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PAPER

Enabling and constraining factors for organic agriculture in Europe: a spatial analysis

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Abstract

The European Commission has set a target of making 25% of its agricultural land organic by 2030. This is part of the farm-to-fork strategy to produce high-quality food in a more environmentally friendly way. However, there are large disparities between and within member states in the share of agricultural land currently managed as organic. Current statistics available on organic agriculture in the EU are limited to national or subnational scale. In addition to that, studies on location factors of organic agriculture are mostly conducted at the national or subnational level. This constitutes a major obstacle in formulating policies to improve the share of organic agriculture within Europe. This study analyses the influence of socioeconomic, climate, and biophysical variables on the spatial distribution of certified organic producers at high resolution throughout Europe. To do so, it maps the location of current organic agriculture throughout Europe, using detailed postcode-level data from certification registries. Subsequently, regression analysis at NUTS 2 and 1 km^2 resolution identify the driving forces for their location. The results indicate that organic agriculture is found predominantly in areas close to markets and with unfavourable biophysical conditions for conventional agriculture. Population density was found to be the single strongest indicator increasing the odds of organic agriculture by 271%. We highlight areas in the EU lacking in uptake of organic agriculture and provide an understanding of what factors help create an enabling or constraining environment for adoption. Our results directly contribute to policy discussions on how to better target efforts for conversion to organic agriculture.

1. Introduction

The agricultural sector is a large contributor to greenhouse gas (GHG) emissions, as it accounts for, respectively, 12% and 10.3% of the world's (IPCC 2022) and EU's GHG emissions (European Commission 2020, IPCC 2022). Additionally, many agricultural practices, such as applying fertilisers and pesticides on land, degrade the environment, biodiversity, and ecosystem functioning (Henle *et al* 2008, Steffen *et al* 2015, Tsiafouli *et al* 2015, Watson *et al* 2021). Agricultural intensification also leads to degraded soils that are less able to provide food for human consumption and other services such as carbon storage or flood mitigation (Kopittke *et al* 2019). Organic agriculture is often suggested as a more sustainable alternative to conventional farming, as evidence shows that organic agriculture has multiple environmental benefits. For example, organic agriculture has higher soil organic matter, and therefore less soil erosion than conventional farming (Bai *et al* 2018). Organic agriculture also leads to increased soil water retention, water use efficiency (Bai *et al* 2018), lower GHG emissions, and less energy use (Lee *et al* 2015). Studies also found less pesticide residues in both soils and food from organic farms (Benbrook *et al* 2021, Geissen *et al* 2021). Organic farming is also found to contribute positively to biodiversity by increasing species richness and abundance of both flora and fauna (Stein-Bachinger *et al* 2021).

In order to combat climate change, reverse environmental degradation, and ensure food security for future generations, the EU has set various targets to reduce the environmental and climate impact of the EU food system. This is part of the EU farm-to-fork (F2F) strategy, which aims to protect and restore natural resources and reverse biodiversity loss. To achieve this goal, the EU aims to increase the share of organic agriculture in Europe to 25% of agricultural land by 2030 (European Commission 2020).

However, in 2020 the share of organic agriculture was 8% of agricultural land in Europe (Debonne *et al* 2022). To reach the policy goal, a lot of agricultural land still needs to be converted to organic systems. This could result in a decrease in agricultural production in the EU, potentially leading to an increase in prices and imports of agricultural product. However, it may also lead to an increase in environmental benefits such as a reduction in GHG emissions and an increase in biodiversity. The scale of both the economic and environmental consequences depends on how the target on organic agriculture expansion is formulated. If each EU member state has to reach the 25% organic target individually, a higher number of farms and smaller farms will have to convert, whereas if the target is only implemented at EU level, countries with lower conversion costs to organic are more likely to convert (Kremmydas *et al* 2024).

More detailed knowledge of the spatial distribution of organic agriculture would enable better targeting from public and private actors to expand organic agriculture (Sapbamrer and Thammachai 2021, Tayleur *et al* 2018). It would also enable future assessments of economic and environmental implications of organic conversion efforts (Kremmydas *et al* 2024) and could shed light on the ability of member states to reach other policy goals related to food security under the F2F strategy and biodiversity under the nature restoration law.

Many studies have looked at adoption factors of organic agriculture such as farmer demographics, household characteristics, farmer attitudes and beliefs, supportive factors such as training and information access, and farm structure (Sapbamrer and Thammachai 2021, Serebrennikov *et al* 2020, Swart *et al* 2023). They found that training in organic production (Sapbamrer and Thammachai 2021) and general attitude and intention to adopt sustainable agricultural practices are the most important adoption factors (Swart *et al* 2023). However, little attention has been paid to climate and biophysical location factors such as soil or terrain (Serebrennikov *et al* 2020). But, the same studies admit that contextual factors such as geographic location play a role in farmers ability to implement sustainable agricultural practices such as organic farming (Sapbamrer and Thammachai 2021, Serebrennikov *et al* 2020, Swart *et al* 2023).

An exception is Malek *et al* (2019), who looked at both socioeconomic and biophysical location factors of organic agriculture on a global scale. They found that beneficial socio-economic factors increase the likelihood of organic farming globally (Malek *et al* 2019). Regional case studies on organic farming adoption suggest that long organic heritage increases the chances of more organic agriculture in a region (Allaire *et al* 2015, Kujala *et al* 2022).

In terms of biophysical characteristics, Malek *et al* (2019) found substantial differences between countries when it comes to the effect of terrain and soil conditions. The study did not find clear results in spatial patterns of organic agriculture in Europe, although eleven out of 27 EU countries were included in the analysis. A lack of available and accessible data on organic certificates hindered some of the analysis. The lack of detail in farming specialisation can also impact the results as different specialisations can have different spatial determinants. Three case studies in Europe also found evidence that organic agriculture is more likely to occur on marginal lands with less optimal soil and terrain conditions for agriculture (Ilbery and Maye 2011, Schmidtner *et al* 2012, Allaire *et al* 2015). However, in Tuscany, Italy, being located on more marginal land decreased the chances of participating in agro-environmental measures to promote organic agriculture (Boncinelli *et al* 2016). Globally organic farmers are located in areas with higher temperature and precipitation (Malek *et al* 2019).

These results show some regional differences in the spatial determinants of organic agriculture in European countries. However, it does not give a clear overview of Europe as a whole, and the number of location factors accounted for is still very limited. The spatial scale at which each analysis has been conducted varies from nomenclature of territorial units for statistics (NUTS) 3 level in Finland and Germany (Schmidtner *et al* 2012, Kujala *et al* 2022) to NUTS 5 level in Poland (Antczak 2021) and microterritories used in France (Allaire *et al* 2015). A European scope is necessary to reflect upon the likelihood of achieving the EU-wide policy goals and potential environmental and economic impacts of that.

This paper aims to address the shortcomings of the studies discussed above by assessing the current state of organic agriculture in Europe at a 1 km^2 resolution and determining the impact of biophysical, climate, and socio-economic conditions on their occurrence. To do so, we first map organic agriculture in Europe to provide the most spatially detailed data set on certified organic agriculture using organic certificate data. Subsequently, we perform a geostatistical analysis on the enabling and constraining factors for organic agriculture based on biophysical, climate, and socioeconomic factors at subnational and high resolution throughout Europe. Together, this can help policy makers gain insight into the driving factors for the occurrence of organic agriculture areas, determine their impacts on agricultural production and the environment, and better target efforts to encourage future conversion to organic agriculture.

2. Data and methods

To provide an overview of the current state of organic agriculture in Europe at 1 km^2 resolution and to determine the factors contributing to their occurrence, we use a combination of organic certificate data and socio-economic, climate, and biophysical spatial data. With this data we both map- and explore the spatial determinants of organic agriculture in Europe.

2.1. Collection of organic certificates

We start by creating a detailed map of organic agriculture throughout Europe. Organic certificates were collected for all EU27 countries and the UK. Data on the location of organic producers in Europe were collected from organic certificate repositories and official national sources (see table S1 for descriptive information for each source per country). When collecting data, the most recent organic certificates available per country were collected, leading to certificate data ranging from 2014 to 2024 between countries. However, for most countries, the certificate data represents 2023 or 2024. Only certificates reporting year, type of organic operator, and postcode information were collected.

For Sweden, Norway, and Switzerland, no organic certification data meeting the requirements was found. Therefore, other statistics were used for these countries. For Sweden, the organic area in hectares was collected by municipality (Karlsson 2023) and divided by the average size of the farm from Jordbruksverket (the Swedish Board of Agriculture) to arrive at an estimated number of organic producers. This resulted in 12 987 farms, which was more than double the number of organic producers reported for Sweden according to the Research Institute of Organic Agriculture FiBL (2024). The highest deviation between the certificates collected in this study and the FiBL statistics for any other country is 17%. Thus the number of organic producers in Sweden was set to a maximum of 17% more than reported in FiBL. For Norway, farms with organic activities were collected by municipality (Digitaliseringsdirektoratet n.d.), and for Switzerland the number of organic producers per Swiss canton was collected (Swiss Federal Statistical Office Employees n.d.). (table S1 provides an overview of the source of certification data used for each country including the certificate years of validity, control authority, source URL and collection method.)

After all certification data were collected, the producers were extracted from the other operator certificates (e.g. manufacturers, processors, importers) if there were any. All duplicates were removed, leaving 355 405 certificates from the original 397 116 (table S2). The remaining certificates were then mapped by locating their postcode to the centroid of a postcode zone derived from the Geographic Information System of the Commission (GISCO 2022). Some postcodes of the certificates did not exist in the postcode centroid file. In these cases, national postcode maps or geocoding was used (see table S3 for spatial layers used and their sources and figure 1 for data processing steps). For France, the certificate data included spatial coordinates which were used for mapping instead of the postcodes.

To increase spatial accuracy of the location of the organic producers, three steps were taken. First, each postcode point was used to create a map of Thiessen polygons, representing the postcode zone since administrative boundary maps of such small areas are not publicly available (see figure S1 for an outline of the Thiessen polygons). Second, since one postcode can have more than one certificate, we generate one point for each certificate belonging to the post code. Third, we allocate these points to the nearest agricultural land pixel (1 km^2 resolution) based on the land use management map from Sandström *et al* (2023). Certificates for livestock producers were allocated to the closest grassland pixel, crop and wine producers to the closest cropland pixel, and mixed and feed producers to the closest agricultural land use pixel. In Norway, Sweden, and Switzerland, the administrative boundaries of the original data such as municipalities and cantons, were used instead of Thiessen polygons because the data was collected at this broader scale, where administrative boundary maps of these areas are publicly available.

For 19 of 30 European countries for which data was collected, we were able to collect information on the type of farming of organic producers. To facilitate an analysis into the type of agricultural production, all certificates with this information were grouped into five main categories. Livestock, Crops, Feed, Wine, and a mixed group with producers who are certified for both livestock and any of the other types (see table S4 for more details on category aggregation for each country). The categories were chosen based on the categories reported in the repository Trade Control and Expert System New Technology, as the most detailed level available for all certificates.

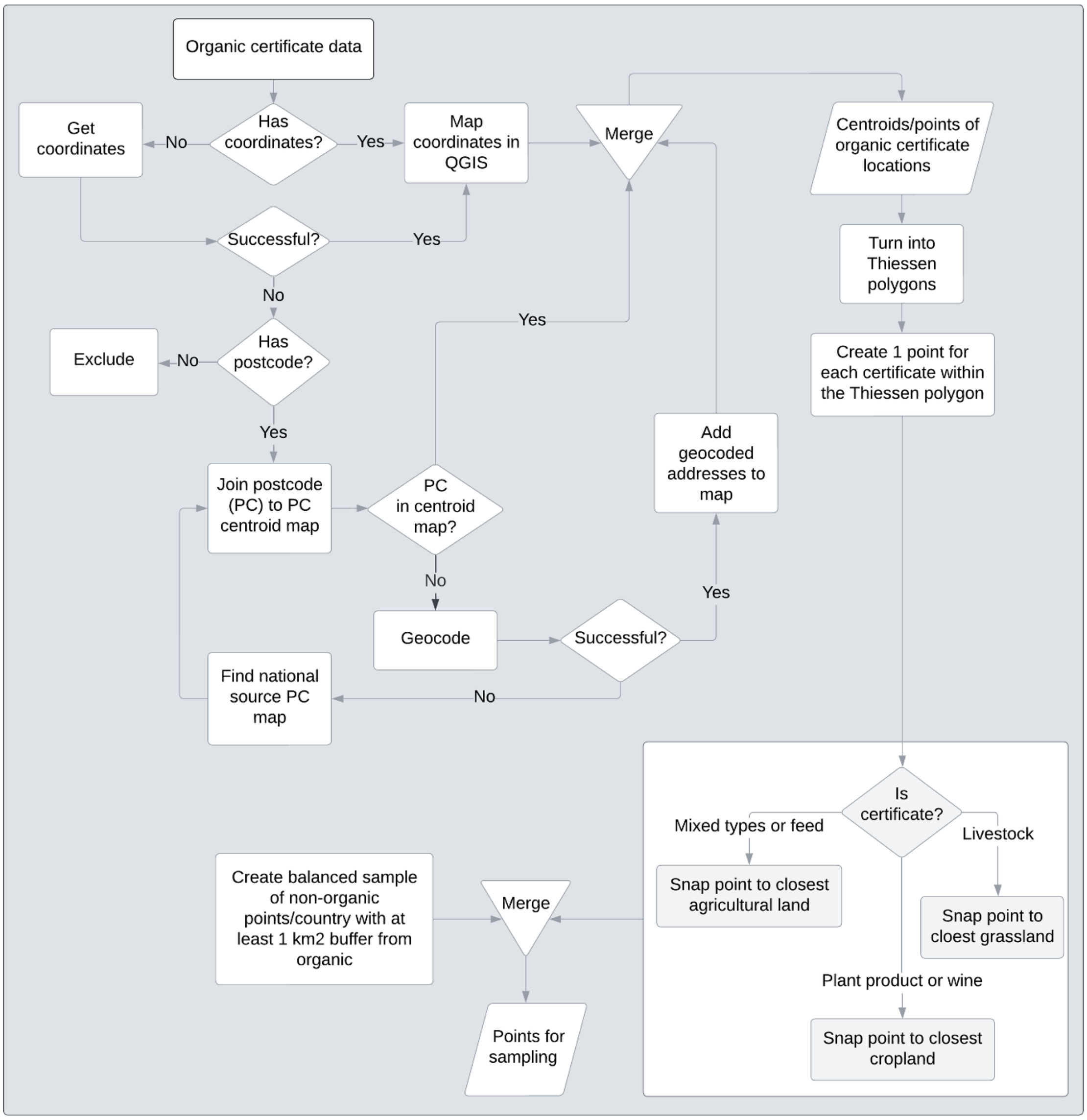

Figure 1. Flow chart of the organic certificate map making process and creation of sample points for binomial regression analysis.

2.2. Enabling and constraining factors of organic agriculture

The enabling and constraining factors of organic producers in EU27, Norway, Switzerland, and the UK were studied by explaining the variations in the share of organic producers at the NUTS 2 and the presence of organic producers at the 1 km^2 level. The NUTS 2 regions are used as they are the regions developed by the EU to collect and analyse regional European statistics, and therefore are the main resolution used for both research and policy making (Debonne *et al* 2022, Eurostat 2023, Kremmydas *et al* 2024). The regression analyses were performed at these two resolutions because the NUTS 2 level allows for a wider range of socioeconomic variable selection whereas the 1 km^2 resolution allows us to be much more precise in the influence of climatic and biophysical variables. At the NUTS 2 level, the dependent variable (DV) is reported as the share of organic certified producers out of total farm holdings (Eurostat 2024). In the high-resolution analysis, the DV is the presence of an organically certified producer in a cell (value = 1) or not (value = 0).

Data for a wide range of potential enabling and constraining factors for adopting organic agriculture at a particular location is gathered, including: climate, biophysical, and socioeconomic variables. These variables are often used to determine agricultural- and management suitability of a location (Montgomery *et al* 2016, Abd-Elmabod *et al* 2020). Table 1 reports all variables that are in the regression analysis, including their description and reference for where the data was obtained. Their choice was based on the following reasoning. Climate variables are selected because they are essential to the performance of any agricultural system (Siebrecht 2020). Climate variables such as temperature and precipitation serve as indicators for the duration of growing seasons (Karger *et al* 2017). Factors such as aridity and evapotranspiration influence plant growth (Zomer *et al* 2022). Favourable climate conditions could also help decrease the disparity in yields between organic and conventional agriculture (Seufert and Ramankutty 2017). Therefore, it is hypothesised that organic producers are located in areas with more favourable agricultural climate conditions.

A common sentiment in the literature is that farmers will choose to convert to organic agriculture if it is more economically viable for them to do so (Kremmydas *et al* 2024). Some natural terrain and soil conditions might create an environment for farmers where this is the case. For example, in the EU, mountain areas with steep slopes and high altitude are designated as less favoured areas for agriculture. Farms in these areas are often inefficient and at higher risk of abandonment due to the lower profits (Klima *et al* 2020). In these areas where it is harder to operate heavy machinery, it might benefit farmers to convert to organic agriculture especially if the farming practices are already extensive and close to organic practices. The farmer could then benefit from the price premiums on organic products, making up for the lower yields with higher prices (Kerselaers *et al* 2007).

This is also the case for farms with low soil fertility. This study uses a combination of physical soil quality variables: clay, silt, sand, coarse fragments, bulk density and available water capacity (AWC) from Ballabio *et al* (2016) and chemical variables: pH value, cation exchange capacity (CEC), nitrogen (N) in soil, soil organic carbon (SOC) from Ballabio *et al* (2019) and de Brogniez *et al* (2015) and phosphorus available for plant uptake (P) from Panagos *et al* (2022) to measure an areas overall soil health.

Besides natural conditions that might result in lower yields for farmers, there are also legislative restrictions on agriculture. Agriculture within Natura 2000 areas is often extensive, less profitable, and at risk of being abandoned (Olmeda *et al* 2018). Converting to organic agriculture in these areas might be a more financially suitable choice for longevity, considering the extra payments farmers can receive in these areas from the common agricultural policy (Pawlewicz *et al* 2022).

Another legislative act of the EU that could impact agricultural areas is the water framework directive (WFD), which has established nitrate vulnerable zones to protect groundwater from pollution (European Commission 2024). Agricultural practices are one of the main contributors to nitrate pollution (Vigliotti *et al* 2020). To limit the pollution from agriculture, less polluting practices must be put in place (EU 1991). Organic agriculture has overall a lower leaching of N per unit area (Seufert and Ramankutty 2017) and could thus be encouraged in nitrate-vulnerable zones. Therefore, it is hypothesised that organic producers are more likely to be located in these areas.

In their global study of spatial determinants of organic crop producers Malek *et al* (2019) found beneficial socioeconomic factors such as population density, access to markets, and low poverty to enable the presence of organic producers. Thus, it is hypothesised that the same is to be true for the European scale. To measure socioeconomic conditions of a location, population density from Schiavina *et al* (2023) is used as a measure of potential consumers. Accessibility (travel time to cities) and road density are used as a proxy for access to markets (Meijer *et al* 2018, Weiss *et al* 2018) and travel time to healthcare facilities is used as a measure of human wellbeing (Weiss *et al* 2020). Irrigation is used as a proxy for the level of mechanisation of the farm (Malek *et al* 2019).

The environmental attitude in a NUTS 2 region is used as a proxy for the societal attitudes toward sustainable agriculture, which is shown to have a positive impact on conversion to organic agriculture (Karipidis and Karypidou 2021). Therefore, it is hypothesised that organic producers are more likely to be located in regions where the environmental attitude is more positive. It is also hypothesised that farm size might impact the conversion to organic; however, the literature is inconclusive on whether small or large farms are more likely to adopt organic agriculture (Sapbamrer and Thammachai 2021). Additionally, in regions where the share of gross value added (GVA) from agriculture out of total gross domestic product (GDP) is higher, more organic producers are expected. It is also hypothesised that organic producers will be found in areas with a higher share of highly educated people. Highly educated people often have a higher income and are more likely to purchase organic products (Hansmann *et al* 2020), creating a higher demand for the products.

2.3. Methods

Two types of regression analyses were performed to assess the impacts of enabling and constraining factors of organic producers in EU27, Norway, Switzerland, and the UK, one at the NUTS 2 level and one at the high-resolution level.

2.3.1. NUTS 2 level analysis

For the NUTS 2 level analysis, a linear regression was used. The DV was logit transformed to comply with the assumption of normal distribution required in a linear regression. The logit transform is recommended for proportional data that is non-binomial, which is the case here (Warton and Hui 2011). The normal

Table 1. Description of the independent variables used in the regressions. (For a complete list of the variables tested for in the regression analysis, see table S5).

Category	Variable name	Short name	Description	Source
Climate	M.A. Air temp	b1	Mean annual air temperature (°C)	Karger *et al* (2017)
	M.D. Air temp	b2	Mean diurnal air temperature range (°C)	Karger *et al* (2017)
	A.R. Air temp	b7	Annual range of air temperature (°C)	Karger *et al* (2017)
	Annual precip	b12	Annual precipitation amount (kg m^{-2})	Karger *et al* (2017)
	Precip season	b15	Precipitation seasonality (kg m^{-2})	Karger *et al* (2017)
	Aridity	ari	Aridity index (0 = high aridity & 10 = high humidity)	Zomer *et al* (2022)
Biophysical (Soil)	Available water capacity	awc	Available Water Capacity (difference of volume water content at 33 kPa and 1500 kPa (volume fraction))	Ballabio *et al* (2016), Poggio *et al* (2021)
	Bulk density	bul	Bulk density (t m^{-3} (g cm^{-3}))	Ballabio *et al* (2016), Poggio *et al* (2021)
	Cation exchange capacity	cec	Topsoil (0–20 cm) cation exchange capacity (cmol(c) kg^{-1})	Ballabio *et al* (2019), Poggio *et al* (2021)
	Coarse fragments	coa	Topsoil (0–20 cm) coarse fragments (%)	Ballabio *et al* (2016), Poggio *et al* (2021)
	pH value	ph	Topsoil (0–20 cm) pH of water in soil (pH)	Ballabio *et al* (2019), Poggio *et al* (2021)
	Sand	sand	Topsoil (0–20 cm) sand content (%)	Ballabio *et al* (2016), Poggio *et al* (2021)
	Soil organic carbon	soc	Topsoil (0–20 cm) soil organic carbon concentration (g kg^{-1})	de Brogniez *et al* (2015)
	Nitrogen	N	Topsoil (0–20 cm) nitrogen content (g–kg^{-1})	Ballabio *et al* (2019), Poggio *et al* (2021)
	Phosphorus availability	P	Available phosphorus in agricultural soils (mg–kg^{-1})	Panagos *et al* (2022), McDowell *et al* (2023)
Biophysical (Terrain)	Elevation	dem	Elevation (m)	European Commission (2012a)
	Slope	slope	Slope (degrees)	European Commission (2012b)
	Flat land	flat	Area in % with Slope < 5 degrees	European Commission (2012b)
Socioeconomic	Accessibility	acc	Travel time to cities (h)	Weiss *et al* (2018)
	Road density	roa	Densities summed across the five road types (m km^{-2})	Meijer *et al* (2018)
	Travel time to healthcare	thc	Motorised travel time to healthcare (min)	Weiss *et al* (2020)
	Protected areas	pa	Natura 2000 and IUCN areas	
	Nitrate vulnerable areas	nv	Nitrate vulnerable zones—nutrient sensitive areas (WFD)	European Environment Agency (2021)
	Population density	pop	Population density (people/pixel)	Schiavina *et al* (2023)
	Irrigation	irr	Total area equipped for irrigation (ha)	Zajac *et al* (2022), FAO (n.d.)
Only in NUTS 2	GVA A/GDP	share_gva	Share of GVA (Agriculture, Forestry and Fishing) out of total GDP 2020	Ardeco, Federal Statistical Office (n.d.), Office for national statistics (n.d.)
	Education	high_edu	Share of people with tertiary education 2022	Eurostat (2024a)
	Population density	Pop_dens	People km^{-2}	Eurostat (2024b)
	Steep slope	steepSlope	Area in % with Slope > 15°	European Commission (2012b)

distribution of residuals and homoscedasticity were examined using graphical analysis (see figures S2 and S3). In addition, a Kolmogorov–Smirnov test was conducted on the normal distribution of residuals where no strong deviation was found ($D = 0.079865$ with a p-value of 0.05273). Spatial autocorrelation was tested for with the Moran's I statistic and no significant effect was found (0.02265, p-value: 0.266).

The spatial variables were aggregated from the high-resolution level (1 km^2) to the NUTS 2 level. The number of organic certificates was aggregated per NUTS 2 region and divided by the total number of farm holdings from Eurostat. The definition of a farm holding can differ between member states and therefore affect the numbers included in the statistics (Eurostat n.d.a). Farms below one hectare may not be counted as a farm holding if all farms below this threshold together account for less than 2% of the total UAA in the country (Eurostat n.d.b). The organic certificates have no size limit, and this could result in mismatches between the data.

The independent variables were aggregated to the NUTS 2 level by applying weights based on the occurrence of agriculture activities per land system in the land system map from Sandström *et al* (2023). This was done to get the average values of the variables for the agricultural land in each NUTS 2 region. Because mosaic and permanent cropland pixels do not predominantly represent agricultural land (respectively on average 47% and 63% of agriculture in the land system), they were weighted differently than grassland and arable cropland (Sandström *et al* 2023). Therefore, agricultural mosaics and permanent cropland are given a weight of 0.5, arable cropland and grassland a weight of one and all other land systems are weighted zero. The sum of the dependent and independent variables at the NUTS 2 level was then divided by the sum of weights in the NUTS 2 regions, creating the weighted average of each variable. Protected area and Nitrate vulnerable areas, which are binary variables at the 1 km^2 resolution, were converted to their percentage of agricultural area in the total size of the NUTS 2 region (see supplementary material for details on processing of independent variables).

Country dummy variables were also added to account for national specific contexts that could affect the share of organic agriculture. Belgium was chosen as the reference country in the NUTS 2 analysis due to having a good representation of both NUTS 2 areas with low and high values of the DV.

The linear regression was performed in R (R Core Team 2024) using lm from the stats package applying a stepwise forward and backward elimination. To reduce multicollinearity, variables with a Pearson correlation of >0.8 or <-0.8 were removed from the analysis (see figure S4 for the correlation matrix). The fit of the model was assessed using the F-value and its associated p-value to test for overall significance, as well as the adjusted R^2 to measure the proportion of variance explained by the model. Environmental attitude was included in the analysis but showed to be nonsignificant. Therefore, it was removed from the analysis to allow more NUTS 2 regions to be included in the regression as this variable covered less regions than the others.

2.3.2. High-resolution analysis

In the high-resolution analysis, a binomial logistic regression was used to find the spatial determinants of organic agriculture. For this analysis all spatial data were projected to CRS EPSG:3035 ETRS89-extended/ LAEA Europe and aligned to 1 km^2 pixels. To reduce multicollinearity, variables with a Pearson correlation of >0.8 or <-0.8 were removed from the analysis (see figures S5 and S6 for correlation plots). Variables with a variance inflation factor of >10 were also removed. Continuous variables were standardised with z-score in R for easier comparison of the regression coefficients. The regressions used a balanced sample of presence and absence points of organic producers (i.e. whether or not an organic producer was located in the 1 km^2 cell). The absence points were created by randomly assigning an equal amount of points per country for each type of agricultural land type, i.e. grass, crop, or mixed, using the land system map of Europe (Sandström *et al* 2023). The absence points were taken at least 1 km away from any point in which organic producers were present.

The regressions were run in R (R Core Team 2024) using GLM from the glmtoolbox (Vanegas *et al* 2024) using both stepwise forward and backward elimination and stepAIC (Venables and Ripley 2002), finding a balance between the best Akaike Information Criterion value and reducing the amount of nonsignificant coefficients. The regressions were run on 80% of the data, leaving 20% for testing the predictive ability of the model. The performance and fit of the regressions were evaluated using the area under the receiver operating characteristic curve (Sing *et al* 2005) on the test data for discriminative ability (see figures S5 and S7 for ROC curves) and McFadden adjusted R^2 for goodness of fit.

A sensitivity analysis was performed to ensure that the logistic regression results were robust to the point allocation method employed to generate presence and absence points. The analysis showed that, although minor differences in coefficient values were observed, the overall directionality and effect sizes were consistent, indicating that the results were not significantly influenced by the allocation method.

The high-resolution regressions were run for three different constellations: pooled for all countries and for all producer types, per producer type, and per country. To understand whether the spatial determinants of organic producers differ between producer types, separate regressions were run for livestock producers, crop producers, and mixed producers. For feed and wine producers, there were less than 20 certified producers engaging fully in these practices, except for France where more than 5000 organic wine producers were recorded. Since this is not enough to get results for the whole study area, separate regressions were run only for livestock producers, crop producers, and mixed producers. In addition to the EU-wide analysis, regressions were also run per country to find differences and similarities between countries. Since not all countries had producer type data, these regressions were run with no distinction between producer types.

Country dummy variables were included in the analysis to indicate other effects not captured by the main variables used in this paper. Such variables might be different national policies or other institutional effects on the presence or absence of organic agriculture. Romania was chosen as the reference country, in the high-resolution analysis, as it was a country that is included across all types of producers and could be used in the regression pooled for all countries and all producers types as well as in the three different producer type regressions. The number of organic certificates in Romania was also close to the average number of certificates per country.

3. Results

First, maps of the density and share of organic certificates are presented together with a comparison of the numbers of organic producers captured in this study compared to FiBL statistics. Second, the linear regression at NUTS 2 level shows what increases the likelihood of organic farming on a regional level. Third, the binomial logistic regressions show spatial determinants of the presence of organic farming in a location.

3.1. Maps, collection, and density

In total, 352 122 organic producer certificates were mapped for the EU27, Norway, Switzerland, and the UK. Figure 2(a) shows the number of organic certificates per agricultural land in each polygon (Sandström *et al* 2025). Organic certificates occur more often in areas with mountainous and sloping terrain such as large parts of Austria and Greece, parts of Italy, southern Spain, the region of Trás-os-Montes in Portugal, and the south of France. Density hotspots can also be found near cities such as Madrid, Paris, Prague, and Riga. In Finland, the high-density areas of organic certificates mostly occur in the Finnish Lakelands.

Figure 2(b) shows the share of organic certificates per total number of farm holdings by NUTS 2 region (see figures S8 and S9 for a detailed view of peripheral islands of Europe). Similarly to figure 2(a), the South of France and parts of Austria and Greece show higher percentages of organic producers. The NUTS 2 regions with the top three highest percentages of organic producers are Prague (282%), Berlin (62%), and Brussels (53%). These three NUTS 2 regions are some of the most population dense regions in Europe (Eurostat 2024b).

The number of certificates collected in this study generally corresponds to the number of organic producers reported in FiBL statistics (FiBL 2024). Only for two countries, Germany and Malta, does this study have less than 60% of the number of organic producers reported by FiBL. Twelve of the twenty-nine countries included in this comparison have between 60%–90% of the number of organic producers represented, and fifteen countries have more than 90% of the number of organic producers reported by FiBL. The countries highlighted in bold in figure 3 have more organic producers in this study than those reported in FiBL (for more details, see table S6).

3.2. NUTS 2 analysis

On a NUTS 2 regional scale, the linear regression analysis shows that socioeconomic variables such as population density, education level, and protected area are the most important variables affecting the share of organic producers in a region (see table 2). They all have positive coefficients with a significance level of $p < 0.05$. Taking education as an example, this means that as the share of educated people increase by one unit in a region, the odds of the share of organic producers increase by a factor of 1.025 or, in other words, by 2.5%. At the NUTS 2 level, most of the climate and biophysical variables show no significant results. One climate (M.D. air temp) and one soil variable CEC have a positive significant impact on the share of organic producers.

Country level dummy variables show positive coefficients for Austria, Czech Republic, Denmark, Finland, France, Sweden, and the UK. On the contrary, Bulgaria, Cyprus, Greece, Spain, Croatia, Hungary, Ireland, Italy, Malta, Poland, Portugal, Romania, and Slovakia have negative coefficients. This suggests that the latter countries decrease the odds of the share of organic producers, while the former increase the odds of the share of organic producers compared to Belgium as the reference country.

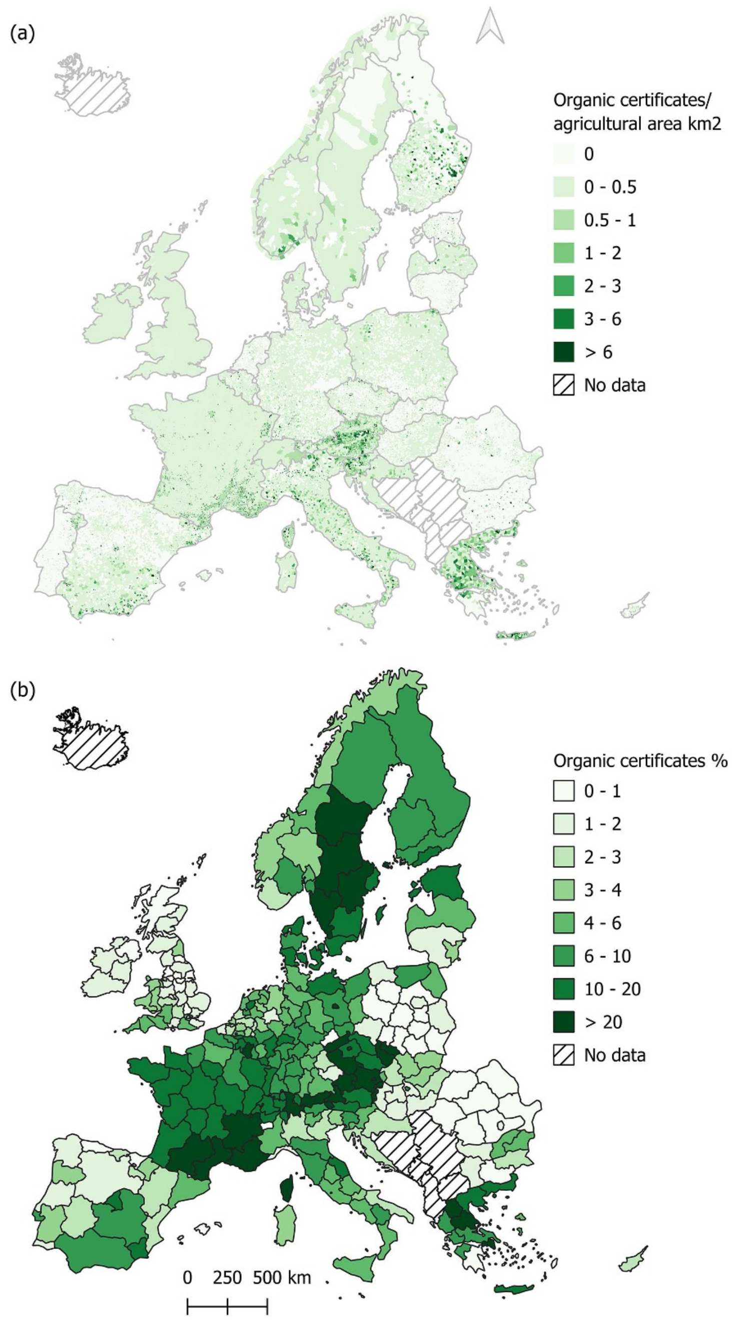

Figure 2. Organic certificate maps. Figure (a) organic certificates per agricultural land km^2. Figure (b) Percentage of organic producers out of total farm holdings per NUTS 2 area. © EuroGeographics for the administrative boundaries. (a), (b) Adapted from Eurostat. CC BY 4.0. © EuroGeographics.

3.3. High-resolution analysis

Although NUTS 2 analyses are frequently employed for comprehensive EU-level assessments, the above section showed that the regional aggregation is too coarse to analyse the impact of climate and biophysical variables. Our unique certificate data provide complete coverage at a resolution of 1 km^2, allowing for a more granular spatial analysis. Furthermore, at this level, it is possible to separate organic producers into livestock, crops, and mixed producers. Table 3 shows the likelihood for organic production certificates to occur for all producer types and by main producer type based on the high-resolution data. Four main factors can be observed in the analysis (1) producers located close to markets; (2) producers located in less favourable areas for conventional agriculture are more likely to be organic; (3) climate drivers of organic agriculture are only visible on high-resolution scale; and (4) National context play a part in the likelihood of having organic agriculture.

	BioC	TRACES	Official national
>= 90%	**Luxemburg**	Austria, **Estonia**, **Greece**, **Hungary**, Slovakia	Belgium, **Czech Republic**, Denmark, **France**, **Netherlands**, **Poland**, **Slovenia**, Switzerland, **UK**
>= 60%	Ireland	Bulgaria, Croatia, Cyprus, Finland, Italy, Latvia, Lithuania, Portugal, Spain, Romania	Norway
< 60%	Germany		Malta

Figure 3. Data comparison matrix between the organic producer certificate numbers of this study and FiBL statistics. The columns show the type of source that was used to collect the organic certificates for each country. The rows indicate in percentages how close the number of organic producers in this study is compared to the FiBL statistics. The countries in bold have more organic producers in this study than reported in FiBL.

3.3.1. Organic producers are located close to markets

Regarding the proximity to markets, all types of organic producers have a higher chance of occurring in areas with high population density and less travel time to cities and healthcare facilities. Showing a strong connection to markets, potential consumers, and human well-being. Road density also has a positive association with organic agriculture, strengthening the connection to markets, although the effect does not emerge as strongly as the previously mentioned variables.

Population density is the most important factor for all producer types. An increase in population density leads to an odd increase of the presence of organic agriculture by 271%. This effect is even stronger when looking at organic crop production and slightly lower when looking at organic mixed or livestock production. Population density is not only an enabling factor of organic agriculture across all producer types but also in each country included in this study except for Sweden where it is not significant (see table S11 for coefficients and p-value of the country regressions).

For accessibility, the odds of all types of organic agriculture increase by 27% and for road density by 19%. When looking at product specific categories, accessibility and road density have stronger enabling effects for organic livestock producers than crops or mixed organic producers. When looking at specific countries, shorter travel time to cities is an enabling factor for organic agriculture in Greece, Cyprus, Malta, Austria, Denmark, Germany, and Italy. However, for Poland, Slovenia, Spain, France, Croatia, Czech Republic, Lithuania, Portugal, Romania, and the UK, longer travel times to cities increase the likelihood of presence of organic producers in a location.

Shorter travel times to healthcare increases the odds of organic agricultural presence by 22%. This effect is stronger if we only look at organic crop production, and weaker for both organic livestock and mixed production. Organic producers are more likely to be located in areas with shorter travel times to healthcare facilities in all countries in the study, except for Latvia, where the opposite is true and Finland, Slovenia, Greece, Cyprus, Malta, France, Estonia, Ireland, and Lithuania where it is not significant.

3.3.2. Organic producers are located in less favourable areas for agriculture

Organic producers are more likely to be located in areas with less favourable biophysical conditions for agriculture. Organic producers are more likely to be located in areas with low pH value, low P available for plant uptake, low N content, low percentage of flat land, steeper slopes, high sand content, high bulk density and with more coarse fragments. While many of the soil quality variables have low effect sizes, some stand out. An increase in P available for plant uptake decreases the odds of organic agriculture presence with 33%, an increase in sand content increases the odds of presence of organic agriculture with 23%, and an increase

Table 2. Linear regression results for 285 NUTS 2 regions. Signif. Codes: *** < 0.001, ** 0.001–0.01, * 0.01–0.05, 0.05–0.1. Odds ratios are calculated by exponentiating the estimate.

Variables	Estimate	Odds ratio	*p*
Education	0.024	1.025	**
Population density	0.000	1.000	***
GVA A/GDP	4.509	90.787	
M.D. air temp	0.196	1.217	***
Bulk density	0.958	2.606	
Cation exchange capacity	0.030	1.030	*
Coarse fragments	0.049	1.050	.
Steep slope	−0.006	0.994	
Travel time to HC	−0.005	0.995	
Aridity	−0.304	0.738	
Protected area %	0.066	1.068	*
Nitrate vulnerable %	−0.007	0.993	.
Austria	0.995	2.705	**
Bulgaria	−2.200	0.111	***
Cyprus	−2.187	0.112	*
Czech Republic	2.109	8.239	***
Denmark	1.457	4.294	**
Estonia	1.051	2.860	
Greece	−0.950	0.387	*
Spain	−2.068	0.126	***
Finland	0.885	2.424	.
France	0.655	1.925	**
Croatia	−1.911	0.148	**
Hungary	−1.444	0.236	***
Ireland	−1.528	0.217	*
Italy	−0.915	0.401	**
Lithuania	−1.031	0.357	
Malta	−3.901	0.020	***
Poland	−1.299	0.273	***
Portugal	−1.694	0.184	***
Romania	−3.404	0.033	***
Sweden	1.508	4.519	***
Slovenia	−0.639	0.528	
Slovakia	−0.929	0.395	.
UK	24.530	45 017 178 576	**

Residual standard error 0.8822 on 249° of freedom
Multiple R-squared: 0.6771, Adjusted R-squared: 0.6317
F-statistic: 14.92 on 35 and 249 DF, *p*-value: < 0.001.

in slope degrees increases the odds by 21%. The effect of steep slopes is even stronger for organic livestock producers with an increase in the odds by 43%.

Most soil quality variables indicate organic agriculture to be more likely located in areas with poorer soil quality. However, higher levels of SOC are positively related to the presence of organic agriculture in a pixel. This effect is strongest for mixed producers, followed by crop producers and livestock producers. Looking at country specific regressions, SOC has a positive or nonsignificant effect on the presence of organic producers in all countries except for in Ireland, Sweden, and the UK where it has a negative effect. Organic livestock producers deviate from the pattern when it comes to N content in soil, where the other organic producer's odds decreases of being in a pixel with higher N content, for organic livestock producers the opposite is true.

Areas with legislative constraints on agriculture such as natural protected areas and nitrate vulnerable areas increase the odds of organic agriculture presence with 12% and 4%, respectively. When looking at only organic crop producers, the odds increase to 28% and 17%, respectively. Some exceptions arise when looking at country specific regressions. Nature protected areas decrease the odds of organic agriculture presence in Finland, Austria, Italy and Romania. Nitrate vulnerable areas decrease the presence of organic agriculture in France, Croatia, Czech Republic, Estonia, Latvia and Sweden.

3.3.3. Climatic determinants of organic agriculture are visible in high-resolution level

The high-resolution analysis found more significant climate variables compared to the NUTS 2 analysis. Livestock and mixed farms have a positive association with a high mean annual air temperature. However, the rest of the climate variables show more differences between producer types. Organic crop producers are

Table 3. Regression results—coefficients with significance levels of p: *** < 0.001, ** 0.001–0.01, * 0.01–0.05, 0.05–0.1. AUC and McFadden adjusted R^2 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.

Product	All		Livestock		Crops		Mixed	
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	
	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio
Accessibility	−0.313***	0.73	−0.763***	0.47	−0.15***	0.86	−0.092***	0.91
Road density	0.172***	1.19	0.462***	1.59	0.195***	1.22	0.11***	1.12
Travel to HC	−0.251***	0.78	−0.099***	0.91	−0.427***	0.65	−0.077***	0.93
Population density	1.311***	3.71	0.927***	2.53	1.875***	6.52	1.286***	3.62
Irrigation	0.08***	1.08	0.229***	1.26				
AWC	0.088***	1.09	−0.031.	0.97	0.015*	1.02	0.112***	1.12
Bulk density	0.048***	1.05			0.014*	1.01	−0.032***	0.97
CEC	0.035***	1.04					0.148***	1.16
Coarse fragments	0.012*	1.01	−0.298***	0.74	0.088***	1.09	0.152***	1.16
Sand	0.211***	1.23			0.218***	1.24	0.139***	1.15
pH value	−0.088***	0.92	−0.163***	0.85	−0.23***	0.79	−0.623***	0.54
Phosphorus	−0.398***	0.67	−0.123***	0.88	−0.442***	0.64	−0.034**	0.97
Nitrogen	−0.089***	0.91	0.191***	1.21	−0.107***	0.90		
SOC	0.192***	1.21	0.149***	1.16	0.275***	1.32	0.38***	1.46
Flat land	−0.14***	0.87	−0.115***	0.89	−0.211***	0.81	−0.19***	0.83
Elevation	−0.261***	0.77			−0.178***	0.84		
Slope	0.194***	1.21	0.36***	1.43	0.221***	1.25	0.186***	1.20
Protected area	0.117***	1.12	0.125***	1.13	0.246***	1.28	0.077***	1.08
Nitrate vulnerable	0.041***	1.04	0.144***	1.15	0.156***	1.17	0.132***	1.14
Aridity	−0.071***	0.93			−0.225***	0.80	0.097***	1.10
M.A. Air temp			0.69***	1.99			0.857***	2.36
M.D. Air temp					−0.046***	0.96	0.14***	1.15
A.R. Air temp	0.17***	1.19	0.288***	1.33	0.218***	1.24		
Annual precip			0.097***	1.10				
Precip season	−0.028***	0.97	0.276***	1.32	−0.177***	0.84		
AUC	0.69		0.79		0.74		0.72	
McFadden adj R^2	0.09		0.2		0.14		0.12	

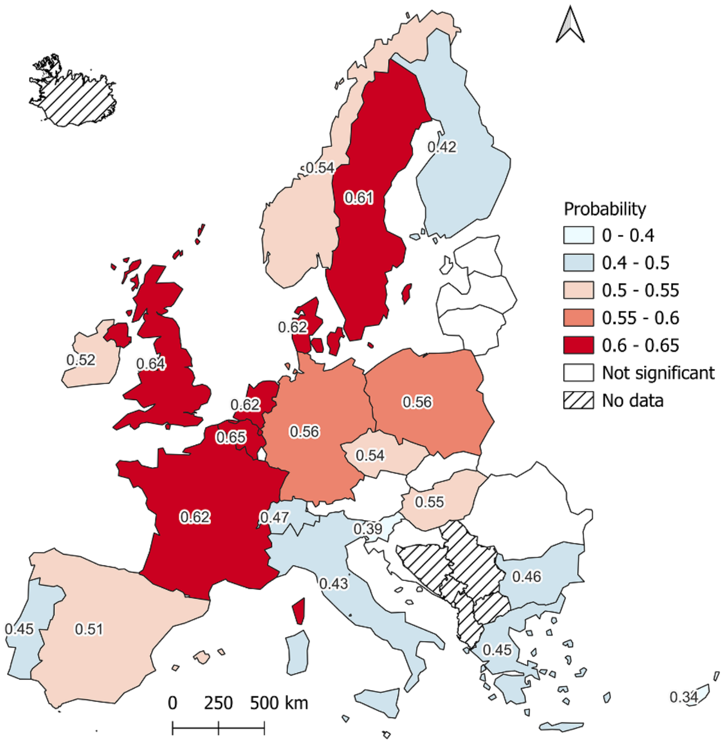

Figure 4. Probabilities, converted from coefficients using the inverse logit function, of having organic producers for each country based on the country dummy variables in the regression for all producers, with Romania as the reference country. Adapted from Eurostat. CC BY 4.0. © EuroGeographics

more likely to be located in arid conditions, while mixed organic producers are less likely to be located in arid conditions. Organic livestock producers are less likely to be located in areas with a high mean diurnal air temperature range, whereas the opposite is true for organic mixed producers. Organic livestock producers are, on the other hand, more likely located in areas with higher precipitation seasonality, while the opposite is true for organic crop producers. High annual precipitation is also positively associated with organic livestock producers, but is not significant for the other types of producers.

In Bulgaria, Estonia, Sweden, Cyprus, Malta, Germany, and the Netherlands organic producers are more likely to occur in areas with more stable climate conditions for plant growth with lower annual range in air temperature, lower precipitation seasonality, and higher annual precipitation, humidity, and mean annual air temperature. In Ireland this is also the case, except organic producers are more likely located in areas with lower mean annual air temperature. For most other countries in Europe, the climate variables indicate that organic producers are more likely to be located in more stable conditions favourable for plant growth, with one or two exceptions.

In Lithuania, Czech Republic, Poland, Finland, Belgium, Luxembourg, Latvia, Hungary, Norway, the UK, Portugal, Slovakia, and Greece organic producers are more likely located in areas with higher annual air temperature range, suggesting in these countries organic producers are located in areas with both cold winters and hot summers such as mountainous regions.

In Spain, Latvia, France, Austria, Denmark, Greece, and the UK, organic producers are more likely located in areas with higher precipitation seasonality. In France, Austria, Denmark, and Greece, organic producers are also more likely located in areas with lower annual precipitation. This suggests that organic producers in these countries might be in more water precarious locations.

The EU-wide analysis covering all producer types shows that organic producers are located in more humid areas except for mixed producers. This is the case for Germany, Slovenia, Spain, France, Lithuania, Czech Republic, Poland, Finland, and Latvia as well, but in Italy, Croatia, Hungary and the UK organic producers are more likely to be located in arid conditions.

3.3.4. *Organic producers have different probability of occurring in different European countries*

According to the country dummy variables, the countries with the highest probability of having unexplained factors contributing to the occurrence of organic producers are in western Europe, most notably Belgium, the UK, France, and the Netherlands (see figure 4). While the lowest probability can be found in countries such as Finland, Cyprus, and Slovenia. Many central and eastern European countries are not significant or have a medium probability of having unexplained factors contributing to the occurrence of organic producers.

The model for organic livestock producers shows positive coefficients for the country dummy variables for Sweden, Estonia, and Finland, implying that in these countries the likelihood of finding organic livestock producers is higher under otherwise similar conditions. In contrast, Spain, Austria, Greece, Cyprus, France, and Italy have negative coefficients. For organic crop producers Croatia, Sweden, Hungary, France, and Czechia have positive coefficients and Italy, Lithuania, Greece, Cyprus, Bulgaria, Portugal and Finland have negative coefficients. For mixed organic producers: Lithuania, Latvia, Hungary, and Estonia have positive coefficients and France, Italy, Finland, Spain, Bulgaria, Greece, Austria, Cyprus, and Portugal have negative coefficients (see tables S7–S10 for tables with the coefficients for each country).

4. Discussion

This study introduces a new high-resolution dataset on organic producers that offers considerable improvements in spatial resolution and information on agricultural production types, providing valuable insights into organic agriculture. Further, it analyses where organic agriculture is located and what the main climatic, biophysical, and socioeconomic drivers for their occurrence are. Operating at the 1 km^2 resolution, the map constitutes a significant improvement from the previous EU-wide maps of organic agriculture only available on NUTS 2 level (Debonne *et al* 2022). Furthermore, using this novel high resolution data, this study allowed the analysis of different types of organic farms and shed more light on the impact of biophysical and climatic drivers.

The aggregation of organic certificates to the NUTS 2 level and subsequent comparison with farm holding data from Eurostat showed especially high percentages of organic certificates near metropolitan areas. This finding is supported by Debonne *et al* (2022) for organically managed land at the NUTS 2 level. However, the range of percentages is higher for our data which measures the share of organic farms rather than the share of organic land. Farm size is typically smaller close to metropolitan areas, implying that there are many organic producers in metropolitan areas, each farming a small area. This could also explain the high percentage of organic certificates in Prague, where there are more organic producer certificates than there are farm holdings reported in Eurostat. Organic producers can also fall under the size threshold used by some countries to be counted as a farm holding in Eurostat statistics. Another possibility is that some farms register the organic certificate to a headquarter instead of the place of operation, and hence, metropolitan areas might be overrepresented in the data.

Regarding socioeconomic indicators, our study showed that especially education and the proximity to markets were strong enabling factors for the occurrence of organic farming. In the NUTS 2 analysis, higher education in a region was positively associated with the share of organic producers. This is in line with our hypothesis that highly educated people are consuming more organic produce (Hansmann *et al* 2020) and organic producers are therefore located in areas with a higher consumer demand. The reason could also be that highly educated farmers are more likely to convert to organic farming and participate in rural development programmes aiming to support organic agriculture (Boncinelli *et al* 2016).

Organic producers are more likely to be located in close proximity to population dense areas and markets. This could be because markets provide access to resources such as other food value chain actors, retailers, farmers markets, and information about organic certification. This theory is in line with other studies which show that organic density increases in regions with good access to food value chain actors and retailers (Schmidtner *et al* 2012, Allaire *et al* 2015). It also aligns with the literature indicating that complying with organic standards requires information that is harder to reach in remote areas (Carter and Hollinsworth 2022). This might imply that organic producers are more dependent on local or direct food supply chains and information from extension agents. Hence, better access to rural areas could encourage the adoption of organic agriculture.

Looking at biophysical drivers, organic producers have been found to be located on more marginal land. This can be explained by the lower profitability of farming on these lands, as they have natural constraints that can make agricultural production less interesting for conventional monoculture farming (Csikós and Tóth 2023). This makes organic price premiums extra relevant in these areas for farmers who want to continue farming and avoid land abandonment. This aligns with previous research stating that the most productive areas of land are being used for intensive agriculture while others are being abandoned (Felix *et al* 2022). This result is also in line with local studies showing that both low soil quality (Schmidtner *et al* 2012) and less favoured areas (Allaire *et al* 2015) are associated with the presence of organic farms. This is also the case in a local study carried out in the UK, where organic price premiums made it economically viable to farm on marginal lands in contrast to conventional farming (Ilbery and Maye 2011). Therefore, increasing the viability of organic agriculture might increase the share of organic producers in Europe.

Organic producers were also more likely to be located in areas designated as natural protected areas according to Natura 2000 and IUCN or nitrate vulnerable by the WFD. This could be due to the mandatory conservation activities farmers in these areas need to take, for example, protecting landscape features according to the good agricultural and environmental conditions standards (European Network for rural development n.d.). Landscape features can in turn improve natural pest control and reduce yield gaps between conventional and organic farming (Klinnert *et al* 2024) creating a synergy between conservation efforts and organic agricultural practices. In France, projects have been piloted with the aim of improving water quality by converting farms to organic specifically located close to water basins at risk of pollution from agricultural practices (Vincent and Fleury 2015).

In addition to spatial patterns, the study also saw an increase in model fit when separating different types of organic producers. This indicates that different types of producers have different enabling and constraining factors for the adoption of organic agriculture. This is evidenced, for example, by the differences between crop and livestock producers in this analysis. For example, higher nitrogen content in soil, less coarse fragments and AWC increases the odds of an organic livestock producer occurring but decreases the odds of an organic crop producer. This shows that policies and interventions aimed at increasing the adoption of organic agriculture should be developed with different types of agricultural producers in mind. This aligns with previous findings that different farm archetypes exhibit varying patterns of adoption of agro-ecological practices (Václavík *et al* 2024).

The analysis of this paper also showed a strong country effect, suggesting that there are still notable differences in unexplained determinants such as national culture, policies, and institutional differences for organic adoption between countries in Europe, which are the result of different political visions and measures to stimulate organic agriculture. Manta *et al* (2023) found that national culture impacts the performance of organic agriculture. Countries that are more individualistic, indulgent and long-term oriented experience higher performance of organic agriculture in terms of growth in land area, numbers of producers, and sales of organic products.

While this study provides valuable insight, there might be other factors not taken into account in this study that further explain the location of organic producers. For example, subsidies earmarked for organic agriculture (Theocharopoulos *et al* 2012, Kujala *et al* 2022), governmental support through policy (Allaire *et al* 2015), motivation programmes from governments or NGOs alike (Sapbamrer and Thammachai 2021) or land prices. Furthermore, the data are based on organic certificate counts, and while this approach captures smaller producers (<1 ha) not always included in the farm holding data from Eurostat, it does not account for the size of farms. This limitation is noteworthy because these smaller organic producers are less likely to be captured by area-based policies and may not be effectively targeted by existing interventions seeking to encourage organic agriculture. As seen in comparison with FiBL data, the count of certificates may not be complete for all countries, although this could also be reflection of the different sources and years reported for the certificates, which differ somewhat between FiBL and the data collection of this study. Future research should aim to explore data collection methods capable of bridging the gap between the number of certificate holders and the area of organic agricultural land to provide an even more comprehensive understanding of the spread of organic agriculture in Europe.

5. Conclusion

This study assessed the current state of organic agriculture in Europe and identified which biophysical, climate and socio-economic factors help create an enabling or constraining environment for adoption. First, organic agricultural certificates were collected to map the share and density of certified organic producers in EU27, Norway, Switzerland, and the UK at two spatial scales. Second, two types of regression analyses were performed to analyse the spatial determinants for organic farming; a linear regression at the NUTS 2 level and binomial logistic regression for the high-resolution (1 km^2) level. The high-resolution regressions were run in three different constellations: one including all countries and all producer types, separated by producer type and on a country-level basis.

Results of the study showed the spatial distribution of organic agriculture across Europe. Hotspots of organic agriculture are found in mountainous regions around Europe and next to cities. The regression results showed that socioeconomic, biophysical and climate variables are important determinants of the location of organic agriculture. They also showed that while general patterns can be drawn for the whole study area, differences in spatial determinants exist between countries and producer types. Looking at socioeconomic factors, organic producers are more likely located in areas close to markets and with high population density as they provide access to consumers as well as resources such as value chain actors and information on organic certification. Biophysically, organic producers are more likely located in areas with less favourable conditions for agricultural practices such as poor soil quality and rough terrain. The most productive land is often used for intensive farming, rougher terrain can also cause constrains on certain intensive practices such as the use of heavy machinery. This leads to the less suitable land to be abandoned as it is no longer profitable for farmers. However, organic price premiums could potentially compensate for this deficit and make farming on these lands viable. This study also found that conducting a high-resolution analysis on 1 km^2 enabled the identification of different climate drivers of organic agriculture not captured on a coarser scale. The regressions also showed different countries have different probabilities of organic agriculture which could be due to their cultural, political and institutional context.

These findings contribute to a better understanding of the spatial distribution of organic agriculture at a high resolution covering 30 countries on the European continent. They also enhance the understanding of the spatial conditions that enable and constrain organic agricultural production at different scales, per producer type and country. These insights are key to help policy makers better target efforts to increase organic agriculture in light with the objectives set by the EU Green Deal, and to assess the impacts of organic agriculture expansion on food production and the environment. For example, increasing accessibility of remote areas to markets and increasing the viability of organic agriculture compared to conventional agriculture will help farmers to convert to organic methods.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.34894/W6OSWL.

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