D6.3 Guidance on econometric model-based assessment of land use dynamics

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Authors	Esther Boere, Tamás Krisztin, Evelina Sandstrom, Davide Tita, Leopold Ringwald

Abstract

This report improves the realism of high-resolution land-use modelling by integrating empirical evidence on how policies influence land and management decisions. Using econometric results (particularly on organic farming uptake) from WP4, we refine the CLUMondo model's parameters, land system definitions, and transition rules. The updated model better captures observed behaviour and enhances the credibility of future land-use projections in LAMASUS. A validation exercise using parcel-level and regional-scale data confirms the predictive value of the new approach, supporting more robust and policy-relevant scenario analysis across Europe.

Keywords

Land-use modelling, ex-post econometrics, organic farming, policy impact assessment, high-resolution scenarios

Internal Technical Auditor	Name (Beneficiary short name)	Date of approval
Task leader	Esther Boere (VUA)	29/08/2025
WP leader	Peter Verburg (VUA)	29/08/2025
Coordinator	Petr Havlík (IIASA)	29/08/2025
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Abbreviations

AME	Average marginal effects
BAU	Business as usual
CAP	Common Agricultural Policy
CAPRI	Common Agricultural Policy Regionalised Impact modelling system
CATS	Common Audit Trail System
CLC	Corine Land Cover
CLUMondo	CLUster-based MOdel of land system dynamics
DG AGRI	Directorate-General for Agriculture and Rural Development
GISCO	Geographic Information System of the Commission
ETL	Ecosystem type level
EU	European Union
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
FiBL	Forschungsinstitut für biologischen Landbau / Research Institute of Organic Agriculture
LUC	Land use change
LUM	Land use and management
MNL	Multinomial logit
NFI	National Forest Inventory
NUTS	Nomenclature of Units for Territorial Statistics
SSP	Shared Socioeconomic Pathway
UAA	Utilised agricultural area
UNFCCC	United Nations Framework Convention on Climate Change
WFD	Water Framework Directive
WP	Work Package

Executive summary

Understanding how farmers and land managers respond to policy incentives is essential for designing effective land-use policies that deliver on Europe's climate, biodiversity, and sustainability goals. This report presents new evidence from the LAMASUS project showing how empirical data on past land-use responses—particularly regarding organic farming uptake—can be used to improve the predictive accuracy of spatial land-use models. Drawing on detailed econometric analyses and high-resolution data covering most EU countries, the report identifies key drivers behind land-use and land-management changes, including policy instruments, biophysical constraints, and socio-economic factors.

These findings were used to refine the CLUMondo model, a high-resolution land-use simulation tool capable of projecting the future impacts of EU and national policies across different regions and landscapes. Notably, new land-use categories for organic farming were introduced, and transition rules were adjusted based on observed uptake patterns. A validation using both parcel-level French data and regional NUTS 3-level data across the EU confirms that the revised model better reflects real-world changes. For policymakers, this means more reliable scenario analysis: the improved model can now simulate how different policy choices may shape land use at local and regional scales, helping anticipate trade-offs, maximize co-benefits, and support more targeted interventions. The enhanced model contributes directly to the scenario work in LAMASUS and strengthens the scientific basis for designing and evaluating future land and agri-environmental policies in Europe.

1. Introduction

Assessing how policies influence land use and land management is essential for designing effective, evidence-based interventions at local, national, and European levels. Understanding how landscapes respond to instruments such as organic farming subsidies under the Common Agricultural Policy (CAP) is particularly important, given that many land-based policies require years or even decades to produce measurable effects on biodiversity and climate mitigation. Reliable ex-ante assessments are therefore crucial to inform decisions before impacts materialise on the ground.

High-resolution land-use models such as CLUMondo are central tools for such assessments. They simulate policy impacts under alternative scenarios and account for local conditions and spatial heterogeneity. When coupled with macro-level economic models, as in LAMASUS, they allow for consistent analysis across scales. However, parametrising these models is challenging. It requires translating a complex set of socio-economic, biophysical, and policy drivers into rules and probabilities that govern land-use and land-management transitions. These parameters are often based on literature or expert assumptions, particularly when representing novel or rapidly evolving policies.

This deliverable addresses that challenge by drawing on recent empirical evidence generated within LAMASUS. Specifically, it links the econometric analyses from WP4 with the spatial simulation framework of CLUMondo to improve the realism and credibility of ex-ante projections. By doing so, it connects two critical parts of the project: (1) the ex-post assessment of land-use and land-management change based on observed behaviour and high-resolution datasets, and (2) the ex-ante modelling of future land-use dynamics at 1 km^2 resolution across Europe.

Chapter 2 of the report presents the ex-post modelling results. Two applications are highlighted. First, a spatial econometric analysis of land-use and land-management drivers using the harmonised geospatial database developed in WP2, together with policy and non-policy variables from WP3. Second, a logistic regression model of organic farming uptake across Europe, based on a harmonised dataset of organic producer certificates.

Chapter 0 documents how these findings were used to update the CLUMondo model. Land system maps were revised to better reflect observed land-use intensities, nitrogen inputs, livestock densities, and forest productivity. New land systems for organic cropland, grassland, and mixed farming were added, with associated yield penalties and transition constraints calibrated using the WP4 evidence.

Finally, Chapter 4 presents a validation of the model's policy relevance. Using parcel-level data from France and subsidy information from the Common Audit Trail System (CATS), we tested whether the model's predicted suitability aligns with actual conversion to organic farming at the NUTS-3 level.

2. Ex-post models and uncertainties

Understanding the real-world impacts of land-use policies requires robust empirical analysis of how land users have responded to past interventions. In this section, we present the ex-post econometric models developed in LAMASUS to quantify these responses. Using high-resolution spatial data and consistent methods, the models estimate the key drivers of land-use and land-management change across Europe, focusing on the uptake of organic farming. These empirical insights not only provide parameter values for ex-ante simulations but also quantify uncertainty around behavioural responses, highlighting where model projections are most robust and where caution is warranted.

2.1. LAND-USE CHANGES

Land-use change (LUC) is driven by socio-economic, institutional, and biophysical factors, and involves shifts across multiple competing land uses. Capturing these dynamics requires more than binary models, which reduce change to simple yes/no outcomes and ignore the set of alternatives at each location. A multinomial logistic (MNL) framework addresses this by modelling transitions across several land-use categories simultaneously and linking them to explanatory variables. This makes it possible to quantify how policies, markets, and environmental conditions affect the relative probability of different land-use outcomes. In this application, we use the MNL approach to assess how CAP Pillar I and Pillar II expenditures influence LUC.

2.1.1. Method & Data

We utilise the LAMASUS LUM geodatabase from WP2 (https://www.lamasus.eu/resources/lum-geodatabase), based on the *Corine land cover (CLC) annual time series* product and including LUC maps between 2000 and 2018 as the dependent variables to estimate the econometric model described below. These land cover products are available at the 100m^2 resolution, and they provide robust and harmonised maps for obtaining gross land-use change transitions between all considered land use classes. In the model setup, we aggregate the initial CLC landcover classes to an augmented Ecosystem Type Level 2 (ETL2) classification. The classification of CLC land cover types to ETL2 land use classes is summarised in Table A1 in the Annex. Moreover, the table also provides the corresponding UNFCCC classification and the ETL2 abbreviations used in the Figures presenting the results. An overview of the modelled LUM classes is provided by Table 1.

Table 1: LUM classes and their abbreviations.

Abbr.	LUM Class	Abbr.	LUM Class	Abbr.	LUM Class
ACRP	Arable cropland	GRSL	Grassland	HCRP	Heterogeneous agricultural areas
HEAS	Heathland and shrub	MARI	Marine	MITW	Marince inlets and transitional waters
PAST	Pastures	PCRP	Permanent crops	RILA	Rivers and lakes
SPVA	Sparsely vegetated areas	URBN	Urban	WOFO	Woodland and forest
WTLN	Wetlands				

In the econometric framework, we model land-use change decisions within an economic framework following Nerlove (1979). In each 10 km² grid cell i (with $i = 1, \dots, N$) considers the decision of a representative land user, who has to economically optimise the division of the cell among J land use classes. In a given time horizon between t and $t + h$ (where h denotes the horizon), the land user decides independently for each land use j (with $j = 1, \dots, J$) on what share of the land is kept in use j or converted to any one of the other $J - 1$ land use classes. The land user decides this based on the net profits associated with switching to the new land use class minus the cost of land conversion.

The utility of land-use conversion from the original land use can be expressed in the framework of the random utility model:

$$u_{ij} = \mu_{ij} + \varepsilon_{ij}, \tag{1}$$

where u_{ij} denotes the utility of converting from the original land use to the land use j. The utility is assumed to be a linear combination of μ_{ij}, a mean process of relative net profits and costs of land use conversion, and ε_{ij}, a random error term.

Based on random choice theory, the land-owner will choose to convert the land to land use class j over an alternative land use class j^* ($j^* = 1, \dots, J$) when the utility of j is higher than that of j^*. When considering land use shares, this implies that the share of land-converted, denoted by y_{ij} – directly depends on the probability:

$$y_{ij} = p(u_{ij} > u_{ij^*}, \forall j \neq j^*). \tag{2}$$

If we assume that ε_{ij} is logistically distributed, the random choice framework in Eq. (2) gives rise to a multinomial logit specification. The multinomial logit prior estimation model is specified as:

$$y_{ij}^{t+1} = \frac{\exp(\mu_{ij}^t)}{\sum_j \exp(\mu_{ij}^t)}. \tag{3}$$

Here, we have introduced the time dimension t (with $t = 1, \dots, T$), with y_{ij}^{t+1} denoting the share of land converted in the time period t to $t + 1$. This is a function of the log-odds μ_{ij}^t at time t. So far we have not specified the construction of these log-odds μ_{ij}^t: it is a linear combination of a set of explanatory variables and their coefficients, which are to be estimated:

$$\mu_{ij}^t = \alpha_j + f(y_i^t)\beta_j^1 + x_i^t\beta_j^2 + z_i\beta_j^3, \tag{4}$$

where α_j is the land use specific intercept, $f(y_i^t)$ is a $1 \times J$ vector of land use area shares at time t, which are dynamically updated when projecting the model. x_i^t is a $1 \times k_1$ vector collecting a set of time-varying (projected) land use change, drivers associated with the 10 km^2 grid cell i. z_i is a $1 \times k_2$ vector with static land use change drivers. β_j^1, β_j^2, and β_j^3 are the corresponding coefficients, which are to be estimated within the framework. The list of land use drivers is outlined in Table 2.

Table 2: Variables included as covariates for estimation.

VARIABLE	DESCRIPTION	TIME	RESOLUTION	TRANSFORMATION	SOURCE
		Dependent variable			
Land use change	Share of land use change transitions	2000 - 2018	$100m^2$	Share of LUC in km^2	Corine land cover annual time series
		Explanatory variables			
Pillar I + II measures (CAP payments)	Agricultural policy variables	2009 - 2018	NUTS3	Absolute difference in million €	Clearance of Accounts Audit Trail System (CATS) database
Natura2000 areas	Nature protection areas	2018	Polygons	Polygon coverage of pixel in km^2	Natura 2000 (vector) - version 2022
Land use	Land use class area change relative to baseline at initial pixel	2000	$100m^2$	Aggregated to 10 km^2, expressed as additive log-ratios (ALR) with origin LU class as reference	Corine land cover annual time series
Population density	Population per km^2	2021	$1km^2$	Mean and variance across $1km^2$ pixel resolution	GISCO census grid (Eurostat)
Altitude	Elevation in m above sea level	2012	$25m^2$		GISCO digital elevation model over Europe (EU-DEM)
Slope	Slope at a point, in degrees (elevation change per horizontal distance)	2012	$25m^2$		

The estimation is carried out in a Bayesian fashion using the framework of Polson et al (2013). We assume a rather non-informative prior setting of a Gaussian with zero mean and 10^4 variance for β_j. The estimation follows the Markov-Chain Monte Carlo algorithm laid out in Polson et al (2013). Our results are based on 5,000 iterations, where the first 3000 were discarded as burn-in.

2.1.2. Results & Discussion

Direct interpretation of the raw coefficients from multinomial logit (MNL) models is often problematic because they represent changes in the *log-odds* of one outcome relative to a baseline category. These log-odds are difficult to interpret in substantive terms, particularly when multiple alternatives and non-linear link functions are involved. Moreover, the magnitude of coefficients is sensitive to the choice of reference category, which complicates comparisons across land-use transitions.

To address these challenges, we present results as average marginal effects (AMEs). AMEs translate the estimated coefficients into probability changes, averaged across the observed data, thereby providing an intuitive measure of how a unit change in a covariate shifts the likelihood of each land-use transition. This representation enables meaningful comparisons across covariates and outcomes, makes effect sizes directly interpretable in terms of transition probabilities, and highlights both the direction and practical importance of drivers of land-use change.

The three figures report average marginal effects (AMEs) from multinomial logit (MNL) models of land-use transitions. Each panel corresponds to a given origin land-use category—cropland (Figure 1), grazing land (Figure 2), and forest or other natural vegetation (Figure 3) — with effects estimated for transitions into a full set of alternative land uses. Rows represent covariates, including policy instruments, biophysical attributes, and socio-economic factors. The shading indicates the sign and magnitude of the effect, while the size of the fill reflects whether zero is excluded from the credible interval. Together, these heatmaps provide a comprehensive overview of which drivers systematically shift the probability of land-use change, and in which direction.

For cropland transitions, the results highlight the relevance of several policy variables. Coupled payments exhibit significant negative effects on conversion of cropland into alternative uses, especially into grazing land, consistent with the role of commodity-specific subsidies in maintaining land under cultivation. In contrast, environmental payments and protected area designations increase the probability of cropland being converted into non-agricultural or natural uses, particularly forests and grasslands. Regional development and market measures also register localized but significant effects, pointing to heterogeneous pathways where economic incentives either reinforce the persistence of cropland or accelerate transitions out depending on context.

For grazing land, we observe a different structure of policy effects. Coupled and decoupled payments display weaker influence, but technical assistance and human capital improvements increase the probability of grazing areas transitioning into more intensive agricultural uses, notably cropland and heterogeneous agricultural mosaics. Conversely, physical capital investments are associated with persistence of grazing, reducing the likelihood of reallocation into forests or wetlands. Natura 2000 designations and environmental schemes again push transitions toward natural land covers, highlighting the capacity of conservation-oriented policy to redirect marginal grazing land into semi-natural habitats.

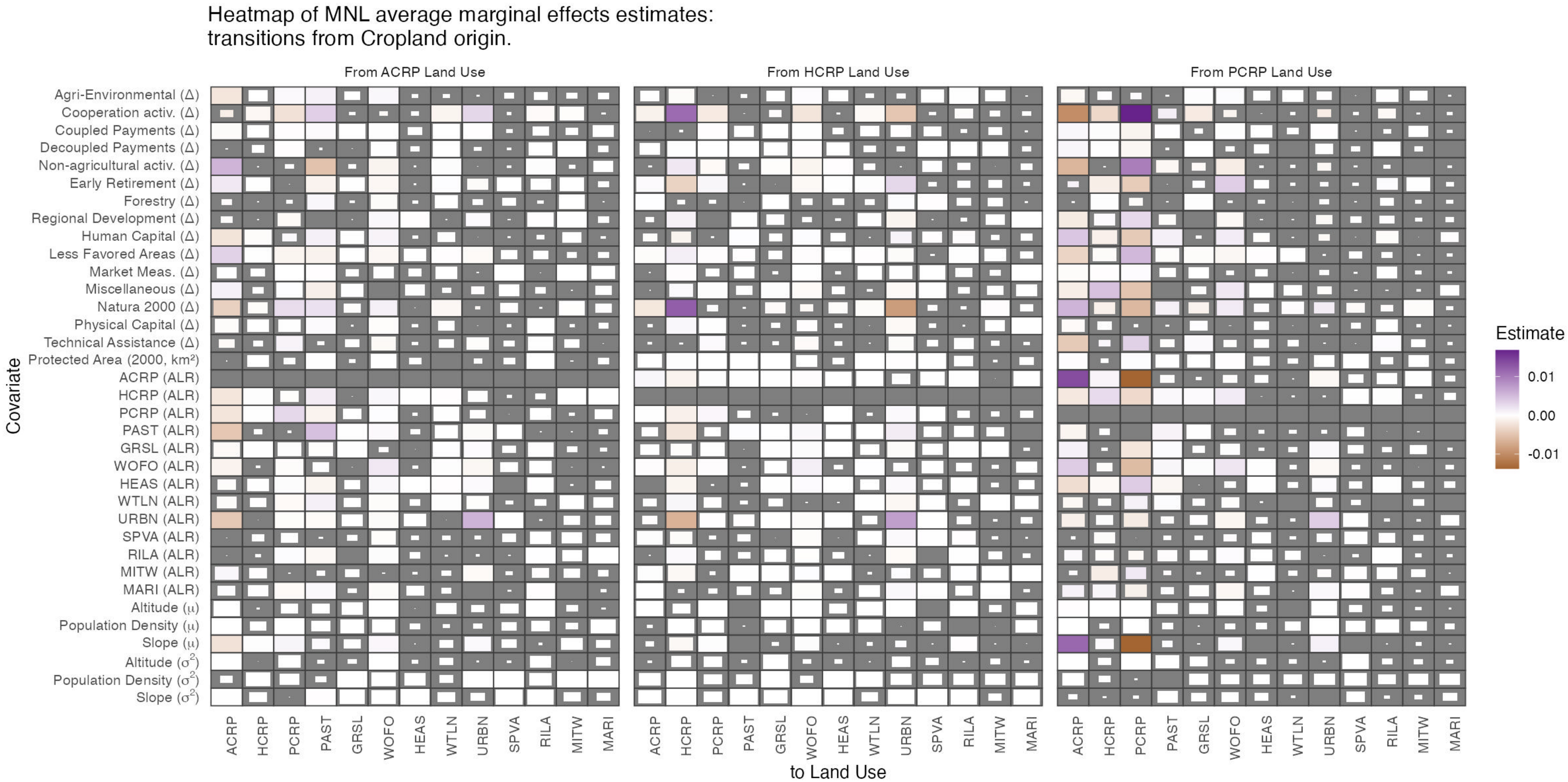

Figure 1: Heatmap of average marginal effects (AMEs) from the multinomial logit (MNL) model of land-use transitions from cropland origin.

Note: *Each panel shows estimated AMEs for transitions from a given cropland origin class (ACRP, HCRP, PCRP) to alternative land-use categories. Rows represent covariates, and colours denote the direction (purple = positive, brown = negative) and magnitude of effects. Effects are expressed in the original units of each covariate, corresponding to the change in transition probability associated with a one-unit increase in the covariate. The size of filled cells reflects the statistical credibility of the effect's sign: fully filled cells indicate that zero is excluded from the credible interval, while progressively smaller fills indicate increasing overlap of zero with the posterior distribution. Fully gray cells indicate cases where no estimate is available.*

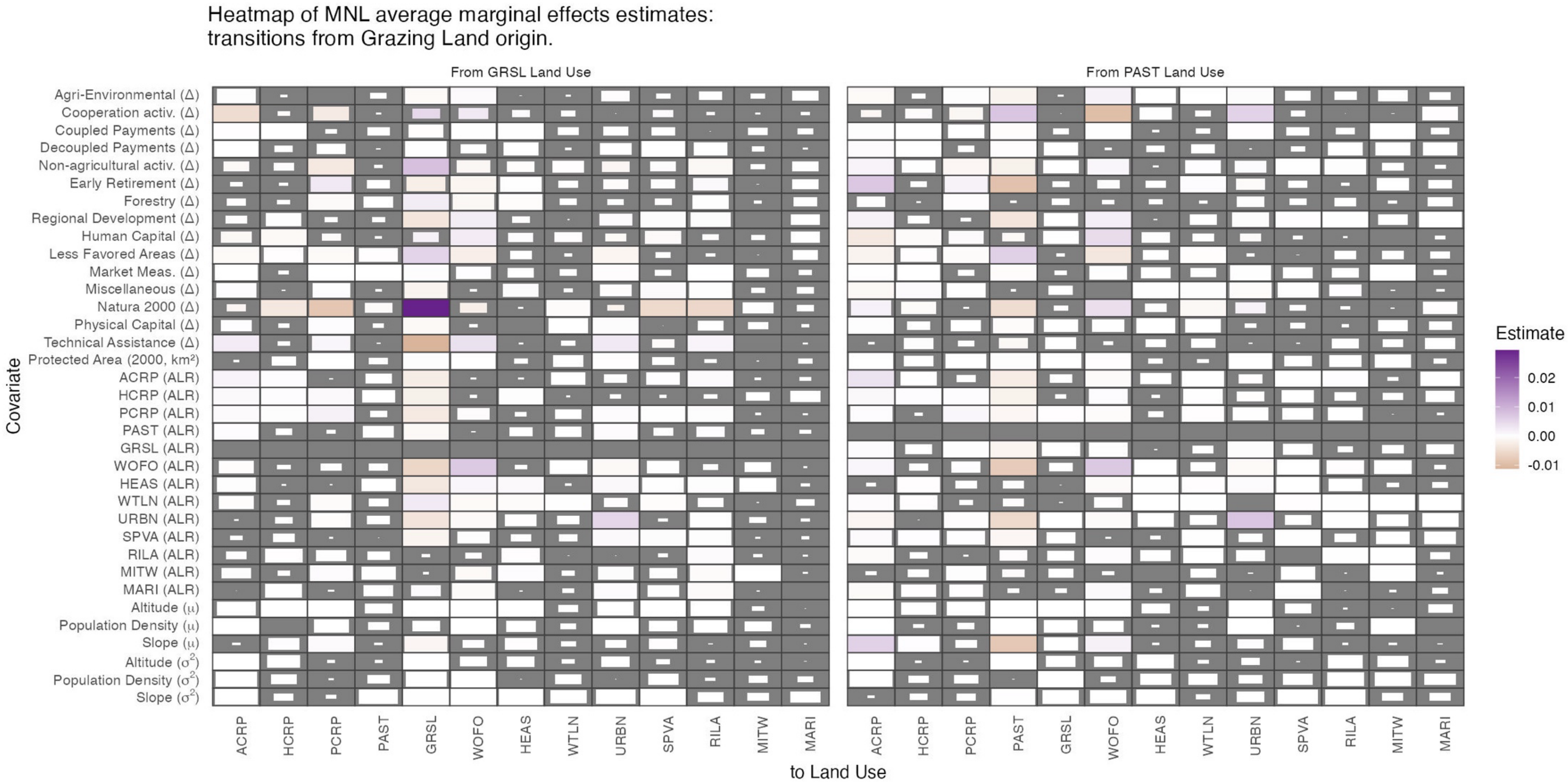

Figure 2: Heatmap of average marginal effects (AMEs) from the multinomial logit (MNL) model of land-use transitions from Grazing Land origin.

Note: *Each panel shows estimated AMEs for transitions from a given grazing land origin class (GRSL, PAST) to alternative land-use categories. Rows represent covariates, and colors denote the direction and magnitude of effects (purple = positive, brown = negative). Effects are expressed in the original units of each covariate, corresponding to the change in transition probability associated with a one-unit increase in the covariate. The size of filled cells reflects the statistical credibility of the effect's sign: fully filled cells indicate that zero is excluded from the credible interval, while progressively smaller fills indicate increasing overlap of zero with the posterior distribution. Fully gray cells indicate cases where no estimate is available.*

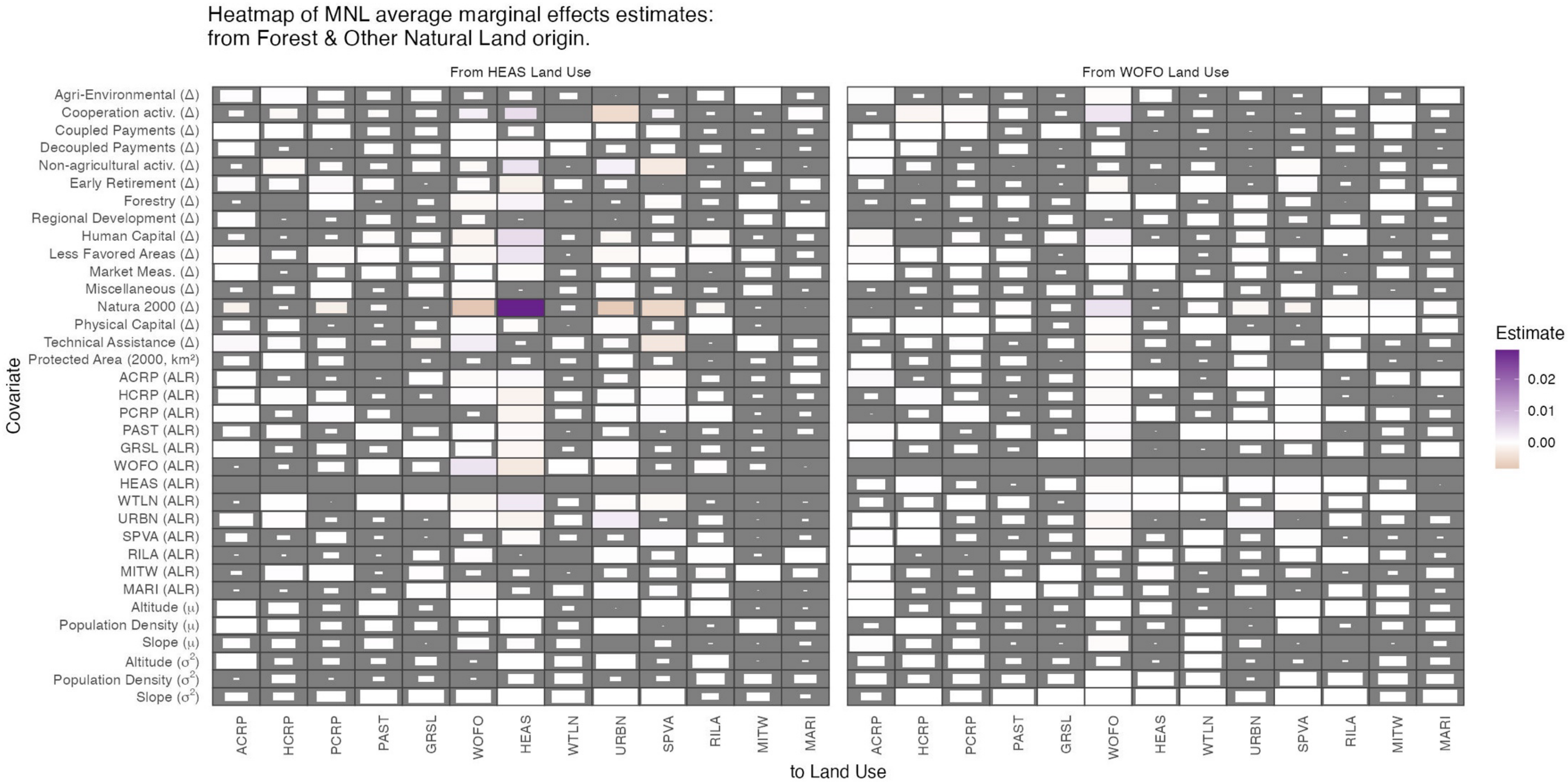

Figure 3: Heatmap of average marginal effects (AMEs) from the multinomial logit (MNL) model of land-use transitions from Forest & Other Vegetation origin.

Note: *Each panel shows estimated AMEs for transitions from a given Other Vegetation & Forest origin class (HEAS, WOFO) to alternative land-use categories. Rows represent covariates, and colors denote the direction and magnitude of effects (purple = positive, brown = negative). Effects are expressed in the original units of each covariate, corresponding to the change in transition probability associated with a one-unit increase in the covariate. The size of filled cells reflects the statistical credibility of the effect's sign: fully filled cells indicate that zero is excluded from the credible interval, while progressively smaller fills indicate increasing overlap of zero with the posterior distribution. Fully gray cells indicate cases where no estimate is available.*

Forest and other natural vegetation origins show fewer significant responses to agricultural support measures, but policy variables remain relevant. Technical assistance and regional development measures occasionally promote transitions into agricultural categories, suggesting that targeted infrastructure or advisory schemes can facilitate forest clearing. By contrast, agri-environmental payments and protected area coverage strongly reduce the probability of such conversions, reinforcing conservation outcomes. Overall, these results underscore that the policy environment — particularly the balance between commodity support and conservation instruments — plays a decisive role in mediating land-use transitions, with effects that are strongly origin-dependent.

2.2. ORGANIC FARMING

Organic farming is a sustainable farming practice with high relevance in current EU policy, such as the Farm-to-fork strategy, which aims to promote a more sustainable food system in the EU. Organic farming is a more broadly adopted and recorded sustainable farming practice with clear rules for production and certification. Therefore, we conducted a spatial analysis of organic agriculture in Europe in WP4. The study aimed to find the enabling and constraining factors of organic agriculture in a location (1x1km grid).

The results of the spatial analysis in WP4 will be used to inform the CLUMondo model. A baseline run, where we assume, based on current trends, that organic farming increases to 15% at EU level by 2030 is presented in Section 3.1. In WP8, these model runs will be expanded to analyse the impacts of the policy target to increase the share of organic agriculture to 25% of total UAA in the EU by 2030 and potential land use trade-offs thereof.

In WP4, we built a logistic regression model to determine what factors enable or constrain organic farming in a location. The model covered the EU27 countries and Norway, Switzerland and the UK. The model was run in four different constellations: for all organic producer types, for organic crop farmers, organic livestock farmers and for organic mixed farmers (See Table 3).

The location of organic farms in Europe was derived from organic producer certificates collected from public online certificate repositories[i] and government websites. The most current certificate data available for each country was collected, ranging from the years 2014-2024. For Sweden, Norway, and Switzerland, no certificate data was found, and national statistics on organic agriculture was used instead. For 19 countries, the certificate data included information on what type of organic production was taking place at the farm. These certificates enabled the separation of producer types to organic crop producers, organic livestock producers, and organic mixed producers (both livestock and crops).

To validate that the collection of organic producer certificates is representative of the organic producer population in each country, the number of certificates collected in this study was compared to the number of organic producers reported in FiBL statistics for each country[ii] in the year 2022. After the collection was complete, the certificates were mapped to a postcode

[i] bioC.info, accessed at webgate.ec.europa.eu

[ii] https://statistics.fibl.org/world/area-world.html

point map and the points were then snapped to the closest agricultural pixel according to the land use map of Europe from Sandström et al. (2024).

Several independent variables commonly chosen to determine agricultural management suitability were used (Abd-Elmabod et al., 2020). First, climate variables such as mean annual air temperature, mean diurnal air temperature range, annual range of air temperature, annual precipitation, precipitation seasonality, and aridity were included. These variables affect growing seasons and plant growth (Karger et al., 2017; Zomer et al., 2022).

Organic farming might be incentivised in areas with low soil fertility or less favoured areas for agriculture because it might become more economically viable to farm in these areas with organic price premiums (Kremmydas et al 2024). We therefore included variables that indicate if an area is less favourable for agriculture, such as slope, the percentage of flat land, and elevation (Klima et al, 2020). Variables that indicate soil health, like available water capacity, bulk density, cation exchange capacity, coarse fragments, pH value, sand, soil organic carbon, nitrogen and phosphorus availability for plant uptake (Ballabio et al, 2016, 2019, Panagos et al, 2022).

Legislative restrictions on farming practices can potentially also cause synergy with organic practices. Natura 2000 protected areas and nitrate vulnerable areas as designated by the water framework directive (WFD) both put constraints on the farming practices allowed on land within their respective areas. These restrictions could be similar to the ones applied to organic farming, hence providing synergy.

Furthermore, previous research found that beneficial socio-economic conditions can enhance the presence of organic farming in an area (Malek et al, 2019). Therefore, we included socio-economic variables such as accessibility to cities, human wellbeing, road density, population density, and irrigation as a proxy for the level of mechanisation on a farm. Country dummy variables were also included in the model to capture any national policy context that could affect the presence or absence of organic agriculture.

All variables were aligned to the same coordinate reference system and spatial resolution of 1 km^2. Variables with a Pearson correlation of > 8 or < -8 were removed from the analysis, as well as variables with a variance inflation factor > 10 to reduce multicollinearity. All continuous variables were standardised with z-score standardisation for easier comparison between variables. A stepwise forward and backwards elimination of variables was conducted to get the best model with the least amount of non-significant variables and the best Akaike Information Criterion value. The model was then evaluated with AUC, ROC, and McFadden adjusted R2. This was done for each constellation of the model.

According to our model, organic producers are most notably located close to markets, where population density is the strongest predictor across all organic producer types (Table 3). Population density and human wellbeing have a stronger positive effect on the location of organic crop farms. Accessibility to cities and road density have a stronger positive effect on organic livestock producers.

Organic producers are also more likely to be found in less favourable agricultural areas. Areas with steeper slopes and lower soil quality are more likely to have organic farms. Steep slopes have a stronger probability for organic livestock farms than crop or mixed farms. Natura 2000 areas increase the odds of organic producers being in a location by 12%. Nitrate vulnerable areas increase the odds by 4%. These effects are stronger for organic crop producers.

Table 3: Results of the logistic regression.

PRODUCT	ALL		LIVESTOCK		CROPS		MIXED	
Variable	Coeff.	Odds ratio	Coeff.	Odds ratio	Coeff.	Odds ratio	Coeff.	Odds ratio
Accessibility	-0.31***	0.73	-0.76***	0.47	-0.15***	0.86	-0.09***	0.91
Road density	0.17***	1.19	0.46***	1.59	0.20***	1.22	0.11***	1.12
Travel to HC	-0.25***	0.78	-0.10***	0.91	-0.43***	0.65	-0.08***	0.93
Population density	1.31***	3.71	0.93***	2.53	1.88***	6.52	1.29***	3.62
Irrigation	0.08***	1.08	0.23***	1.26				
AWC	0.09***	1.09	-0.03.	0.97	0.02*	1.02	0.11***	1.12
Bulk density	0.05***	1.05			0.01*	1.01	-0.032***	0.97
CEC	0.04***	1.04					0.15***	1.16
Coarse fragments	0.01*	1.01	-0.30***	0.74	0.09***	1.09	0.15***	1.16
Sand	0.21***	1.23			0.22***	1.24	0.14***	1.15
pH value	-0.09***	0.92	-0.16***	0.85	-0.23***	0.79	-0.62***	0.54
Phosphorus	-0.40***	0.67	-0.12***	0.88	-0.442***	0.64	-0.034**	0.97
Nitrogen	-0.09***	0.91	0.19***	1.21	-0.11***	0.90		
SOC	0.19***	1.21	0.15***	1.16	0.28***	1.32	0.38***	1.46
Flat land	-0.14***	0.87	-0.12***	0.89	-0.21***	0.81	-0.19***	0.83
Elevation	-0.26***	0.77			-0.178***	0.84		
Slope	0.19***	1.21	0.36***	1.43	0.22***	1.25	0.19***	1.20
Protected area	0.12***	1.12	0.13***	1.13	0.25***	1.28	0.08***	1.08
Nitrate vulnerable	0.04***	1.04	0.14***	1.15	0.16***	1.17	0.13***	1.14
Aridity	-0.07***	0.93			-0.23***	0.80	0.10***	1.10
M.A. Air temp			0.69***	1.99			0.86***	2.36
M.D. Air temp					-0.046***	0.96	0.14***	1.15
A.R. Air temp	0.17***	1.19	0.29***	1.33	0.22***	1.24		
Annual precip			0.10***	1.10				
Precip season	-0.03***	0.97	0.28***	1.32	-0.18***	0.84		
Countries included in analysis	EU27, NO, CH, UK		AT, BG, CY, CZ, EE, EL, ES, FI, FR, HR, HU, IT, LT, PT, RO, SE, SK		BG, CY, CZ, EE, EL, ES, FI, FR, HR, HU, IT, LT, MT, PT, RO, SE, SK		AT, BG, CY, CZ, EE, EL, ES, FI, FR, HR, HU, IT, LT, LV, PT, RO, SK	
Sample size	559,114		30,588		266,939		112,261	
AUC	0.69		0.79		0.74		0.72	
McFadden adj R^2	0.09		0.20		0.14		0.12	

Note: Coefficients with significance levels of p: *** < 0.001, ** 0.001 – 0.01, * 0.01 – 0.05. AUC and McFadden adjusted R2 for each producer category, including all categories. Odds ratios are calculated by exponentiating the coefficients. Empty cells mean the variable is not significant for that producer category. Data from Sandström et al 2025.

Climate is more varied across the producer types. Organic livestock and mixed farms are more likely to be located in areas with higher mean annual temperature. Organic crop producers are more likely to be located in arid areas.

Country context plays a role in the probability of the presence of organic farms. Most notably, western European countries seem to have a higher probability of having organic farms due to their country context (Sandström et al., 2025).

3. Ex-ante high-resolution adaptation and technical implementation

3.1. Baseline Changes

In Deliverable 6.1, Conceptualizing the LAMASUS Toolbox, we introduced the CLUMondo model. Here, we reflect on the modifications made based on expert feedback. This section highlights the main adjustments to the model after completing D6.1, focusing on model calibration, validation with existing literature and post-modelling results, and model enhancements to represent organic farming as a distinct land system.

In the updated CLUMondo model, we reconstructed the baseline land-use map to correct the previous overrepresentation of high-intensity agricultural classes by integrating the revised nitrogen-input estimates from Koeble et al. (*in press*). This refinement better represents management intensity in the base year of the model and thereby allows the model to track an SSP2 pathway more faithfully, capturing both intensified production on high-productivity systems and reduced contribution in low-productivity areas (Popp et al., 2017; Riahi et al., 2017). Forest-management intensity classes have also been refined following the methodology of Scherpenhuijzen et al., (2025), now accounting for both anthropogenic and natural disturbance regimes across all forest types.

A logistic-regression model was developed for the newly defined “forest” and “low-intensity arable cropland” classes. This enables the model to incorporate these land-use changes endogenously, ensuring consistency and to consider the principal independent variables that will be the main driver for each LUM intensity.

Table 4 shows that percentage changes in land allocation compared to CLUMondo’s initial land cover map from D6.1 are mostly related to those land systems that include management intensities. This highlights that while GIS data sources are valuable for describing land cover, they provide limited insights into management intensity. To capture this aspect, we need information on human responses, which can be more effectively derived through modelling approaches that incorporate behavioural elements, such as ex-post econometric modelling.

Table 4: Area changes of the different land use and land use change classes in the new baseline map.

CLASS	2020 D6.1 (KM²)	2020 NEW (KM²)	Δ (NEW-D6.1)	Δ %
Low-density Rural Settlement	60,563	60,563	0	0.00
Medium-density Peri-urban Settlement	105,296	105,296	0	0.00
High-density Urban Settlement	127,367	127,367	0	0.00
Wetlands	64,043	64,043	0	0.00
Forest, Shrub and Cropland Mosaics	393,588	393,588	0	0.00
Forest, Shrub and Grassland Mosaic	598,823	598,823	0	0.00
Low-intensity Arable Cropland	7,367	156,984	149,617	2.94
Medium-intensity Arable Cropland	265,012	613,929	348,917	6.86
High-intensity Arable Cropland	675,545	177,011	-498,534	-9.80
Low-intensity Grasslands	104,139	111,919	7,780	0.15
Medium-intensity Grasslands	182,931	205,875	22,944	0.45
High-intensity Grasslands	123,913	93,189	-30,724	-0.60
Permanent Cropland	96,175	96,175	0	0.00
Close To Nature Forestry + Primary Forest	303,548	404,140	100,592	1.98
Combined Objective Forestry	734,978	700,146	-34,832	-0.68
Intensive forestry + very intensive forestry	693,880	628,120	-6,576	-1.29
Water Bodies	156,597	156,597	0	0.00
Bare Rock and Shrubs	391,379	391,379	0	0.00

Changes in the lusmatrix

Building on the updated baseline map and revised class intensity counts, another key modification concerns the adjustment of productivity levels across the different LUMs. This adjustment is implemented in CLUMondo through the so-called *lusmatrix*, which specifies the average productivity of each land system. For each land system, a 'productivity indicator' was used. These are populations for urban systems, crop production for arable systems, livestock density for grassland systems and wood production for forestry systems. For mosaic systems, a combination of these indicators was used. Subsequently, the ratios of productivity between different systems with a similar indicator were calculated. For example, a high-intensity cropland has a higher productivity of arable crops compared to a low-intensity cropland, thereby having a higher ratio. These ratios of change subsequently influence the likelihood of changes to a different land system, for example, based on changes in overall demand for arable crops. These ratio changes are informed by econometric post-modelling estimates, land use and statistical information. In the following section, we will explain all the modifications that have been made to better represent these ratio changes.

Population mainly drives urban land systems; however, other land systems also provide housing. Because of this reason, all land systems of the Sandstrom et al. (2024) map are overlaid with the population grid of Batista e Silva et al. (2021). Final calculations result in Table 5, these values are going to be used per each land class intensity to avoid misrepresentation of urban areas in rural contexts.

Table 5: Average population size per km² in arable land, grassland, and forest areas

	WESTERN REGION	EASTERN REGION	NORTHERN REGION	SOUTHERN REGION
Arable land (pop/km²)	45	44	33	23
Grassland (pop (pop/km²)	47	62	32	24
Forest (pop (pop/km²)	15	13	5	19

Arable crops can be located on arable cropland land systems and the mosaic of forest, shrubs, and croplands. In the other land systems, no arable crops are produced. Medium intensity cropland was overlaid with GlobalWheatYield4km (Luo et al., 2022). To better harmonise the ratio between low, medium and high intensity compared to the land system map of D6.1, the nitrogen input map was used (Koeble et al., in press). The ratio differed per region, however, South and East Europe showed the best results as they best represented all intensity classes. Because of the non-linear relationship between nitrogen input and crop yield, the ratio between high and medium is adjusted downwards following the Michaelis-Menten curve and natural nitrogen uptake by arable crops (Kuppe & Postma, 2024; Liu et al., 2024; Meloni et al., 2024). The ratio used (low/medium/high): 0.75/1/1.2 (Table 6). Then this ratio is multiplied by the value found for medium-intensity cropland (Table 7).

Table 6: Nitrogen ratio of the different arable land intensities

MANAGEMENT INTENSITY	REGION				EU	RATIO
	Western	Eastern	Northern	Southern		
Low intensity arable cropland	0.63	0.46	0.74	0.57	0.45	0.75
Medium intensity arable cropland	1.00	1.00	1.00	1.00	1.00	1.00
High intensity arable cropland	1.41	1.00	1.34	1.54	1.44	1.20

Table 7: Production of arable crops per intensity class (in t/km²)

	WESTERN REGION	EASTERN REGION	NORTHERN REGION	SOUTHERN REGION
Low intensity arable cropland (t/km²)	544.68	416.32	658.07	199.47
Medium intensity arable cropland (t/km²)	726.24	555.09	877.43	398.93
High intensity arable cropland (t/km²)	871.49	666.11	1052.92	797.86

For the mosaic land systems, the share of arable cropland within the mosaic is calculated and multiplied by low-intensity cropland. The reasoning behind this is that mosaic croplands have a relatively low amount of nitrogen input. A validation has been done by overlaying GlobalWheatYield4km with the mosaics. Wheat is considered as a good indicator of arable crop productivity, as it is produced throughout Europe and has the highest production of cereal types (Luo et al., 2022).

Permanent crops have no distinction between classes; the start value of permanent crop production from CAPRI is divided by the area of permanent crops. This has not changed with respect to the previous version.

Livestock can be placed on grassland systems and the mosaic forest, shrubs and grassland. Grassland classes are overlaid with data from Malek et al. (2024). Cattle grazing and sheep and goat density are used as indicators of grassland productivity. Note that the values from sheep and goats' density have been converted into Livestock Units (LSU).

Also, for grasslands, a ratio between the intensities is calculated (Table 8). The ratio is based on the livestock data layer of Malek et al. (2024), in which the three intensity classes of that data source are used. The same ratio is applied to the whole of Europe (low/medium/high): 0.4/1/1.6 (

Table 9). For grassland mosaics, the same procedure as the mosaic of arable cropland is applied (

Table *10*).

Table 8: Ratio of livestock units (per km²)

	WESTERN REGION		EASTERN REGION		NORTHERN REGION		SOUTHERN REGION		EU LEVEL	RATIO EU
	N° Obs	Ratio	N° Obs	Ratio	N° Obs	Ratio	N° Obs	Ratio	N° Obs	Ratio
Low intensity	2,642	0.71	26,721	0.58	16	0.75	21,245	0.22	50,621	0.47
Medium intensity	102,507	1.00	14,050	1.00	1534	1.00	25,402	1.00	133,887	1.00
High intensity	82,577	1.21	1	0.83	5	0.93	472	1.22	72,395	1.62

Table 9: Livestock production in grassland LUMs (in LSU/km²)

	WESTERN REGION	EASTERN REGION	NORTHERN REGION	SOUTHERN REGION
Low intensity grassland (t/km²)	62.22	51.52	62.22	12.05
Medium intensity grassland (t/km²)	133.44	110.49	133.44	25.84
High intensity grassland (t/km²)	215.65	178.56	215.65	41.76

Table 10: Final outcomes of livestock production for the mosaic (LSU/km²)

	WESTERN REGION	EASTERN REGION	NORTHERN REGION	SOUTHERN REGION
Grassland in FOREST SHRUB AnD grassland mosaics (%)	0.38	0.38	0.38	0.33
Final Production in Mosaics (LSU/KM²)	23.70	19.54	23.79	4.04

Wood is produced in the forest classes and grassland and cropland mosaics. The wood production ratios are derived from National Forest Inventory (NFI) data. We used data for 10 countries: Norway, Sweden, Germany, Austria, Poland, Slovenia, Spain, Belgium, Czechia, and Ireland. The dataset records the volume of standing trees for each plot at two time points, as t0 (vol0) and t1 (vol1). The percentage change between the volume measurements t0 and t1 was then calculated for each plot and subsequently grouped into categories with 20% intervals. We overlaid the plot locations with the forest management map, and for each forest management class, we derived the final distribution over the intervals. This distribution was corrected for the average timespan between vol0 and vol1, per forest management class.

To calculate the ratios of forest productivity, we used this distribution, indicating the yearly occurrence of a volume decrease per 20% interval per forest management class. We only considered the volume intervals indicating a decrease in volume. The yearly occurrences found over those volume decrease intervals are the following (Table 11).

Table 11: Ratios for volume per forestry class

% ALL	UNMANAGED FOREST	CLOSE-TO-NATURE FORESTRY	COMBINED OBJECTIVE FORESTRY	INTENSIVE FORESTRY	VERY INTENSIVE FORESTRY
0-0.2	0.20	0.07	0.24	0.39	0.63
0.2-0.4	0.00	0.09	0.18	0.20	0.36
0.4-0.6	0.00	0.18	0.28	0.30	0.39
0.6-0.8	0.40	0.50	0.59	0.63	0.57
0.8-1	2.83	1.71	1.63	1.69	1.12

Next, we applied a formula to calculate the ratios. We multiplied the annual occurrence of a volume decrease per 20% interval with the average value of that interval (for the interval of 80 to 100% decrease in volume this value is 0,9; for the interval of 60 to 80% it is 0,7; for the interval of 40 to 60% it is 0,5; for the interval of 20 to 40% it is 0,3; and for the interval of 0 to 20% it is 0,1).

The results after applying the formula are presented below for the five forest management classes. Those ratios were normalized to medium = 1 (Table 12).

Table 12: Volume ratio of five forest management classes

UNMANAGED FOREST	CLOSE-TO-NATURE FORESTRY	COMBINED OBJECTIVE FORESTRY	INTENSIVE FORESTRY	VERY INTENSIVE FORESTRY
0.58	0.54	0.83	1.00	1.30
0.70	0.65	1.00	1.21	1.57

Unmanaged forests have very few plots and are protected. Therefore, this number was ignored. So low intensity forestry = close to nature forestry, medium = combined objective forestry, and high = average of intensive forestry and very intensive forestry (Table 13).

Table 13: Final volume ratio for the three forest class intensities

LOW INTENSITY FORESTRY	MEDIUM INTENSITY FORESTRY	HIGH INTENSITY FORESTRY
0.65	1.00	1.39

Those ratios were multiplied by the average wood production (m^3/km^2) (Table 14). This was calculated by dividing the total regional roundwood production (estimated by FAOSTAT) by its total forest area.

Table 14: Final wood production (in m^3/km^2) with ratio applied

REGION	LOW INTENSITY FORESTRY (m^3/km^2)	MEDIUM INTENSITY FORESTRY (m^3/km^2)	HIGH INTENSITY FORESTRY (m^3/km^2)
North	154.78	237.06	329.82
East	252.66	386.99	538.41
South	84.64	129.63	180.36
West	285.33	437.03	608.04

For the mosaics, the same procedure as for arable crops and grassland has been applied. Here we utilised, as described in the previous paragraph, the FAOSTAT production, as they provide more recent numbers compared to Verkerk et al., 2015. Then, we derived the production by multiplying the values from the low intensity forest class to the percentage of forest contained in the mosaics. The final values are summarised in Table 15.

Table 15: Wood production (in m^3/km^2) of the forest in shrub cropland and grassland mosaics.

	WESTERN REGION	EASTERN REGION	NORTHERN REGION	SOUTHERN REGION
Forest in Shrub and cropland mosaic (%)	0.40	0.43	0.48	0.28
Forest in shrub and grassland mosaic (%)	0.38	0.44	0.35	0.27
Final Production in Mosaic CROPLAND (m^3/km^2)	114.73	107.76	73.70	23.98
Final Production in Mosaic GRASSLAND (m^3/km^2)	109.98	112.03	54.22	23.26

3.1.1. Conversion rules updates

In CLUMondo the conversion elasticity ranges from 0 to 1, determining the resistance of land use types to change. Higher values impose stronger conversion restrictions. A value of 1 implies a full conversion restriction, keeping the land system constant over time (as is e.g. the case for high-density urban settlements).

Building upon the work on the Modelling Toolbox described in D6.1, we improved the model elasticities by lowering the restriction of conversion for low and medium density settlements, allowing an intensification of urban areas, and the possibility of sprawl to new settlements.

We kept wetlands stable at 0.9 because we allow some agricultural activity in those areas, especially in regions like Western Europe where this is still happening in the current socio-economic conditions Giersbergen et al., (under review). Table 17 shows that the decrease of wetlands for all agricultural activities is rather negligible.

Similarly to the urban areas, we lowered the conversion elasticities of low and medium intensity arable land to better depict a process of intensification of agricultural activities (Table 16). Furthermore, we lowered the mosaic elasticities to avoid the overrepresentation in the satisfaction of the wood and agricultural demand that was observed in the previous version. Grassland was not altered as the SSP2 is not projecting a huge increase of livestock products in the near future (2050), in line with the Fricko et al., (2017).

Regarding the forestry classes, we increased the conversion elasticities for the close to nature forestry class, to represent a pathway of protection of natural areas under SSP2, with an increase of this class expected in Iberian and Carpathian areas (Štěrbová et al., 2024; Vadell et al., 2022). Conversely, we reduced the elasticities of combined and very intensive forestry to permit more flexible management transitions and push in region that with climate change will also increase new plantations in the intensive forestry management (i.e., northern UK, Sweden and Baltic region).

As mean annual temperatures rises, we expect a modest shift toward more intensive farming, as declining productivity in some areas leads producers to intensify elsewhere. Figure 4 (next section) illustrates this in arid or abandonment-prone contexts, for example in parts of Spain, France, and the Baltic region, where cropland and grassland intensification classes occur under the new elasticities and where an increase of land degradation is observed (Engman et al., 2025; Erb et al., 2016).

Table 16: Conversion elasticities LUC (0 from 15 are following the same order of the previous table)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
New	0.5	0.6	1	0.9	0.4	0.4	0.3	0.4	0.5	0.4	0.5	0.6	0.6	0.7	0.4	0.5
Old	0.8	0.9	1	0.9	0.5	0.5	0.3	0.4	0.7	0.4	0.5	0.6	0.6	0.4	0.5	0.6

3.1.2. Changes in future land use projections

Following the rationale of SSP2, the Figure 5 and Figure 6 below compare our updated results with the previous projections. The main differences are a more constrained expansion of high-intensity cropland in Eastern Europe, better preservation of near-natural forests, increased close-to-nature forest cover across the Iberian Peninsula alongside intensified forestry activity in Portugal and Spain, in line with the historical trend (Vadell et al., 2022). At the same time, a rise in high-intensity grassland in central Spain compared with both the base year and the earlier projection has been observed (Schils et al., 2022). In Western Europe, particularly France, an expected intensification in the Loire, Britanie, and Normandie regions can be observed, in line with the pathway of current input increase in the area (Billen et al., 2018). Finally, Latvia, Lithuania, Sweden, and Norway have shown an increase in intensive forestry management, as warmer temperatures will favour new plantation establishment (Blattert et al., 2023; Di Fulvio et al., 2024). The full details of the projections are summarised in Table 17.

Lastly, the model shows an overall improvement in its performance, primarily due to a refined representation of management intensity classes. This allows for more accurate outcomes when capturing processes such as cropland intensification and the protection of natural areas. These improvements were made possible through ex-post econometric modelling information, which provides a more realistic depiction of anthropogenic activities.

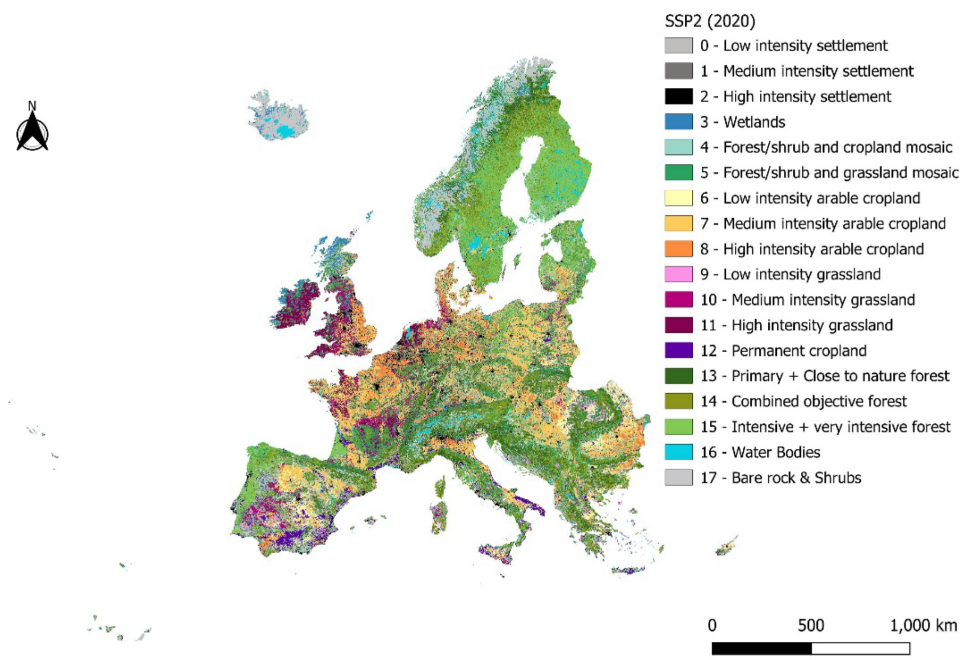

Figure 4: Ex-ante restructured base year (2020).

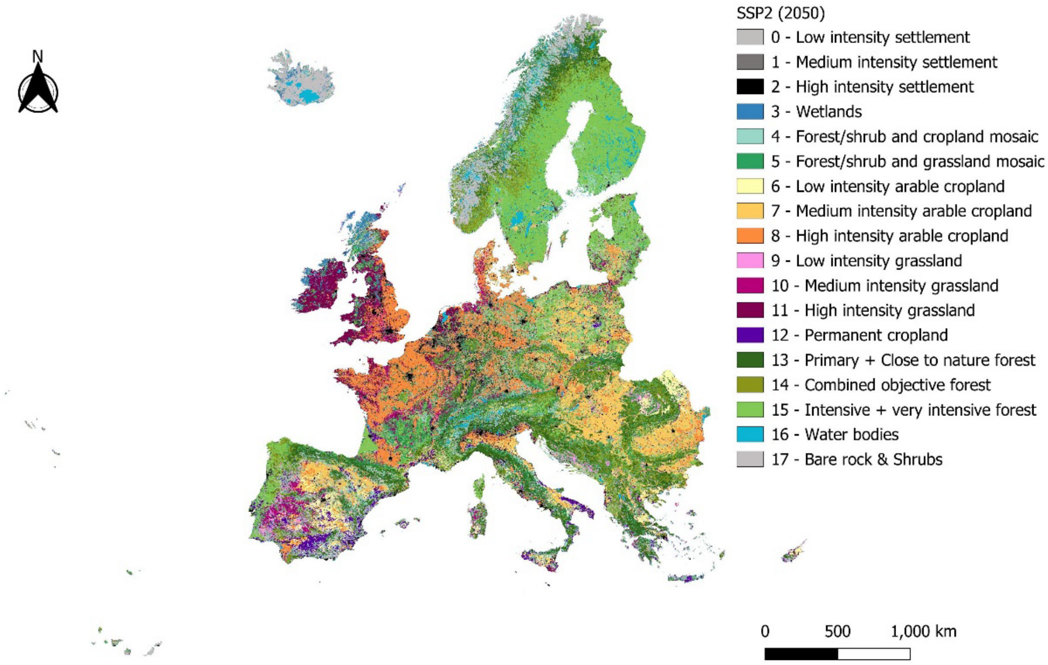

Figure 5: Final SSP2 projections 2050.

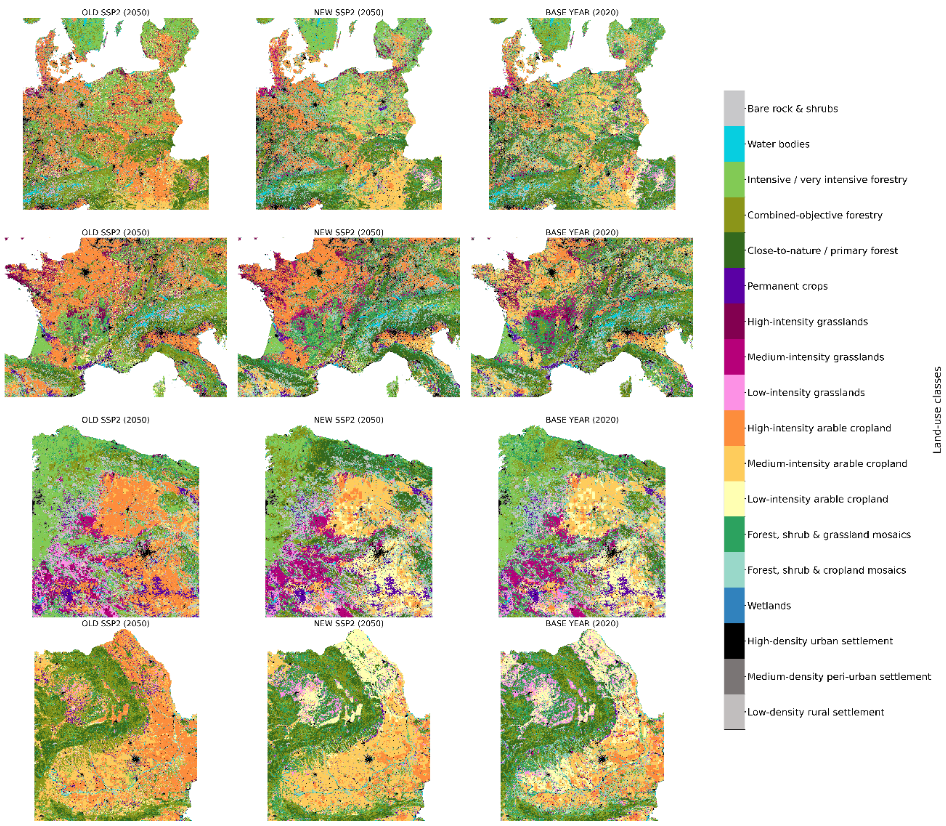

Figure 6: Spatial comparison of land-use allocations in CLUMondo regions for the base year (2020) and SSP2 projections for 2050 under old and new model parameterizations.

Table 17: Area changes in SSP2 projections 2020-2050

CLASS	2020 (KM²)	2050 (KM²)	Δ (KM²)	Δ %
Low-density Rural Settlement	60,563	61,300	7,370	0.0145
Medium-density Peri-urban Settlement	105,296	130,776	25,480	0.501
High-density Urban Settlement	127,367	127,370	3	0.001
Wetlands	64,043	63,261	-782	-0.015
Forest, Shrub and Cropland Mosaics	393,588	343,482	-50,106	-0.985
Forest, Shrub and Grassland Mosaic	598,823	416,589	-182,234	-3.583
Low-intensity Arable Cropland	156,984	127,488	-29,496	-0.580
Medium-intensity Arable Cropland	613,929	474,328	-139,601	-2.745
High-intensity Arable Cropland	177,011	486,436	309,425	6.084
Low-intensity Grasslands	111,919	73,400	-38,519	-0.757
Medium-intensity Grasslands	205,875	150,492	-55,383	-1.089
High-intensity Grasslands	93,189	175,930	82,741	1.627
Permanent Cropland	96,175	103,278	7,103	0.140
Close To Nature Forestry + Primary Forest	404,140	492,324	88,184	1.734
Combined Objective Forestry	700,146	430,564	-269,582	-5.301
Intensive forestry + very intensive forestry	628,120	880,150	252,030	4.956

3.2 ORGANIC UPDATES TO CLUMONDO

Based on the WP4 work on organic agriculture and following section 2, organic land systems were added to the CLUMondo model for Europe. The WP4 work provided two main things: First, a map of the current location of organic farms across Europe, which was used to determine which agricultural pixels in the land system for CLUMondo are organic (see Table # for a land system comparison of the base year). Second, predictors and beta coefficients for the predictors can be used to determine the future location suitability of each land system.

All other settings were adapted to include three organic systems in the CLUMondo model: Organic cropland, Organic grassland and Organic mixed systems. The settings were adopted from the SSP2 scenario, whereas demand for arable cropland, permanent cropland and livestock was derived from CAPRI data. Table 18 reports the percentage by land system with and without the three organic systems included.

Table 18: Percentage of each land system in CLUMondo 2020 in the versions with and without organic land systems

LAND SYSTEM	CLUMONDO ID	PERCENTAGE	
		Without organic	With organic
Water and glacier		3.1	3.1
Low-intensity settlement	0	1.2	1.2
Medium-intensity settlement	1	2.1	2.1
High-intensity settlement	2	2.5	2.5
Wetlands	3	1.3	1.3
Forest, shrub and cropland mosaics	4	7.7	6.9
Forest, shrub and grassland mosaic	5	11.8	10.9
Low-intensity arable cropland	6	3.1	2.8
Medium-intensity arable cropland	7	12.1	11.4
High-intensity arable cropland	8	3.5	3.3
Low-intensity grasslands	9	2.2	2.1
Medium-intensity grasslands	10	4.0	3.8
High-intensity grasslands	11	1.8	1.8
Permanent cropland	12	1.9	1.5
Primary forest	13	0.3	0.3
Nature forest management	13	7.7	7.7
Multifunctional forests	14	13.8	13.8
Intensive forest management	15	10.2	10.2
Plantation forests	15	2.1	2.1
Bare, rock and shrub		7.7	7.7
Organic mixed systems	16		0.6
Organic cropland	17		1.9
Organic grassland	18		1.2

In the map with organic land systems, the share of conventional agricultural land systems has decreased to give room to organic. We see that the organic classes came primarily from the mosaic classes and medium-intensity cropland. In the new map, we then have 0.6% organic mixed systems, 1.9% organic cropland and 1.2% organic grassland out of the total land area, including lakes in the map.

In the CLUMondo model, the lusmatrix indicates how much one pixel of each land system can contribute to fulfil demands for food production, wood production and housing, which are reflected in land systems from which production or population demands can be derived. The organic land systems will contribute to population, arable cropland, permanent cropland, livestock and organic land demand. To calculate what the organic land systems contribute to the demands, we assume a 24% yield gap for organic arable cropland compared to medium intensity arable cropland in the model based on yield gap estimates from de la Cruz et al (2023) and Alvarez (2022). For organic permanent cropland, we assume a 5% yield gap compared to conventional permanent cropland. For permanent cropland, the literature is a little bit less certain on what the yield gap is, with large variations between different crops. However, most literature ends up stating a yield gap between 0-10% (Kniss et al., 2016; Lesur-Dumoulin et al., 2017; Cárceles Rodríguez et al., 2023). For livestock, we assumed the stocking density to be 15% less on organic grasslands than medium intensity grasslands, following the logic applied in Basnet et al. (2023).

For organic mixed systems that have both arable and/or permanent crop and livestock production, the land system contribution to each demand is calculated by taking the value ascertained from the above yield gap calculations and multiplying that by the average share of the land system contained within the pixel. For example, one organic cropland pixel contributes 551 tons to the overall arable cropland demand. One organic mixed system pixel contains, on average, 24% arable cropland (38% grassland, 1% permanent cropland), so the 551 tons are multiplied by 0.24 to get the contribution to arable cropland demand from the organic mixed system.

The conversion elasticities for all organic land systems were set to 0.6. That way, the elasticity is slightly higher than the conversion elasticity for all conventional agricultural land systems. This is to reflect the reality of the effort that it takes for farmers to convert to organic practices.

As a business-as-usual (BAU) scenario, we assume an increase to 15% of organic land out of the total utilised agricultural area (UAA) by 2030. This is based on a linear trend of organic growth from historical data in the EU. CLUMondo is run per macro-region; north, south, west and east. As each region at the start year 2020 has different shares of organic land, we assume each region are trying to reach the 15% target but given the different starting ratios in the end we assume the north has 17%, the south 16%, the west 15% and the east 14% organic land out of total UAA. For preliminary results, see Figure 7.

Because the north already had a lot of organic area from the start there is not much increase of organic land in this region. In the west of Europe, specifically grassland areas in the Netherlands, Germany and Belgium, there is a lot of conversion from conventional agriculture to organic grassland and organic mixed land. In France, there is a large expansion of organic grassland in the provinces Occitania and Aquitaine close to the border to Spain and around the city of Toulouse. Lithuania is seeing some expansion of organic mixed and cropland around cities. There is also an increase in organic land in Poland and the Czech Republic, in these countries it is more scattered with a slight clustering around cities. Hungary, Croatia and Slovakia has a smaller increase in organic land. In Greece, there is conversion to organic land on low-intensity cropland. The south Italy see some expansion of organic land close to already organic areas, and the north sees an increase in organic land around cities. In Spain and Portugal, there is an increase in organic land around Seville and Lisbon. However, these results are preliminary and changes to the model and therefore the results are still pending implementation.

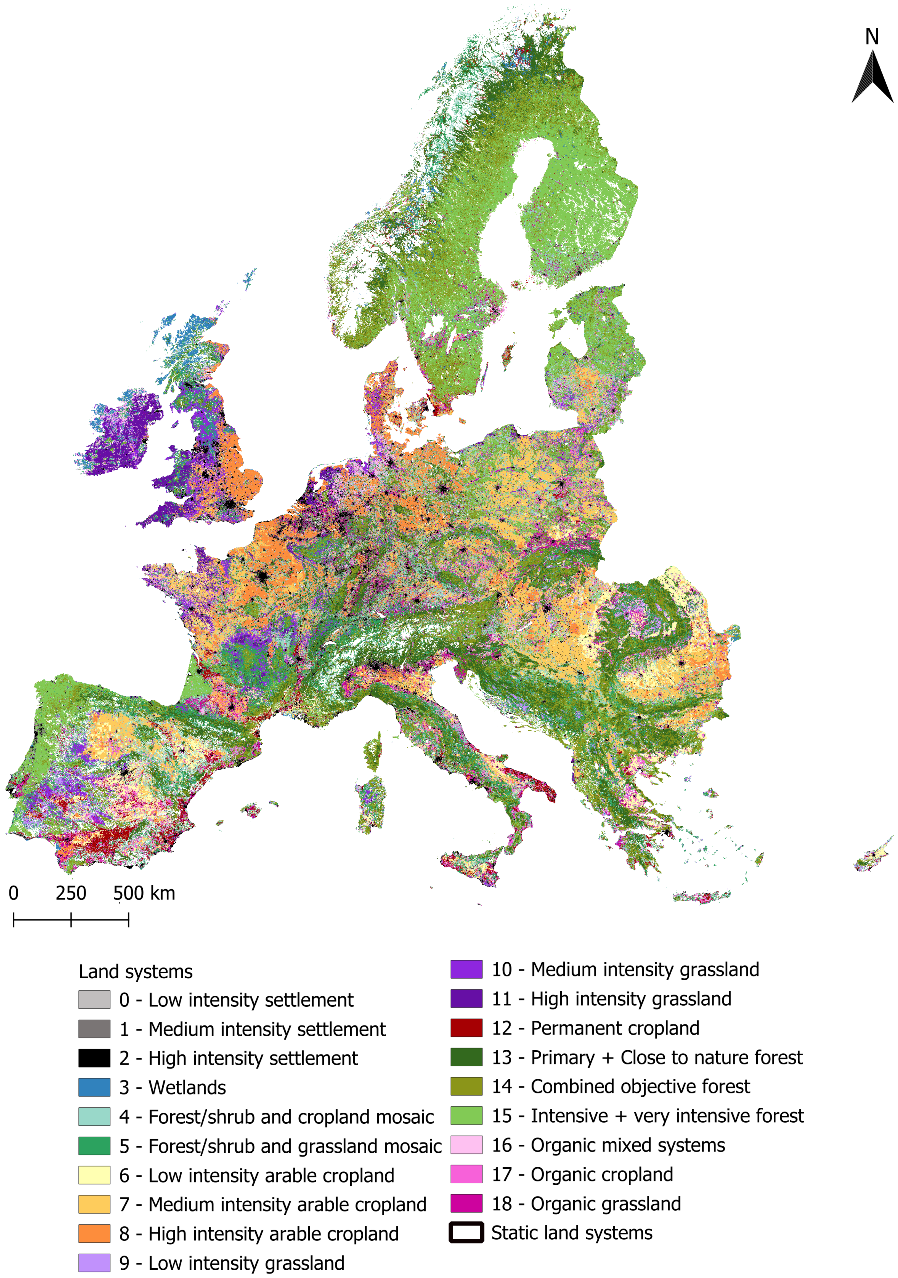

Figure 7: Land system map of preliminary results from running the 15% share of organic land scenario in CLUMondo.

Note: The static land system are water, permanent snow and glaciers and bare, rock and shrub. These land systems are shown in white and are static in the model meaning they do not change.

4. Policy relevant validation

This section presents the validation of the improved CLUMondo model with organic farming as separate land systems against independent, policy-relevant data sources to assess its accuracy. Specifically, it tests whether the spatial predictions of organic farming suitability—derived from ex-post econometric modelling—correspond with observed uptake patterns at the regional and parcel levels. Two complementary validation exercises are conducted: one using high-resolution parcel-level data from France to assess recent organic conversions, and another using CAP payment data from the Common Audit Trail System (CATS) at the NUTS-3 level across Europe. Together, these validations evaluate the model's ability to capture real-world responses to policy incentives and strengthen its credibility for use in forward-looking scenario analysis.

4.1. VALIDATION WITH FRENCH PARCEL DATA

To assess whether the Organic Suitability Map is a good predictor of future organic farming adoption, we compared the predictions from the Organic Suitability Index with the new organic certifications in France in 2021 and 2022. The Organic Suitability Index contains the probabilities calculated from the regression in Section 2.2 made into a 1x1km pixel map, where each pixel has a probability value of 0-1. For this analysis, we excluded all land parcels that were already organically certified in 2020 from the sample, to avoid endogeneity issues, since these plots contributed to the construction of the index. The sample includes conventional farmed plot and land that was newly converted to organic in 2021 or 2022 (as shown in Table 19.

Table 19: Number of Utilised Agricultural Areas (in million ha) by farming type, excluding plots certified organic in 2020

YEAR	CONVENTIONAL	ORGANIC
2020	24.48	0.00
2021	24.26	0.54
2022	24.14	0.82

The validation data used in this analysis comes from the French Land Parcel Identification System (LPIS), which provides comprehensive geospatial information on all agricultural plots receiving CAP subsidies in France. This ensures near-complete coverage of the French agricultural landscape (Cantelaube and Carles, 2014). Using these data, we can identify each year whether a plot is certified organic or conventionally farmed. By merging the Organic Suitability Map with the LPIS data, we are able to assign each plot a predicted probability of conversion to organic farming and compare it with its actual farming status.

Figure 8 shows that plots converted to organic in 2021 and 2022 had significantly higher average suitability scores than plots that remained conventional. Specifically, in 2021, newly organic plots had an average suitability score of 0.482 compared to 0.441 for conventional plots. In 2022, the gap persisted, with scores of 0.488 for organic plots and 0.441 for conventional ones. Table 20 shows the results of a probit model assessing the probability that a plot is organically certified based on its suitability score. The findings reveal a significant and positive association between the Organic Suitability Index and the likelihood of organic certification.

This analysis supports the predictive validity of the Organic Suitability Index in identifying plots most likely to convert to organic farming. However, it is important to note that this validation focuses exclusively on agricultural land, while the index itself assigns suitability scores to all types of land.

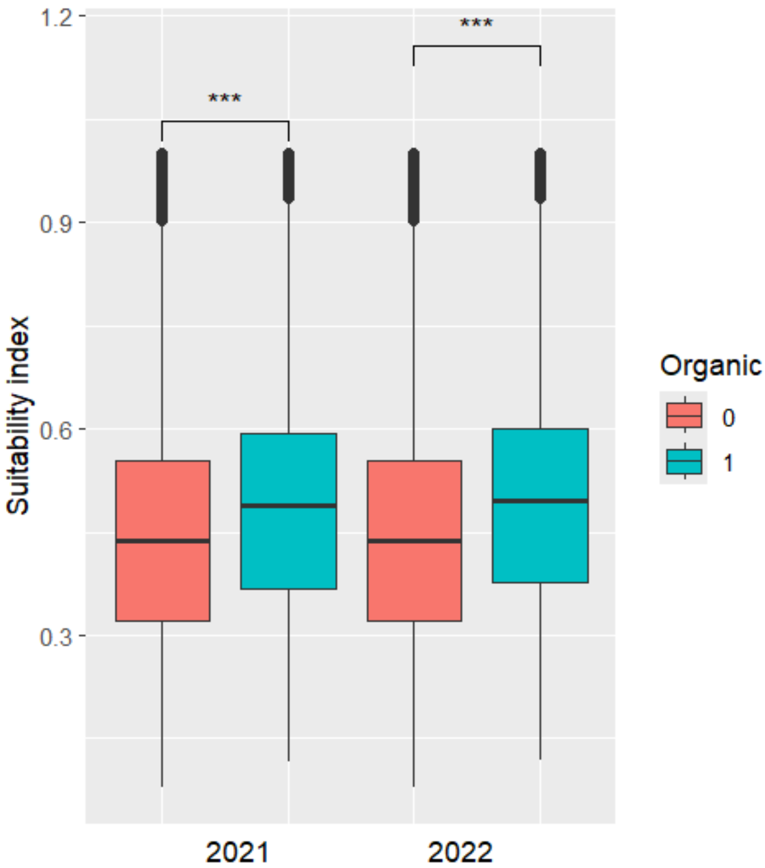

Figure 8: Suitability Index by Organic Status in 2021 and 2022

Note: We compare conventional and newly converted organic practices for the years 2021 and 2022. *** indicates a statistically significant difference in mean Suitability Index between the two groups ($p \leq 0.001$).

Table 20: Probability that land is organically certified as a function of the Suitability Index

	2021 (1)	2022 (2)
Suitability index	0.720*** (0.0058)	0.891*** (0.0049)
Intercept	-2.287*** (0.0029)	-2.164*** (0.0024)
AIC	2,111,377	3,027,444
N	9,034,093	9,151,036
% organic	2.52	3.98

Note: This table reports the results of a probit model estimating the likelihood that a land parcel is organically certified as a function of the Organic Suitability Index. Column 1 refers to the situation in 2021, and Column 2 to 2022. Standard deviations in parentheses. ***$p < 0.001$.

4.2. VALIDATION ACROSS EUROPE USING NUTS-3 DATA

To assess the spatial validity of the organic farming suitability index generated through CLUMondo, we rely on high-resolution administrative data from DG AGRI on certified organic farming areas. This confidential dataset provides detailed NUTS-3 level coverage across all EU Member States (except the Netherlands) and includes the United Kingdom. As of the time of analysis, it represents the most spatially detailed and up-to-date official dataset on organic farming areas available at the European scale. By comparing these regional statistics to the modelled suitability outputs, we can evaluate whether the model assigns high suitability scores to regions where organic farming is taking place. This allows for a policy-relevant validation of the model's performance at a level of aggregation that reflects how funding and regulatory decisions are typically made.

We make use of the CATS database (Clearance Audit Trail System), which contains official records of agricultural subsidy payments made under the Common Agricultural Policy (CAP). These financial accounts, maintained by the European Commission, provide comprehensive NUTS-3 level data on actual CAP expenditures to beneficiaries across all budget lines. Unlike FADN data, which is limited to larger commercial farms, CATS includes the full population of recipients and thus avoids sample selection bias associated with structural thresholds. This broader coverage is critical when validating spatial policy models, as it better captures regional variation in farm types, practices, and conditions.

The dataset we received from DG AGRI covers the period 2014–2022 and includes, per CAP measure, the amount of quantity claimed by beneficiaries, the quantity verified through measurement, and the final quantity determined after administrative and/or on-the-spot checks. These three measures offer insights into both the demand for support and the effectiveness of administrative validation. Discrepancies between claimed and determined quantities—often due to rejected applications, eligibility issues, or non-compliance—provide useful information on administrative bottlenecks and implementation gaps that can inform model interpretation.

CLUMondo projections begin in 2020 and are produced annually. We therefore restrict our comparison to the years 2020, 2021, and 2022, aligning the CLUMondo outputs with the CATS and DG AGRI datasets over this three-year period. While the time span is limited, the analysis covers a broad cross-section of European regions, with data available for 1,063 NUTS-3 units. This provides a solid empirical basis to assess how well the model reproduces recent regional patterns of organic farming expansion and CAP measure uptake.

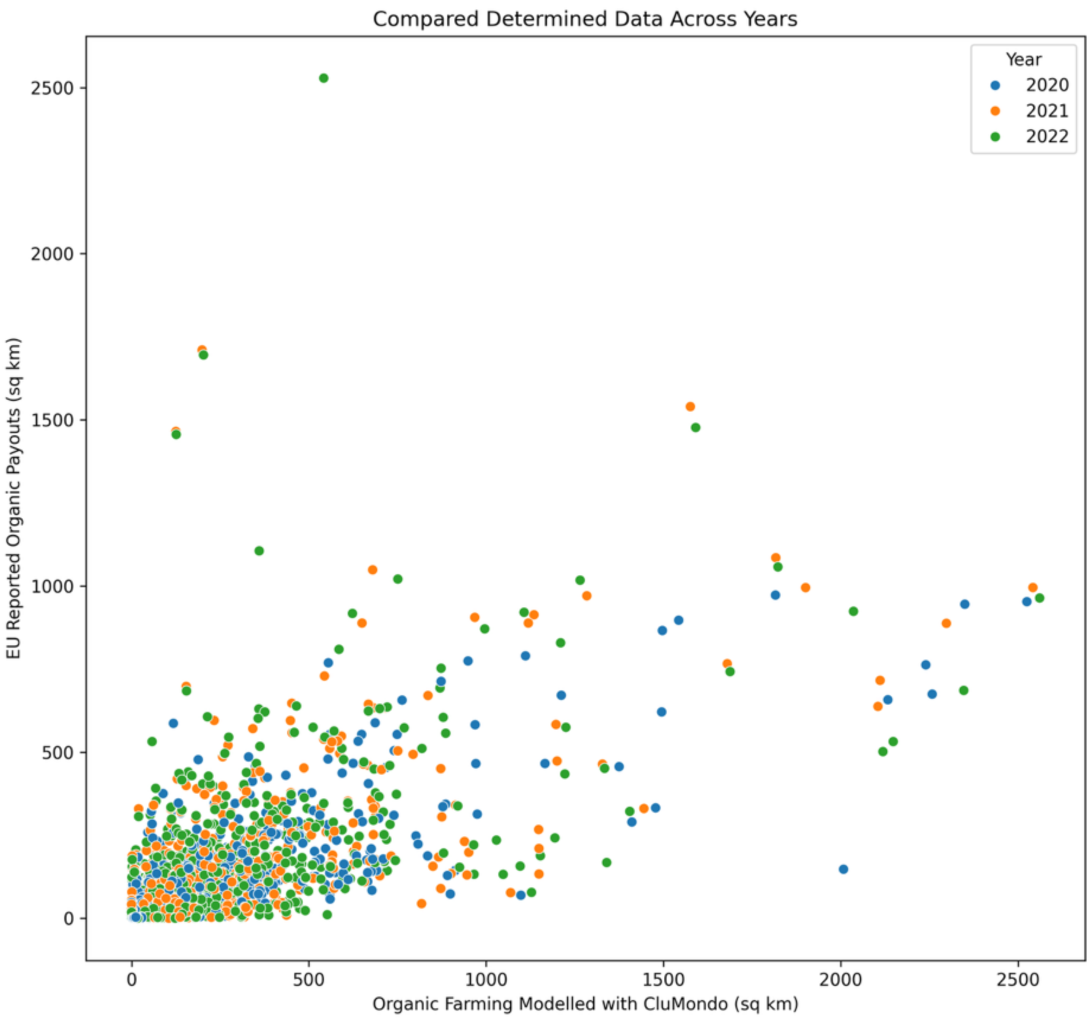

Figure 9: Comparison of CLUMondo-modelled organic farming area and CAP-reported organic support.

Note: CAP-reported organic support (CATS, determined quantity) at NUTS-3 level for 2020–2022. Annual R^2 values: 0.71 (2020), 0.65 (2021), 0.69 (2022).

The comparison of absolute levels of organic farming area modelled with CLUMondo and reported through CAP subsidy data (CATS, determined quantity) at the NUTS-3 level shows (see Figure 9) a consistent and positive correlation across 2020, 2021, and 2022. With R^2 values between 0.65 and 0.71, the model captures regional differences in organic farming reasonably well, indicating that the spatial allocation of organic systems within CLUMondo aligns with where organic practices are actually supported. This provides confidence in the empirical basis and spatial logic used to parameterize the suitability maps and transition probabilities in the model. Regions with high organic support tend to have high modelled organic area, suggesting that the modelled patterns broadly reflect real-world outcomes.

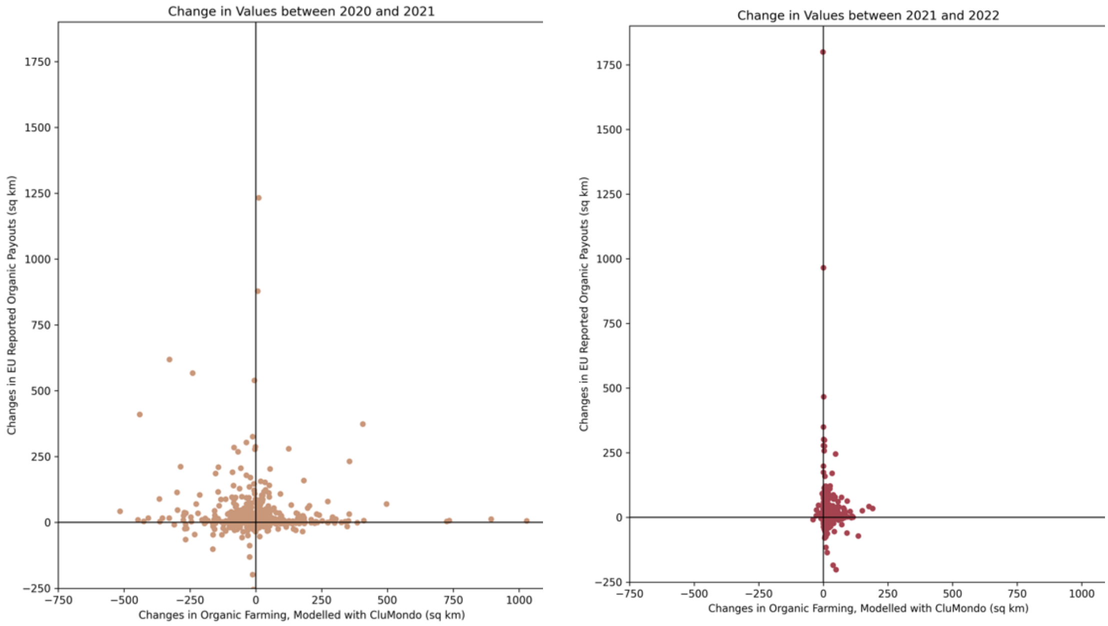

Figure 10: Annual changes in organic farming area modelled by CLUMondo and CAP-reported organic support.

Note: CAP-reported organic support (CATS, determined quantity) at NUTS-3 level. Left panel: changes from 2020 to 2021. Right panel: changes from 2021 to 2022.

Interpreting the year-on-year changes is more nuanced (see Figure 10:). As shown in the second figure, the association between annual changes in modelled and reported organic area is weaker, with most points clustered near zero and several large outliers. This reflects, in part, the difference in purpose and resolution: CLUMondo is designed to simulate longer-term structural changes rather than short-term fluctuations, while the administrative data may reflect short-term policy changes, reporting lags, or reclassification effects. Additionally, changes in organic certification may not be immediately visible in land-use patterns at the resolution used in the model. In the current version, the model also exhibits comparatively larger changes than the reported statistics, particularly in 2021, with stronger negative as well as positive shifts. This pattern is less pronounced in 2022 and may reflect an adjustment effect, where the first simulated year shows more relocations because certain land systems are initially forced into locations where they are not stable. Nonetheless, the direction of change remains broadly consistent in many regions, and the model does not systematically over- or under-predict uptake across years. This suggests that while short-term shifts are harder to capture, the medium- to long-term spatial trends remain well represented.

5. Conclusion

This report has shown how ex-post econometric evidence can be used to recalibrate high-resolution land-use models. Two strands of analysis were central: a spatial econometric model of land-use and land-management drivers based on the harmonised WP2–WP3 database, and a logistic regression of organic farming uptake using harmonised certificate data. These models quantify how policy and non-policy factors affect land-use choices, and provide explicit measures of uncertainty around those effects.

The results were used to update CLUMondo in three ways: revising land system maps to better reflect observed input intensities and productivity, adding explicit organic land systems with calibrated yield penalties and transition constraints, and deriving suitability maps for organic uptake from the estimated probabilities. This ensures that transition rules in the model reflect observed behaviour rather than stylised assumptions.

Validation against parcel-level French data and NUTS-3 level European data confirms the predictive value of the empirical suitability maps. The model reproduces observed patterns of organic conversion more accurately when informed by the econometric estimates, improving external validity and policy relevance.

These updates strengthen the basis for forward-looking projections in LAMASUS. By grounding CLUMondo's transition dynamics in observed behavioural responses, the model can provide more credible inputs for WP8 scenario development and stakeholder engagement. The framework captures medium- to long-term land-use trends while signalling the degree of uncertainty, making it a more reliable tool for ex-ante policy analysis at both EU and national levels.

Overall, this deliverable demonstrates how high-resolution land-use models like CLUMondo can be empirically grounded using the harmonised databases and policy evidence developed within LAMASUS. The resulting improvements in parameterisation increase the credibility of the scenario outputs produced in WP8. They ensure that projections reflect both observed behaviour and uncertainty, which is critical for informing stakeholder engagement and supporting robust, science-based policy design.

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7. Annexes

Table A1: Mapping between DownscaleR and CLC land use classes

CLC level 3	Ecosystem type level 2 (ETL2) augmented	ETL2 augmented abbreviations	UNFCCC
Continuous urban fabric	Urban	URBN	Settlements
Discontinuous urban fabric	Urban	URBN	Settlements
Industrial or commercial units	Urban	URBN	Settlements
Road and rail networks and associated land	Urban	URBN	Settlements
Port areas	Urban	URBN	Settlements
Airports	Urban	URBN	Settlements
Mineral extraction sites	Urban	URBN	Settlements
Dump sites	Urban	URBN	Settlements
Construction sites	Urban	URBN	Settlements
Green urban areas	Urban	URBN	Settlements
Sport and leisure facilities	Urban	URBN	Settlements
Non-irrigated arable land	Arable cropland	ACRP	Cropland
Permanently irrigated land	Arable cropland	ACRP	Cropland
Rice fields	Arable cropland	ACRP	Cropland
Vineyards	Permanent crops	PCRP	Cropland
Fruit trees and berry plantations	Permanent crops	PCRP	Cropland
Olive groves	Permanent crops	PCRP	Cropland
Pastures	Pastures	PAST	Grassland
Annual crops associated with permanent crops	Heterogeneous agricultural areas	HCRP	Cropland
Complex cultivation patterns	Heterogeneous agricultural areas	HCRP	Cropland
Land principally occupied by agriculture with significant areas of natural vegetation	Heterogeneous agricultural areas	HCRP	Cropland
Agro-forestry areas	Heterogeneous agricultural areas	HCRP	Cropland
Broad-leaved forest	Woodland and forest	WOFO	Forest area
Coniferous forest	Woodland and forest	WOFO	Forest area

CLC level 3	Ecosystem type level 2 (ETL2) augmented	ETL2 augmented abbreviations	UNFCCC
Mixed forest	Woodland and forest	WOFO	Forest area
Natural grasslands	Grassland	GRSL	Grassland
Moors and heathland	Heathland and shrub	HEAS	Other Land
Sclerophyllous vegetation	Heathland and shrub	HEAS	Other Land
Transitional woodland-shrub	Woodland and forest	WOFO	Forest area
Beaches dunes sands	Sparsely vegetated areas	SPVA	Other Land
Bare rocks	Sparsely vegetated areas	SPVA	Other Land
Sparsely vegetated areas	Sparsely vegetated areas	SPVA	Other Land
Burnt areas	Sparsely vegetated areas	SPVA	Other Land
Glaciers and perpetual snow	Sparsely vegetated areas	SPVA	Other Land
Inland marshes	Wetlands	WTLN	Wetlands
Peat bogs	Wetlands	WTLN	Wetlands
Salt marshes	Marine inlets and transitional waters	MITW	Other Land
Salines	Marine inlets and transitional waters	MITW	Other Land
Intertidal flats	Marine inlets and transitional waters	MITW	Other Land
Water courses	Rivers and lakes	RILA	Other Land
Water bodies	Rivers and lakes	RILA	Other Land
Coastal lagoons	Marine inlets and transitional waters	MITW	Other Land
Estuaries	Marine inlets and transitional waters	MITW	Other Land
Sea and ocean	Marine	MARI	Other Land