LAMASUS
Land Management for Sustainability

D6.2 Regional case studies to verify high-resolution model using ex-ante behavioural models

This project has received funding from the European Union's Horizon Europe Research and Innovation programme under Grant Agreement No 101060423. The information and views set out in this deliverable are those of the author(s) and do not necessarily reflect the official opinion of the European Union. Neither the European Union institutions and bodies nor any person acting on their behalf may be held responsible for the use which may be made of the information contained therein.

Funded by the European Union

Date
31.08.2025

D6.2

Grant Agreement	101060423
Call identifier	HORIZON-CL6-2021-GOVERNANCE-01
Project full title	Land use and management modelling for sustainable governance
Work package	WP6
Due date	31/08/2025
Deliverable lead	BOKU
Authors	Elisabeth Jost, Lennart Kokemohr, Verena Kröner, Till Kuhn, Evelina Sandström, Erwin Schmid, Davide Tita

Abstract

Deliverable D6.2 advances the objectives of the LAMASUS project by developing behavioural models at the level of land-use decision makers, who can analyse microeconomic implications of policies consistent with the macro-level dynamics simulated with the large-scale economic models. Two ex-ante behavioural farm/regional models are used: FAMOS/PASMA for Austria and FarmDyn for Germany and Norway to verify the high-resolution spatial land use model CLUMondo. The high-resolution model verification is critical for developing an advanced high-resolution land system model as part of the LAMASUS model toolbox. The approach developed here ensures that the high-resolution model accurately represents farm and regional-level decision-making.

The work conducted for this deliverable focuses on identifying differences in input data and model structures between CLUMondo and the ex-ante behavioural models, quantifying the spatial mismatches in land use allocations in the case study regions, as well as discussing the implications of these model differences for effective policy development and assessment. Overall, the deliverable demonstrates the added value of integrating ex-ante behavioural models for policy assessments, contributing to a more robust policy analysis and supporting the development of the LAMASUS modelling toolbox. Further to this approach, an agent-based model is used to link to CLUMondo to better be able to determine land abandonment decisions in land use models.

Keywords

Model verification, land use allocation, agricultural and land use policy

Internal Technical Auditor	Name (Beneficiary short name)	Date of approval
Task leader	Erwin Schmid (BOKU)	23/08/2025
WP leader	Esther Boere (VUA)	22/08/2025
Coordinator	Petr Havlík (IIASA)	22/08/2025
Project Management Office (PMO)	Eleonora Tan (IIASA)	25/08/2025

Dissemination level

PU	Public, will be published on CORDIS	✓
SEN	Sensitive. Confidential information, only for members of the Consortium (including the EC services)	

Nature of the deliverable	*R*

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Abbreviations

ABM	Agent-based modelling
DFA	Discriminant Function Analysis
EC	European Commission
EU	European Union
GHG	Greenhouse gas
IACS	Integrated Administration and Control System
NRW	North Rhine-Westphalia
px	Pixels

Executive summary

Deliverable D6.2 advances the objectives of the LAMASUS project by verifying the high-resolution spatial land use model CLUMondo through regional case studies. Two ex-ante behavioural farm/regional models are used: FAMOS/PASMA for Austria and FarmDyn for Germany and Norway. The high-resolution model verification is critical for developing an advanced high-resolution land system model as part of the LAMASUS model toolbox. The approach developed here ensures that the high-resolution model accurately represents farm and regional-level decision-making. The work conducted for this deliverable focuses on identifying differences in input data and model structures between CLUMondo and the ex-ante behavioural models, quantifying the spatial mismatches in land-use allocations in the case study regions, as well as discussing the implications of these model differences for effective policy development and assessment. Overall, the deliverable demonstrates the added value of integrating ex-ante behavioural models for policy assessments, contributing to a more robust policy analysis and supporting the development of the LAMASUS modelling toolbox.

1. Introduction

The overall aim of LAMASUS is to support the development of policies in the framework of the European Green Deal by creating tools for an innovative governance model. A key element is the development of the high-resolution spatial land system model that captures regional differences in agricultural production. Spatially explicit land use models are essential for effective policy development due to their capacity to capture regional and structural differences in the agricultural landscape.

Deliverable D6.2 contributes to the LAMASUS project by verifying the high-resolution spatial land use model CLUMondo through regional case studies employing two ex-ante behavioural farm models: FAMOS/PASMA for the Austrian case study and FarmDyn for the case studies in Germany and Norway.

For generating the new high-resolution spatial land system modelling as a component of the LAMASUS modelling toolbox, the verification of model rules of the high-resolution model is key to ensuring that such a model accurately reflects farm/regional level decisions and the variations therein. For that purpose, ex-ante behavioural models at the level of land-use decision makers, i.e., farmers, were developed to analyse the policy change impacts at the farm and regional level and to provide land-use decision-making level insights.

The work carried out for the task of high-resolution model verification using ex-ante behavioural modes aims i) to identify differences in input data and model structure between CLUMondo and the farm/regional level models, ii) to quantify spatial mismatches in land use allocations for each case study region and iii) to discuss the implications of these differences for facilitating policy analysis and development.

The following questions can be answered with this deliverable:

1. How do the high-resolution spatial model and the ex-ante behavioural models complement each other for policy assessment?
2. What do ex-ante behavioural models add to high-resolution spatial models?
3. What could be the benefits of linking behavioural elements from agent-based models to high-resolution land use models such as CLUMondo?

For the Austrian case study analysis, the following data sources were used: Farm Survey Structure 2020, and the database of the Integrated Administration and Control System (IACS). These data sources provide detailed information about the agricultural landscape on the farm and regional level, i.e., farm characteristics, farm endowments, participation in policy programmes and the agri-environmental policy program ÖPUL. For Germany, a statistically based synthetic farm population from Pahmeyer et al. (2021) is used that links farm-level data from the federal state of North Rhine-Westphalia to the grid level. This link requires a comparison of the parametrisation of CLUMondo that operates at the grid level. The synthetic population builds on work from Schäfer & Kuhn (2018) and relies on the Farm Structure Survey and data from IACS. Similarly, Norway uses official data on farm subsidies and the related activity data as model inputs (Landbruksdirektoratet 2024). In comparison to the CLUMondo model, the data used in the ex-ante behavioural models is actual farm micro data, well-suited to farm responses to policy changes.

The report is structured as follows: Chapter 2 provides an overview of the models used for the high-resolution model verification exercise (see Chapter 2.1) and an overview of the model verification framework (see Chapter 2.2). This is followed by the results section (see Chapter 3) presenting model verification results for the case studies Austria, Germany, and Norway. Chapter 4 describes various approaches and studies aimed at unraveling agricultural land dynamics and farmer responses, moving from aggregate macro-economic analyses to fine-grained, context-specific realities. The report concludes with a discussion (see Chapter 5) and a description of the conclusions to draw from the results obtained (see Chapter 6).

2. Verification of high-resolution model using ex-ante behavioural models

This deliverable presents the results obtained from a case study-based application of a project-specific model verification routine. We conducted a two-fold case-study analysis comparing 1) land use modelling with CLUMondo and FAMOS/PASMA to compare a global-scale spatially explicit and dynamic land system model (CLUMondo) to land use allocation performed by a bottom-up non-linear programming model (FAMOS/PASMA), and 2) baseline land use intensity maps of CLUMondo and FarmDyn, which allows for assessing heterogeneity of model outputs and for a quantitative discussion of potential information losses regarding the representation of land use intensities using CLUMondo.

This section describes the methodology of high-resolution model verification using ex-ante behavioural models within the LAMASUS project. First, an overview of the models employed for the model verification exercise is provided, followed by an overview of the model verification framework.

2.1. MODEL CHARACTERISTICS

Table 1 provides a high-level overview of the three models applied in this deliverable: CLUMondo, FAMOS/PASMA, and FarmDyn.

Table 1: Model characteristics of CLUMondo, FAMOS/PASMA, and FarmDyn.

Model	Model type	Spatial resolution	Data	Method	
				Land use allocation	Land use expansion/ abandonment
CLUMondo	Land allocation model	1 km grid	CORINE land cover, Copernicus grassland data, EU Crop Map 2018	Land suitability	Rule-based allocation of land
FAMOS/PASMA	Bottom-up non-linear programming model	Farm/regional level (municipality, NUTS3)	Calibration farm structure survey 2020, IACS	Prices, yields, variable production costs	Opportunity cost approach; legal and agronomic restrictions
FarmDyn	Bio-economic farm model based on mixed-inter programming	Farm level	Farm typology, farm management data	Based on optimisation	Decision option to work off-farm and rent additional land

The models under analysis differ in spatial resolution, underlying modelling approach and assumptions, as well as the level of data aggregation regarding data inputs and outputs. Model verification was conducted for the reference year 2020 and focuses on applied decision rules for land use allocation as well as model inputs.

2.1.1. CLUMondo

CLUMondo conducts global land use change modelling at the interface of macro-economic demands (demand scenarios) and the local physical and socioeconomic context (local suitability and conversion rules) (cf. van Asselen & Verburg, 2013). Results are obtained for the 1km grid.

In the LAMASUS project, CLUMondo is run at the European level. CLUMondo requires five main inputs to run the land use allocation procedure. First, we have the basemap, which is a land system map in 1x1 km pixels describing the land use management of the study area (Europe) for the base year 2020. In the current baseline version used for CLUMondo this map contains the land use management classes: Low, medium and high intensity urban settlements, low, medium, and high intensity arable cropland, low, medium, and high intensity grassland, forest shrub and grassland mosaics, forest shrub and cropland mosaics, permanent cropland, wetlands, close to nature forestry, combined objective forestry and very intensive forestry. Second, we have land use demands, these demands are the main driver of the land use changes in the model. The default drivers are population change, arable and permanent crop production, livestock numbers, and wood harvest. More demands can be added depending on the scenario to be simulated. The demands are often derived from partial or general equilibrium models, scenarios, or trends. Each land use management class can contribute to fulfilling one or more of the demands. How much they can contribute to each demand is defined in a land use provisioning file. Third, we have land use conversion rules, which determine which land use class can be converted into another and how long that conversion should take. Fourth, we have spatial policies and restrictions that can be added to change land use conversion rules in certain areas, for example, nature reserves. Fifth, we have the location suitability of a certain land use class, which is derived from logistic regressions using socio-economic, climate, and soil factors.

The model will try to fulfil the demands for each timestep in the model by allocating the land use classes that can do this. If one demand is not met with the area available, then the model will choose to intensify. The land use classes will be in the most suitable areas available for each land use class.

2.1.2. FAMOS/PASMA

FAMOS/PASMA operate at the farm and regional levels – specifically, at the municipality or NUTS3 level for PASMA, and at the individual farm level for FAMOS. In PASMA, each region can be understood as one single farm, whereas in FAMOS, results from different farm types are aggregated to the regional level (Sinabell et al., 2011). Both models are driven by a land allocation decision module that simulates farmers' decisions regarding crop selection, setting the level of livestock activities and deciding the type of management. Decisions are constrained by historically observed management options and resource endowments.

A scenario module allows for the adjustment of various variables that might influence farmers' decision-making, e.g., input and output prices, premiums of agricultural programs, and resource constraints. Input data stems from Statistics Austria's farm structure survey and the EU IACS.

The spatially explicit agricultural land use optimisation models maximise total net benefits of crop and grassland production subject to agricultural land endowments at 1 km grid resolution in Austria. Total agricultural land is kept constant, whereas the sum of grassland categories, i.e., intensive/ extensive grassland, and alpine pastures does not decline within a grid cell. This ensures compliance with national regulations on land preservation. Average gross margins are calculated using the simulated dry matter crop and grassland yields, respective commodity prices and variable production costs (e.g., costs of tillage, seeds, fertilisers, labour and insurance). Agricultural premiums, i.e., direct payments, and agri-environmental payments, are considered. The commodity prices represent a three-year average from Statistics Austria (2015–2017), and variable production costs are derived from the standardised gross margins catalogue. The commodity prices, variable production costs, as well as the agricultural policy premiums are kept constant in order to single out the effects of climate change and the mitigation policy scenario. The objective function maximises the total net benefits of agricultural production ($\boldsymbol{NB}$, in €) and is defined as

$$\max NB = \sum_{i,j,k} GM_{i,j,k} * X_{i,j,k} - \begin{cases} \sum_{i,j} \frac{\eta_{i,j} * \tilde{X}_{i,j}^{a}}{\alpha \, (X_{i,j}^{0})^{(\alpha-1)}}, & x_{i,j}^{0} > 0 \\ \sum_{i,j} \eta_{i,j} * \tilde{X}_{i,j}, & x_{i,j}^{0} = 0 \end{cases} \tag{1}$$

where GM refers to gross margins (€/ha), and X is land use (ha). The index i denotes the grid cell, with I = 71,604 for Austria, j the land use category, with J = 4 (cropland, intensive grassland, extensive grassland, and alpine pastures), and k represents land management practices, with K = 11 (including three alternative crop rotations; three tillage systems including conventional tillage, reduced tillage, and conventional tillage with winter cover crops; one fertilizer application level derived from N-balance calculations; rainfed and irrigated cropland and grassland; two mowing frequencies and pasturing). We add flexibility to the model by assuming no additional costs for converting cropland to grassland. Land use category change within each 1 km grid cell is restricted to land use categories of grassland and cropland available in the historical reference period (1981–2020), and agricultural land cannot be abandoned.

The first term of the objective function sums the product of gross margins and land use for each *i, j,* and *k*. *GM* includes a linear (i.e., variable) cost component from standard gross margin calculations. The second term represents the non-linear cost function. The product of the marginal value η for each *i, j* and modelled land use $\tilde{X}$ (defined by Eq. 3) to the power of the coefficient $\boldsymbol{\alpha}$ is divided by observed land use from the calibration period X^0 and summed over grid cell *i* and land use category *j*. The coefficient $\boldsymbol{\alpha}$ is assumed to be 2 representing a quadratic cost function, which is usually used if further information is not available (see e.g., Howitt,

1995) (Howitt, 1995). For technical reasons, the quadratic part of the cost function is used if the observed land use category is greater than zero; otherwise, the linear equation component is used in the model. It is assured that the model is also calibrated to the reference crop rotation in each cropland grid cell i. The equality equations 2 and 3 ensure that land use $\tilde{X}_{i,j}$ summed over management practices k equals total land endowment b by land use category j and grid cell i.

$$\sum_j \tilde{X}_{i,j} = b_{i,j}\ \forall i,j \tag{2}$$

$$\tilde{X}_{i,j} = \sum_k X_{i,j,k}\ \forall i,j \tag{3}$$

The model results are available on the level of 1 km grid cell and can be aggregated to agricultural production regions in Austria.

Both CLUMondo and FAMOS/PASMA distinguish different intensity levels for both grass and cropland, determined by the amount of fertiliser applied and/or mowing frequency. However, other land use categories are not as easily aligned across the models. For example, CLUMondo includes mosaic land use categories, which represent a mixture of forest, shrub, and crop-/grassland uses. Instead, FAMOS/PASMA captures this only indirectly, by specifying the area under each land use type within each pixel. FAMOS/PASMA explicitly highlight "alpine pasture" as a distinct land use category, which holds particular importance in the Austrian agriculture and land use context, whereas CLUMondo does not separately identify this category in its land use classification. In CLUMondo, alpine pastures could be captured by both the grassland classes, low-to high intensity, forest, shrub and grassland mosaic and possibly the bare, rock and shrub mosaic. As each pixel in CLUMondo is 1 km^2, the area within this pixel is not completely homogenous and, in reality, contains multiple land systems. The cut-off threshold for a pixel to be classified as one class is that it needs to contain 50% or more of one land system. On average, the grassland pixels contain 66% grassland, while the mosaic classes on average contain 27% grassland, and bare, rock and shrub contain 8% grassland. Notably, FAMOS/PASMA does not include forest land use data. Table 2 shows which land use management categories of both CLUMondo and FAMOS/PASMA are used for comparison and which have been excluded.

Table 2: Land use management categories of CLUMondo and FAMOS/PASMA included and excluded from comparison (2000 reference year)

CLUMONDO	FAMOS/PASMA
Mosaics (forest, shrub, grass- or cropland)	Alpine meadows/ pastures
Arable cropland (low-, medium-, high-intensity)	Arable cropland
Low-intensity grassland	Grassland – 1 cut
Medium-intensity grassland	Grassland – 2 cuts
High-intensity grassland	Grassland – 3 or more cuts
Permanent crops	Permanent crops (vineyards and fruit orchards)

Excluded: • Forest • Water and glaciers • Settlements • Wetlands • Bare, rock, shrub	

source: own elaboration

2.1.3. FarmDyn

FarmDyn is a bio-economic farm model based on mixed-integer programming. The model is realised as a flexible, modular template that covers multiple farm branches, including dairy, suckler cows, beef fattening, pig fattening, piglet production, arable farming, and biogas plants. Farm branches may be operated individually or in various combinations, thereby allowing for the modelling of a wide range of farms and farm types. FarmDyn reflects the economic and biophysical flows at the farm level, providing a high degree of detail in the description of technology and processes. The model optimises farm management to select the activities that yield the highest profit, as measured by the net present value of the farm.

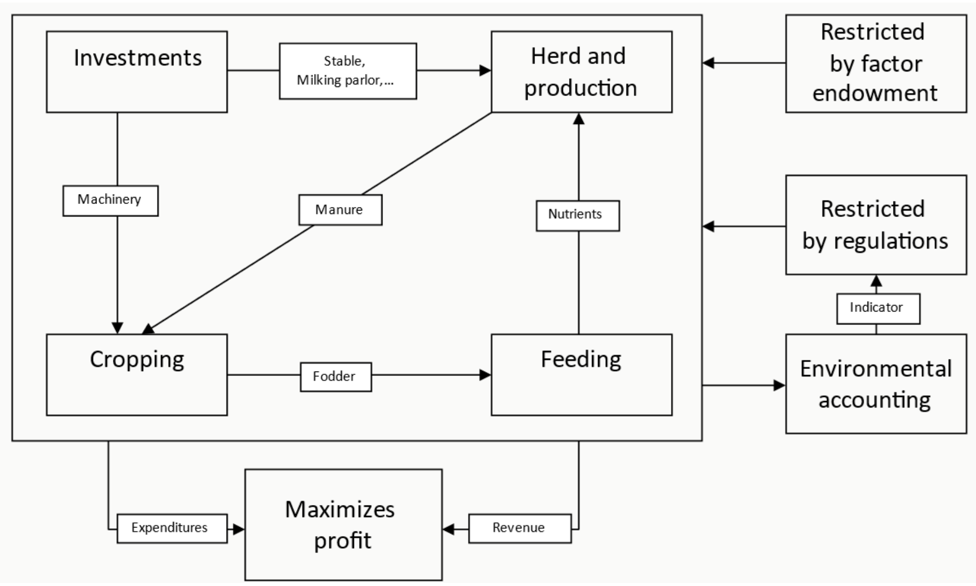

Figure 1: Overview of the FarmDyn model (own figure based on Lengers et al., 2014)

Past research conducted with the FarmDyn model dealt with topics such as GHG abatement (Lengers et al., 2014), technology adoption (eg, Pahmeyer & Britz, 2020; Kuhn et al., 2022), policy impact assessment (Kuhn et al., 2019; Heinrichs al., 2021), and sustainability analysis (Kokemohr et al., 2022). The aforementioned studies primarily relied on case studies and samples from typical farms or smaller farms, with limited geographical coverage. In these studies, due to the reduced sample size, a greater data depth could be realised; however, this came at the cost of compromising spatial coverage, thereby limiting the generalizability of the findings across broader regions. Therefore, within the LAMASUS project, we build upon and advance this methodology to address these limitations and apply FarmDyn in a spatially explicit setting. Different approaches are used in the German and Norwegian case studies. For Germany, a synthetic farm population that provides farm-level data in combination with spatially explicit plots (Pahmeyer et al., 2021) is processed for the first time for an application in FarmDyn and linked to the grid level, requiring data processing before and after the FarmDyn simulations. For Norway, we use the Norwegian Farm Subsidy Database, which publishes all subsidies and public payments farms receive alongside the activity data farms receive payments for and spatial information on the farmstead (Landbruksdirektoratet, 2024). We use the farmstead to localise the farms and to visualise results in maps.

2.2. OVERVIEW OF THE MODEL VERIFICATION FRAMEWORK

The LAMASUS modelling toolbox (see D6.1 LAMASUS Modelling Toolbox) consists of models differing in spatial resolution, scale, and land-use representation. The high-resolution spatial land system change model CLUMondo is verified using ex-ante behavioural models developed for regional case studies. Specifically, FAMOS/PASMA is applied to the Austrian case study, while FarmDyn is applied to Germany and Norway. Figure 1 provides a graphical overview of the model verification framework.

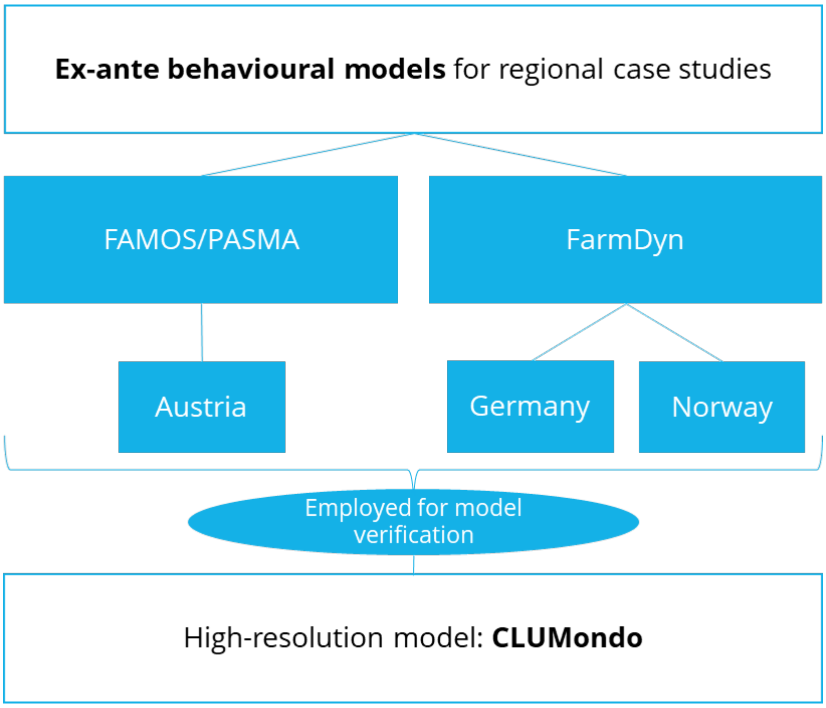

Figure 2: Overview of the model verification framework (source: own illustration).

FAMOS/PASMA – Case study Austria

For the Austrian case study, we compared the baseline land use input data of CLUMondo and FAMOS/PASMA for the reference year 2020. Figure 2 schematically represents the steps of the model comparison that we followed. First, each set of input datasets, i.e., of CLUMondo and FAMOS/PASMA, is described and analysed individually to showcase the representation and distribution of individual land use categories. Second, a spatial overlay of each individual set of land-use categories considered agriculturally used area from FAMOS/PASMA and CLUMondo is conducted using QGIS geographic information systems. This is done to find key similarities and differences between the baseline land use datasets of the two models.

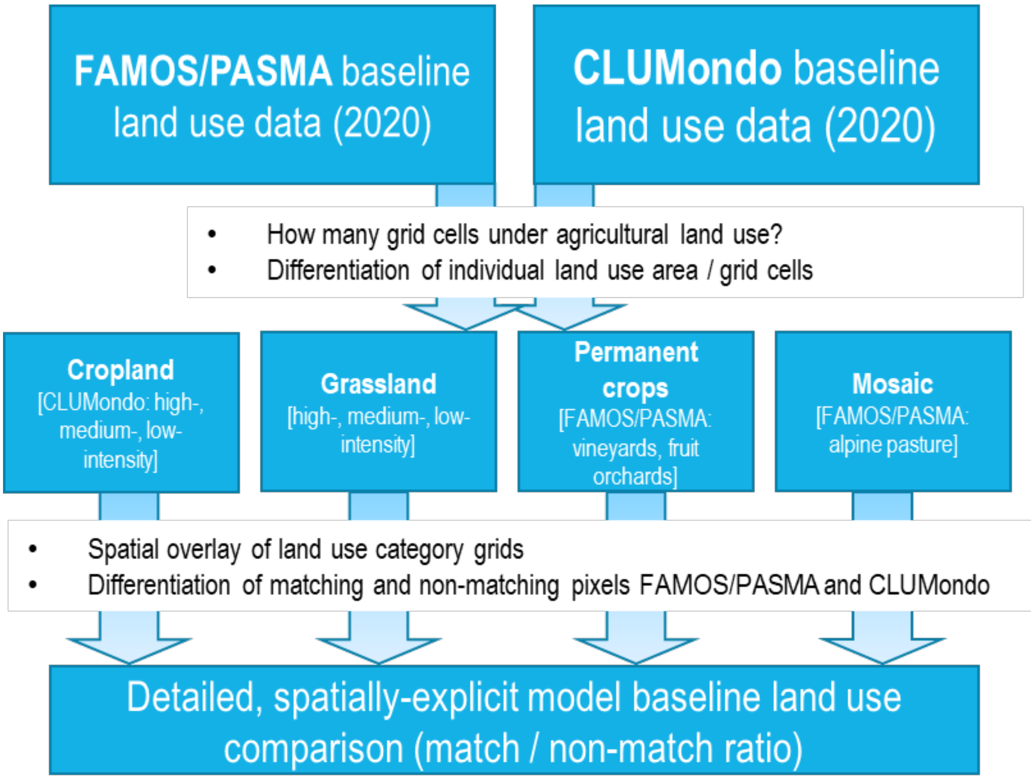

Figure 3: Schematic representation of the model verification routine for the Austrian case study (source: own illustration).

FarmDyn – Case study Germany and Norway

FarmDyn is a bio-economic farm model that provides optimal allocation of production decisions at the farm level under given restrictions, being described in more detail in section 2.2.3. Within the LAMASUS project, the FarmDyn model is extended and calibrated to larger, spatially-explicit farm samples to display land-use management changes affected by political intervention. The current depiction of land-use management in FarmDyn is reflected in the farming activities, as well as the corresponding inputs, technologies, and management practices, including fertiliser use, mowing intensity, and labour input. To realise the model comparison, the land use classification of CLUMondo is replicated in FarmDyn. The aim of this comparison is to understand fundamental differences of the models and help to verify the model rules and parameterisation of the high-resolution spatial models. Grassland management is chosen for this purpose as it is a common characteristic across models and case studies. The grassland intensity indicator from CLUMondo is depicted in Figure 4 below:

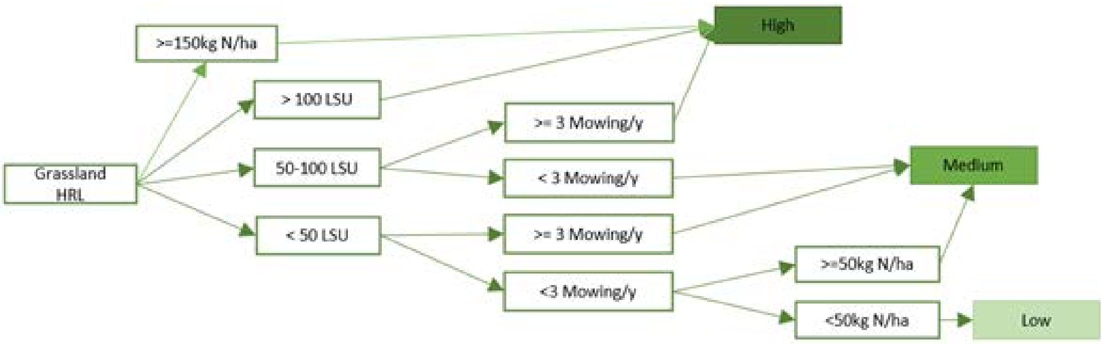

Figure 4: Grassland intensity indicator in CLUMondo (Sandström et al., 2025).

In CLUMondo, grassland is classified into three levels —high, medium, and low— based on livestock density unit (LSU), mowing frequency per year, and nitrogen input per hectare. High-intensity grasslands (dark green) are characterised by high livestock loads (>100 LSU), frequent mowing (≥3 times/year), or high nitrogen input (≥150 kg N/ha). Low-intensity grasslands have low livestock density (<50 LSU), infrequent mowing (<3 times/year), and minimal nitrogen input (<50 kg N/ha). Medium intensity covers all other moderate values for the three indicators.

The following steps were taken to perform the comparison:

1. Identify regional overlap: Identify the regions covered by FarmDyn and use the model to create the grassland intensity indicators of CLUMondo on a 1x1 km raster for each of the overlapping regions.
2. Raster selection: Select rasters for comparison that have the relevant land use (Low-intensity grasslands, Medium-intensity grasslands, High-intensity grasslands). For the German case, 10 rasters are selected as a random sample of the study region of North Rhine-Westphalia, a large Federal state with a diverse agricultural structure and grassland management. For the Norwegian case, all rasters that are classified as grassland from the CLUMondo baseline results within the municipality of Time, which is characterised by intensive livestock farming, are used. This includes roughly 60 rasters.
3. Merging farm data to raster: Spatially explicit farm data is matched to the selected rasters. For the German case, plots within the 10 selected rasters are selected from the synthetic farm population developed by Pahmeyer et al (2021) for NRW, and the corresponding farms are identified. FarmDyn usually operates at the level of case study farms that are not spatially explicit. The synthetic farm population combines IACS data at the plot level with a farm typology from Kuhn & Schäfer (2018), providing farms with spatially explicit plots that can be located in grids. Specifically, dairy farms

are sourced from the population as they are considered most important in grassland management in the case study region, covering around 60 farms for the comparison. Farms are related to the grid as soon as one of their plots is within a grid. For the Norwegian case, all cattle farms in the municipality Time are simulated as this is the most important farm branch in Norway in terms of economic output.

4. Setting up farms: In the next step, the FarmDyn is calibrated to the observed land use and number of animals by restricting the farms' endowments. This ensures that the observed farm characteristics are represented by the model. The FarmDyn model allows for a wide range of grassland intensities that can be adapted to the respective case studies. For the German case study region in North Rhine-Westphalia (NRW), the grassland management options allow a range from 1 to 5 cuts per ha, yields of 5 to 12 t dry matter per ha, while for Norway cuts in a range from 1 to 3 cuts per ha and yields of 3 to 7 t dry matter per ha. The FarmDyn model chooses a cost-efficient mixture of grassland management options to sustain the specified herd size, considering energy, protein, and fibre requirements.
5. Model run and intensity creation: In the following, the FarmDyn model is run for all farms that have land in the selected grid. In the post-model result creation, the values required to estimate grassland intensity in CLUMondo are calculated for every farm, including stocking density, nitrogen application, and number of cuts.
6. Result aggregation: In the final step, the farm results are reallocated to the selected grids as FarmDyn is not spatially explicit and runs independently of the grid cells. Farms and their plots are linked via identifiers to the grids and the post model allocated to the grids. Finally, the shares of the different intensities are estimated.

3. Results

This section describes the high-resolution model verification results of CLUMondo using the ex-ante behavioural models FAMOS/PASMS and FarmDyn. The section is structured along the three different regional case studies: Austria (FAMOS/PASMA), Germany and Norway (FarmDyn).

3.1. CASE STUDY AUSTRIA

FAMOS/PASMA and CLUMondo baseline land use data

When comparing the baseline land use input datasets for the application of FAMOS/PASMA and CLUMondo, several challenges arise. Land-use classification of FAMOS/PASMA defines 75,135 pixels of a total of 85,708 pixels (a share of 87,7%) in Austria as containing some form of agricultural usage. CLUMondo, on the other hand, defines a smaller portion of only 43% of pixels in Austria to be found under agricultural usage. This difference is given by the fact that FAMOS/PASMA integrates pixels containing several agricultural uses, i.e., one pixel can contain various land uses, whereas in CLUMondo one pixel will be classified as being under only one exclusive form of agricultural management depending on the share of one individual land within a particular pixel (having to contain at least 50% of one individual land use to be classified as such). Additionally, CLUMondo integrates shares of other land uses, such as forest, bare rock, water, or settlements within one pixel in order to derive a particular land use category, whereas FAMOS/PASMA does not.

Given these differences, we find that in FAMOS/PASMA, 58.5% of all pixels in Austria contain cropland, 39.7% contain low-intensity grassland, 52% contain medium-intensity grassland, 47.8% contain high-intensity grassland, 8.6% contain permanent crops, and 26.8% contain alpine pastures. Please note that one pixel can contain multiple types of land use. Hectare extents of individual land uses in PASMA/FAMOS align with agricultural statistics reported for the year 2020 by the Federal Ministry of Agriculture (BMLRT, 2021).

The CLUMondo land use classification, on the other hand, reports 12% of pixels as being found under cropland usage, 1.3% as grassland, 0.5% as permanent crops and a large share of 29% being classified as mosaics of either crop- or grassland dominance. The majority of Austria (57.2%), following CLUMondo classification, is defined as other land use, such as forest, settlements or other, which is not depicted in FAMOS/PASMA.

The differences in the two classification schemes explain the difference in the maps provided in Figure 4, representing the baseline land use datasets of FAMOS/PASMA and CLUMondo (note that the colour of each pixel in the FAMOS/PASMA map shows the land use category, occupying the largest proportion of the agricultural land area within each 1km^2 pixel.

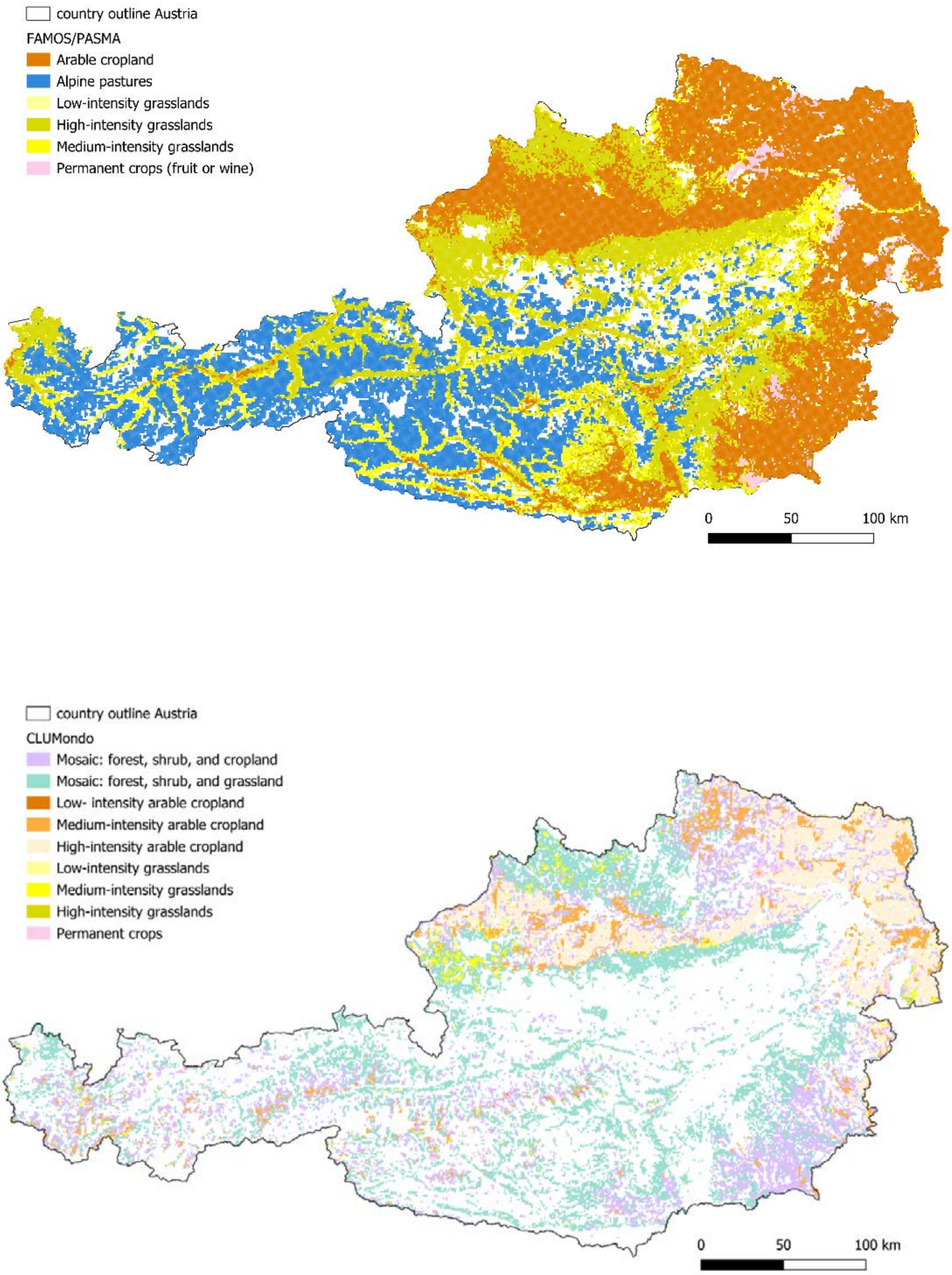

Figure 5: FAMOS/PASMA and CLUMondo baseline land use input data for Austria (year 2020)

The spatial overlay of individual land use categories from FAMOS/PASMA and CLUMondo (following Table 2) shows that 20% (16,887 pixels) of all pixel classifications of the two model baselines match. Figure 5 provides details on the land use categories of CLUMondo baseline land use data found within each land use category of FAMOS/PASMA that do not match, i.e., where land use categories differ between FAMOS/PASMA and CLUMondo.

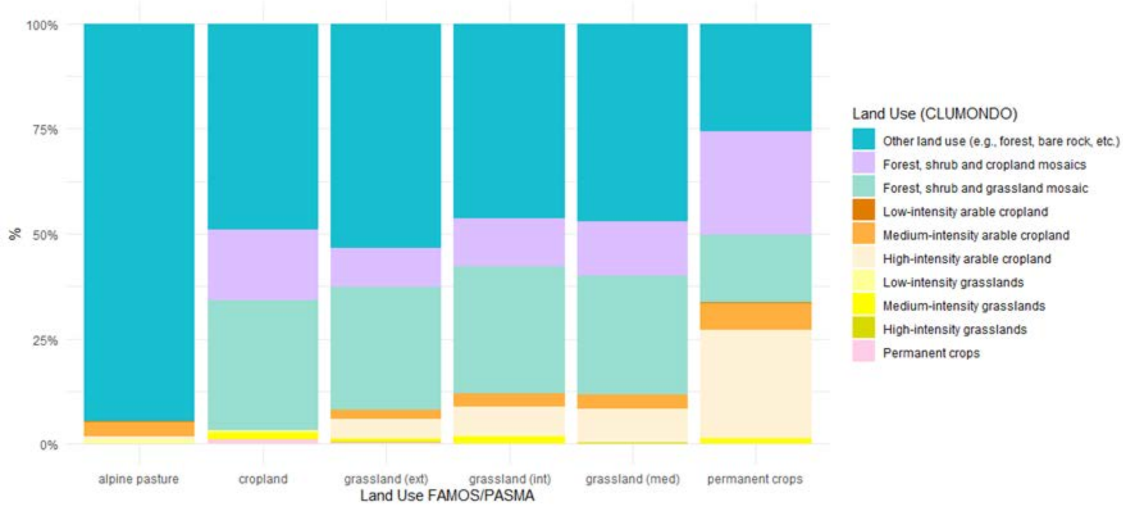

Figure 6: Percentage distribution of non-matching CLUMondo land use categories within each land use category of the FAMOS/PASMA baseline.

The FAMOS/PASMA cropland land use categories contain small shares of what has been classified as permanent crops or medium-intensity grassland in CLUMondo; the largest share is made up of mosaic pixels or other land use categories considered non-agricultural. FAMOS/PASMA grassland categories contain small shares of grassland attributed to a different intensity level in CLUMondo, and some are classified as cropland. The largest shares, same as for cropland, belong to CLUMondo categories for mosaic or non-agricultural land use. The permanent crops category contains large shares of what has been classified as low- or medium-intensity croplands in CLUMondo, very small shares of grassland, but also mosaic and other land use pixels. Alpine pastures in the FAMOS/PASMA baseline dataset are mostly found in the other land use categories of CLUMondo and a very small share of pixels classified as crop or grassland.

3.2. CASE STUDY GERMANY

We focus our analysis on the German Federal state of North Rhine-Westphalia (NRW). A synthetic farm population developed by Pahmeyer et al. (2021) is used. It combines the spatially explicit plot data of the IACS and a farm typology based on the Farm Structure Survey. The typology is presented in detail by Kuhn & Schäfer (2018). Compared to other sources, this typology provides spatially explicit farm data at the plot level. To transfer the grassland management intensity quantification from CLUMondo to the FarmDyn metrics, LSU per km^2 is transferred to LSU per ha, where 100 LSU per km^2 correspond to 1 LSU per ha.

For the German case study, the ten selected grids cover the LUMs “Low-intensity grasslands”, “Medium-intensity grasslands”, and “High-intensity grasslands” (Table 3). The grids are randomly spread across the German Federal state of NRW, but cluster in the grassland and dairy production regions in the northwest and south of the state. Comparing the intensity classes, FarmDyn and CLUMondo identify the same high-intensity grids. For these grids, FarmDyn identifies high shares of high-intensity grassland, ranging from 64.22% to 100% of the land in the grids categorised as high intensity by FarmDyn. In the model, most of these farms have around four cuts on their grassland and have more than 1 LSU $ha^{-1,}$ which makes them qualified as high-intensity.

For the medium intensity, the results of CLUMondo and FarmDyn differ more. In general, FarmDyn identifies most of the land in medium-intensity grids based on CLUMondo as high-intensity, with medium-intensity land accounting for only a minor share, ranging from 0% to 12.33%. In contrast, CLUMondo classifies these mostly as medium-intensity due to having more than 1 LSU ha-1, and to a lesser extent, due to having more than 3 cuts ha-1. Only two grids in the random grid selection are classified as low-intensity grasslands by CLUMondo.

In line with the medium intensity, FarmDyn classified the majority of the land as being under high intensity, resulting in shares of 87.67% and 69.39%. Again, the classification of FarmDyn is strongly driven by the LSU ha^{-1} exceeding the threshold of 1. This effect is strongly driven by the different approaches to estimate stocking density within the modelling framework.

In summary, the intensity fit between CLUMondo and FarmDyn is relatively poor, likely due to conceptual differences in the modelling approaches, such as how stocking density is reflected, being discussed in Section 5. On trend, grids that CLUMondo classifies as medium or low-intensity managed grassland, the FarmDyn results tend to also have more land in these categories. Furthermore, FarmDyn, as a farm-level model, shows that there is a relevant heterogeneity of grassland intensity within one grid that is lost in the scale at which CLUMondo operates. This has implications for the accuracy of how the land use model reflects policy impacts in relation to farm-level decisions and their varying impact on land use.

Table 3: Comparison between intensities in FarmDyn and CLUMondo for the German case study in ten selected grids (in %)

LUM class	CLUMondo: LUM intensity	FarmDyn grassland intensity (%)		
		Low intensity	Medium intensity	High intensity
620	Medium-intensity grasslands	0	12.33	87.67
620	Medium-intensity grasslands	9.75	19.58	70.67
610	Low-intensity grasslands	0	1.87	98.13
620	Medium-intensity grasslands	0	7.21	92.79
610	Low-intensity grasslands	0	30.61	69.39
630	High-intensity grasslands	0	0	100
630	High-intensity grasslands	0	0	100
620	Medium-intensity grasslands	0	0	100
630	High-intensity grasslands	0	35.78	64.22
630	High-intensity grasslands	0	0	100

3.3. CASE STUDY NORWAY

The Norwegian case study is chosen to be the municipality Time, in the county Rogaland, on Norway's west coast. The municipality is shown in Figure 13 below. The landscape is fairly flat and used for agriculture, while the east of the municipality is dominated by moorland. The predominant land use, according to Nibio AR50, a Norwegian national land resource dataset, is cultivated land (land that is ploughed, and oftentimes used as intensive grassland) in the west, and outfield pasture in the east (NIBIO, 2023). The municipality is chosen for the model comparison as a large share of its land is predominantly covered with grassland and therefore allows for the comparison of the land use bound to grassland in FarmDyn and CLUMondo.

Farm data to set up the FarmDyn model is sourced from the Norwegian subsidy database, which gathers publications of governmental aid payments to legal entities and private persons, including agricultural holdings. The respective payments, alongside details of the agricultural land, livestock, grown crops, and harvest for which farmers received payments, are published in accordance with the Norwegian Freedom of Information Act (2009).

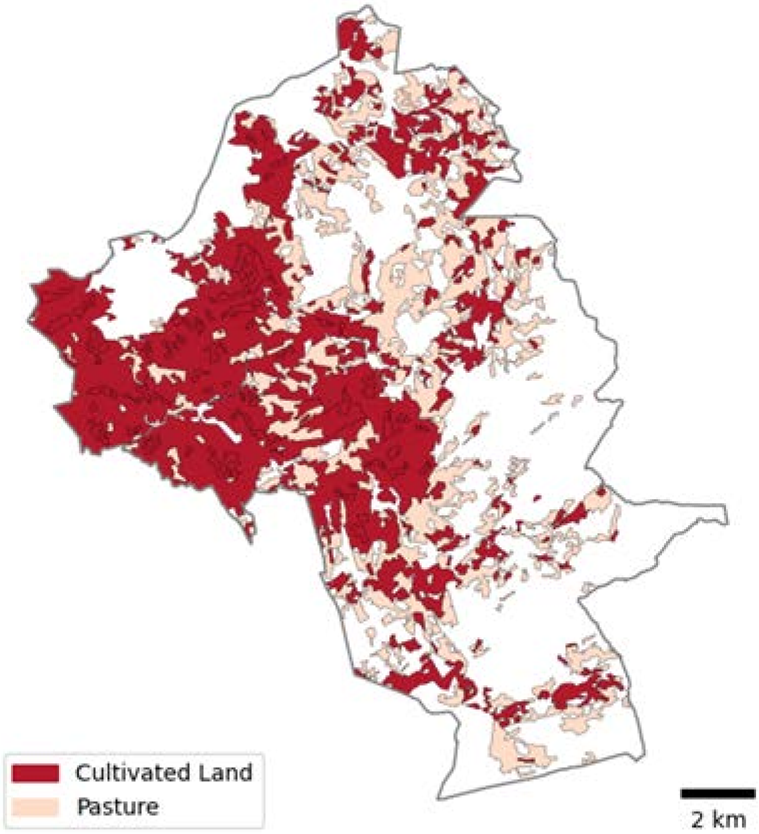

Figure 7: Land use in the municipality of Time according to Nibios AR50 land use classification

Figure 8 shows the CLUMondo pixels with grassland in the municipality, while the colouring indicates the aforementioned grassland intensity. As can be seen, they roughly match the land types of the AR50 map in that higher intensity grassland management can be found in the west and less intensive in the east. The predominant land use is class 2 (Medium intensity grassland), with a few pixels in the south and west that have high-intensity grassland. Low-intensity grasslands are missing from the CLUMondo results altogether.

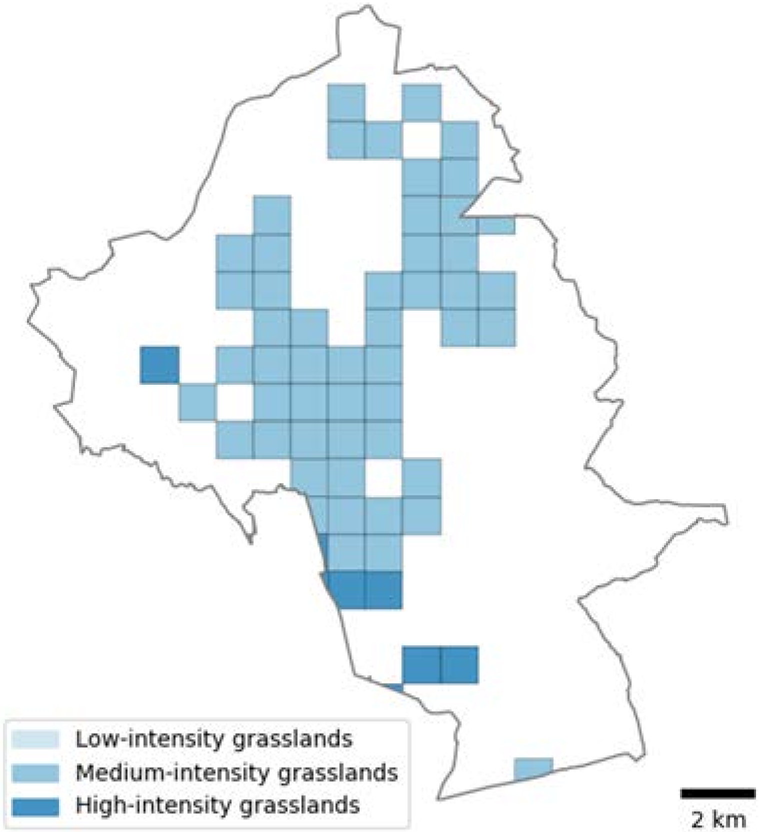

Figure 8: CLUMondo grassland categories in Time

The FarmDyn results for farms in Time can be seen in Figure 9. The figure outlines the CLUMondo pixels from before and shows the individual farm run results. Each dot in the figure symbolises a single farm located in one of the pixels from CLUMondo. The size of the dots represents the relative farm size in Ha. Note that the dots are upscaled, meaning they are not following the scale of the rest of the map. This is done to show the results of small farms. The colouring matches the CLUMondo land use classes, similar to Figure 14.

Ten of the analysed farms are found to have high-intensity grassland, 40 have medium-intensity grassland, and 15 have low-intensity grassland management. The area of the farms totals 224.3 ha for high-intensity grasslands, 1064.8 ha for medium-intensity grasslands, and 585.9 ha for low-intensity grasslands. The results confirm the pattern shown in CLUMondo and Nibios AR50 maps in Figures 7 and 9: Farms in the western part of the municipality have a higher intensity than those in the eastern part. Notably, several farms have low-intensity grasslands on average. This land use class is completely absent in the CLUMondo results for the same region. Furthermore, some farms situated in CLUMondo pixels with medium-intensity grasslands have high-intensity grassland use in the FarmDyn results. This shows the variability of intensity on the farm level, which is hidden in the upscaled CLUMondo results. A more general pattern is that smaller farms seem to have higher intensity than larger ones, indicating that these seem to offset a lower land endowment with higher production intensity.

This highlights the potential of farm-level models to provide insights into the effects of farm structure.

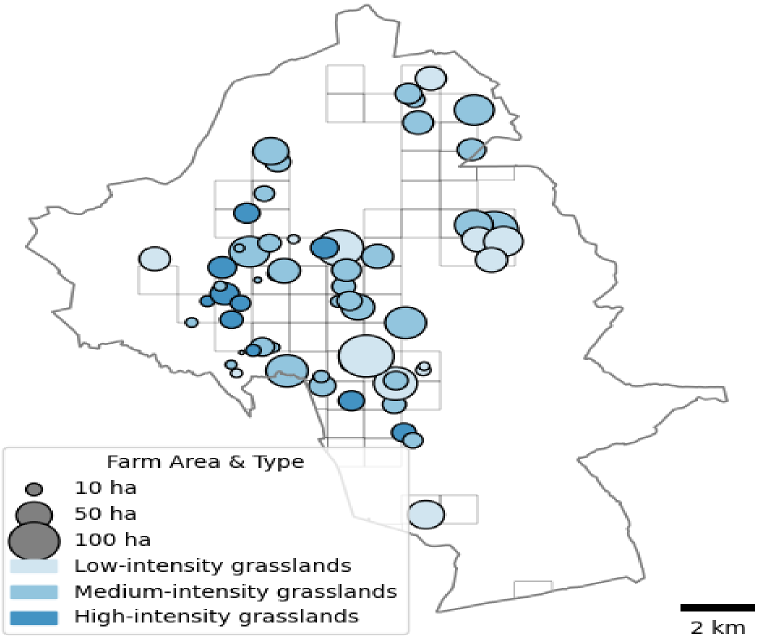

Figure 9: Land use classes following CLUMondo as calculated in FarmDyn.

4. Agent-based models to link land abandonment decisions to spatial data

Macro-economic models are indispensable for analysing agricultural dynamics at aggregate scales, spanning farm-household to national production levels—but they frequently obscure the fine-grained, context-specific realities in which these processes unfold. To address this limitation, a suite of studies has projected future land-use trajectories across Europe (Popp et al., 2017; Stürck et al., 2018; Zabel et al., 2019), evaluated land-based strategies for achieving sustainability targets (Lee et al., 2019; Roe et al., 2019), and examined megatrends poised to reshape these trajectories (Debonne et al., 2022; Krzysztofowicz et al., 2020). In most of this work, agriculture is treated predominantly as an economic sector, its evolution driven by shifts in commodity demand, supply, and trade (EC, 2023; OECD/FAO, 2023). Narrative scenarios are employed to incorporate divergent worldviews, social preferences, and policy interventions, ranging from dietary changes and environmental awareness to farm-subsidy reallocations and agri-technology investments (Delzeit et al., 2018; Mitter et al., 2019; Popp et al., 2017).

An analysis of alternative land abandonment processes was studied in a recent analysis in the case study of Terra O Trao Montes, in Portugal (Imbrechts et al., 2024). Building on the results of Imbrechts et al. (2024), it is critical to dissect the drivers of land abandonment, a process that can both precipitate rural intensification and be easily misinterpreted when its underlying mechanisms are insufficiently understood. Imbrechts et al. (2024) constructed a land-use matrix to capture change trajectories at both the start and end of each case-study period (see Figure 1). This approach builds on Fayet et al. (2022) and shifts the focus from fixed landscape outcomes to the processes driving change, thereby bypassing regional disparities. The regional occurrence of each trajectory was mapped to visualise local-scale spatial patterns of landscape change, enabling us to profile individual localities by the prevalence of specific trajectories (see Figure 1). The authors then applied logistic regression, estimating coefficients for each independent variable to gauge their significance and direction of influence on a binary outcome (Corbelle-Rico et al., 2012), to the most common trajectories in four separate "change regressions" (Hatna & Bakker, 2011). In mountainous areas, climate and slope emerged as the primary drivers of progressive land-abandonment trajectories. Interestingly, when modelling returns to agriculture, slope also exhibited a significant positive effect, highlighting its dual role in both abandonment and re-cultivation processes. The presence of this shift supports distinguishing between abandonment and post-abandonment trajectories, as these pathways may respond differently to the same set of underlying drivers. These findings underscore the need to reassess policies aimed at stimulating rural development. This is particularly true in regions that suffer from poor connectivity to urban centres and climate vulnerability to ensure that interventions are tailored to the specific processes governing landscape change, as demonstrated also in the work of Imbrechts et al. (2024), and other rural studies.

	Land use / Land Cover (t+1)					
Land use / Land Cover (t)	**LULC category**	Urbanised	Agriculture	Forest (natural)	Shrubland	Plantation (forestry)
	Urbanised	*No change*	*Unlikely*	*Unlikely*	*Unlikely*	*Unlikely*
	Agriculture	Urbanisation	*No change*	Natural succession	Natural succession	Afforestation
	Forest (natural)	Urbanisation	Recultivation	*No change*	Deforestation	Afforestation
	Shrubland	Urbanisation	Recultivation	Forest transition	*No change*	Afforestation
	Plantation (forestry)	Urbanisation	Recultivation	Natural succession	Deforestation	*No change*
	Direction of landscape change	**Urbanisation**	**Return to agriculture**	**Spontaneous revegetation**		**Managed revegetation**

Figure 10: Land use matrix and associated change trajectories at the beginning (t) and end (t + 1) of each study period. Adapted from Imbrechts et al. (2024).

While the study of Imbrechts did not yet progress into agent-based modelling (ABM), earlier work of Zagaria et al. (2018, 2021) illustrates how ABM can bridge broad-scale projections of land abandonment and site-specific realities, e.g., by acknowledging the effects of declining olive prices and tourism development on land use in Lesvos, Greece. However, ABM also presents a key methodological challenge: modellers must encode context-dependent decision rules while producing outputs tailored to the study area. Meeting this challenge requires (1) integrating high-resolution socio-economic data with qualitative insights from stakeholders, (2) explicitly representing spatial heterogeneity, and (3) iteratively validating model behaviour against empirical observations and expert knowledge.

Contextualising the model through structured farmer interviews, as in Zagaria et al. (2018), consolidates existing literature on local management practices and farming systems. Finally, clustering model outputs by trajectory type and linking them to distinct demand scenarios and land-use objectives avoids overly uniform conclusions driven solely by technical change, instead yielding a more nuanced understanding of how different drivers shape landscape transformations (Diogo et al., 2025).

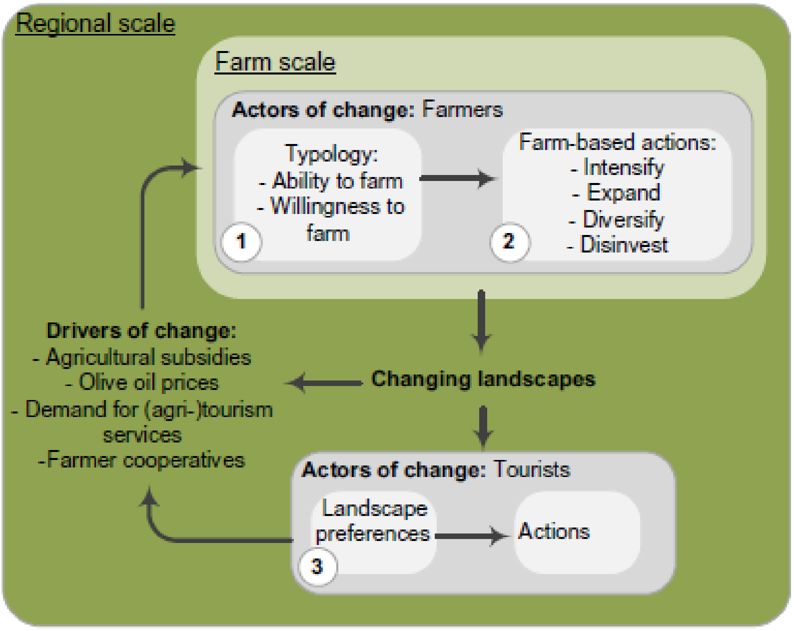

Figure 11: Conceptualisation of the framework used in the study of Zagaria et al. to develop an agent-based model.

Survey responses were synthesised into a reduced set of indices by aggregating related questionnaire items into broader categories. Specifically, indices were adopted for: (1) knowledge sources, (2) on-farm practices, (3) current land uses, and (4) future sector outlooks to minimise dimensionality. Historical trends in farm area—both owned and rented—were likewise consolidated into one index. A "cultural drive" index was derived from items reflecting willingness to transfer land to successors, reluctance to relinquish ownership, and the prevalence of inherited land. Finally, to quantify each farm's capacity for change, were aggregated indicators of professional engagement, formal agricultural education, participation in training programs, and reliance on external knowledge sources, into a single "engagement" index.

The aggregated indices served as inputs to a cluster analysis that identified distinct farmer typologies. To validate these empirically derived groups and examine their relationship to individual capacities and motivations, we performed a discriminant function analysis (DFA) following Hair et al. (2010). The DFA confirmed the stability of the cluster solution and quantified how farmers' skills, resources, and motivations predict their membership in each typology (Fig. 2).

By combining clustering with DFA, we disentangled the diverse drivers of landscape change and characterised farmers not as a homogeneous mass but as individuals occupying different intensity classes. This approach also illuminated the multifaceted nature of land-abandonment trajectories, which cannot be attributed solely to declining commodity prices and lack of willingness to cultivate the landscape, but also that tourism can offer a tool to maintain and cultivate the landscape and buffer the extensification of the abandonment phenomenon.

Another approach of ABM can be used in more climate adaptation contexts, which are relevant to land abandonment, as the inability to adapt often leads to abandonment. We study an example of ABM modelling concerning the type of irrigation choices, as in Zagaria et al. (2021). The ABM that they developed explores the effect of changing climate, water policy, and farmer attitudes and values on adaptation decision-making by individual farmers in Romagna. A farmer's annual decision-making process begins with a perceptual phase: farmers establish whether they perceive a risk of future drought damage and whether they perceive a possibility to adapt. The model in this case was divided into external entities (i.e., external environment and individual characteristics of the farmers (i.e., assets, values, goals, farm, field) and the perceived adaptation options (i.e., options). All these inputs were used to divide the structure of the model itself into sub-models. The sub models are divided as follows:

- Demographic and soil wetness
- Adaptation decision making
- Implementation of adaptation and feedback.

The model comprised three sequential sub-models, each operating on an annual time step through to 2050. In the first sub-model, agents' ages and farm structures evolved within irrigated systems, and soil moisture was updated to detect any drought-induced damage. The second sub-model then recalculated annual farm profits and updated each farmer's perception of drought risk; it used these inputs to compute the utility of available adaptation measures. In the final sub-model, additional practical constraints were evaluated, and the adaptation option with the highest utility was implemented before advancing to the next year.

Zagaria et al. (2021) evaluated the full model under a range of behavioural scenarios, climate scenarios (across multiple RCPs), and policy frameworks. Results indicate that scenarios designed to heighten farmers' perception of drought risk yield the greatest uptake of both transformational and incremental adaptations. These effects are most pronounced under drier climate projections, with farmers exhibiting highly adaptive decision-making and under water-use policies that tightly regulate irrigation. Under these combined conditions, the region experienced minimal loss of cultivated area, increased irrigation intensity, and a concentration of profitability among fewer farms, thereby amplifying current consolidation and intensification trends.

5. Discussion

The comparison between the FAMOS/PASMA land use categories and the CLUMondo classification reveals notable discrepancies across several land use categories. The FAMOS/PASMA cropland land use category is classified as other land use, forest and mosaics; small shares of the cropland pixels in FAMOS/PASMA are classified as medium intensity grassland and permanent crops. Similarly, this is the case when comparing alpine pasture pixels and grassland pixels. These differences can be explained by several factors. Firstly, a single pixel in FAMOS/PASMA can encompass multiple land use categories due to its spatial resolution and the presence of heterogeneous landscapes. This results in mixed pixels that might be classified differently in CLUMondo, which uses distinct classification thresholds and land use allocation rules. Secondly, forest is a dominant land use in Austria, but it is not explicitly included in the FAMOS/PASMA land use categories analysed here. Even in pixels classified as grassland or cropland in FAMOS/PASMA, there may be a significant proportion of forest area, which complicates a direct comparison between the CLUMondo and FAMOS/PASMA baselines. The absence of forest as a separate land use category in FAMOS/PASMA leads to ambiguities, as forest areas are incorporated into other land use categories, like mosaic in CLUMondo. This underlines the importance of considering forest land use and mixed land use patterns when comparing land use datasets for Austria.

Some conceptual differences hinder the comparison of intensities between the FarmDyn and CLUMondo models. CLUMondo operates at the grid level. The number of livestock per ha (stocking density) is related to the total land area in a grid, not to the farmland. The non-agricultural land in a grid reduces the stocking density related to the land area. This results in a systematically higher stocking density of the farm data reflected in FarmDyn compared to CLUMondo. As a behavioural model assuming a profit-maximising farmer, the model allowed for providing optimal grassland intensity for a given animal stock, using the model design to deal with the scarcity of observed and detailed grassland management intensity. Also, the grassland management intensity is subject to considerable uncertainty, which hinders the alignment of the results from the two models. The estimation of grassland management intensity in CLUMondo is based on LSU, mowing frequency, and nitrogen application. The LSU data is derived from a global dataset with an original resolution of 0.083 decimal degrees (approx. 10km at the equator) (Gilbert et al, 2018), and the mowing frequency original resolution is 3000m (Estel et al., 2018). These two datasets have been downscaled in QGIS using the nearest neighbour method to 1000m resolution for CLUMondo. A challenge for CLUMondo is to find intensity indicator data that covers the entire study area. For the nitrogen application data, the data from Koeble et al. (2024) does not cover Norway, Switzerland, or the Balkans. In this case, the intensity classification from another land use management intensity map of Europe from Dou et al. (2021) is used. Another more conceptual uncertainty is the definition and grading into low, medium, and high intensity. In the case of CLUMondo, these thresholds have been based on earlier literature attempting to set boundaries for when a management practice becomes detrimental to biodiversity (Mayel et al., 2021).

For the German case study, a synthetic population is used that distributes farms from aggregated statistics. The population has information on the location of farms at the county level, but then randomly distributes them in accordance with the observed land use. Hence, the exact location of farms and their land is not reflected in the data, and, therefore, they cannot be allocated to 1x1 km grids as the unit of comparison. However, the animal stock is the central driver of the grassland intensities in FarmDyn. The limitations of the synthetic population also cause differences to the CLUMondo results, which are based on more reliable data on N excretion and stocking density.

In the Norwegian case study, the mismatch of the results also partially reflects limitations in the database of the Norwegian case study. As only the farm address is available as a spatial identifier, only farms within a pixel of managed grasslands in CLUMondo are considered. Neighbouring farms that might influence the land use within a pixel are not considered. Furthermore, not all identified farms could be modelled due to data gaps and missing farm branches in FarmDyn, namely sheep, which is important in the Norwegian context.

Furthermore, FarmDyn does not use observed management data on N application and mowing frequency, as such data is scarce at the farm level. In the German case study this data these variables are estimated by the model through fixing the animal stock of farms. In this way, the required intensity of grassland production must match the forage needs of the observed herd. This reflects that grassland-based farms for dairy and beef production usually grow most of the forage on-farm. However, the amount of additional concentrate feed can vary between farms. Forage losses during silage production and storage impact the actual share of the yield used for feeding, and the models only provide average milk yields. All these aspects impact the required grassland management intensity to sustain a dairy or beef herd.

While ABMs are mostly made in a context-specific manner for case-study conditions, they can add to broad-scale modelling as conducted dominantly in LAMASUS. However, the underlying framework of ABM models can be readily transferred to other European contexts by first identifying the country-specific drivers of land-use change and climate-adaptation practices. By explicitly representing heterogeneous farm-level attributes, such as resource endowments, decision heuristics, and risk preferences, ABMs capture the diversity of adaptation responses across landscapes (Reidsma et al., 2010; Stringer et al., 2020). All these examples can lead to a better description of how policies are going to be projected into the future, accounting for the heterogeneity of landscapes and drivers. In that sense, ABM must not be seen in comparison to large(r)-scale modelling, but rather in a complementary manner allowing more in-depth analysis of behaviour-oriented drivers.

6. Conclusion

The high-resolution model verification using ex-ante behavioural models highlights both the potential and challenges of integrating different land use models. While FAMOS/PASMA provides valuable insights into agricultural land use decisions at the farm and regional level, significant discrepancies emerge when compared to the CLUMondo classifications. Due to the differences in spatial resolution, land use category definitions and rules for classification, as well as mixed land use pixels lead to the poor matching of pixels.

Concluding the model comparison between FarmDyn and CLUMondo, the land use categories between CLUMondo and the data used in FarmDyn fitted relatively well, although this was not the unit of comparison. When looking at the intensities in detail, the fit of the identified intensities, however, was relatively poor. This is strongly driven by conceptual differences between the models and uncertainties in the intensity estimation within each model, as discussed above. The results also provide an idea of the heterogeneity of intensities within one grid that is lost in CLUMondo due to its level of aggregation. As a behavioural model operating at the core unit of the supply side of the agricultural system, FarmDyn is suited to capture this heterogeneity and its change in response to policies. The developed approach to align the two models and compare their results allows for the future use of them to analyse the same policy scenarios, examining the topic from different perspectives. Thereby, the farm model can directly capture farmers' behaviour and response to changing policies, providing a useful addition to a large-scale modelling approach.

Summarising the comparison between CLUMondo and FarmDyn, CLUMondo covers an extensive range of land uses and geographical regions, but compromises on detailed information at the plot or farm level. In contrast, FarmDyn, as a bio-economic farm model, can provide such detail and also approximate farmers' behaviour. However, the latter is usually applied to smaller case studies and has a high data need, which often leads to restrictive assumptions. Therefore, both models need to be seen as complementing each other, addressing agri-environmental research questions from different perspectives.

The findings underscore the importance of transparent methodological harmonisation when combining land use information from different models. This deliverable might be used as a basis for developing and giving policy advice, accounting for the differences in the model representation of land use categories and management. Different models might be used and developed for specific policy and research questions. The choice of the model must be suitable for answering potential research questions and providing policy recommendations.

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