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European Union multi-year spatial crop diversity from the Copernicus High Resolution Layers

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Abstract. Spatial crop diversity and its temporal evolution matters for biodiversity, ecosystem services, soil health, production stability, and food-system resilience. Yet, harmonized multi-year assessments across the European Union (EU) remain limited. We assess spatial crop diversity across the EU-27 using the Copernicus Land Monitoring Service High Resolution Layers (HRLs) on Croplands and Grasslands from 2017 to 2023. We combine the Crop Types (CTY), Herbaceous (HER), and Grassland (GRA) products to generate annual wall-to-wall crop-type mosaics containing 19 crop classes and a derived temporary grassland class. Crop diversity is calculated as Shannon-based effective diversity and partitioned into α, β, and γ components across regular grids, Local Administrative Units (LAUs), and NUTS regions. EU-wide crop diversity increased modestly over the seven-year period. Local, or α-diversity, increased by 6.7%, from 3.83 in 2017 to 4.09 in 2023, indicating the higher spatial differentiation of the typical pixel's neighborhood, while γ-diversity increased by 5.0%, from 7.79 to 8.18, showing the trend holds at regional scale, whereby the internal nested spatial unit structure is ignored. Following this, β-diversity remained relatively stable from 2.03 in 2017 to 2.00 in 2023, showing a 1.63% decrease, indicating limited change in spatial turnover among local cropping systems. Crop-diversity patterns were strongly spatially structured: 17.2% of LAU/NUTS4 regions were persistently high diversity (γ equal or higher than 5.694), while 20.0% were persistently low diversity (γ equal or lower than 3.365). Linear mixed-effects models showed a 0.008 effective crop types per year increase in overall EU-wide in γ-diversity, but with heterogeneous regional trends. The dominance of the Most Represented Crop (MRC) was the strongest factor associated with regional crop diversity, outweighing broad-scale environmental and land-cover/use variables. These results show that annual Copernicus HRLs can be used to estimate landscape- and regional-scale crop diversity across Europe. HRL-derived crop-diversity indicators could complement farm-level data and support policy evaluation, regional benchmarking, and the targeting of agri-environmental interventions under the Common Agricultural Policy (CAP). However, the operationalization of any future indicators would require regular reprocessing of the HRL layers to guarantee that they accurately reflect the impact of land management decisions.

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1 Introduction

Crop diversity refers to the variety and abundance of cultivated crops within an agricultural system, including differences among crop types and, in some contexts, among cultivars within crop types (Khoury et al., 2022). It contributes to agricultural biodiversity (FAO, 1999; CBD, 2008) with multiple benefits including increased yields (Li et al., 2009; Zhao et al., 2022), greater yield stability under variable weather conditions (Gaudin et al., 2015; Renard and Tilman, 2019; López-Angulo et al., 2023), improved regulation of pests and diseases (Hajjar et al., 2008; He et al., 2019), and enhanced soil health (Sprunger et al., 2020; Li et al., 2025). Spatial crop diversity is defined as the composition and distribution of crop types within fields, across farms, and across landscapes within a given year. Temporal crop diversity arises when rotating crops on the same field via sequential planting or through genetic diversity within crop species. Importantly, we do not compute temporal diversity, but rather focus on informing on typical within-year spatial spread of crop diversity, as well as computing trends of spatial crop diversity.

The Common Agricultural Policy (CAP) in the European Union (EU) supports crop diversification as a sustainable agricultural practice (European Commission, 2023). To receive income support under the CAP, farmers must manage their land in accordance with Good Agricultural and Environmental Conditions (GAECs)(European Commission, 2023; European Commission). GAEC 7 is concerned with the preservation of soil productivity and quality through crop diversification (European Commission). Currently, after derogation of the existing rotation requirements, GAEC 7 includes requirements for what is termed "crop diversity". In the CAP, the conditionality requirements for crop diversity are based on the area of the farm holding. Previously, for holdings between 10 and 30 ha, at least two different crops must be grown with no more than one crop covering 75% of the arable land, while larger holdings must contain at least three different crops, with maximum area per crop also specified; exemptions are made when holdings are less than 10 ha or greater than 75% of the holding is grassland (European Commission, 2024). More recently, farm holdings of less than 30 ha are now exempt (European Commission, 2025). Minimum standards are also set individually by EU Member States in their CAP Strategic Plans, which have included temporary derogations to GAEC 7 related to Russia's war on the Ukraine (European Commission, 2022) and weather conditions in 2024 (DDT Nièvre, 2024). Despite these changes, supporting crop diversification through e.g. eco-schemes, remains an important part of agri-environmental policy in the EU.

Parcel-based declarations have enabled detailed crop-diversity analyses in several countries and regions. Yet, their uneven availability, harmonization challenges, and access restrictions limit their use for consistent EU-wide monitoring. Parcel-based farmers' declarations submitted through the Geo-Spatial Application (GSA) under the CAP (European Commission, 2021) can be used to calculate crop diversity, but these are not openly available for all EU countries. Nevertheless, efforts such as EuroCrops (Schneider et al., 2023), EuroCrops V2.0 (Claverie et al., 2026) and Europe-LAND (Jänicke et al., 2025) have harmonized and published publicly available parcel-level crop-type datasets for several EU countries. Several studies have used this parcel data to calculate crop diversity using metrics such as the Shannon entropy index (Shannon, 1948), which has been extensively used in many different fields including ecology and land use (Magurran, 2004; Sherwin et al., 2006; Tabner, 2007; Uuemaa et al., 2009). Examples cover single regions and years such as the state of Brandenburg in Germany for 2017 (Uthes

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et al., 2020) and Flanders for 2012 (Mahy et al., 2015), or entire countries such as France for 2007 (Donfouet et al., 2017). The presence of dominant maize monoculture in parts of France and Flanders is highlighted in these studies as a specific challenge to landscape diversity while all three studies show that the spatial distribution of crops is heavily influenced by soil conditions and climate. Others have also considered a temporal element, using a time series of GSA data to compute crop diversification statistics for Sweden for 2001 to 2018 (Schaak et al., 2023), showing that crop diversity has declined since 2001 and stayed at a lower level, and for England, Denmark and France, considering data from three to eight years, depending on availability (Bohan et al., 2021). These authors found that crop diversity was broadly similar across the three countries although there were significant areas with exceptionally low diversity in France.

Another source of data for calculating spatial crop diversity is Earth Observation (EO) derived crop type maps. In Ye et al. (2024), historical changes in crop diversity for the United States were calculated from 1850 to 2021, using statistical and gridded data sets until 2009 and the remotely sensed Crop Data Layer (CDL) from 2010 onward. The results showed that crop diversity has declined significantly during the last 60 years, primarily due to the increased planting of maize and soybean and decreases in the area of other cereal crops. Using the first 10m pan-European crop type map for the year 2018 (d'Andrimont et al., 2021), Machefer et al. (2024) produced an EU wide characterization of crop diversity at scales from 1 km to 100 km. They calculated three types of diversity indicators based on the Shannon index: α, β and γ. The α-diversity is a local diversity indicator, calculated at a 1 km resolution. The authors found that the highest levels of α-diversity were associated with smaller farms, highlighting their importance in maintaining high levels of crop diversity at the local scale. In contrast, the γ diversity was calculated for larger areas to capture landscape and regional diversity patterns, where the results showed that crop diversity increases as the scale increases, leveling off at around 10 km. Finally, β diversity is the ratio of the γ to the α diversities to indicate how crop diversity changes from local levels to larger regional or national scales. Some countries like Cyprus showed little difference across scales while countries like Italy and Portugal indicated a significant increase in crop diversity when moving from local to national scale. Comparing the EO-based crop diversity by Machefer et al. (2024) with calculations based on >323k parcel declarations in the Netherlands, van der Velde et al. (2024) found agreement in spatial patterns and derived crop diversities (R^2 = 0.62). Changes over time also suggested a positive response to the 2014 CAP greening policy.

Despite this growing literature, three gaps remain. First, parcel-based studies are spatially fragmented because harmonized crop declarations are not publicly available across the EU. Second, EO-based studies have so far been limited mainly to single-year pan-European crop maps or national products, restricting their ability to assess persistence and change over time. Third, existing indicators often focus either on local diversity or broad regional diversity, while less attention has been given to how diversity changes across spatial scales and how these multi-scale patterns evolve annually. These gaps are also relevant for policy monitoring. The CAP Performance Monitoring and Evaluation Framework (PMEF) has one context indicator on crop diversity (C.22) and one impact indicator on increasing agro-biodiversity in farming systems (I.22) (Monitoring and Framework). These indicators are currently based on crop richness derived from EUROSTAT's Integrated Farm Statistics (IFS), rather than on spatially explicit crop diversity. EO-based indicators cannot replace holding level information required for assessing farm-level conditionality, but they can complement existing monitoring by providing harmonized, annually repeated and spatially explicit measures of crop diversity across agricultural landscapes.

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The release of the Copernicus Land Monitoring Service (CLMS) High Resolution Layers (HRL) on Croplands and Grasslands from 2017-2023 (Stumpf et al., 2025b) provides a new opportunity to monitor spatial crop diversity across the EU in a harmonized and spatially consistent way. The HRLs provide annual 10 m crop-type maps for 19 crop types, as well as temporary grassland in arable land, enabling wall-to-wall analysis across the EU-27 over seven consecutive years. Building on the multi-scale approach of Machefer et al. (2024), this paper advances on previous work in 4 ways. First, it extends EO-based crop diversity assessment from a single year analysis to an annual 2017-2023 time series. Second, it provides harmonized wall-to-wall coverage for the EU-27, allowing consisent comparison across countries, regions and agricultural systems. Third, it jointly analyzes local, between-grid and regional diversity through α, β and γ indicators, allowing crop diversity to be interpreted across spatial scales rather than at one aggregation level only. Fourth, it evaluates both persistent spatial patterns and temporal trends, thereby linking EO-derived crop diversity indicators more directly to the needs of the CAP and agri-environmental policy monitoring. In particular, we address the following:

1. What is the status of regional crop diversity in and across the EU-27?
2. Have local and regional crop diversity changed over time in and across the EU-27?
3. Where are the hotspots of low and high regional crop diversity located across the EU-27 and what are their dynamics?
4. Which crop types, land-cover contexts, and agricultural system characteristics are associated with different crop-diversity patterns?

2 Materials and Methods

2.1 Data

Both raster and vector data are used in this study. The raster data consist of tiles of the HRL product for Crop Types (CTY) and Grassland, while the vector data comprise administrative boundaries for 37 countries in the EEA, excluding the UK, at five levels of granularity, together with seven Europe-wide grids from Eurostat (ESTAT). The finest spatial grid, at 1 km resolution, is used to represent crop diversity at the local landscape scale. Once processed and stored in this way, the data can be used, following the methodology described below, to generate a type of report card for each administrative or spatial unit at any scale. As an example, we present the most diverse LAU/NUTS4 region in the EU-27, Roumoules (FR_04172), in Figure 1.

2.1.1 The Copernicus High Resolution Layers

The HRLs consist of several products covering the forest, grassland and cropland domains (Stumpf et al., 2025a). The CTY from the HRL Croplands product identifies the crop cultivated during the main agricultural season at a 10 m resolution. The CTY layer uses a hierarchical classification system, with level 1 comprising seven crop groups and the more detailed level 2 comprising 19 crop types. The Minimum Mapping Unit (MMU) is 0.25 hectares. The CTY layer is accompanied by the Crop Type Confidence Layer (CTYCL), which provides the probability of the selected/winning crop type (Stumpf et al., 2025b).

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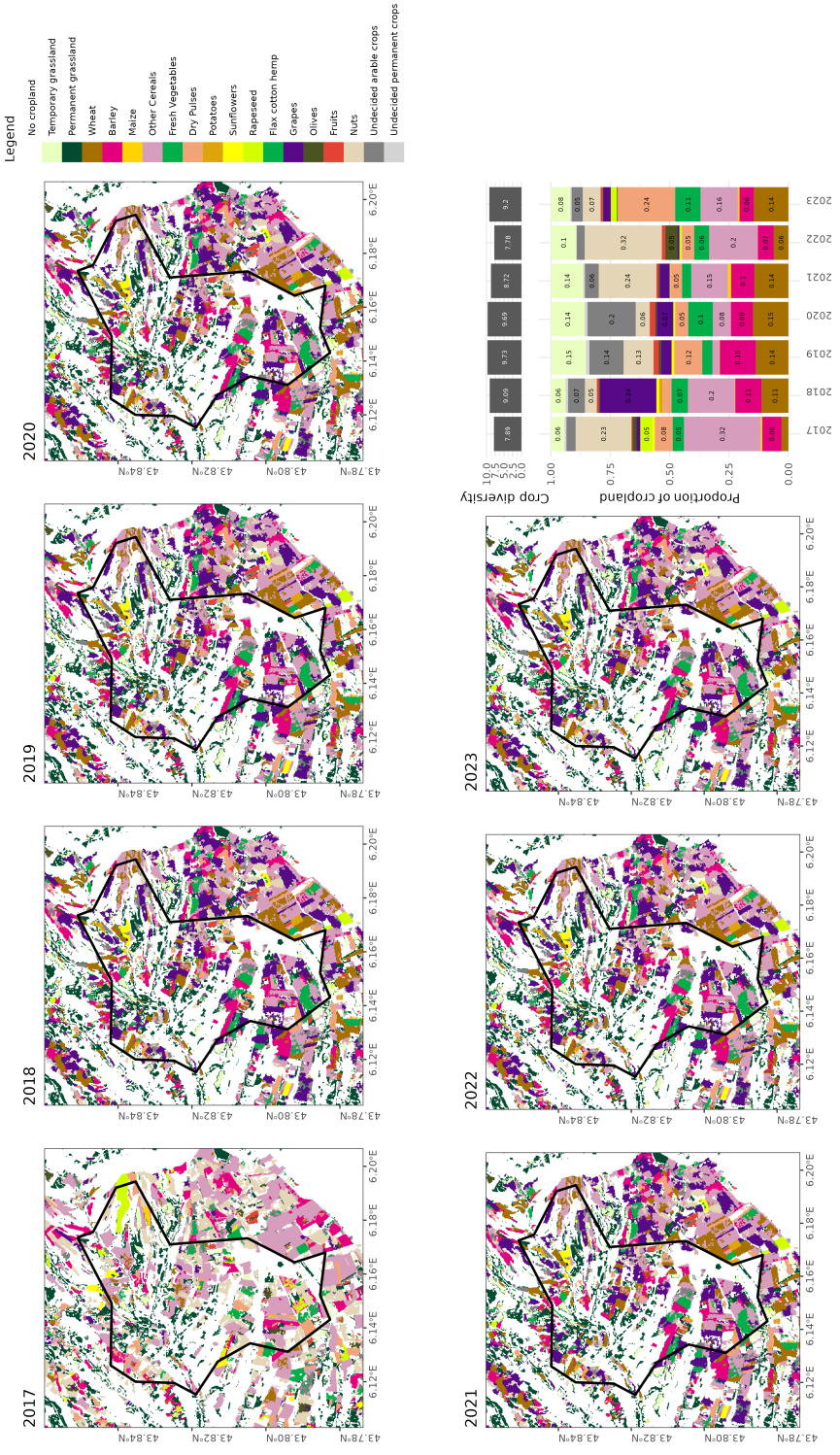


Figure 1. The most gamma diverse LAU (FR_04172 - Roumoules, Alpes-de-Haute-Provence (FRL01), Provence-Alpes-Côte d'Azur (FRL0), Alpes-Maritimes (FRL), France) per year of data, along with the relative share of each crop type and the overall mean .

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In addition, we used two binary layers from the HRL Grasslands product to derive temporary grassland. The first layer is the annual Herbaceous layer (HER), which indicates whether a pixel is grassland, either temporary or permanent. The second is the annual Grassland layer (GRA), which identifies permanent grassland, defined as grassland that has remained not ploughed, for at least five consecutive years (Langanke; Prochnow et al., 2009). The GRA layer is derived by combining the HER layer with the Ploughing Indicator (PLOUGH), which is also part of the HRL Grasslands product. By restricting the HER layer to the agricultural areas based on the CTY for all years and removing areas classified as permanent grassland in GRA, we derived a temporary grassland layer that remains consistent with the internal logic of the HRL products (see section 2.2.1).

In total, 5,950 CTY, HER and GRA tiles cover the study area for the seven available years, from 2017 to 2023. For each year, 850 tiles were compiled into a single mosaic.

2.1.2 GISCO Administrative boundaries

Crop diversity was calculated for 5 administrative boundary levels across the EU-27 and 10 additional European countries, using data from the Geographic Information System of the Commission (GISCO) service of ESTAT. The Nomenclature of Territorial Units for Statistics (NUTS) provides four geographically nested levels corresponding to administrative boundary levels; in order to have the crop statistics extracted and aggregated over the same areas the study makes use universally of the 2016 dataset Commission and Eurostat (2018): NUTS0, corresponding to national scale; NUTS1, representing major socio-economic regions; NUTS2, representing basic regions for regional policy; and NUTS3, representing smaller regions such as provinces or districts. In addition, Local Administrative Units (LAUs), sometimes referred to as NUTS4, were used from the same year as the NUTS dataset to represent the municipal level. LAUs were used as the Minimum Aggregation Unit (MAU) for calculating crop diversity.

Although the NUTS hierarchy is designed to be nested, LAUs are not always perfectly aligned with NUTS3 boundaries. In 0.01% of cases, a NUTS3 boundary intersects an LAU, creating a mismatch between the two levels. To obtain the most accurate nesting between NUTS3 and LAU units, each LAU was assigned to the NUTS3 region with which it had the largest polygon area of overlap.

2.1.3 GISCO grids

In addition to administrative boundaries, we used the GISCO grids available from the ESTAT website at resolutions of 1 km, 2 km, 5 km, 10 km, 20 km, 50 km and 100 km. The 1 km grid, representing the finest spatial resolution, was used as the minimum aggregation unit (MAU) for grid-based processing. To ensure full nesting across grid resolutions, the origin, coordinate reference system, and cell-naming convention of the 1 km MAU grid were retained, with only grid resolution changed.

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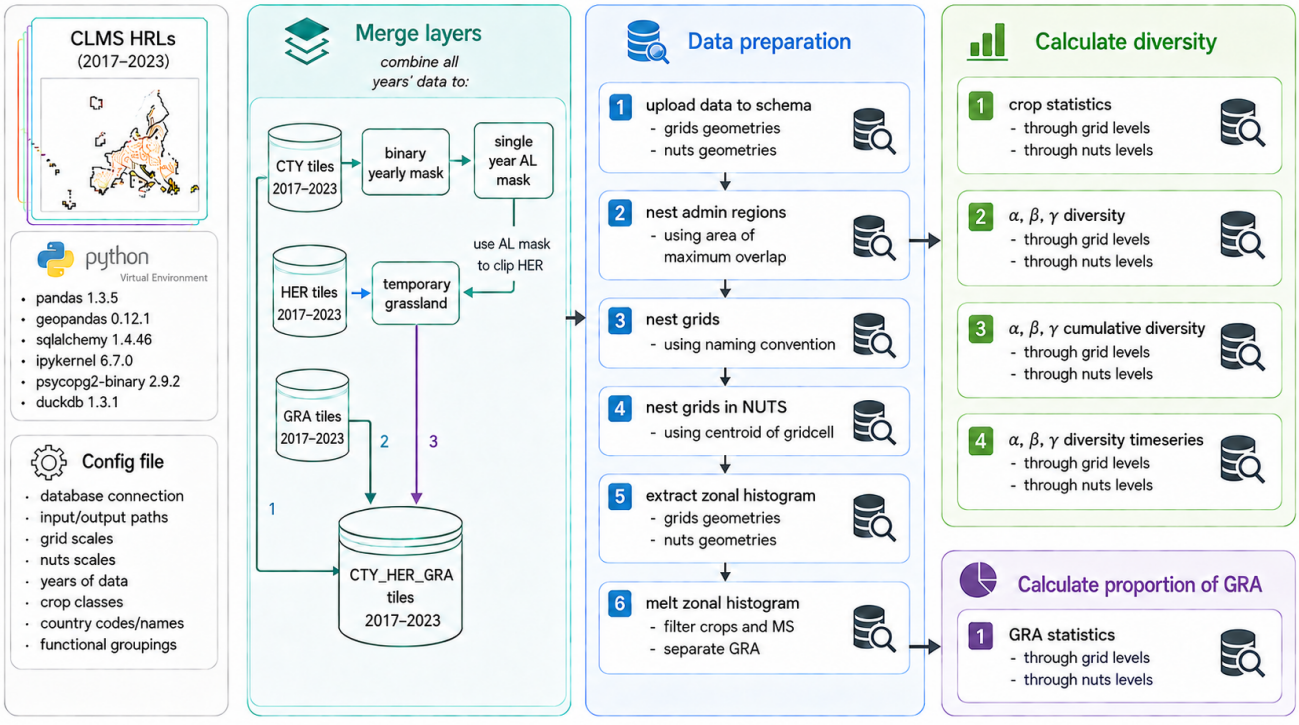


Figure 2. Flow diagram of the processing pipeline used to calculate the different diversity metrics. The input data, programming environment, and system configuration file are on the left, while the sequence of operations is indicated by arrows from left to right. The vector art icon indicates the processing steps after which spatial and other indices are build to reduce runtime.

2.2 Methodology

2.2.1 Data processing and calculation of crop diversity

An overview of the data-processing pipeline is provided in Figure 2. The first step involved merging the CTY, HER and GRA layers from the CLMS HRLs. A binary crop mask was created for each year, indicating the presence or absence of crops. These annual masks were then combined through a spatial union to create a multi-year agricultural land mask. Using this multi-year mask, the HER layer for each year was restricted to areas identified as agricultural land by the CTY layer. The resulting subset of HER pixels was interpreted as temporary grassland. Permanent grassland was derived directly from the annual GRA layers. These three data streams were then combined into a single annual layer, with priority given first to CTY, then to GRA, and finally to HER. The final output consists of seven wall-to-wall crop type maps covering the European continent, each containing 19 crop types and one temporary grassland class, since we exclude the permanent grassland class from the analysis.

The second step, shown in Figure 2, involved data preparation. The processed CLMS HRLs data, the GISCO grids, and NUTS boundaries were uploaded to the database. The nesting of the NUTS regions and grids at different resolutions was

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carried out as described in Sections 2.1.2 and 2.1.3, respectively. Each cell of the grid-based MAU was then assigned to an LAU by intersecting the centroid of the grid cell with the LAU boundaries. The number of unique crop types was extracted using the QGIS Zonal Histogram tool, and the share of pixels belonging to each crop type within each MAU, whether grid-based or NUTS-based, was calculated. Zero, null, and GRA pixels were excluded from the crop-diversity calculations.

Crop diversity was calculated in the third step following the approach outlined by Machefer et al. (2024), where diversity is expressed as the exponential Shannon entropy for each spatial unit. First, the proportion of cropland occupied by each crop type was calculated for each aggregation unit, together with the Shannon entropy. Second, the number of unique crop types, referred to as crop richness, was calculated. Following the rules of multiplicative partitioning Jost (2007), Tuomisto (2010), Aramburu Merlos and Hijmans (2020), three types of crop diversity were then calculated for each aggregation unit and grid resolution: α, β and γ diversity.

The α diversity represents the local crop diversity and is calculated as the geometric mean weighted by the cropland-area of the effective MAU-level Shannon entropies, essentially answering the question of how diverse the typical cropland pixel's MAU-level neighbourhood is. By mathematical constraint, the α and γ components for the MAU-level estimation are identical, because at the lower spatial level there is only one MAU considered. The values diverge once we start aggregating up the spatial levels. The γ diversity pools all crop pixels from each MAU nested within a a larger spatial unit, thus capturing crop diversity across this broader region. The question for γ is how many effective common crop types are present if one ignores the internal MAU structure and combine all cropland inside the bigger spatial unit. Finally, β diversity is calculated as the ratio of γ to α diversity. The β diversity therefore indicates the degree of differentiation in cropping systems among the MAUs within a larger aggregation unit Aramburu Merlos and Hijmans (2020). A $\beta = 1$ means no additional differentiation arising from differences among MAUs. In other words, β describes the factor by which α increases when MAUs are pooled. These diversity metrics are defined as follows:

$$\alpha = \exp\left(-\sum_{i=1}^{M}\sum_{j=1}^{S} \frac{c_{ij}}{\sum_{k=1}^{M}\sum_{l=1}^{S} c_{kl}} \ln\left(\frac{c_{ij}}{\sum_{l=1}^{S} c_{il}}\right)\right) \tag{1}$$

$$\gamma = \exp\left(-\sum_{j=1}^{S} \frac{\sum_{i=1}^{M} c_{ij}}{\sum_{k=1}^{M}\sum_{l=1}^{S} c_{kl}} \ln\left(\frac{\sum_{i=1}^{M} c_{ij}}{\sum_{k=1}^{M}\sum_{l=1}^{S} c_{kl}}\right)\right) \tag{2}$$

$$\beta = \frac{\gamma}{\alpha} \tag{3}$$

where M is the number of constituent MAUs within each aggregated spatial unit, S is the number of crop types in that unit, c_{ij} is the number of 10m pixels that belong to crop type j in constituent spatial unit i, and k and l are dummy indices of i and j respectively, which are used to avoid repeating the original indices inside nested sums.

Annual cumulative crop diversity was then calculated for each year, followed by a time series analysis of α, β and γ diversity for each aggregation unit to support the identification of temporal trends.

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2.2.2 Identification of trends and associated factors

To identify temporal trends in spatial crop diversity and assess the factors associated with crop diversity, we fitted several Linear Mixed-effects Models (LMMs) (Bolker et al., 2009). LMMs extend linear models (LM) by including random effects to the already present fixed effects. The latter estimate the average relationship between exploratory variables and the response variable, while the former account for structured variation among grouping units. In the presented models γ-diversity is the response variable, centered calendar year (2017-2023) is the continuous fixed-effect predictor, and NUTS3 regions as grouping units. This modeling approach is relevant for our data because observations are repeated over time and nested within spatial units, either administrative regions or grid cells. Observations from the same spatial unit in different years are therefore not independent. Random effects allow us to account for this dependency by modeling region-specific deviations from the overall relationship, without estimating a separate fixed effect for each region. Region-specific random intercepts and slopes are leveraged to make sense of differences in baseline diversity and and temporal trajectories among regions (Pinheiro and Bates, 2000). Regional trends are then calculated based on the population-level fixed slope and the predicted region-specific random slope deviation. These estimates are conditional and are thus greatly improved from partial pooling, which regularizes individual estimates toward the population-level trend. This is done to reduce the sampling variability associated with short time series (Gelman and Hill, 2007). Assuming observation within the same region across years are likely correlated, means that the residuals are also not independent. The residuals were modeled using a first-order autoregressive structure, $\varepsilon_{it} \sim \mathrm{AR}(1)$, to account for temporal autocorrelation, meaning that unexplained deviations in one year may partly persist into the following year.

In the first model (LMM1), each region has its own intercept, while all regions share the same slope and is defined as follows:

$$\gamma_{it} = \alpha_{int} + \beta_{slp} \cdot \mathrm{year}_{it} + \varepsilon_{it} \tag{4}$$

where γ_{it} is the crop diversity of region i in year t, β_{slp} is the fixed-effect slope, which is shared across all regions, α_{int} is the region-specific intercept, and ε_{it} is the residual error, modeled without AR(1) this time (see Section 3.3). LMM1 assumes that all regions change at the same rate. This is useful for benchmarking, but may be unrealistic from an agroecological perspective. In the second model (LMM2), each region has both its own intercept and its own slope and allows the rate of change to vary among regions:

$$\gamma_{it} = \alpha_i + \beta\,\mathrm{year}_{it} + b_i\,\mathrm{year}_{it} + \varepsilon_{it} \tag{5}$$

where b_i is the region-specific deviation from the overall slope. By combining the fixed and random effects, we obtain partially pooled regional slope estimates. Partial pooling, or shrinkage, reduces uncertainty in regions with noisy or extreme slope estimates by pulling them towards the overall mean. Regions with weaker or less reliable signals are shrunk more strongly, while regions with clearer temporal signals remain closer to their individual estimates. This makes each regional slope a weighted compromise between the region-specific trend and the overall EU-wide trend, reducing overfitting, extreme

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noise, and multiple testing instability (Gelman and Hill, 2007). Model configurations were tested against one another using the Aikake Information Criterion (AIC), which balances how well a model fits the observations against its complexity Akaike (1974).

To investigate crop system and land cover/use characteristics associated with crop diversity, we considered several potential explanatory variables. The first was the proportion of the dominant crop grown in a region, referred to here as the dominance of the Most Represented Crop (MRC). For each spatial unit and year, the MRC was identified as the crop class occupying the largest proportion of total crop area. The second variable was crop richness, calculated as described in section 2.2.1. Additional variables captured broader land cover and land use characteristics through the urban-rural, mountainous, and coastal typologies, assigned to each NUTS3 region (Commission and Eurostat, 2018). Finally, we assigned each NUTS region to the environmental stratum (Metzger et al., 2005) occupying the largest area within that region.

We then fitted a model to investigate the relationship between the regional crop diversity and these explanatory variables. The model (LMM_d) is defined as follows:

$$\begin{aligned}\gamma_{it} = {} & \beta_0 + \beta_1 \,\mathrm{MRCProp_z}_{it} + \beta_2 \,\mathrm{Rich_z}_{it} \\ & + \beta_3 \,\mathrm{MOUNT}_i + \beta_4 \,\mathrm{URBN}_i + \beta_5 \,\mathrm{COAST}_i + \beta_6 \,\mathrm{EnZ}_i \\ & + \beta_7 \,\mathrm{Year}_t + u_i + \varepsilon_{it}.\end{aligned} \tag{6}$$

where β_1 is the effect of the proportion of the MRC in region i and year t (standardized MRCProp_z$_{it}$), β_2 is the effect of crop richness in region i and year t (standardized Rich_z$_{it}$), β_3 is the effect of the region's urban class (URBN$_i$), β_4 is the effect of the mountainous class (MOUNT$_i$), β_5 is the effect of the coastal class (COAST$_i$), and β_6 is the effect of the dominant environmental stratum (EnZ$_i$). The term $Year_t$ represents the temporal assumed linear trend around a centered year, u_i is the random intercept for region i, and ε_{it} represents the residual error for region i and year t. The residuals were again modeled with $\varepsilon_{it} \sim \mathrm{AR}(1)$. Model configurations were also tested against each other using AIC.

2.3 Spatial autocorrelation and clustering

In order to assess the degree of Spatial AutoCorrelation (SAC) of geometric mean γ-diversity at LAU/NUTS4 level, we compute global and local Moran's I indexes, as well as Local Indicators of Spatial Association (LISA). The global variant takes into account the full dataset of adjacent spatial units (Sections 2.1.3, 2.1.2) and helps us understand if there is any SAC, its direction (positive/clustering, negative/dispersion, or random), and its magnitude. It presents a single value, measuring the strength of the spatial pattern of a given variable with itself for a neighborhood, which we define using queen adjacency with a row-wise weighting policy (Getis, 2009). The local variant computes a similar kind of standardization of the variable of interest to help identify exactly where the SAC is occurring and what patterns it is exhibiting. Local Moran's I also outputs Z-scores, which give the direction of SAC, and p-values, which help determine significance. Using these - the standardized values of γ-diversity, the standardized scores of the adjacent (lag) values, and the p-values per spatial unit, we can compute LISA (Anselin, 1995). This will show the spatial units of high diversity, surrounded by other such units (High-High); the spatial

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units of low diversity, surrounded by other such units (Low-Low); the other two combinations (High-Low and Low-High); and the non-significant units.

3 Results

3.1 Status of crop diversity at the EU and national level

The geometric mean (Aramburu Merlos and Hijmans, 2020) α- and γ-diversity values for the EU-27 as a whole were 3.92 and 7.97, respectively, while β was stable at around 2.02. Over the seven year period, α-diversity, defined here as the effective diversity of the average cropland pixel in the EU, increased by 6.7% from 3.83 in 2017 to 4.09 in 2023. Over the same period, the γ-diversity increased by 5.0%, from 7.79 in 2017 to 8.18 in 2023. In contrast, β-diversity changed very little - from 2.03 in 2017 to 2.00 in 2023, or a decrease of 1.63%.

At the national level, some countries showed noticeable inter-annual variation, including Finland in 2017; Cyprus, Denmark, Croatia in 2018, Estonia, Latvia, Lithuania, Luxembourg in 2017 and 2018; and Malta in 2020 (Figure S1). However, the inter-annual variation within countries was small relative to differences among countries in distributional shape and central tendency. For this reason, we present the geometric mean γ-diversity across all years for each country. As shown in the left panel of Figure 3, this measure is based on the distribution of LAU-level γ-diversity values within each country and therefore reflects the spatial structure of crop diversity rather than pooled national crop composition.

Some countries showed a wide dispersion of LAU-level γ-diversity values, indicating substantial intra-national heterogeneity in cropping systems. This was the case for Austria, Bulgaria, Germany, Spain, France, Croatia, Italy, Latvia, Malta and the Netherlands. Other countries showed a pronounced concentration of values around the national mean, including Cyprus, Czechia, Estonia, Finland, Ireland, Luxembourg. Several countries displayed bimodal distributions, including Belgium, Denmark, Greece, Portugal, Sweden, and Slovenia, while others showed skewed distributions, either to the right, as in Greece, Finland, and Slovenia, or to the left, as in Slovakia. Comparing these diversity distributions with the area shares of the five most represented crops in each Member State (right panel of Figure 3) shows that national crop shares do not translate directly into spatial crop diversity. For example, Latvia and Slovakia have similar national crop-share profiles, yet crop-specific spatial organization results in crop diversity that is approximately one effective crop type higher in Latvia.

3.2 Spatial patterns of crop diversity

The left-hand side of Figure 4 shows the spatial distribution of the mean γ-diversity per NUTS3 region, together with a histogram of values. The histogram indicates that 64% of NUTS3 regions in the EU-27 have geometric mean γ-diversity values above the EU-wide geometric average of 5.98, with a small number of highly diversified regions. Areas of high diversity are visible in eastern Austria, southwestern Bulgaria, western Germany, northeastern Greece, much of central and western Italy, southern Portugal, and southeastern France. The latter includes Roumoules, the most diverse LAU/NUTS4 region identified in the EU-27 (Figure 1).

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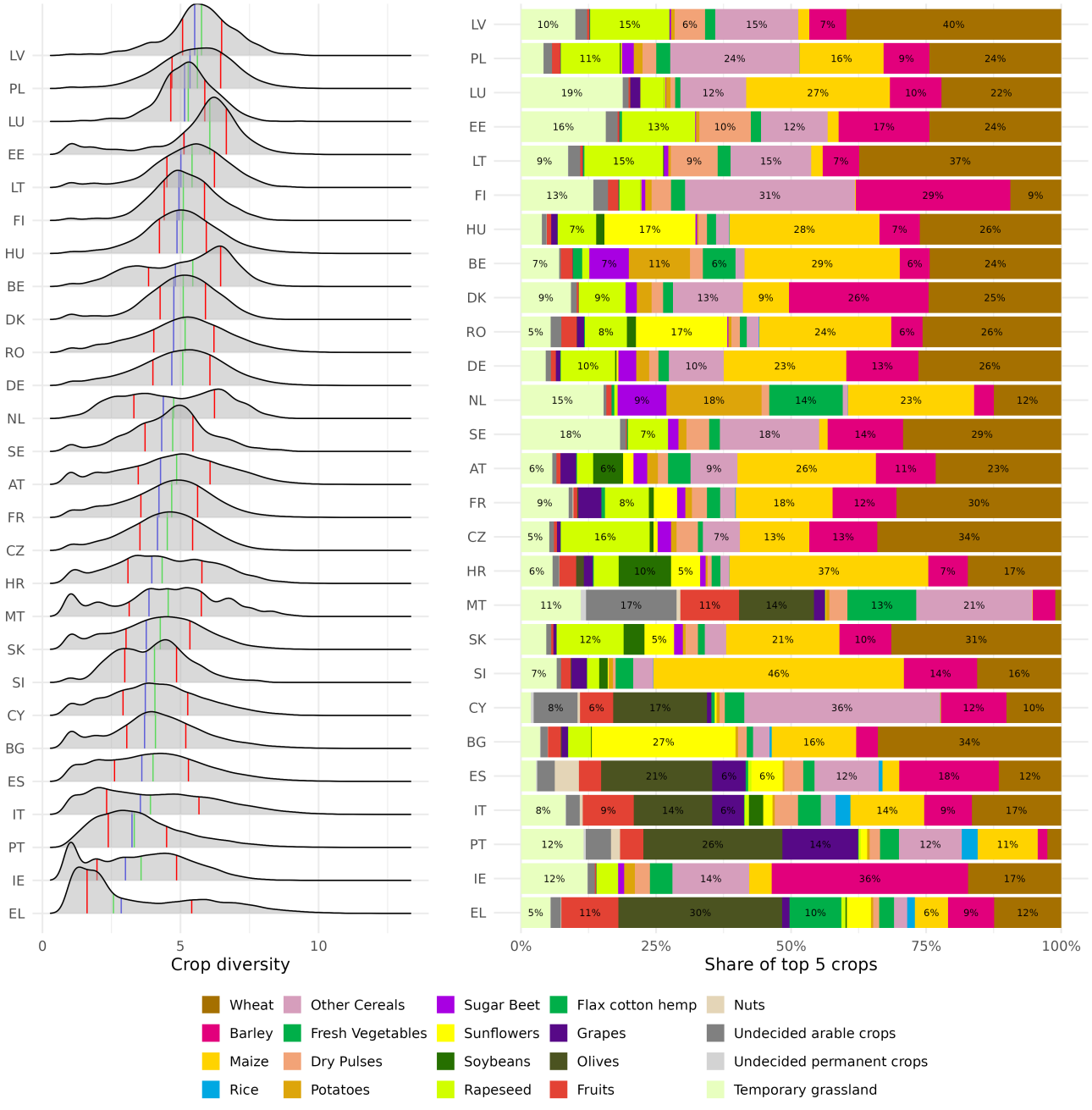


Figure 3. Left panel: density ridges of mean γ-diversity at LAU/NUTS4 level across all seven years, shown by Member State (for country code reference see Table S1) in descending order based on mean of γ-diversity. Red lines indicate the first and third quartiles, the green line indicates the median, and the blue line indicates the geometric mean. Right panel: crops by area share for each Member State.

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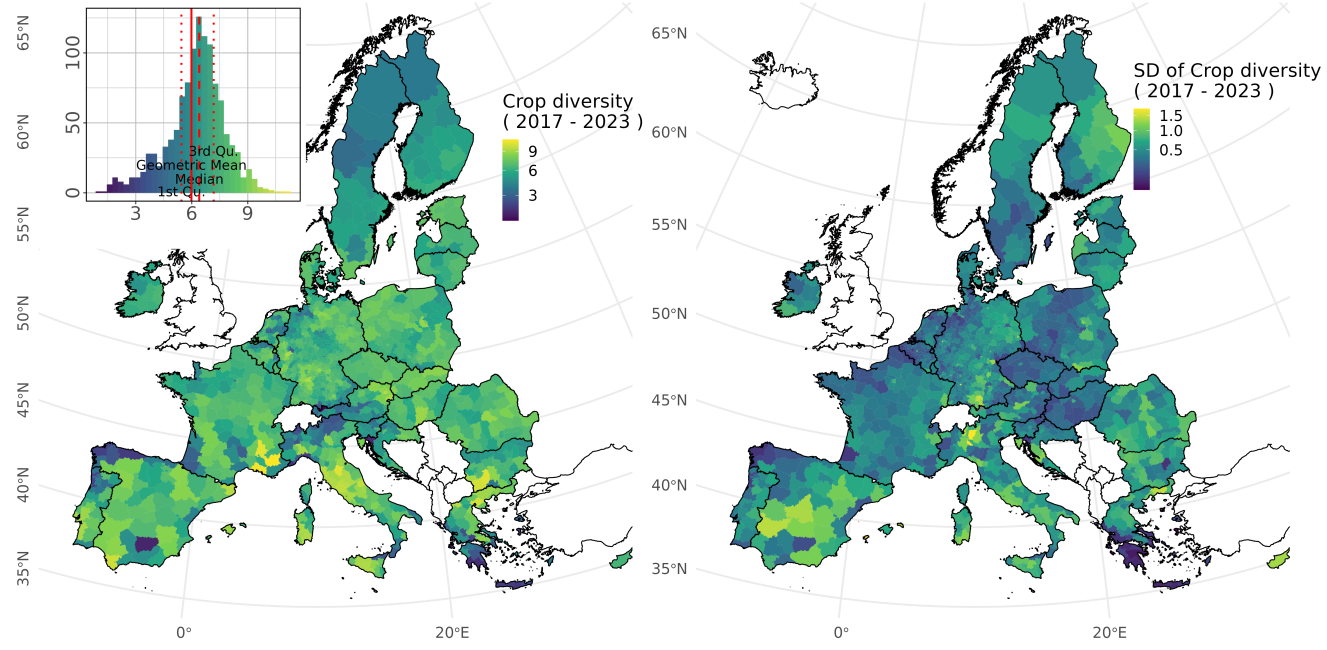


Figure 4. Mean γ-diversity and inter-annual standard deviation across all seven years by NUTS3 region. Descriptive statistics from the histogram are as follows: minimum = 1; first quartile = 5.45; median = 6.4; geometric mean = 5.98; third quartile = 7.17; maximum = 11.16.

In contrast, areas of low diversity are found in northern coastal Spain, particularly Galicia and Asturias, as well as Jaén; western coastal Croatia; several coastal regions of Italy, including Liguria, Calabria, and Messina; mountainous regions such as Ossola in Italy; and parts of Greece, including the Peloponnese and Crete. Crete contains Karyes, the least diverse LAU/NUTS4 region identified in the EU-27 (Figure S2).

The right-hand side of Figure 4 shows the inter-annual standard deviation of the γ-diversity at the NUTS3 level. Clusters of elevated temporal variability are visible in Lombardia, particularly Lodi, Bergamo, and Brescia; southern Germany, including Oberallgäu; and central Austria, particularly Liezen.

Using the LAU/NUTS4 distribution of γ-diversity across the EU-27, low- and high diversity regions were defined using the first and third quartiles, respectively. These thresholds were 3.365 for low diversity and 5.694 for high diversity and are shown for each year in Figure S3. We then condensed this annual information into a single stability map to identify regions with structurally persistent high or low crop diversity across the seven-year period (Figure 5). This was done using a majority rule across the seven years. Regions were assigned to four categories: (i) persistently high diversity, where at least five out of seven years were classified as high diversity; (ii) low diversity, where at least five out of seven years were classified as low diversity; (iii) switching, where at least one year was classified as high followed by at least one year classified as low; and (iv) intermediate, covering all remaining combinations.

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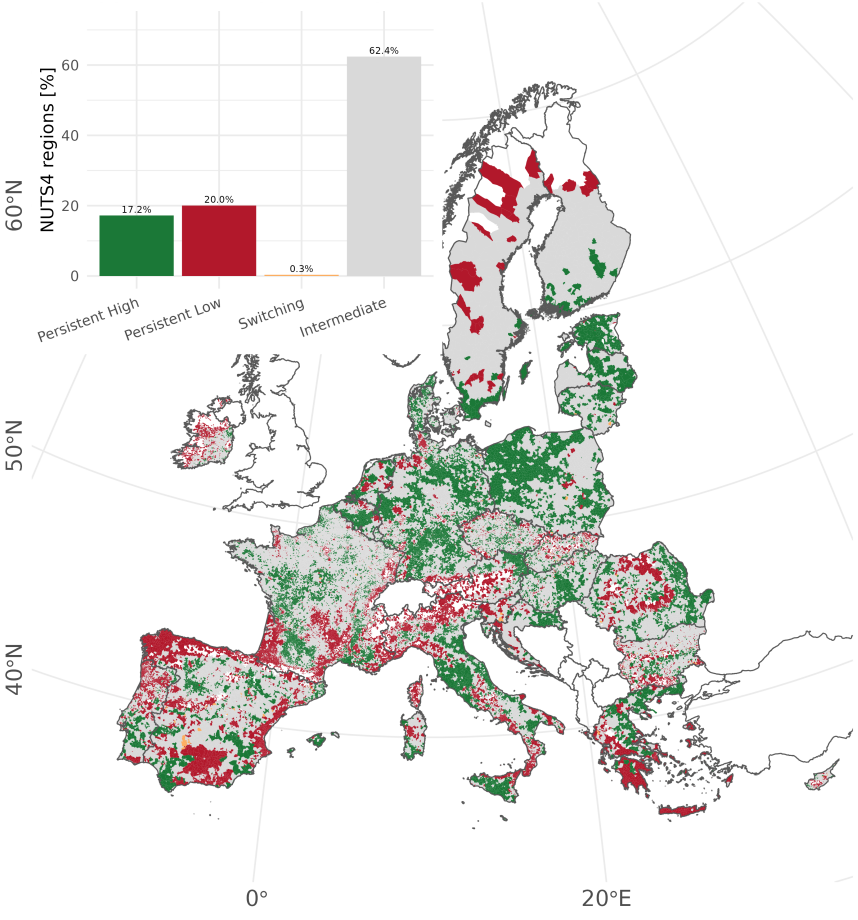


Figure 5. Structural persistence of crop-diversity patterns at municipal LAU/NUTS4 level across the EU-27. Regions are classified into four persistence categories based on their high- or low-diversity status across the seven-year period. The inset bar plot shows the percentage of LAU/NUTS4 regions in each category.

The results show that 17.2% of municipal LAU/NUTS4 regions were persistently high diversity, 20% were persistently low diversity, 62.4% were intermediate, and only 0.3% were switching. A global Moran's I test confirmed strong positive spatial autocorrelation in geometric mean γ-diversity (I = 0.666, $p < 2.2 \times 10^{-16}$), indicating that high- and low-diversity cropping systems are spatially clustered. Local Indicators of Spatial Association (LISA) further identified High–High clusters in central and northern Europe and Low–Low clusters in Mediterranean regions, closely aligning with the spatial persistence patterns shown in Figure 5.

We then assessed changes in the area classified as high diversity (Figure 6a) and low diversity (Figure 6b) at national level. To increase robustness and reduce the influence of single-year fluctuations, we calculated the mean area for the first three years

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of the time series (2017-2019) and subtracted it from the mean area of the last three years (2021-2023). The EU-27 average is shown at the top of each plot, using both an area-weighted mean, where larger countries have greater influence and therefore reflect total EU cropland redistribution, and an unweighted mean, where each country contributes equally regardless of size and therefore reflects the average Member State-level change.

At the EU-27 aggregate level, the area-weighted share of high-diversity areas increased by 4.3%, while the unweighted country-level average increased by 2.9%. This difference indicates that larger countries, particularly France, Germany, and Spain, accounted for much of the increase in high-diversity areas. For low-diversity areas, the area-weighted increase was around 1%, with only a small difference of 0.2% between the weighted and unweighted estimates, suggesting that changes in low-diversity areas were more evenly distributed across Member States. Because both the upper tail, representing high-diversity areas, and the lower tail, representing low-diversity areas, increased over time during the study period (Figures 6a and 6b), the share of cropland in the middle distribution must decrease by mathematical definition (annual histograms Figure S3). In other words, the observed redistribution reflects a gradual shift of cropland towards the distributional tails rather than a widespread spatial reclassification, consistent with the strong structural persistence shown in Figure 5.

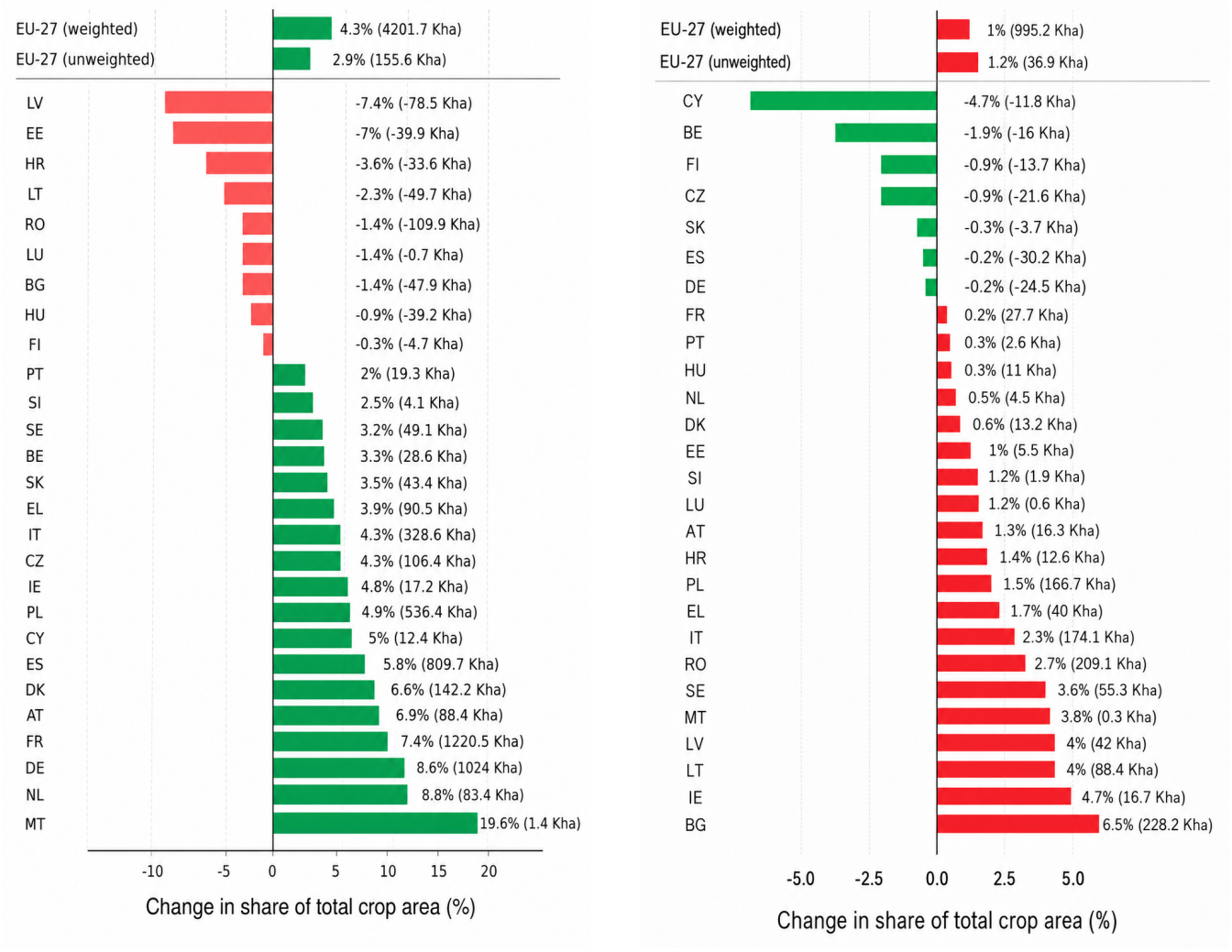
3.3 Temporal trends in crop diversity

In cases where the signal is weak (Figure S4), distributed and hierarchically structured, LMMs provide a more appropriate framework for assessing temporal trends with greater statistical power (Section 2.2.2). We used LMMs to assess whether there was a general EU-wide trend in γ-diversity while accounting for repeated observations within NUTS3 regions. The best model fit in terms of residuals handling and year centering was assessed by ranking them based on the resulting AIC (Table S2).

For LMM1, each region was allowed to have its own baseline level of γ-diversity level, while all regions shared the same temporal slope. The model performed significantly better with AR(1) and year centering (Table S2) and resulting in a ϕ-coefficient of 0.12, indicating weak positive residual autocorrelation between consecutive years. The fixed-effects estimate indicated that, on average, γ-diversity increased by 0.05 effective crop types per year across the EU-27. The random-intercept standard deviation was 1.53, indicating substantial differences among regions in baseline crop diversity, while the residual standard deviation was 0.55, indicating relatively low year-to-year unexplained variation within regions.

For LMM2, both the baseline level and the temporal slope were allowed to vary by region. Here residuals were not modeled with AR(1), as this model showed a better fit (Table S2). This suggests that much of the positive temporal dependence from LMM1 is associated with unmodeled differences in regional trends. Accounting for those trends through random slopes, there is little remaining evidence for positive lag-one residual autocorrelation. The fixed-effects estimate again indicated an average EU-wide increase of 0.05 effective crop types per year. The random effects showed large differences among regions in baseline diversity, with an intercept standard deviation of 1.53, as well as slight variation in regional slopes, with a slope standard deviation of 0.08. This slope variability is slightly larger than the mean EU-wide slope of 0.05, indicating that the small average increase does not reflect a uniform increase across all regions. Rather, some regions increased while others decreased, with these opposing regional trends partially canceling each other out at the EU scale.

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(a) High-diversity areas

(b) Low-diversity areas

Figure 6. Percentage change in high- and low-diversity areas between the mean of the first three years of the time series (2017–2019) and the mean of the last three years (2021–2023), with absolute changes in hectares shown in brackets. The EU-27 mean is provided at the top of each plot, both area-weighted and unweighted. Countries are ranked in ascending order from the largest decrease to the largest increase. Note that the colour interpretation differs between panels: an increase in high-diversity area is shown in green, whereas an increase in low-diversity area is shown in red; conversely, a decrease in high-diversity area is shown in red, whereas a decrease in low-diversity area is shown in green.

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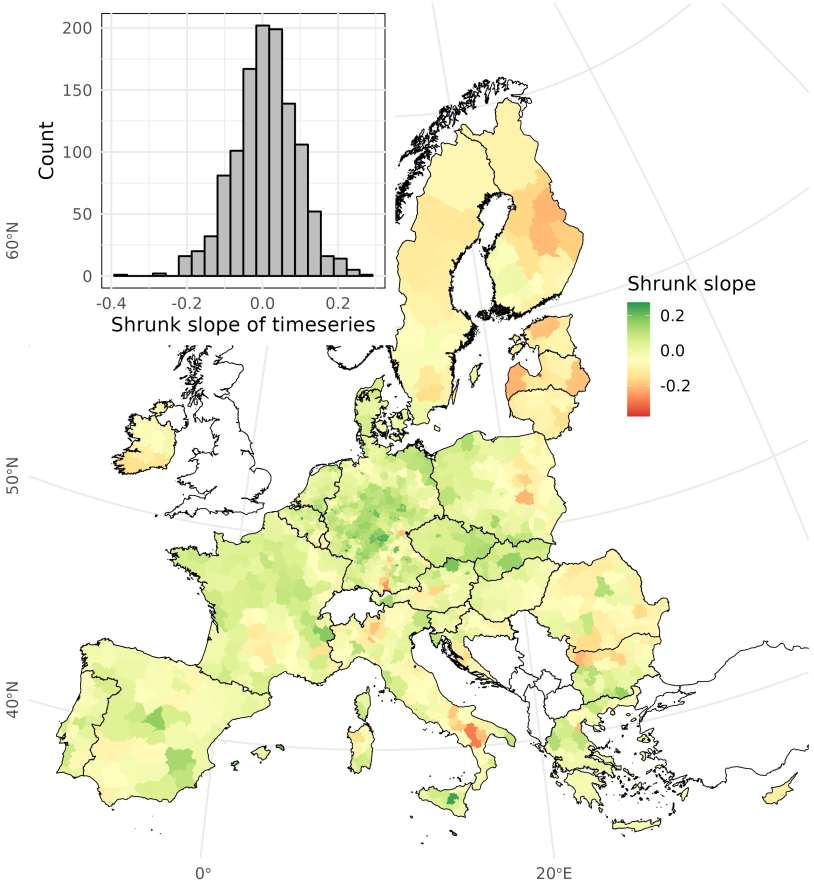


Figure 7. Spatial crop γ-diversity trends at NUTS3 level, measured as the partially pooled (shrunk) slope from the 2017-2023 time series.

Partially pooled, or shrunk, slope estimates provide the best estimate of each region's trend by combining information from the region-specific time series with the overall EU-wide pattern. These estimates are shown in Figure 7. The partial-pooling correction produces a cleaner and more conservative spatial pattern, with a more constrained distribution and fewer extreme values. Mild positive clusters are visible in Germany, Czechia, Slovakia, Western Poland, parts of France, Spain, and Sicily. Most NUTS3 regions, however, have slopes close to zero, indicating little or no change in γ-diversity over the study period. Mild negative trends are visible in parts of Scandinavia, the Baltic countries, the Balkans, and small areas of Italy.

3.4 Crop-system and landscape characteristics associated with crop diversity

Several model fits were tested and the best supported model among the four candidate structures according to AIC is the one that uses regional random intercepts and year slopes, plus AR(1) residual correlation (Table S3). Results from this model in

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terms of analysis of crop-system and land cover/use characteristics associated with crop diversity are presented in Figure 8. The dataset exhibits a very pronounced structural signal between γ-diversity and the proportion of the MRC (dominance), evidenced by a Pearson correlation coefficient -0.853. This is to be expected as both are calculated from the same crop shares. With that in mind, the interpretation of EU-27 crop diversity is done through the lens of the degree of regional crop specialization. The model estimated a ϕ value of 0.06, showing a slight residual corelation between consecutive years, conditional on the fixed and random effects.

Predictor groups were evaluated by their increase in AIC upon removal from the full model, retaining the same random-effects and temporal correlation structure (Table S4); with standardized dominance having by far the largest deterioration in model support, followed by richness, environment, and finally the fixed year effect. The main predictor shows that a one-SD increase in dominance is associated with a decrease of 1.18 (95% CI: -1.2 to -1.16) effective crop types. This relationship is shown in Figure 8c, which displays a strong triangular pattern. Regions dominated by a single crop have consistently low crop diversity, whereas regions with lower dominance can reach substantially higher levels of diversity. This relationship remains broadly consistent across environmental strata (Figure 8d, reinforcing the interpretation that crop specialization is the main factor associated with regional crop diversity. The geographical distribution of regions with high and low MRC dominance is shown in Figure 8b.

The effect of crop richness was weaker than that of MRC dominance. A one-SD increase in crop richness was associated with an increase of 0.24 (95% CI: 0.22 to 0.26) in effective crop types. Environmental and land cover/use variables (URBN, MOUNT, COAST, and EnZ) removal produced a smaller AIC increase than removing dominance or richness. At the same time, the model computes a random effects standard deviation of 0.68 for the region variance component, 0.36 for the residual one, and a 0.094 for the slope. This shows that although the specific environmental predictors do not capture this well, regional differences provide for substantial unaccounted-for regional heterogeneity. Among the environmental category contrasts, both urban and the non-coastal-coastal had 98% confidence intervals excluding zero. Non-coastal regions had a slightly higher γ-diversity than coastal ones (0.17, 95% CI: 0.06 to 0.28), and predominantly rural regions had slightly lower γ than predominantly urban regions (-0.311, 95% CI: -0.428 to -0.194) after adjustment for crop dominance, richness, environmental characteristics, and time.

4 Discussion

The results show a significant but small increase in crop diversity across the EU-27 over the seven-year study period, with detectable increases in both α- and γ-diversity. The observed increase in α-diversity from 3.83 in 2017 to 4.09 in 2023, representing a 6.7% rise, and in γ-diversity, from 7.79 to 8.18, representing a 5% rise, indicates a modest positive shift in local and regional crop diversity. By mathematical necessity, this difference defines the range in which β-diversity can fluctuate (2.03 - 2.00 between 2017-2023). The slight decrease of 1.63% in β suggests that spatial turnover among LAUs has changed little over time. It also indicates that the total EU crop portfolio remains more than twice as diverse as the average local cropping system. At the national level, the inter-annual variation in crop diversity was minor compared with the substantial differences

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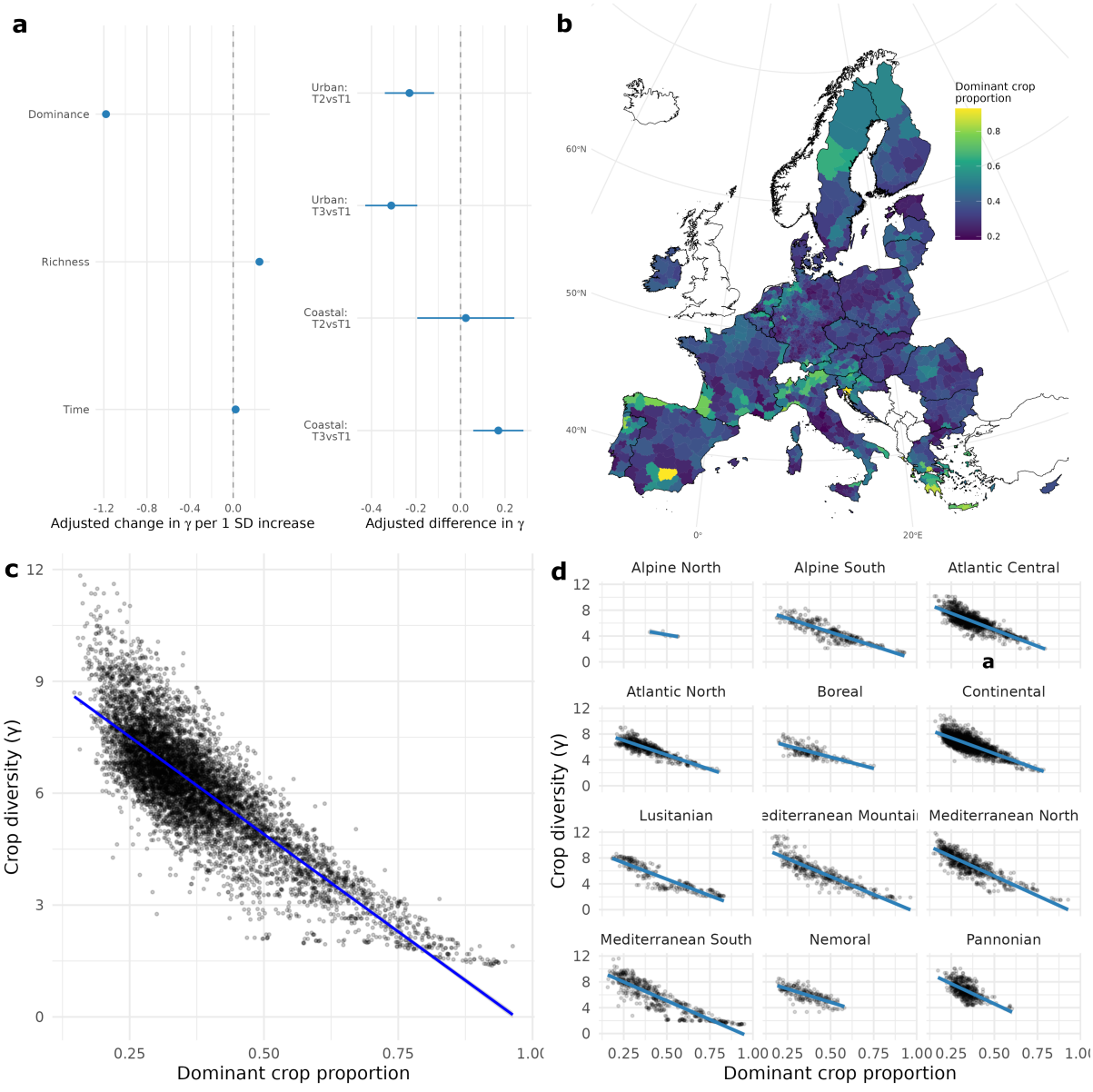


Figure 8. Analysis of the crop system and landscape characteristics associated with γ-diversity. (**a**) Adjusted fixed-effects estimates with 95% confidence intervals from the full linear mixed model (LME_d). Continuous predictors were standardized, and categorical predictors were interpreted relative to their respective reference categories. Urban: T1 = predominantly urban, T2 = intermediate, T3 = predominantly rural. Coastal: T1 = coastal, T2 = ≥50% population within 50 km of coast, T3 = non-coastal. (**b-d**) Analysis of the most influential predictor: the dominance of the most represented crop (MRC). (**b**) Map of mean annual MRC dominance over the 2017-2023 period. Relationship between γ-diversity and MRC dominance (**c**) at the European level and (**d**) within environmental strata.

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observed among countries. For example, Austria, Germany, and Spain exhibited considerable intra-national heterogeneity in γ-diversity, suggesting diverse agricultural systems and environmental conditions within these countries. In contrast, countries such as Cyprus and Czechia showed more concentrated distributions of diversity values, indicating more spatially uniform agricultural landscapes. This variation highlights the need for agricultural policies and interventions that account for national and sub-national differences in cropping systems, environmental conditions and production contexts.

The spatial analysis showed that 55.8% of NUTS3 regions in the EU-27 had mean γ-diversity above the EU-wide average, with regions in eastern Austria, southwestern Bulgaria, and central and western Italy identified as particularly diverse. Conversely, areas in northern Spain and coastal Croatia showed lower diversity, highlighting persistent geographical disparities in crop production and agricultural specialization. The identification of high- and low-diversity clusters using global Moran's I further confirms that crop diversity is not randomly distributed, but spatially structured. These patterns are likely shaped by a combination of agricultural specialization, environmental conditions, farm structure, markets, and regional production histories. The analysis of crop-system and land cover/use characteristics indicated that MRC dominance was the strongest factor associated with γ-diversity, with increasing MRC dominance associated with lower regional crop diversity. This finding aligns with the wider literature suggesting that agricultural specialization constrains crop diversity (Franco et al., 2022; Revoyron et al., 2022). The relatively small role of broader environmental and land cover/use variables further suggests that regional crop diversity is shaped more strongly by agricultural practices and specialization than by environmental constraints alone. The strong inverse relationship between crop dominance and diversity indicates that efforts to enhance regional crop diversity should focus not only on increasing the number of crop types present, but also on reducing the spatial dominance of monocultures within regional agricultural systems.

Compared with our earlier work Machefer et al. (2024), the present study uses the annual Copernicus HRLs, which provide a more consistent time series for assessing spatial crop diversity. To support comparison, we focus on 2018, the year analyzed by Machefer et al. (2024). Direct comparison between the two datasets is difficult because of differences in crop lists, the total number of classes, and the treatment of temporary and permanent grassland. In addition, compared with the experimental JRC EU Crop Map d'Andrimont et al. (2021), the HRLs provide more spatially continuous classifications with less speckle, supporting more robust crop diversity calculations. At the national level, Machefer et al. (2024) reported diversity values of 2.3–4.4 for α, 1.2–2.3 for β, and 3.5–7.5 for γ diversities. In the present study, the corresponding values were higher, at 2.9–6.0 for α, 1.2–3.2 for β, and 5.7–11.0 for γ. One might expect the patchier and more speckled output of the EU Crop Map 2018 to produce artificially higher diversity estimates, because more crop types may be incorrectly identified as present. However, when upscaled to national estimates, this patchiness can dilute the signal from correctly classified crops and may reduce estimated diversity. We therefore interpret higher estimates in the present study as resulting from the additional crop class available in the HRL data, the ability to remove the permanent grassland fraction, and the cleaner and more spatially coherent classification output of the HRL products.

An alternative approach is to use farmers' declarations as the basis for crop diversity calculations Schaak et al. (2023); van der Velde et al. (2024). van der Velde et al. (2024) reported 2018 γ-diversity ranges for the Netherlands of 1–7 using the EU Crop Map and and 2–12 using Dutch GSA data. Using the HRL Crop Type layer for the same year, territory, and grid

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scale, we obtained a γ-diversity range of 1–8.4, which falls between the estimates derived from the EU Crop Map and the Dutch GSA. The number and definition of crop classes, including the treatment of grassland, are crucial for interpreting these differences. The EU Crop Map contains 19 classes, the GSA codes were aggregated to 40 unique codes, and the HRL data used here contain 20 classes. Moreover, the EU Crop Map does not distinguish permanent and temporary grassland, whereas the GSA and HRL-based approaches allow this distinction.

Finally, Brutti et al. (2025) used administrative data for Spain from 2022 to evaluate farmers' decision-making in response to the EU crop diversification strategy, with particular attention to farm-size effects. Because their data are available at the level of individual farm holdings, while the present analysis is landscape-based, direct comparison is limited. Nevertheless, after sub-setting, formatting, and binning the data in the same way as Brutti et al. (2025), we were able to confirm one of their main findings: larger crop areas tend to contain more crop types. We found an r-squared value of 0.11, indicating that area matters, but that other factors, including climate, region, cropping system, topography, and specialization, also play important roles. Our crop richness values by area bin were consistently higher by at least one crop type, which is expected because landscape cells can accumulate crops from multiple holdings, whereas an individual farm accumulates crops from a single management unit. However, the shape of the relationship differs. While Brutti et al. (2025) reported a monotonic increase, our results show a reverse parabolic pattern, with richness increasing until cropland area reaches 18 ha, then plateauing around 19-20 ha, and eventually decreasing at 21 ha. The two studies converge only in the largest comparable bin, around 25 ha, where crop richness is approximately 3.7. This intuition is supported by running a Generalized Additive Model (GAM), which confirms the non-linear nature of the relationship (edf = 8.99) and explains a significantly larger percentage of the deviance (r-squared = 0.332). Interestingly, although the mean crop richness decreases with increasing cropland area, the maximum is maintained high. We interpret this as two competing processes operating simultaneously - more area can support more crops (positive), and intensive agricultural regions tend to become specialized (negative), identifying the cutoff point around 19 ha where region-specific specialization takes over as more important compared to cropland area in fluctuating richness. Further to this point, when using γ-diversity or the most represented crop the behavior of the GAM is almost identical, though less pronounced (r-squared = 0.173 and 0.154 respectively), with a cutoff at around 16 ha. Additionally, the corelation at the binned-response level between diversity and the most represented crop is -0.943. This shows there is a potential for a real agro-ecological threshold around cropped area of this size, rather than a statistical artifact.

The observed increase in crop diversity is encouraging and suggests that more diverse agricultural landscapes are possible within the EU. However, the persistence of low diversity regions and the dominance of specific crops raise concerns about the sustainability and resilience of some regional agricultural systems. In their analysis of crop diversification pathways of European farms, Revoyron et al. (2022) found that crop diversification was hindered by technological lock-in around major crops. Conversely, Wesemeyer et al. (2024) showed that reallocating crops spatially, without changing field boundaries and farm-level crop composition, could reduce the gap between observed and attainable crop diversity. More broadly, a variety of crop diversification strategies have been associated with generally positive, although context-dependent, outcomes (see e.g. Beillouin et al. (2021)). These outcomes vary across regions and depend on interactions with other soil and crop management strategies Hofmeijer et al. (2021).

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On the policy side, the proposed diversity indicators could greatly aid CAP evaluation. Currently, CAP supports crop diversity through through conditionality, eco-schemes and agri-environment-climate commitments. However, these policy mechanisms cannot be effectively evaluated due to the lack of open, high-resolution, EU-wide data. The methodology presented in this paper enabled DG AGRI's first analytical brief on Europe's crop diversity status (European Commission, 2026). An online dashboard allows for the interactive assessment of Europe's diversity (European Commission, Joint Research Centre). The next logical step would be to include the proposed indicators in the CAP PMEF. The EO-based indicators in this paper would offer a more comprehensive assessment for indicators C.22 and I.22 than the current statistical estimates based on regional crop richness. The main barrier to bridge this gap is the need to operationalize the production of EO-based indicators (Urraca et al., 2026). As show in this paper, transforming Copernicus layers into policy relevant indicators is complex and beyond the scope of Copernicus services. To effectively support evaluation frameworks, a clear governance framework is needed to establish which EU institution is responsible for systematically producing these indicators. A prerequisite for operationalization is the regular and consistent reprocessing of HRL layers to ensure that annual products accurately reflect land management decisions over time. This requires correcting detected classification errors and ensuring that the same or comparable reference data, classification schemes, and algorithms are used across the annual time series.

From a policy perspective, these results suggest that efforts to enhance crop diversity should address both the composition and spatial organization of cropping systems. Financial incentives for diversified cropping systems could include support for cover crops, inter-cropping, legumes, mixed cropping or the maintenance of traditional crop varieties. However, because this study focuses on spatial crop diversity rather than farm-level rotations or holding-level diversification, the results are most relevant for landscape and regional monitoring. Future research should further investigate the socio-economic and institutional factors shaping regional crop diversity patterns, including market access, farm structure, advisory systems, processing infrastructure, and policy incentives. Another key challenge to evaluate whether agricultural landscapes are moving towards greater sustainability and resilience is to define a robust and interpretable crop diversity metric. In this study, we used Shannon diversity and distinguished between α, β, and γ measures, each of which captures a different aspect of spatial crop diversity. Alterative metrics include inverse Simpson diversity, Gini–Simpson diversity, crop richness, evenness, or metrics that explicitly account for the sustainability characteristics of specific crops, for example, in the context of crop rotations (Geniaux et al., 2009; Janssen et al., 2026). Another key consideration is the spatial scale at which crop diversity is calculated: the metric must be meaningful at EU scale, but also interpretable and policy-relevant at local and regional scales. A combination of metrics may ultimately be most useful, forming a composite crop diversity indicator that can track the effects of land management and policy decisions across the EU.

5 Conclusions

This study presents the first use of continental-scale CLMS HRLs raster mosaics to analyze crop diversity across the EU at multiple levels of spatial aggregation. We developed a methodology for combining three CLMS HRLs products to make use of the 19 available crop types and add a new class on temporary grasslands. Following established diversity-partitioning

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approaches, we estimated the α, β, and γ components of crop diversity at multiple spatial scales, capturing crop diversity patterns from the local level, represented by LAUs, to the national level, represented by NUTS0 regions. The results show a modest but detectable increase in crop diversity over the seven-year period. At EU level, α-diversity increased by 6.7%, from 3.83 in 2017 to 4.09 in 2023, while γ-diversity increased by 5.0%, from 7.79 to 8.18. In contrast, β-diversity remained relatively stable, indicating that the relationship between local and regional diversity changed little over time. This suggests that the EU crop portfolio became slightly more diverse overall, but without a major restructuring of spatial turnover among local cropping systems.

We used linear mixed-effects models to identify temporal trends in crop diversity and assess crop system and land cover/use characteristics associated with these patterns. The dominance of the Most Represented Crop was the strongest factor associated with regional γ-diversity, indicating that agricultural specialization is a key constraint on spatial crop diversity. At EU level, we estimated a modest 5% increase in regional γ-diversity over the 2017-2023 period, as well as a small (4.3% and 1% respectively) increase in persistently high and low diversity areas, defined as belonging, respectively, to the third and first quartile of the pooled multi-year distribution of γ-diversity values. We explored the spatial distribution of regional diversity and present compelling narratives that allow for fine-scale analysis of specific areas in the EU-27 with the potential to provide targeted scientifically-determined policy advice.

The results also demonstrate the value of distinguishing among local, regional, and cross-scale dimensions of crop diversity. Local diversity, regional diversity, and spatial turnover capture different properties of agricultural systems and should not be treated as interchangeable. In particular, national or regional crop portfolios may appear diverse even where local landscapes remain specialized, while local diversity may be high without substantially altering broader regional patterns. Multi-scale indicators are therefore essential for interpreting the structure of European cropping systems and for identifying where policy interventions may be most relevant.

From a policy perspective, HRL-derived crop-diversity indicators could improve the current PMEF indicators for evaluationg crop diversity interventions (C.22 and I.22) , as these currently only assess crop richeness based on statistical surveys. Because EO-derived crop maps do not identify farm holdings, they cannot directly assess holding-level crop-diversification requirements. However, they can provide consistent information on landscape- and regional-scale crop diversity, which is relevant for biodiversity, resilience, and the spatial organization of agricultural production. Such indicators could help identify persistent low-diversity regions, monitor changes in crop-specialization patterns, and support the targeting of agri-environmental interventions.

Several conditions are important for operationalizing this type of indicator. First, the HRL time series must be processed consistently across years, with comparable classification schemes, reference data, and algorithms. Second, classification errors and uncertainty should be documented and, where possible, corrected through regular reprocessing. Third, the choice of crop-diversity metric and spatial scale must be transparent and policy-relevant. Shannon-based effective diversity provides an interpretable measure of the effective number of crop types, but complementary metrics such as crop richness, dominant-crop share, inverse Simpson diversity, or composite indicators may be useful for specific policy questions.

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Overall, this study shows that annual Copernicus HRLs provide a robust basis for monitoring spatial crop diversity across Europe. The approach developed here enables consistent comparison across countries, administrative levels, and grid resolutions, while revealing persistent spatial inequalities and heterogeneous temporal trends in crop diversity. As longer HRL time series become available, these indicators could support more systematic assessment of how European agricultural landscapes are changing and whether policy interventions are contributing to more diverse, resilient, and sustainable cropping systems.

Code and data availability. The processing pipeline is designed to run in a custom virtual environment because specific versions of several software libraries are required. These dependencies are listed in Figure 2. Global variables are defined in an auxiliary JSON configuration file, allowing the source data to be changed and different parts of the pipeline to be run flexibly.

The processing workflow uses two parallel but equivalent processing threads. One extracts crop distributions using the 1 km grid as the minimum aggregation unit (MAU), while the other uses the LAU dataset as the MAU. Aggregation is then performed through the hierarchy of each respective MAU. This approach avoids artefacts that could arise if one spatial mapping unit, such as the grid, were used to aggregate crop diversity or other metrics to another spatial framework, such as NUTS regions, since both crop diversity and spatial aggregation are highly scale-dependent (see Section 4).

The output data are initially produced in wide format. Because this structure is inefficient for subsequent analysis, the tables are reshaped to long format and filtered by pixel value and Member State. We share all produced output on the open JRC FTP.

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