn,"","","PDIMax",PaymRecep,%1) / p_result(rn,"","","PDIMin",PaymRecep,%1);

* Payment degressivity index standard deviation per region and payment recipient
  p_result(rn,"","","PDIStdDev",PaymRecep,%1) $ p_result(rn,"","","PDICount",PaymRecep,%1)
    = SQRT( 1/p_result(rn,"","","PDICount",PaymRecep,%1)
      * sum(curFarm$rn_f(rn,curFarm),
          SQR(p_result(rn,"",curFarm,"PerUnitPaym",PaymRecep,%1) - p_result(rn,"","","PDIMean",PaymRecep,%1))));
```

PDIMaxMin is defined as the relative difference between the highest and the lowest per-unit payment rate for payment recipient *PaymRecep* in region *rn*. It can take values including and above one. *PDIStdDev* is the standard deviation of the distribution of per-unit payment rates for payment recipient *PaymRecep* in region *rn*.

The scenarios differ with respect to the degree of the farm-specificity of the payment rates. Farm-specificity in the base year 2014 is set to the index value 100, while zero farm-specificity corresponds to uniform regional payment rates per payment recipient. Scenarios are developed for each 10 per cent step between full farm-specificity and zero farm-specificity. Technically, the payment amount per payment recipient and farm are scaled with the degree of farm-specificity and the remaining payments are distributed with regionally uniform payment rates. For example, a farm-specificity of 60 implies that 60 per cent of base year payments are retained as farm-specific payments with different payment rates across farms, while 40 per cent are distributed as regional payments with identical payment rates for farms in the same region. This is done for all payment recipients. In a sensitivity analysis, the degree of farm-specificity is varied for cows only, while payment farm-specificity is maintained for all other payment recipients.

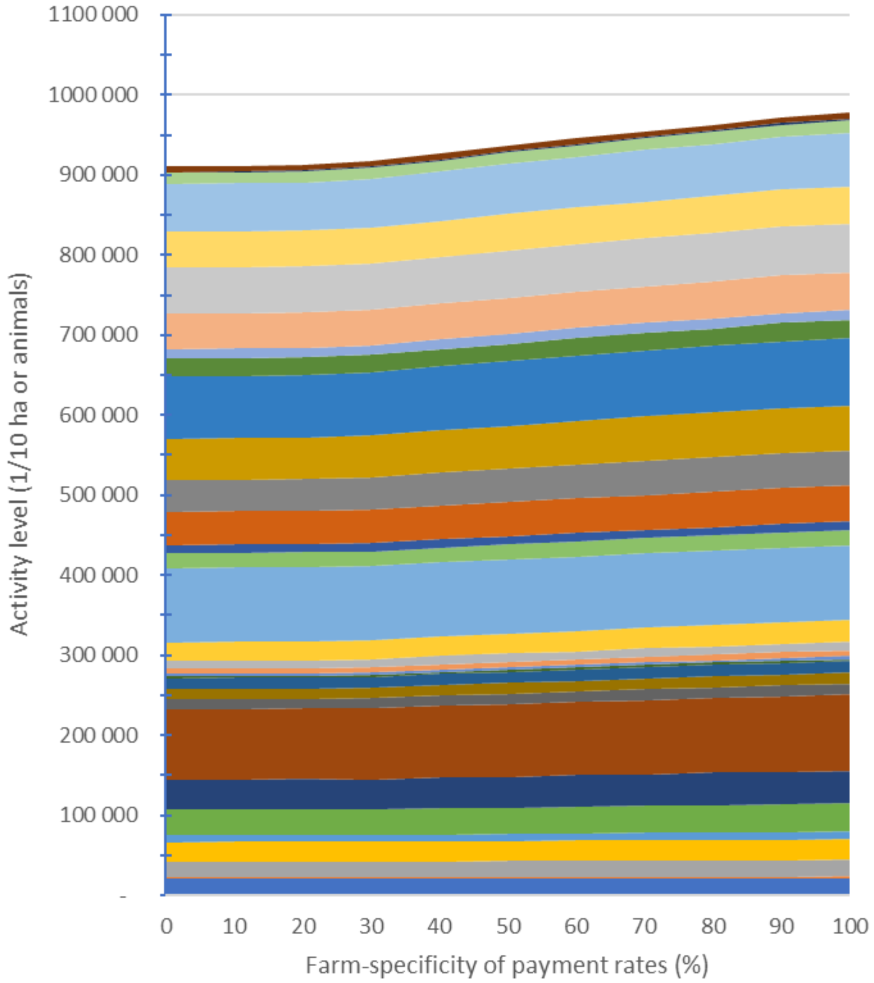

Figure 1. Number of cattle by degree of farm-specificity of payment rates (Base year = 100)

Figure 1 shows an example of the relationship between the activity level and the degree of farm-specificity of the payments. The vertical axis shows the number of cattle. Each horizonal bar indicates one of 32 regions in the model. The total number of cattle decreases from about 965 000 under full payment farm-specificity in the base year to about 900 000 animals under zero payment farm-specificity.

Figure 2 shows an example of the relationship between the number of farms with cattle and the degree of payment farm-specificity and indicates a positive relationship. In other words, the larger the difference in per-unit payments per cattle between the farm with the highest and lowest per-unit payments, the larger the total number of farms. The reason is that payment degressivity counteracts economies of scale at the farm level, reduces the optimal farm size, and maintains a larger number of farms.

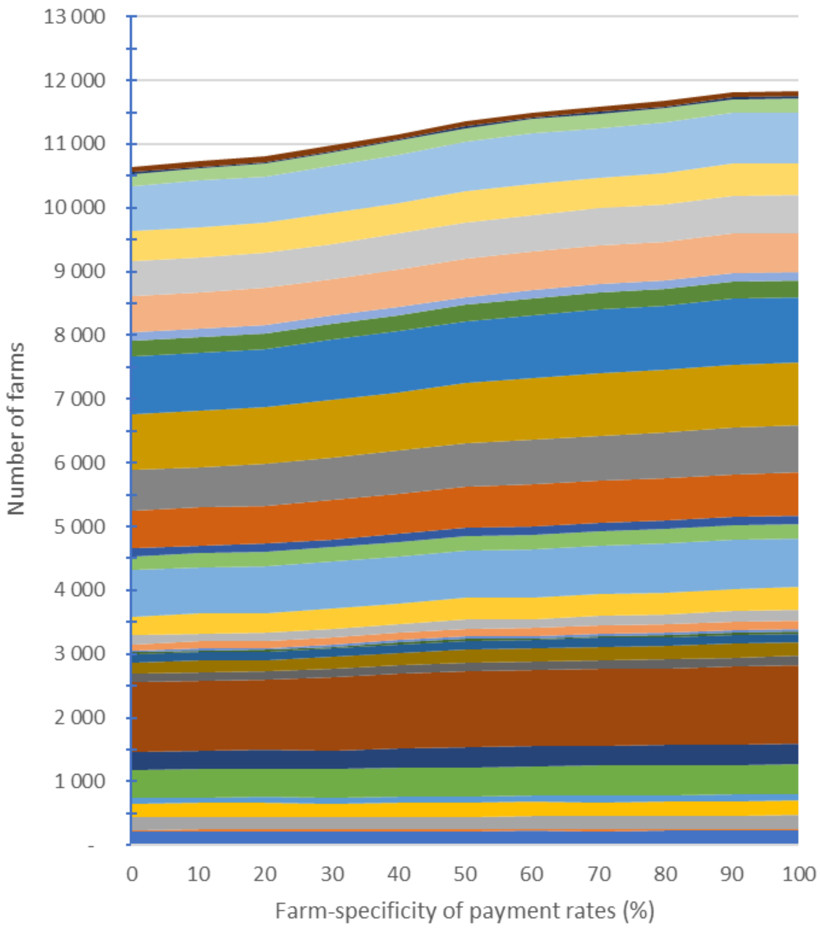

Figure 2. Number of farms with cattle by degree of payment farm-specificity (Base year = 100)

Table 1 shows the values for the *PDIMaxMin* index for all of the 32 regions in the model. Flat regional payments, or zero degree of payment farm-specificity, yields identical payment rates for all farms in a given region so that *PDIMaxMin* equals 1. *PDIMaxMin* increases in general with a increase in payment farm-specificity. According to table 1, region 112205 has the largest difference between the farms with the highest and lowest per-unit farm-specific payment rates. The per-unit payment rate of the farm with the highest payment rates is 9.2511 times higher than the per-unit payment rate of the farm with the lowest payment rate in the base year case of full payment farm-specificity. The region 195207 has the least variation in payment rates with a *PDIMaxMin* of 2.1384. The weighted regional average has a *PDIMaxMin* index of 6.4729 under full payment farm-specificity.

Table 2 shows the corresponding values of the *PDIStdDev* index. They also tend to be positively related to the degree of payment farm-specificity.

Table 14. PDIMaxMin index for farm-specificity for cattle for all 32 regions in the model by degree of payment farm-specificity

Region	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
011101	1.0000	1.2517	1.7413	2.2021	2.3615	3.0408	3.4600	3.8830	3.7724	4.7405	5.1751
021101	1.0000	1.1517	1.3219	2.1659	1.7113	1.8840	2.0088	3.6591	4.0220	2.5558	4.7356
021103	1.0000	1.4870	2.0500	2.7085	2.8151	3.9179	4.5206	5.1299	5.7459	5.1974	6.9986
041101	1.0000	1.2999	1.6978	2.1268	2.8401	3.3015	3.7635	4.2261	4.6892	5.1529	5.6171
041203	1.0000	1.3665	1.8225	2.6500	3.2414	3.1119	4.4937	5.1572	5.8478	6.5671	7.3169
041205	1.0000	1.3756	1.5759	1.8931	2.6649	3.1055	3.5566	3.1840	3.4734	4.9763	5.4732
051103	1.0000	1.3036	1.6962	2.1554	2.5058	3.0070	3.4558	3.9226	4.4084	4.9146	5.4425
051205	1.0000	1.5934	1.7482	2.9951	3.7072	4.7305	5.2100	6.4182	7.3103	8.2370	9.2005
061101	1.0000	1.2267	1.4811	1.7686	2.2224	2.4505	2.8121	3.1018	3.2805	3.5508	3.5138
061205	1.0000	1.2391	1.8190	2.6459	3.1849	4.2714	4.2486	5.5400	6.1660	6.7867	7.4019
071101	1.0000	1.3490	2.2397	2.2148	2.6467	3.0613	5.0709	3.8941	4.3123	4.7317	5.1523
081103	1.0000	1.1607	1.3358	1.5275	1.6920	1.8463	1.9940	2.1356	2.2715	2.4019	2.5273
081203	1.0000	1.2035	1.4306	1.9247	1.8968	2.5126	2.7984	3.0790	3.3546	3.6252	3.8911
081205	1.0000	1.3242	1.4578	2.0544	2.0042	3.6416	3.0893	4.6754	5.1876	5.6967	6.2026
092205	1.0000	1.2398	1.8054	2.6654	3.2399	3.8267	4.4192	6.0922	6.8720	7.6660	6.9074
102205	1.0000	1.3810	1.8676	2.3128	2.5947	3.8167	5.5466	6.4149	7.6380	8.6301	9.2511
112102	1.0000	1.5913	2.2857	3.1128	3.9214	4.7059	4.3060	6.3468	7.2055	6.5078	7.2178
112203	1.0000	1.4497	1.9645	2.5399	2.4945	3.5759	4.0967	4.6194	5.1439	5.6705	6.1989
112105	1.0000	1.3346	1.7091	2.0901	2.4413	2.8180	3.1262	3.4603	3.7889	4.1123	4.4304
112205	1.0000	1.6512	2.4095	2.1902	3.9787	4.9401	5.7801	6.3867	7.5169	8.4150	9.3337
123205	1.0000	1.3962	1.8707	2.2979	2.8593	3.2932	3.8372	4.5661	5.2103	5.8986	6.6355
143205	1.0000	1.4328	1.9411	2.4361	2.9485	3.4792	4.0294	4.6000	5.1922	5.8073	6.4465
153205	1.0000	1.3795	1.8189	2.2556	2.6835	3.1189	4.6729	5.3235	5.9770	6.6264	7.3131

164104	1.0000	1.2251	1.5393	1.8493	2.6924	3.0679	3.4940	4.0067	4.3592	4.9054	5.2423
164204	1.0000	1.2148	1.4634	1.7185	1.9655	2.2165	2.4714	2.7305	2.9938	3.2614	3.5334
164205	1.0000	1.2830	1.6093	1.9300	2.1579	2.5664	2.8896	3.2163	3.3654	4.2523	4.6332
174104	1.0000	1.4022	1.8691	2.4176	2.9181	3.4162	3.9220	4.4359	4.9579	5.4882	6.0271
174205	1.0000	1.3717	1.8021	2.2475	2.6747	3.1077	3.1064	3.9918	4.4431	4.9008	4.6103
185206	1.0000	1.3214	1.7047	2.1604	2.5235	4.8218	5.6660	6.5401	7.4457	8.3847	5.3746
195206	1.0000	1.2777	1.5711	1.8836	2.1861	2.4581	2.7617	3.1187	3.4382	3.7622	4.0909
195207	1.0000	1.1177	1.2383	1.3263	1.4711	1.5377	1.6986	1.8104	1.9210	2.0303	2.1384
205207	1.0000	1.1360	1.2756	1.4115	1.5390	2.1396	1.8012	2.5811	2.7989	2.2017	3.2288
Weighted average	1.0000	1.4076	1.8452	2.3763	2.9226	3.6675	4.2019	4.9697	5.5916	6.1290	6.4729

Table 15. PDIStdDev index for farm-specificity for cattle for all 32 regions in the model by degree of payment farm-specificity

Region	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
011101	782	776	812	843	885	952	1015	1051	1138	1174	1229
021101	1042	1048	1091	1065	1167	1276	1265	1513	1486	1629	1716
021103	691	701	706	715	761	833	891	954	981	1062	1135
041101	552	571	575	595	639	698	724	790	829	882	946
041203	1064	1080	1088	1152	1227	1322	1443	1471	1554	1659	1743
041205	527	539	555	591	627	659	723	743	790	829	901
051103	439	448	450	468	509	562	578	628	661	721	754
051205	471	472	481	523	557	616	665	711	746	785	860
061101	705	736	722	755	816	845	906	977	991	1079	1121
061205	691	713	742	764	830	844	979	988	1096	1116	1219
071101	796	809	848	847	888	960	1047	1089	1174	1219	1277
081103	950	953	943	1005	1053	1088	1181	1199	1320	1281	1412
081203	785	771	731	703	845	891	990	973	1062	1160	1180
081205	902	923	881	963	946	1014	1090	1199	1270	1325	1489
092205	606	597	589	667	659	738	776	880	960	1003	954
102205	414	407	425	460	503	509	581	625	741	769	793
112102	213	206	220	229	262	286	305	342	378	399	420
112203	337	355	372	374	419	465	484	539	577	596	664
112105	547	557	577	590	602	672	744	783	819	879	912
112205	543	567	574	584	663	695	756	822	863	926	989
123205	885	919	909	972	1040	1092	1155	1223	1300	1391	1465
143205	728	738	744	803	883	916	969	1012	1103	1139	1230
153205	442	450	454	486	515	564	609	638	693	731	796
164104	294	319	321	325	343	393	389	451	470	508	555

164204	276	317	303	351	391	380	427	469	473	502	589
164205	491	484	502	524	576	598	680	710	753	783	843
174104	386	396	405	422	457	489	521	559	588	628	671
174205	347	349	357	389	414	451	493	518	567	590	622
185206	609	605	630	665	714	752	832	863	916	974	1009
195206	1230	1269	1262	1333	1424	1513	1598	1669	1732	1847	1952
195207	1940	1976	1785	1979	1983	2079	2265	2391	2545	2465	2721
205207	637	694	657	707	772	907	978	967	1022	1086	843
Weighted average	520	528	537	568	613	657	708	752	804	849	904

The values of the PDIMaxMin and the PDIStdDev indexes can be used to calculate elasticities measuring the effect of a relative change in the respective index on the relative change in the activity level:

$$\varepsilon = \frac{\frac{LEVL_1 - LEVL_0}{LEVL_0}}{\frac{PDI_1 - PDI_0}{PDI_0}}$$

where $LEVL_0$ and $LEVL_1$ denotes the activity level (animal numbers or area), and PDI_0 and PDI_1 denote the PDI index (PDIMaxMin or PDIStdDev) for two levels of payment farm-specificity indexed 0 and 1.

Table 3 shows the elasticities for all payment recipients for the range zero and full payment farm-specificity with respect to the activity level. For instance, the number of cattle increases with 0.0134 per cent for a one per cent point increase in the value of the PDIMaxMin index.

Table 16. Elasticities for the range between zero and full payment farm-specificity with respect to activity level by payment recipient and PDI index

Payment recipients (Activity level)	PDIMaxMin	PDIStdDev
Cereals (GRCL)	0.0163706	0.1138098
Other arable crops (OACR)	-0.0527054	1.0017450
Vegetables (VEGE)	-0.0002655	-0.0035681
Fruits (FRUT)	0.1190224	1.0419403
Gras (GRFD)	0.0639230	-1.8017413
Cattle (COWS)	0.0134166	0.0993176
Sheep and goat (SHGT)	-0.0153232	-0.8451711
Pigs (PIGS)	0.0000567	0.0011466
Poultry (PLTY)	-0.0000008	-0.0000105

The elasticities for the PDIMaxMin index vary between -0.0527 (other arable crops) and 0.119 (fruits). There is no clear pattern for the elasticities. The elasticities tend to be larger for crops compared to animals with the exception of vegetables. They are positive and negative within both crops and animals. Farm payment-degressivity is in general higher for ruminants compared to non-ruminants and crops, but this pattern is not immediately reflected in the elasticities. A reason for that may be that the elasticities are calculated based on the successive reduction of payment farm-specificity for all payment recipients at the same time. However, varying the payment farm-specificity for cattle only and keeping full payment farm-specificity for all other payment recipients does not change the broad picture. Table 4 show the elasticities for cattle under these conditions compared to the elasticities under a change of all payment recipients.

Table 17. Elasticities for cattle under different assumptions of payment farm-specificity by ranges between zero and full payment farm-specificity for PDIMaxMin index

	0-100	0-20	20-50	50-80	80-100
All payment recipients	0.013417	0.002594	0.026663	0.052713	0.112217
Only cattle	0.011872	0.004796	0.029086	0.043745	0.095295

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For the full range between zero and full payment farm-specificity, the elasticity for cattle changes from 0.013417 if the payment farm-specificity is changed for all payment recipients to 0.011872 if payment farm-specificity is varied for cattle only. For other ranges, the elasticities do not change significantly. Since payments for cattle are those with highest farm payment degressivity, we expect that corresponding changes for other payment recipients will be similar or even smaller.

Likewise, the values of the PDIMaxMin and the PDIStdDev indexes can be used to calculate elasticities measuring the effect of a relative change in the respective index on the relative change in the number of farms:

$$\varepsilon = \frac{\frac{Farm_1 - Farm_0}{Farm_0}}{\frac{PDI_1 - PDI_0}{PDI_0}}$$

where $Farm_0$ and $Farm_1$ denotes the number of farms with respective payment recipients, and PDI_0 and PDI_1 denote the PDI index (PDIMaxMin or PDIStdDev) for two levels of payment farm-specificity indexed 0 and 1.

Table 5 shows the elasticities for all payment recipients for the range zero and full payment farm-specificity with respect to the number of farms. For instance, the number of farms with cattle increases with 0.0203 per cent for a one per cent point increase in the value of the PDIMaxMin index. The elasticities are highest for farms with fodder production (GRFD) with an elasticity of 0.1240 and lowest for farm with poultry (PLTY) with an elasticity of about zero. As farms with cattle and sheep/goat also have fodder production, the low elasticity for cattle (0.0203) and sheep/goat (0.0017) may be explained with the high elasticity for gras (GRFD). Comparing the elasticities based on PDIMaxMin and PDIStdDev, the elasticities for gras shift sign. This means that the standard deviation decreases with an increase of payment farm-specificity, while the difference between the two farms with the highest and lowest per-unit payment increases.

Table 5. Elasticities for the range between zero and full payment farm-specificity with respect to the number of farms by payment recipient and PDI index

Payment recipients (Number of farms)	PDIMaxMin	PDIStdDev
Cereals (GRCL)	0.0658365	0.5002937
Other arable crops (OACR)	0.0481145	6.9790881
Vegetables (VEGE)	0.0003942	0.0106203
Fruits (FRUT)	0.0721681	1.4578840
Gras (GRFD)	0.1239886	-2.9424374
Cattle (COWS)	0.0203079	0.1540327
Sheep and goat (SHGT)	0.0017467	0.1059934
Pigs (PIGS)	0.0017362	0.0337521
Poultry (PLTY)	-0.0000021	-0.0017160

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4.4. Conclusions

The simulations show that payment farm-specificity, i.e., different levels of per unit payments for eligible animals or crops within a region, matters for the supply of agricultural products as payment farm-specificity affects both structural change (i.e., the number of farms) and activity levels (i.e., the number of animals and farmed area). That is, a change in payment farm-specificity results in a change in activity levels and the distribution of the activity level across farms. The quantitative impact of a change in payment farm-specificity differs for payment recipients with no clear link between the characteristics of the payment recipients and their impact. More systematic simulations with Agrispace or other suitable models would be necessary to shed light on this issue and the importance of implementing payment farm-specificity in agricultural sector models that do not explicitly account for farm structure and structural change and therefore do not allow to directly implement payment farm-specificity.

The described research allows to propose an implementation of these elasticities into agricultural sector models that do not explicitly account for farm structure and structural change such as the CAPRI model. This work will be undertaken in MIND-STEP subtask 5.2.3.

4.5. References

Mittenzwei, K. and Britz, W. 2018. Analysing farm-specific payments for Norway using the Agrispace model. Journal of Agricultural Economics 69(3): 777-793

5. THE IMPROVEMENT OF AN EXISTING LAND MARKET MODEL PROTOTYPE DEVELOPED FOR THE IDM MODEL IFM-CAP

5.1. Introduction

Various models are used to represent land supply, allocation, and markets. The models vary in their level of abstraction, with Computable General Equilibrium (CGE) models being the most abstract, followed by higher resolution Partial Equilibrium (PE) models, and then models with land exchange between farm agents as the most detailed. CGE models use Constant-Elasticity of Transformation (CET) functions to model land competition, and some also include land supply functions and transformation functions between land types. PE models typically use a CGE-type structure to depict production and CET-factor distribution functions to allocate land. Non-economic land cover models use actual land cover maps in a grid representation, and Spatial Land Cover Change models use transition probabilities to predict changes in the total area of certain land cover classes. Finally, Agent Based Models combine spatial competition logic with land cover change algorithms to model land markets.

IFM-CAP land market draw upon land transformation and market mechanisms typically used in general and partial equilibrium models described above. The approach is spatially scalable and therefore able to use more detailed information on farm locations that becomes available in this project.

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5.2. The land market of IFM-CAP

The land market is based on the following assumptions/methodological choices:

- Agricultural land is not fixed, instead agriculture competes with other activities uses such as forestry for land. Those other activities are external to the farm models of IFM-CAP.
- Competition for agricultural land primarily takes place among individual farms that are operating in the same geographical region.
- Decisions on conversion of land between arable and grassland and farm's decision to trade land are simultaneously modelled by a representative land agent interacting with the farms in a geographical region.

From the assumptions above, the model derives a system with two main components: **one regional land market model** and the existing set of single farm models from **IFM-CAP**. The land market handles competition among farms, but also between agriculture and other uses for land and land-transformation between different land use classes. The two components are iteratively linked.

Regional land market agents allow interactions in-between farms or between farms and other sectors supplying or demanding land. Technically, those markets do not require detailed information about farm-specific technology and can therefore be modelled separately from the single farm optimization models. Modelling land markets separately is appealing from a code modularization point of view. If land markets are not activated, the system still functions in the same way as before with land endowments in the individual farm models fixed. Furthermore, modular land markets allow for future methodological extensions of those markets without interfering with the farm models.

The regional land market agent works within geographical regions, we call cells. A cell is an area within which competition for land takes place. The standard spatial resolution of the cells is aligned with available information on the farm's location in administrative regions (NUTS2 or NUTS3). For the present project, we test the delineation of that cell based on the results of the FADN spatial allocation maps, introduced in the next section. Generally, the land within each cell, independent of the delineation, is homogeneous, and all farms in a cell compete with all other farms in the same cell, but not with any farms in neighbouring cells. The land market agent treats arable land and grassland as different goods with their own prices but allows for (costly) transformation into each other and between agricultural and non-agricultural land.

Each single farm model (i.e., FADN data record) represents several farms from the full farm population, as indicated by the farm weight. This implies that the single farms represented by one IFM-CAP farm model are spatially dispersed. In the standard version, it was assumed that they are all entirely contained within one cell. The general modelling setup allows for a more complex alternatives developed in this project to split up the weights and allocate one FADN farm to several different cells to capture land competition and have some reparameterization to capture different land qualities associated with these "subfarms" more appropriately.

The single farm models do not transform land between arable land and grassland, but rather technically interact with the land market agent transforming the land subject to a transformation cost. The transformation cost is based on the biophysical characteristics of the land as defined by the cells.

Since the land market model within each cell is not spatial, it does not specify which hectares of a cell are used for grassland or arable land. However, there is spatial information available on potential yields of grass or (say) cereals. Furthermore, it is reasonable to assume that grass is growing on land that is relatively more suitable to grass considering the opportunity cost of arable crops. This assumption together with land qualities considered to be evenly distributed across the farms in the cell allows to approximate the land transformation costs of the farm models.

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The farms interact with the land agent also to trade land in or out (with or without transformation). The participation in the land market may be triggered by a sufficient difference between the farm's marginal value of land and the land price in the cell. "Sufficient" means to cover a transaction cost associated with the participation in the land market. Each iteration between farms and the land market agent would then determine participations of farms and determine equilibrium transactions among participating farms.

To conclude the following sequence of steps, assuming that the single IFM-CAP model is parameterized based on FADN and calibrated to the observed production program:

- Allocate each FADN farm to a geographical cell (yet to be defined).
- Compute a point-approximation of the land netput functions (arable and grass land) for each cell farm, based on simulation experiments with the models.
- Repeat the following until convergence:
    - Solve cell models at given endowments of grass and arable land
    - Calibrate land netput functions for each cell separately for arable and grassland observing transaction costs and using land netput elasticities and current land rents and quantities.
    - Solve for the land market equilibrium simultaneously considering transformations between land types within cell
    - Update each farm model's land endowments in the cell
- Update farm classifications in the cell

5.3. New delineation of the land market in IFM-CAP

Several approaches have been developed to link farming systems and agricultural holdings to their spatial location at the EU-wide scale. One such approach is the method developed by Kempen et al. (2011), which uses a constraint optimization (CO) approach to link farms in the Farm Accountancy Data Network (FADN) sample to their environmental endowment (climate, soil attributes, etc.) using small-scale spatial units called Farm Mapping Units (FMUs). However, the authors of the study concluded that the prior information used was insufficient to allocate certain farm types and proposed to further develop the spatial unit such that it represents homogenous regions of farming systems rather than single production systems. Shortcomings in this approach have been addressed in subsequent projects, see WP2 Del. 2.7/2.8) conducted by the Joint Research Centre (JRC), Eurocare, and the Thuenen Institute, which have improved the allocation mechanism by using a statistical representation factor to allocate farms to spatial units, using a new spatial unit called the Homogeneous Spatial Unit (HSU) to define FMUs, and integrating data from Eurostat containing information about the share of utilised agricultural area per farm type on a 10km x 10km grid level as an additional constraint in the CO model. Another approach is the method developed by Cantelaube et al. (2012), which uses geographical downscaling to map outputs provided by an economic optimization model called AROPAj by estimating the probabilities of FADN farm groups being in 100 x 100 m grid cells within EU-15 FADN regions. This method is like the one by Kempen et al. (2011), but it allocates farm groups based on altitude zone and crop area shares rather than farms based on their representation factor. Both approaches aim to improve the allocation of farms to spatial units to better understand the relationships between farming systems, agricultural holdings, and the environment in the EU.

5.3.1. Spatial information from FADN

The current spatial downscaling approach, developed in WP2, allows the generation of spatial maps on the variables and indicators based on the latest developed spatial unit, called FSU (see also Deliverable 2.7). The map summarizes the probability and that a certain farm is in a spatial unit and represents the average value of farms estimated to be in an FSU.

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In order to present allocation results at European scale the individual farm data from FADN (data source: EU-FADN – AGRI) have been aggregated to farm types according to their specialization based on the official EU classification illustrated in table 4.

Table 4: Definition of farm types based on EU classification

EU classification			Classification used
1-Digit code	2-Digit code	Label	
1	13	Specialist cereals, oilseed and protein crops	Arable farming
	14	General field cropping	
2	20	Specialist horticulture	Horticulture
3	31	Specialist vineyards	Permanent crops
	32	Specialist fruit and citrus fruit	
	33	Specialist olives	
	34	Various permanent crops combined	
4	41	Specialist dairying	Grazing livestock
	42	Specialist cattle-rearing and fattening	
	43	Cattle-dairying, rearing and fattening combined	
	44	Sheep, goats and other grazing livestock	
5	50	Specialist granivores	Granivores
6	60	Mixed cropping	Mixed cropping
7	71	Mixed livestock, mainly grazing livestock	Mixed livestock
	72	Mixed livestock, mainly granivores	
8	81	Field crops-grazing livestock combined	Mixed crops and livestock
	82	Various crops and livestock combined	

The results are compared with the FSS data to validate the used allocation procedure. The results in figures 3-10 show the percentage of UAA covered by each of the farm types in the corresponding HSUs. The results of the extended constraint programming model show that for the farm types without

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livestock (Arable farming, Horticulture, Permanent Crops, Mixed Cropping) the spatial distribution is very similar to the FSS data (see figure 3-6). However, results for arable farms are underestimated in Austria and Scotland.

Figure 3: Arable farming

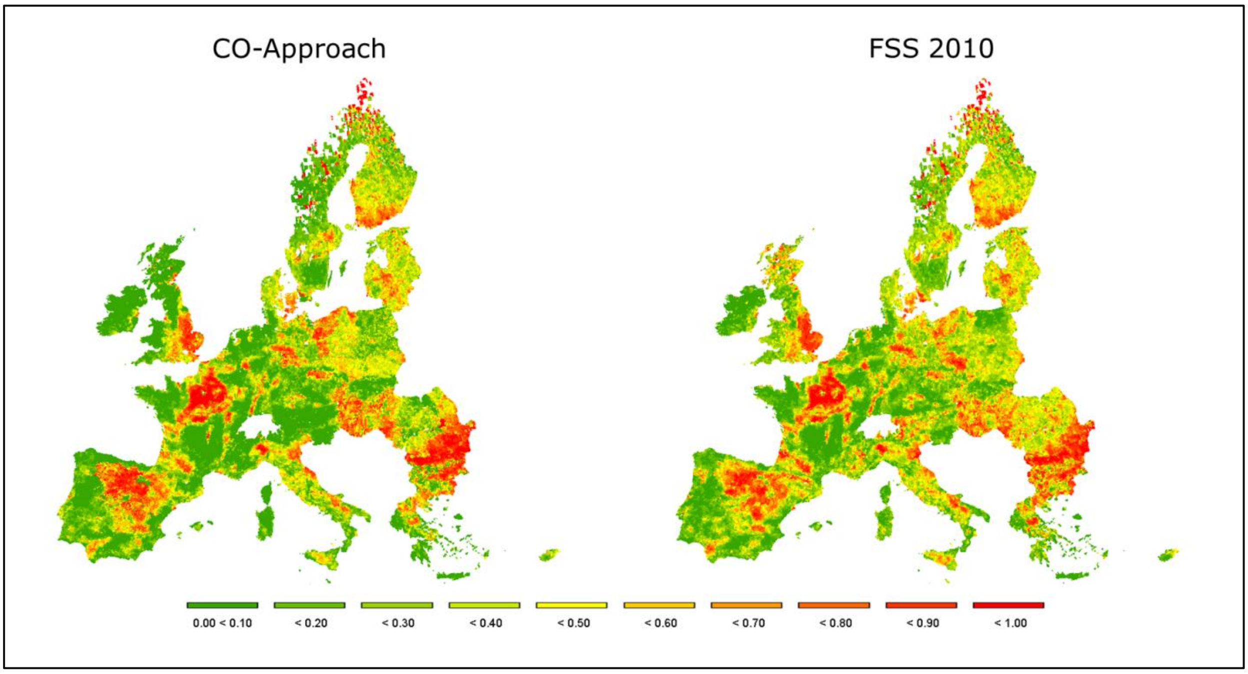

Figure 4: Permanent crops

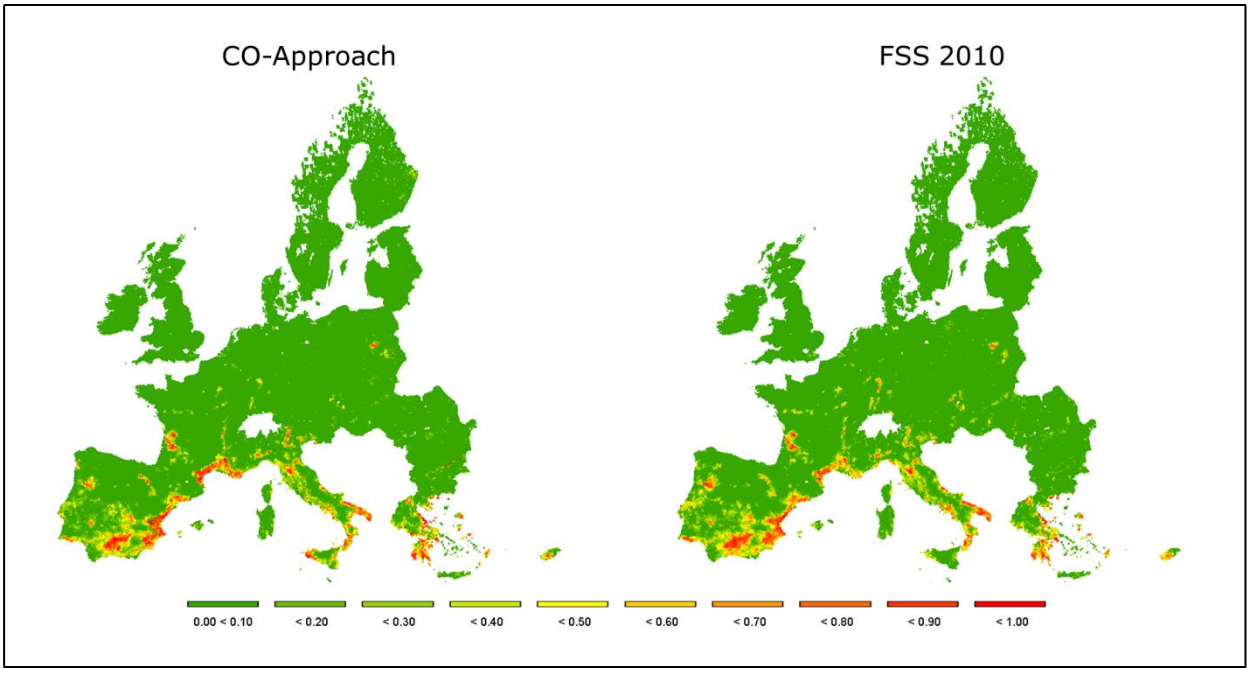

Figure 5: Horticulture

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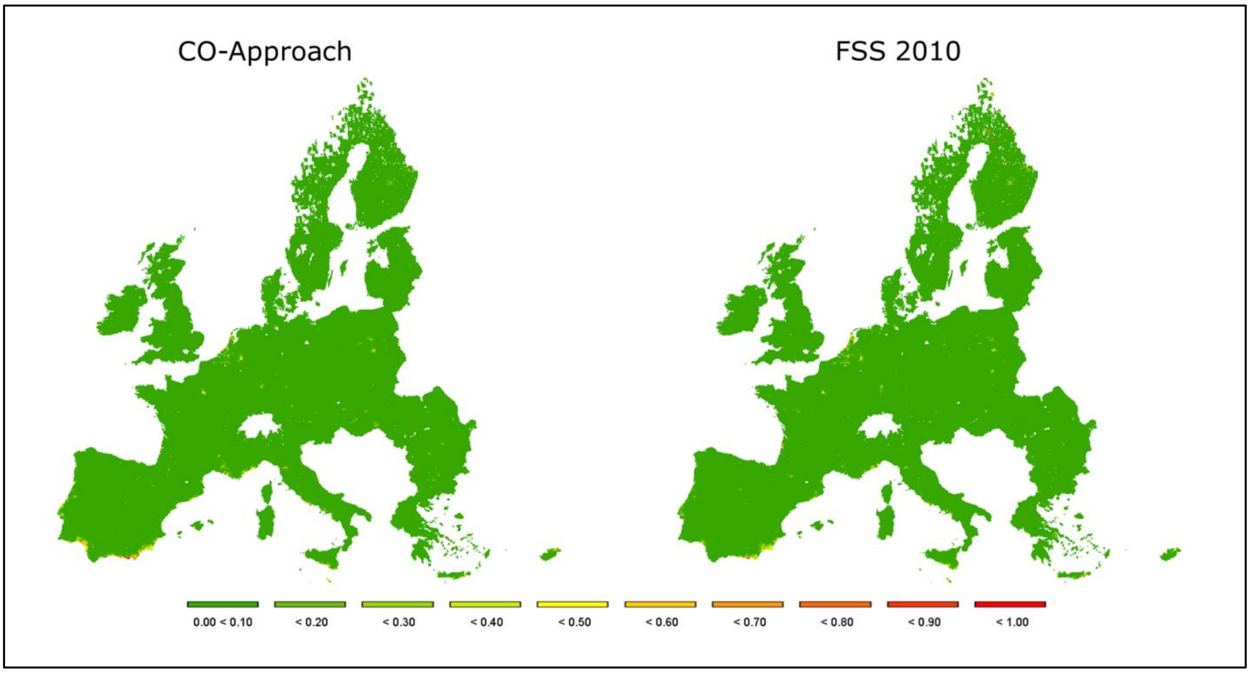
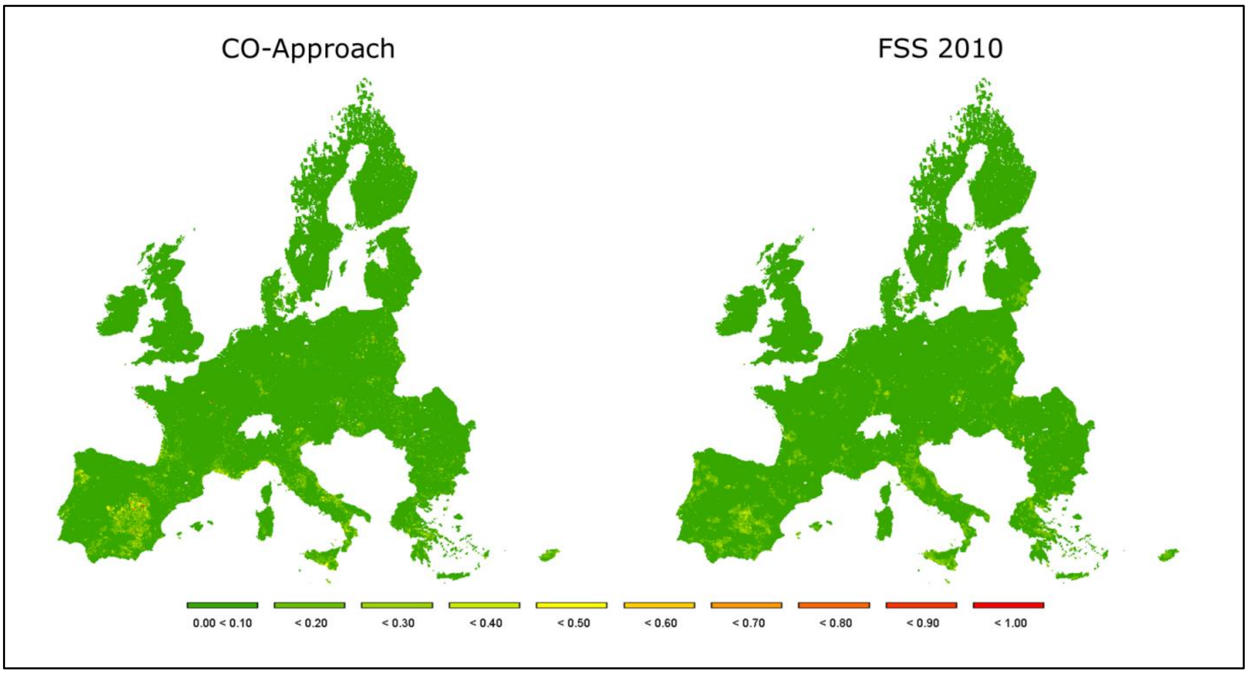


Figure 6: Mixed cropping



In Figure 7-10 it can be seen that particularly for the farm types with low land-dependency and hence with low UAA per farm (e.g., granivores, grazing livestock) for which the allocation procedure in Kempen et al. 2011 provided weak results the usage of prior information about the share of UAA per farm type on a 10km² grid level resulted in a very similar distribution as in FSS. Particularly for granivore farms using grid data as priors can improve the results of environmental analysis in the EU as they account for a significant share of emissions from animal production.

Figure 7: Granivores

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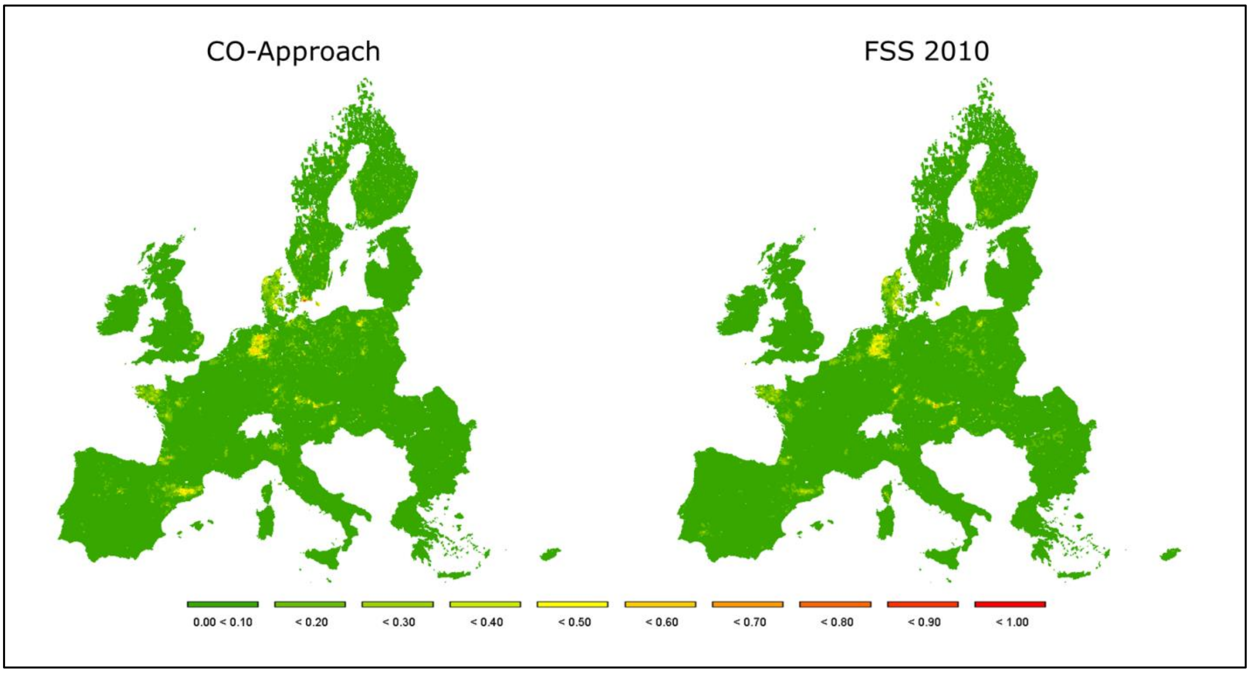

Figure 8: Grazing livestock

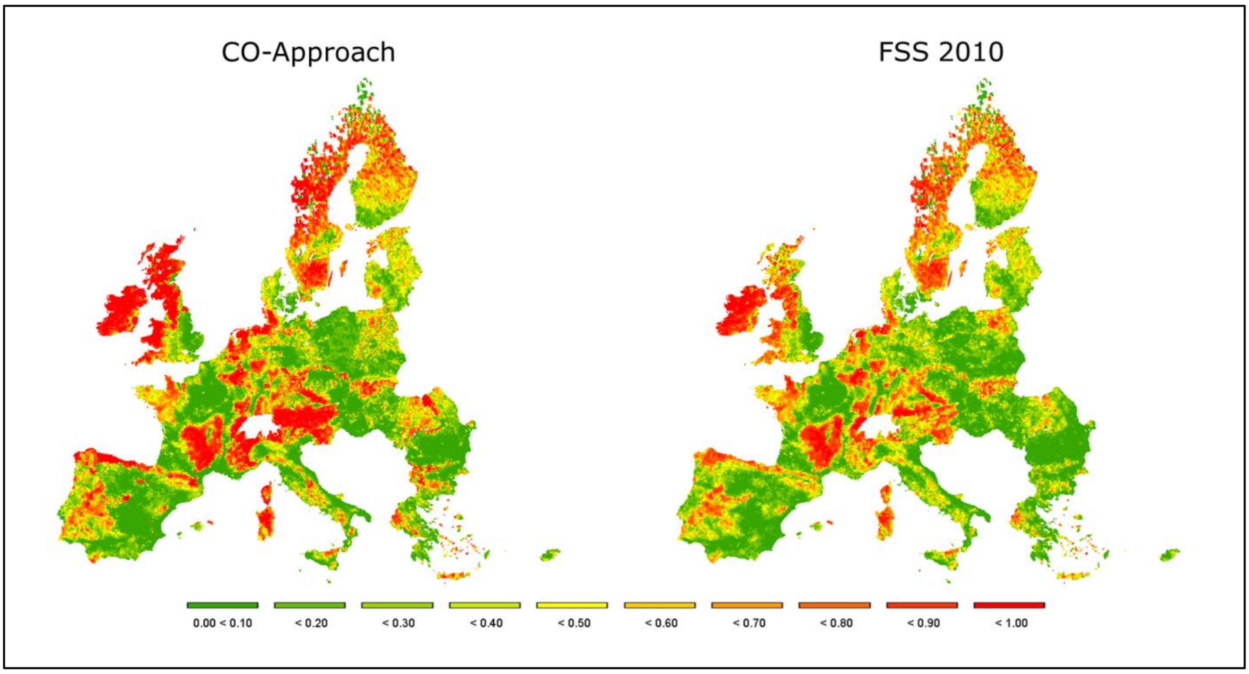

Figure 9: Mixed livestock

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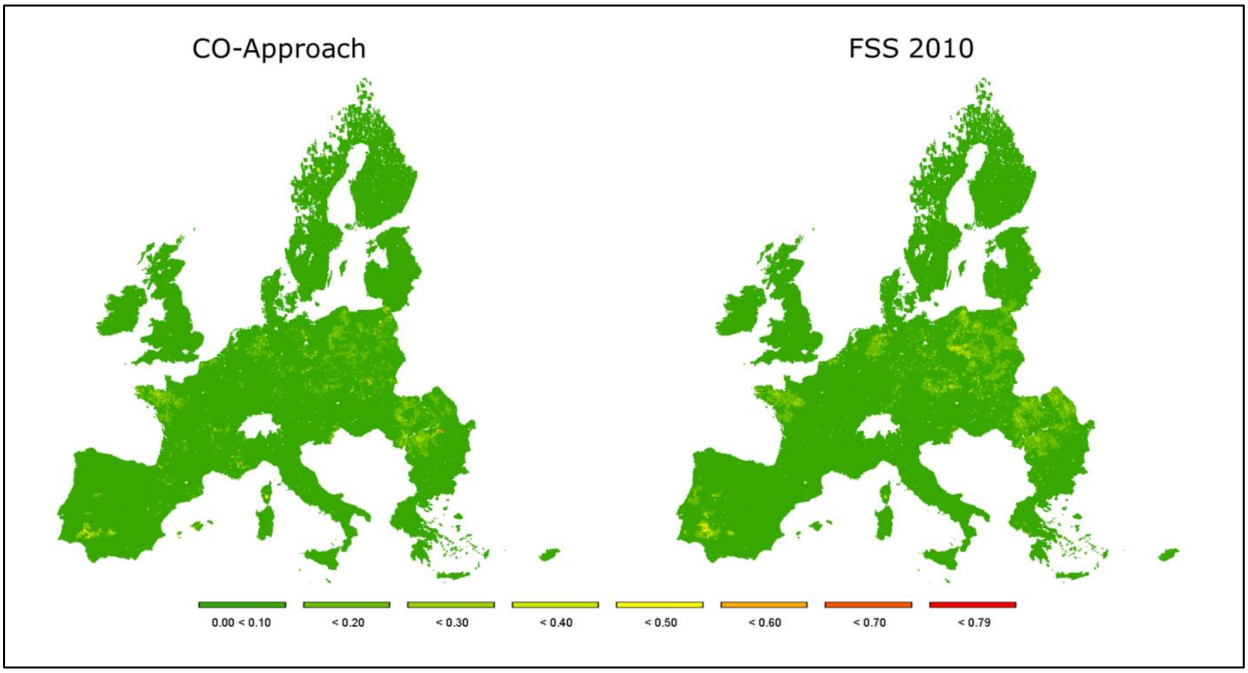
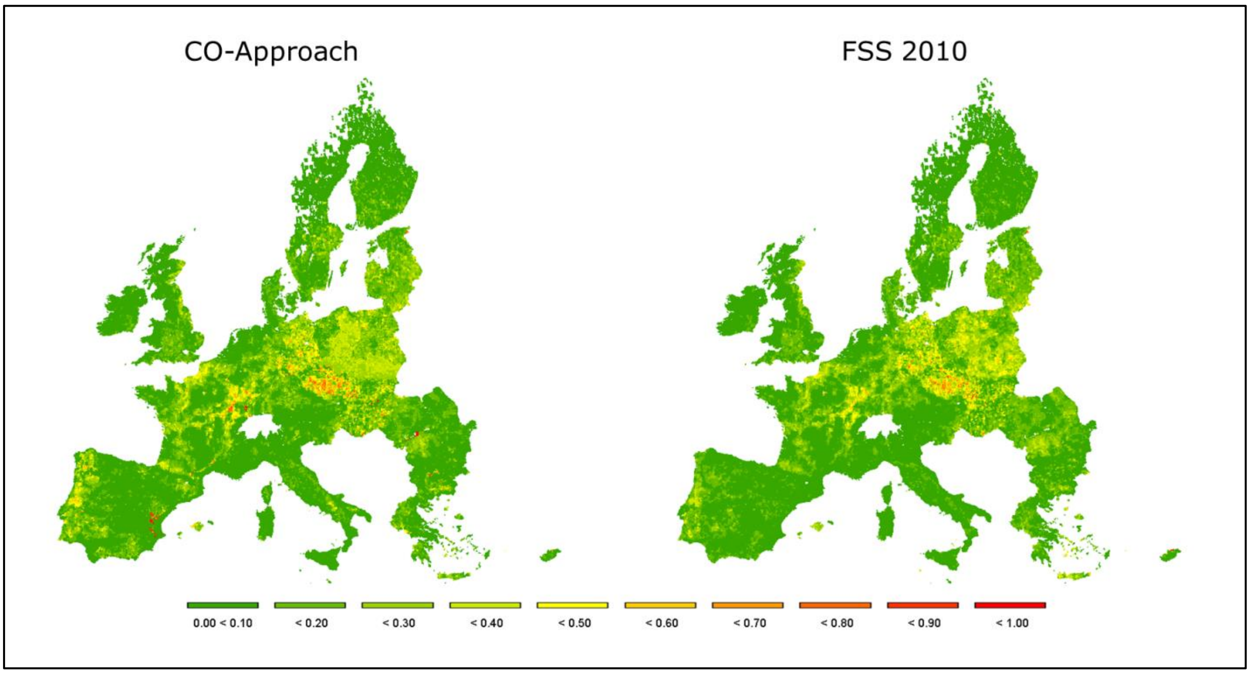


Figure 10: Mixed crops and livestock



However, for the farm type grazing livestock the share of UAA is higher than in FSS in some regions (e.g. Northern UK, Austria). These differences may stem from inconsistency of the data (most likely cut off and rounding criteria for confidentiality reasons in FSS database and limited FADN sample as compared to the FSS comprehensive survey) and to the low frequency of other farm types in these regions. It has to be kept in mind that the FADN sample does not include non-commercial farms and does not sufficiently represent small and part-time farms. This likely implies that farms in the more marginal farming areas are not well represented.

Our findings hold important implications for a more efficient and target-oriented agricultural and environmental policy measures in the EU as it extends the analytical capabilities to agri-environmental evaluation and improves the aggregation of the results to more representative environmental zones (e.g. Nitrate Vulnerable Zones, Areas with Natural Constraints) also in the context for land market.

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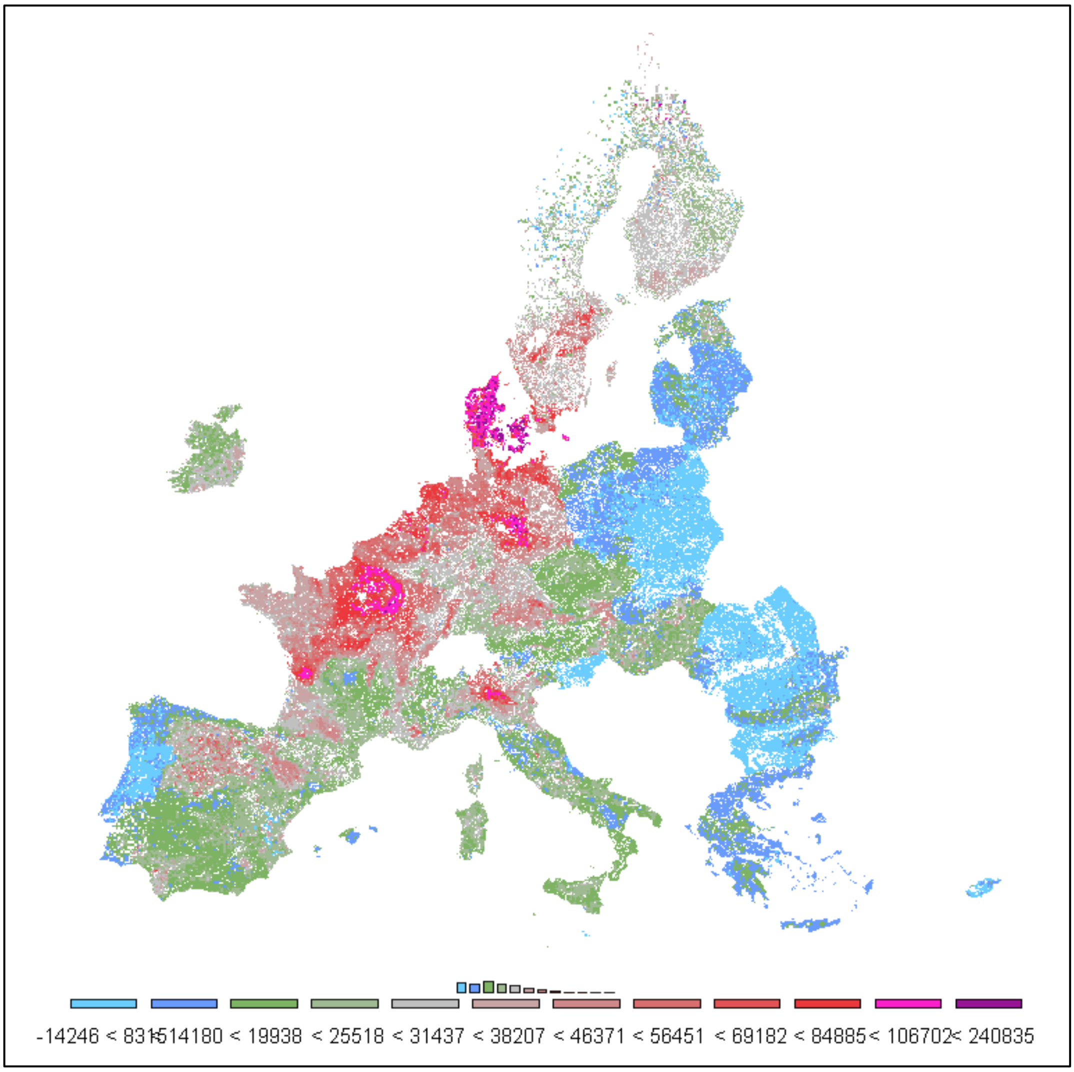

Figure 13: Farm Net Value Added /AWU by FSU in Euro from FADN 2012 for all farms, independent of the specialisation

a) b)

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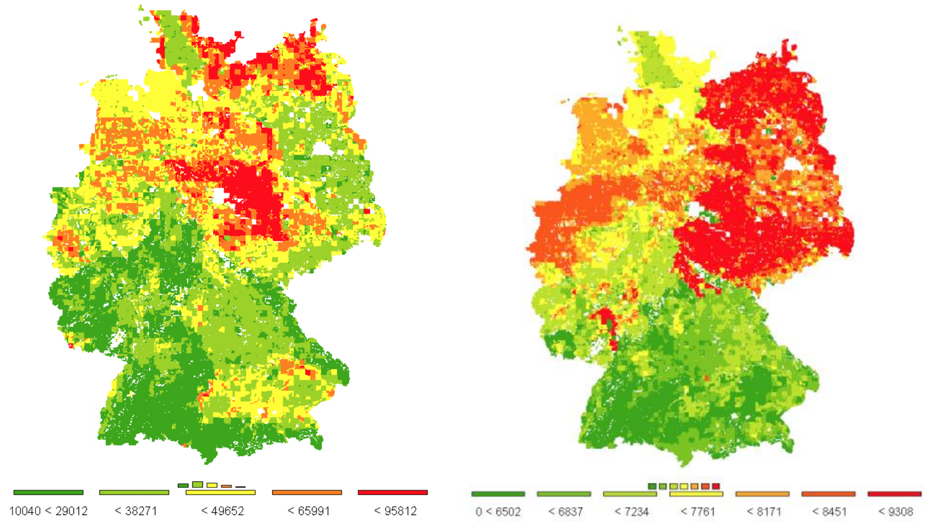

c) d)

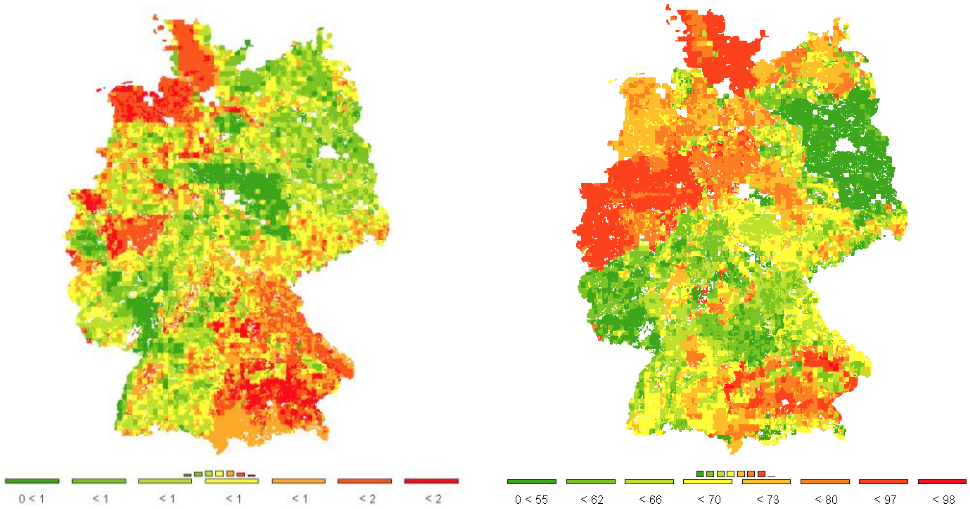

Figure 14: a) Income per AWU in Euro, b) milk yield in tones per cow, c) Stocking Density in LU/ha, d) wheat yield in quintals/per ha from FADN presented by spatial FSU units for 2012

If we simulate a policy in IFM-CAP which affects a certain activity (e.g., fodder maize and grassland) only for farms which have certain related attributes like the farm specializations (e.g., grazing livestock), the change, using the estimates of CO- approach, is applied only to spatial units where those farms are most probably located. If the indicator formula depends on the spatial unit, which is the case for the soil loss, then the use of the CO approach compared to the CAPRI downscaling reduces the aggregation error and results in a better spatial representation of the policy effect and hence in a better indicator calculation.

5.4. Outlook

The current land market model does not yet account for a new delineation. The implementation using the FSU delineation for at least ten selected regions in Germany compatible with the farm exit estimations from section one will be conducted in WP Task 5.2.3. „Subtask 5.2.3 Structural change representation in current models“. The target is to build cluster of FSU with similar homogenous factors for land and to account for the pressure on the land market from intensive animal production. The delineation will be based on a cluster of the presented for parameters on income per AWU in Euro,

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milk yield in tones per cow, stocking density in LU/ha and wheat yield in quintals/per in Germany. The cluster is then the new cell to run the IFM-CAP farm inside the cells which are located in the cluster together with the land market model.

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APPENDIX 1

Table 18: List of variables in literature

Explanatory variables	Definition	Source	Level	Dependent variable	Notes	Authors
Farm size	Standardised gross margin (10,000 € per farm)	FADN	NUTS1	net farm exit rate at NUTS1 between 1993 and 1997		Breustedt & Glauben, 2007
Crops	Share of crop and vegetable farms	???	NUTS1			
Animals	Share of livestock farms	???	NUTS1			
Subsidy	Subsidies per farm (1000 €)	???	NUTS1			
Price	Agricultural output price index (1985 =1.00)	???	Country			
Off-farm work	Share of farm operators working more than 50% of their time off-farm	???	NUTS1			
Age	Share of farm operators aged 44 or older	???	NUTS1			
Family worker	Family members working on the farm (persons per farm)	???	NUTS1			
Owned land	Share of land owned by the farm operator	???	NUTS1			
GDP	Gross Domestic Product (10,000 € per head)	???	NUTS1			
Unemployment	Unemployment rate %	???	NUTS1			
Population density	Population density (100 inhabitants per km2)	???	NUTS1			
Country dummies	West vs East Germany and for countries generally	???	NUTS1			

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Farmland	Hectares, total utilized agricultural area of holding. Does not include areas used for mushrooms, land rented for less than one year on an occasional basis, woodland and other farm areas (roads, ponds, non-farmed areas, etc.). It consists of land in owner occupation, rented land, land in share-cropping.	FADN	Farm	Kazukauskas et al, 2013
Capital	EUR, building, machinery, breeding stock.	FADN	Farm	
Direct Cost	EUR, costs linked to the agricultural activity of the holder and related to the output of the accounting year, i.e. crop-specific inputs (seeds and other specific crop costs), livestock specific inputs (feed and other specific livestock costs) etc.	FADN	Farm	
Farm value added per labor unit	EUR, farm net value added expressed per agricultural work unit as defined by FADN	FADN	Farm	
Gross Investment on fixed assets	EUR, net investment without depreciation, it includes purchases and sales of fixed assets	FADN	Farm	
Farms with investment grant	Dummy variable, =1 if farm received investment subsidy.	Constructed	Farm	
Subsidy dependency rate (dr)	%, total direct farm payments on current operations (not investments) divided by farm total output in the accounting year	Constructed	Farm	
Size dummies	10 dummy variables, categorized in terms of European size units (ESU) in the Community	FADN	Farm	

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	typology (Reg. 85/377/EEC).			
Farm system dummies	17 dummy variables, categorized by agricultural specialization on the basis of the codes for the types of farming (TF) in the Community typology (Reg. 85/377/EEC).	FADN	Farm	
Less-favored areas	Dummy variable, =1 indicating the location of the *majority*of the farmland of the holding in an area are covered by provisions of Art. 18 to 20 of Regulation (EC) No 1257/1999.	FADN	Farm	
Age			Farm	
Country dummies			Farm	
area	Total UAA (ha)		Farm	Saint-Cyr et al, 2019
agri_profit	Per partner agricultural profit (1,000 Euros)		Farm	
median_age	Median age of the farm holders (years)		Farm	
lowlanduse	Low-land-use farm dummy (1 if yes)		Farm	
middlelanduse	Middle-land-use farm dummy (1 if yes)		Farm	
highlanduse	High-land-use farm dummy (1 if yes)		Farm	
corporate	Corporate farm dummy (1 if yes)		Farm	
area_mun_deviation	Deviation from average farm size		Municipality	
gini_mun	Gini coefficient of land distribution		Municipality	
agri_profit_mun_deviation	Deviation from average agricultural profit		Municipality	

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median_age_mun_deviation	Deviation from average median age of farm holders	Municipality	
highlanduse_mun_share	Share of high-land-use farms (%)	Municipality	
corporate_mun_share	Share of corporate farms (%)	Municipality	
average_sar_area	Average farm size	Higher than municipality	
average_sar_agri_profit	Average per partner agricultural profit	Higher than municipality	
average_sar_median_age	Average median age of farm holders	Higher than municipality	
sar_highlanduse_share	Share of high-land-use farms (%)	Higher than municipality	
sar_corporate_share	Share of corporate farms (%)	Higher than municipality	
regional_unempl_rate	Unemployment rate (%)	Regional	
Farm exits (ei)	ln (farm proprietors in 1997 over 1987 av)		Goetz & Debertin,
Net loss counties (qi)	0,1 dummy variable (1=net loss)		
Off-farm work (dˆo87i)	Farmers working off-farm 150+days, %, 1987		
Family farms (su87)	Farms that are family-owned, % of total, 1987		
Operator age	Average farm operator age, years, 1987		
Operator age squared			
Value of land and buildings	Value of land and buildings per farm, $, 1987		
Corn, soybeans, and hogs	Agricultural dependence index (0, 1); excluded category		

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Dummies for farm specialization		
Regional dummies		
CV of net farm income	Coefficient of variation of net farm income, 1987 av	
Irrigated farmland	Farmland that is irrigated, % of total, 1987	
Government payments	Federal farm payments,$ ‘000 per farm, 1987 av	
Adjacent	Metro-adjacent rural county (0,1)	
Population density	Population per square mile, 1990	
Population growth	Population growth rate, 1980–1990, in %	
Farmland	Percent of county land in farms, 1987, %	
Unemployment	Local unemployment rate, 1987	
Farm proprietorships	Number of farm proprietorships, 1987 av	
Farmer age		Pietola_Väre_Oude-Lansink, 2003
Share of farms in the North (Finland)		
Land area		
Forest area		
Output price index		
Subsidy rate per ha of feed barley		
Pension		
Share of farmers having a spouse		

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Herd size	Number of milking cows in operation (100 head)	Dong et al, 2016
TE	Technical efficiency calculated from SPF	
bSTp	1 if the milking herd received bST two years ago; 0 otherwise	
college	1 if operator has a college degree; 0 otherwise	
Age		
years	Number of years this operation has been producing milk	
successor	1 if primary operator is 57 or older and one of other operators is over 10 years younger, or primary operator is younger than 57; 0 otherwise	
op off farm	1 if operator worked off-farm over half time; 0 otherwise	
op spouse off farm	1 if operator's spouse worked off-farm over half time; 0 otherwise	
land	Total farm and ranch land in the operation (acres)	
Farm size	Log livestock units * 100	Weiss, 1999 (Agrarwirtschaft)
Age	Age and Age^2*100	
Agricultural education		
General education		
Parttime farming	Zuerwerb - over 50% and less than 90% of work dedicated to farm	
"Side business"	Nebenerwerb - less than 50% of work dedicated to farm	
Farm operator marriaged		

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Family workers 1	How many family members working on farm below age 6		
Family workers 2	How many family members working on farm betwenn age 6 and 15		
Family workers 3	How many family members working on farm over age 15		
Gender farm operator			
Regional dummes			
Other dummies	Categories how "hard" it is to operate a farm in this speicific region		
SGM	Standard gross margin/100 (EURO), (Sum of the standard gross margins of nine different products; calculated using average yields, prices and costs)		Glauben, Tietje, Weiss, 2004
LU	Livestock units/100(units)		
LEASE	Leased out land (hectare)		
CREDIT	Dummy variable for subjective credit load (1 = farm operator considers credit load to be high, 0 = else)		
HHI	Hirschmann–Herfindahl Index (The HHI is defined as the sum of the squared shares sj of nine different products)		
Parttime farming	Dummy variable for part time farming: (1 = more than 50% off-farm income, 0 = else)		
Age			
Experience	Farm operator’s experience (years as a farm owner)/ 100 (years)		

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FAM-M	Number of male family members in the farm household between 15 and 30 years of age
FAM-F	Number of female family members in the farm household between 15 and 30 years of age
Farm operator marriaged	
Gender farm operator	
Regional dummes	
Other dummies	Categories how "hard" it is to operate a farm in this specific region

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MIND STEP WP4 TEAM

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Consortium description

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

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

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

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