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Agricultural Land Markets – Efficiency and Regulation

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Saskia Wolff *, Silke Hüttel **, Claas Nendel ***, Tobia Lakes ****

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Abstract

The increasing demand for agricultural commodities for food and energy purposes has led to intensified agricultural production. This trend may manifest in agricultural compositions and landscape configurations that can have mixed and adverse impacts on the provision of ecosystem services. We rely on the EU's plot-based data from the Integrated Administration and Control System (IACS) to identify different types of agricultural landscapes and their spatial distribution in Brandenburg, Germany, a study region strongly characterised by intensification trends. Based on a set of landscape metrics, we are able to characterise agricultural land use and identify six types of agricultural landscapes. We rely on a two-step cluster analysis for a hexagonal grid and find that agricultural land is dominated by cropland with different degrees of fragmentation. By providing a framework using landscape metrics derived from IACS data, our approach involves clustering to identify typologies that are transferable to other regions within the EU based on existing data. This framework can offer more tailored environmental and agricultural planning based on sophisticated measures that take into account local and regional characteristics.

Keywords: agricultural land use; landscape metrics; cluster analysis; sustainable land use; land use intensity

JEL codes: R14, Q15

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1 Introduction

European agricultural landscapes have experienced considerable shifts towards intensification and marginalisation, and these major trends are expected to continue in the future (Lambin et al., 2000; Rounsevell et al., 2003). A sustainable pathway is needed to maximise agricultural production and achieve food security in the future while simultaneously reducing the negative environmental effects of agricultural land use. In recent years, the provision of ecosystem services from agricultural land has been increasingly highlighted by science and enacted in policy changes (Schaller et al., 2018).

According to Lüker-Jans et al. (2016), marginal agricultural landscapes can be characterised by unfavourable biophysical conditions, such as steep slopes, shallow and/or poor soils, and inferior accessibility. These elements, however, are important for the functioning of the ecosystem and often result in increased biodiversity and habitat richness when paired with low-input intensities of cultivation, wide crop rotation, permanent grassland and small-parcelled mosaics. Conversely, intensive agricultural use often goes along with larger plot sizes, monoculture and narrow crop rotation, as these are the results of continuous scaling in mechanisation to achieve higher economic efficiency (Stoate et al., 2009; Ruiz-Martinez et al., 2015). In eastern Germany, where the state of Brandenburg—our case study region—is located, induced by the process of disappropriation in the Soviet Occupation Zone, large-scale agricultural land use emerged after 1945 (Batáry et al., 2017). To date, average plot sizes in this region have remained considerably larger than elsewhere in Germany, despite restituted ownership of land during the transition process (Hartvigsen, 2014). This allowed for highly efficient and intense management of cropland, including heavy-duty machinery, with lower heterogeneity and less complex habitat structure (lynchets, groves, hedges and other typical regional landscape elements). The consequences of this include a decrease in biodiversity and negative effects on the environment, i.e. soil and water quality (Thomson et al., 2019), a situation that has been termed the Farmland Rental Paradox: land degradation can be observed despite high ownership fragmentation (Sklenicka et al., 2014).

These trends of land degradation and homogenisation have evolved despite the EU's massive financial support for sustainable land management practices as part of the Common Agricultural Policy (CAP). Against this backdrop, a question arises: how can a landscapes' potential for contributing to the protection of biodiversity, enhancing ecosystem services and preserving habitats and landscapes be evaluated? In past decades, quantitative landscape metrics have been applied to characterise and compare (agricultural) landscapes across space and time (Uuemaa et al., 2013). Typically, the number, size, shape and arrangement of patches of different land use/land cover types are used to quantify the landscape structure, composition and dynamics. Lately, metrics such as the area under cultivation, mean patch size and Shannon's Diversity Index (which indicates agrobiodiversity) have also been used as proxies for characterising agricultural land use intensity (Schlesinger and Drescher, 2018). Other researchers have analysed inputs, such as labour, capital or management practices, and outputs, including yields (Shriar, 2000) and the dependence on industrial goods, such as machinery and fertiliser (Temme and Verburg, 2011; Zasada et al., 2013), to characterise agricultural land use intensity. Many of these studies face the problem of data availability as they are often restricted to small areas and selected farms.

A promising dataset to achieve area-wide characterisation of different types of agricultural landscapes comes from the Integrated Administration and Control System (IACS), a dataset that is derived from the CAP payment entitlement for which farmers apply. Several studies have successfully used this dataset to analyse agricultural land use change (Lüker-Jans et al., 2016; Tomlinson et al., 2018) and to characterise farms based on crop choice and land use (Lomba et al., 2017; Uthes et al., 2020).

The aim of this paper is to identify and characterise different types of agricultural landscapes and to depict their spatial patterns using landscape metrics and a cluster analysis for the case of Brandenburg, Germany. While landscape metrics are most frequently applied to grids and administrative areas, we use hexagons, which have been shown to better capture spatially continuous phenomena, such as agricultural landscapes, because of their spatial smoothing effect towards the edges (Birch et al., 2007; Schindler et al., 2008).

The outcomes of this study may provide important insights and new units of analysis, which can be used to develop environmental and agricultural policies that are better tailored to local and regional characteristics.

2 Material and Methods

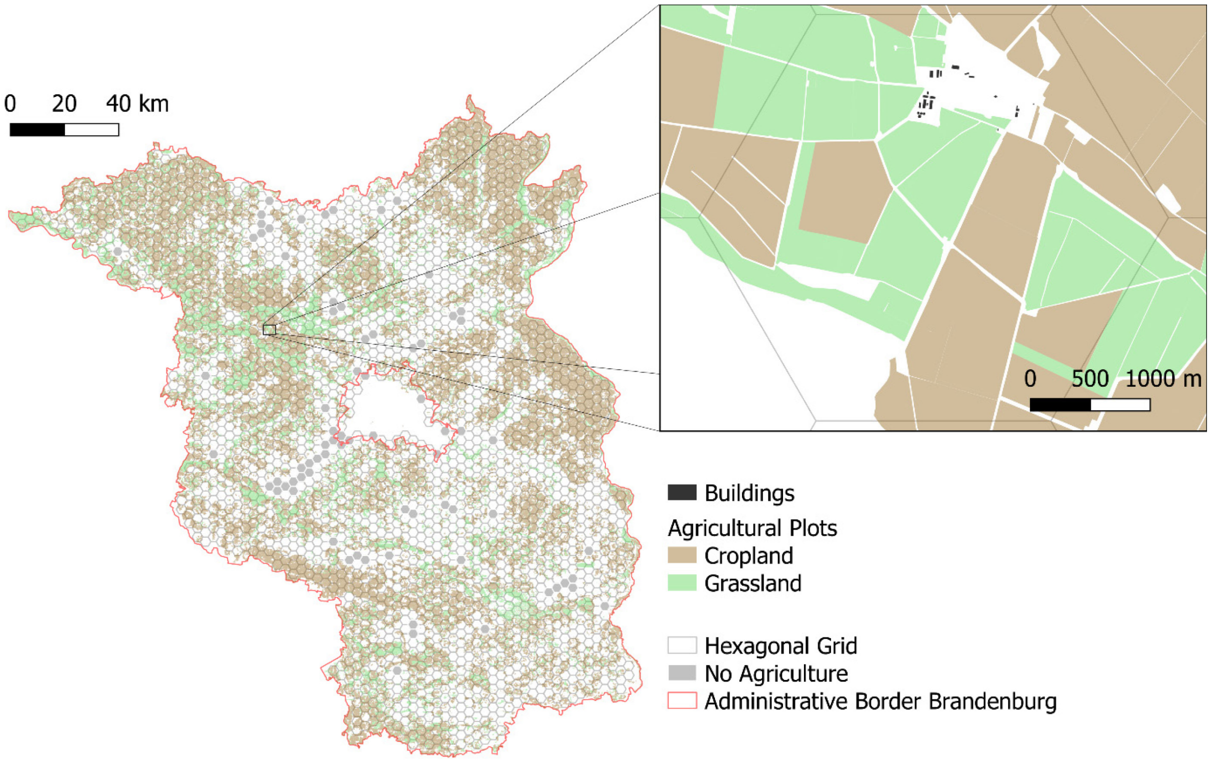
2.1 Study Area

We focus on the state of Brandenburg, which is located in north-eastern Germany and covers 29 640 km². It is an excellent case study because it is an agricultural state characterised by intensive use; approximately 45 % of its area is dedicated to agricultural land use. Compared to other German states, Brandenburg shows a relatively high share of organic agriculture (12 % of the agricultural area), and this share is continuously increasing (Ministerium für Landwirtschaft, Umwelt und Klimaschutz (MLUK), 2019). Since 2000, the total size of the agricultural area has remained largely constant. Approximately one-third is used for crop cultivation, one-third is used for fodder crops and one-third is used for combined crop and livestock production. Brandenburg completely surrounds the city of Berlin, the capital of Germany, and is heavily influenced by its location. For example, there is steady pressure on agricultural land due to demands for rededication into residential land in the suburban areas of Berlin. In addition, Berlin citizens have an increasing demand for regional food production in the neighbouring state. Gutzler et al. (2015) anticipated increasing use of cropland for renewable energy production based on the strong increase of maize production for biogas fermentation after implementation of the Act on Granting Priority to Renewable Energy Sources in 2000 (Federal Environmental Ministry, 2000), especially in Brandenburg.

Brandenburg's agricultural land exhibits a high share of low-quality soils; almost two-thirds are sandy and sandy-loamy soils. This situation, paired with low rainfall (on average, less than 600 mm/year), makes agricultural production challenging. This is one reason why Brandenburg farmers either produce in the organic niche, benefiting from the high prices paid in Berlin for regional, organic food, or apply a high level of technology, including heavy-duty machinery and intensive use of fertilizers and agrochemicals (Gutzler et al., 2015). Maize replaced rye as a main crop in 2013, followed by wheat and rapeseed (Troegel and Schulz, 2018). As in all eastern German federal states, agricultural practice in Brandenburg is dominated by large farm enterprises with an average size of approximately 250 ha, which is four times the German average (Gutzler et al., 2015; Troegel and Schulz, 2018). In addition, 8 % of the area within Brandenburg is designated as conservation area, and it has important effects on biodiversity and, in particular, bird biodiversity (Amt für Statistik Berlin-Brandenburg, 2017).

For this initial study, we focus on cropland and grassland and do not consider the number of livestock on farms. The latter is not expected to have a great impact on the agricultural landscape, as Brandenburg does not have a high number of livestock, particularly cattle, in contrast to Lower Saxony or Bavaria (Statistisches Bundesamt, 2019). Furthermore, insufficient information on livestock is present within the available data to allow for meaningful calculation of indicators (Uthes et al., 2020).

Figure 1 – Overview of the hexagonal grid within Brandenburg borders, overview of IACS data (cropland and grassland categorised in 2018) and Open Street Map building footprint



As a base for our indicator and cluster calculation, we created a hexagonal grid with a cell size of 10 km² (N = 2 836). In total, 178 cells were deleted because of missing data (Figure 1). The size of the cells captured the landscape level and the spatial configuration of plots within each cell. Since the administrative areas vary in size and form, the hexagonal grid provides a smoother surface for analysis of the agricultural landscape in the whole state of Brandenburg. All the used grid cells are completely within the Brandenburg administrative region. Cells that share an area with adjacent federal states or land were not considered in order to avoid including cells that do not provide agricultural data due to overlapping administrative boundaries. However, overlaps with the Berlin administrative areas are included due to the availability of IACS data and its affiliation with Brandenburg's agricultural landscape.

2.2 Data

We used plot-based information on the cultivation of agriculture in Brandenburg in 2018 to identify agricultural characteristics using the IACS, which is provided by the EU. Farms apply for area-based payments to ensure income support according to EU CAP regulations. This support is managed and controlled in a standardised way in all EU Member States through IACS. Farmers can digitise and register their land parcels via an online system on an annual basis before 31 May each year. According to the Council Regulation (EC) No 73/2009, the Land Plot Information System must be used by farmers to localise and quantify agricultural land that is eligible for EU support both for farmers' applications and for supervision by government authorities. In Brandenburg, the baseline map for the registration is a digital cadastre of field blocks established in 2015. The field block cadastre covers the agricultural area in Brandenburg that is eligible for EU subsidies based on location, size and additional information, and it is updated based on orthophotos. A field block is a coherent agricultural area surrounded by permanent borders (e.g. roads, paths, trees) with predominantly uniform main land use. One or more farmers can use a field block, meaning that the area of one field block may be split between each farmer who applied for subsidies. In addition, the size and outlines of plots registered for subsidies can change over time. As a result, the georeferenced land use data that we use pertains to those plots for which farmers applied for subsidies. The outlines of the plots are mostly aligned with the underlying field blocks, but they may have been edited by the farmer due to the specific land use in a specific year. In addition to agricultural use at the plot level, landscape elements located in a field block, such as hedges, rows of trees and single trees, are registered. In Brandenburg, landscape elements were registered and located with a single point until 2016, and now they are digitised with spatial outlines (e.g. groups of trees). The available data include very detailed information about land use according to the IACS classification. We focused on the categories of 'grassland', 'cropland' and 'landscape element', which are assigned based on crop types (*Kulturart*) for 2018. To identify plots that have likely been cultivated without crop rotation, we used 'maize' as a specific crop type.

In addition to IACS data, we considered Open Street Map (OSM) data and data regarding regional planning, soil quality and biogas plants. We used the OSM data for all building footprints in Brandenburg from September 2019 to assess the degree of urbanisation in each hexagon. OSM is an open-source, crowd-sourced mapping platform that has high coverage in countries like Germany (Jokar Arsanjani et al., 2015). The building footprints provide data on single buildings as artificial structures. We used settlement data from the Landesentwicklungsplan Hauptstadtregion Berlin Brandenburg from April 2019 for calculating the mean Euclidean distance to settlements for each cell. The Bundesanstalt für Geowissenschaften und Rohstoffe (2014) provides a soil quality rating (SQR, 0 - 102 points; Mueller et al., 2007) with modified input variables, which we used to estimate the crop yield potential. Soil quality points indicate the potential productivity of respective soils in Germany, an official measure that was constructed to unify pedologic, scientific and (agro-) economic considerations within one measure (Hüttel et al., 2016). A low (high) number represents very low (high) productivity (BMJV, 2007; Scheffer et al., 2010). The location and capacity of biogas plants from 2016 are provided by the Ministerium für Wirtschaft und Energie des Landes Brandenburg (MWE).

2.3 Methods

2.3.1 Indicator calculation and landscape metrics

We selected a set of landscape metrics to characterise agricultural landscapes based on a literature review: median plot size (ha), edge density (calculated as a share of the total hexagon area in km/10 km²), organic share of total agricultural area (%), cropland share of total agricultural area (%), maize share of total agricultural area (%), mean biogas plant density, Shannon Diversity Index (SDI), share of landscape elements in total agricultural area (%), agriculture share of total hexagon area (%), soil quality (values from 0–102), number of buildings (N) and mean distance to settlements (km). We calculated the respective indicator values for the year of 2018 at the aggregated level of the hexagons. We focus on measures to describe agricultural land use, management, agricultural intensity and diversity and spatial configuration.

Plot size captures the spatial configuration of plots and is frequently used to characterise agricultural landscapes (Dengler, 2009; van der Zanden et al., 2016). We calculated median plot size within hexagons from the reported management units in the IACS data by using the centroid of the plots and thus assigning each plot only once. The ecological roles of habitat diversity and plot edges for farmland biodiversity (including functional biodiversity) has been demonstrated by several authors (Weissteiner et al., 2016). We therefore calculated edge densities and the SDI.

Edge density thereby characterizes the physical fragmentation of the agricultural landscape, i.e. with increasing edge density, the number of farmland patches increases and their patch size decreases (Su et al., 2014). Organic agriculture is a production type in which mineral fertiliser and synthetic pesticide usage are subject to more strict regulations than conventional agriculture (Gabriel et al., 2010). For this reason, organic production is considered less harmful to the environment and key for more sustainable agricultural production. To differentiate between cropland and grassland, we included the share of cropland (of the total agricultural area), following the argument that most grasslands in eastern Germany are managed rather extensively (Matzdorf et al., 2008). Though grasslands can also be managed intensively, particularly in regions with high livestock densities, we note that Brandenburg is mainly characterised by low ruminant livestock and rather extensively used grasslands under agro-environmental measures, where farmers receive additional compensation payments through the EU CAP for extensively managed grasslands (Matzdorf et al., 2008). We measured cropland intensity by the share of maize that is likely to be used for biogas and cultivated as a long-term self-following crop (i.e. without crop rotation; (Gutzler et al., 2015; Lüker-Jans et al., 2016). We included both maize types (i.e. silage maize and corn maize) in our analysis. According to the Fachagentur Nachwachsende Rohstoffe e. V. (FNR) (2013), the expansion of maize monocultures are expected to be on par with intensification of crop production (Vergara and Lakes, 2019). Additionally, we calculated a density map of biogas plants weighted by their capacity. This map indicated intensive production of maize for biogas, which often comes at the expense of loss of food production areas (Grundmann and Klauss, 2014; Lüker-Jans et al., 2016).

The SDI, as a measure of diversity, defines variety and agrobiodiversity, and it is widely used in ecology studies (Vaz et al., 2014; Uthes et al., 2020). It considers the number of different crop types as well as their abundance. We calculated the SDI for all listed crop types within the IACS data (N = 158) according to the following formula:

$$SDI = -\sum_{i=1}^{n} p_i \, lnp_i$$

where
p_i = share (%) of crop/crop and usage *i* in total agricultural area
lnp_i = natural logarithm of p_i

According to Uthes et al. (2020), landscape elements such as hedge or tree rows are important features for a diverse landscape structure. We calculated the share of landscape elements in the total agricultural area within each hexagon.

Furthermore, we used the SQR as a measure for yield potential. This measure has often been used in land market analyses, such as those of Hüttel et al. (2016) and Ritter et al. (2015). To assess the degree of urbanisation, we calculated the number of buildings in each hexagon and the mean distance to settlements. According to Su et al. (2011), proximity to urban centres parallels the intensity of urbanisation, and changes in landscape characteristics can reflect the degree of human influences on the environment. Additionally, Piorr et al. (2018) emphasise that agricultural landscapes ‘differ in the way they are influenced by the proximity to urban areas, being part of functional urban-rural linkages, urban pressures and opportunities’.

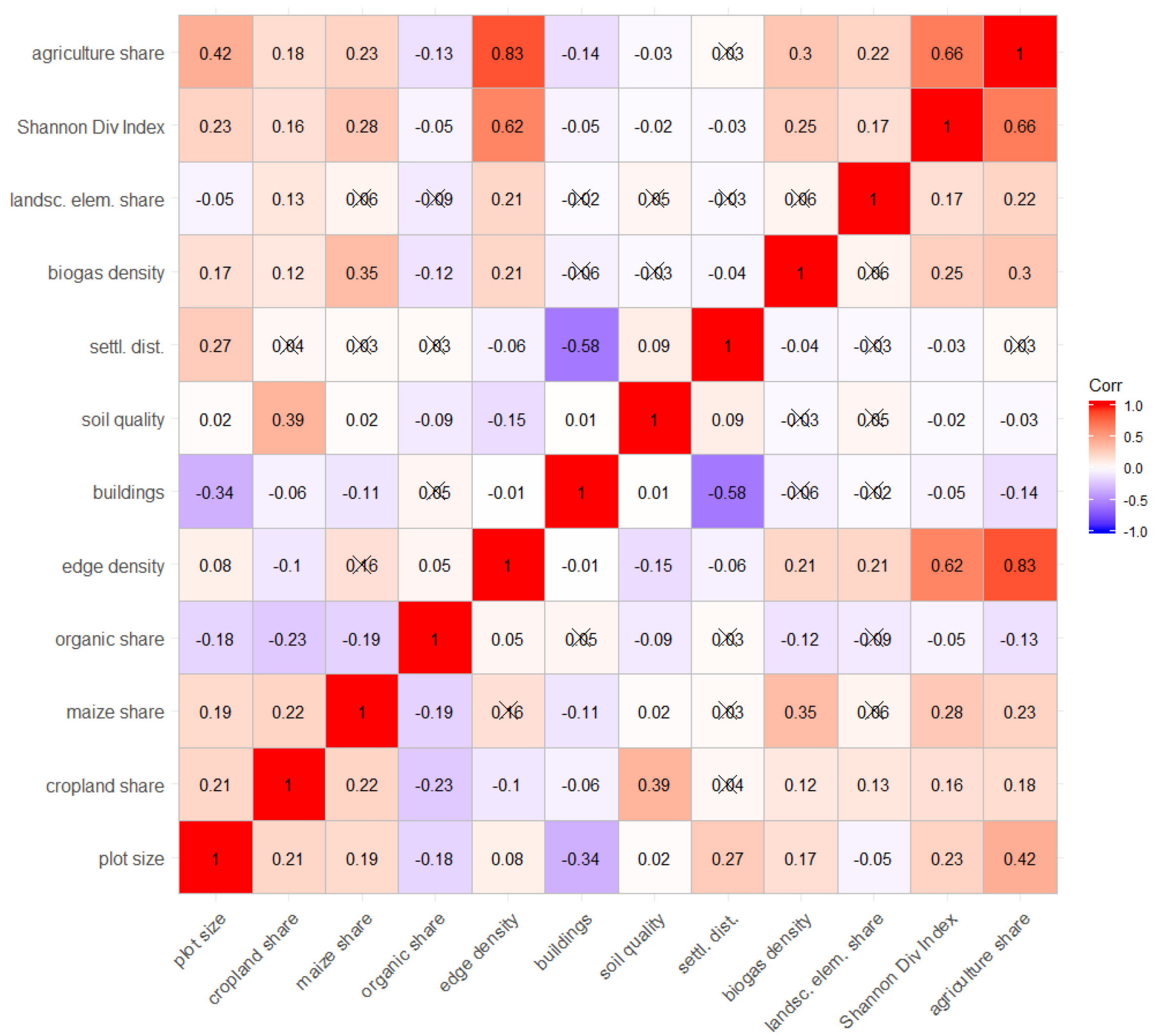
2.3.2 Cluster analysis for identifying agricultural landscape types

We apply a cluster analysis using the calculated landscape metrics to identify different types of agricultural landscapes in Brandenburg. Lausch and Herzog (2002) emphasise that when working with landscape metrics, one is confronted with the question of which indicators are relevant for the area and the problem under investigation. We therefore determined Spearman’s correlation coefficients to reduce redundancies (Lausch and Herzog, 2002). We follow the approach of Lüker-Jans et al. (2016), who characterised agricultural land use patterns using k-means clustering. Here, we use a similar method for the characterisation of agricultural landscapes, applying a two-step cluster analysis. We decided to apply a two-step cluster analysis because of its ability to deal with large datasets, including variables that are not normally distributed, and the possibility of automatically determining the optimum number of clusters (Chiu et al., 2001). In the first step, the Bayesian information criterion (BIC) is calculated for each cluster within a specified range, and then this is used to generate an initial estimate of the number of clusters.

The second step refines the initial estimate by determining the greatest change in distance between the two closest clusters in each hierarchical clustering stage (SPSS, 2001). To validate the cluster number, the model fit was evaluated using the silhouette coefficient, which is a measure of the cohesion and separation of clusters. A value above 0.2 indicates *fair* cluster quality (Tkaczynski, 2017). For our Spearman correlation analysis, we rely on seven selected indicators that show values of < 0.4 (Figure 2).

Additionally, the share of landscape elements was not included because (1) the values are generally very low in the hexagonal grids, with low variance except for a few outliers (65 % of all hexagons have a < 1 % share) and (2) if included in the cluster analysis, the results showed no variance within clusters. Biogas density was not included because it represents the same issue of potentially high intensity management as maize after maize cultivation, i.e. no crop rotation, monoculture cultivation, but with higher uncertainties of the calculated values. The final input indicators include soil quality; number of buildings; edge density; shares of organic agriculture, cropland and maize; and median plot size for each hexagon in 2018.

Figure 2 – Correlation matrix of indicators (crossed = not significant)



Finally, we calculated the spatial correlation values for each indicator and each identified landscape type from the statistical cluster analysis. For continuous indicators, we used Global Moran's I statistics, which characterise the spatial dependency of values between the hexagons (Moran, 1950). We used all six neighbours (Queen's contiguity) of each hexagon. The value of Moran's I ranges from −1 (perfect negative autocorrelation) to 1 (perfect positive autocorrelation), with 0 indicating spatial randomness (Moran, 1950). Since cluster values are categorical, Moran's I could not be applied, so we calculated the join count instead (Plant, 2012). This determines the degree of clustering or dispersion among a set of spatially adjacent polygons. To calculate the join count for each cluster value, we set the reference cluster value to 1 and all other cluster values to 0, and we calculated the join count separately for each cluster.

3 Results and Discussion

3.1 Spatial Characteristics and Patterns of the Agricultural Landscape in Brandenburg

Brandenburg, 45 % of which is devoted to agricultural land use, features a large number of rural hexagons with a low number of buildings (Figure 3). In Brandenburg, the highest settlement densities are in cells adjacent to Berlin and to regional centres like Neuruppin, Schwedt/Oder, Fürstenwalde, Cottbus and Jüterbog. At the same time, most of the areas are characterised by short mean distances to the nearest settlement with high spatial autocorrelation (Moran's I = 0.51). Approximately 66 % of cells show a mean distance below 2 km (Figure 3). The agricultural area share of the cell area is evenly distributed between the classes, except for those with a high agricultural share (> 80%, N = 349 of 2 761; Figure 3). Therefore, the majority of hexagons are covered by agriculture, and more than 40 % include cropland, grassland and ecological priority areas. The highest agricultural shares are found in cells with highest values for soil quality (> 62). Only 75 hexagons feature no agricultural land at all. These cells are mostly covered by forest, urban land cover or water surface. The spatial autocorrelation of agriculture share is measured by Moran's I = 0.59. Most of the agriculturally used areas are characterised by a high share of cropland (53 % of cells and more than 80 % of the total agricultural area), and cells with a low share of cropland have low soil quality (Figure 3).

In contrast, the maize share is below 20 % in 1 955 of 2 761 cells (71 %), with low spatial clustering (Moran's I = 0.30). We note that maize can be cultivated with crop rotation. However, we used it as a proxy crop type that tends to be grown with narrow crop rotation or for bioenergy production (Lüker-Jans et al., 2016). The biogas station density tends to be higher in areas with a high share of maize (Figure 4), which is indicated by the relatively high correlation value of 0.35. Best (2006) states that farmers' decision to switch to organic management is dependent on multiple factors, but might include socialisation factors, such as neighbours' perception and social connectivity. Additionally, the decision to switch is influenced by, for example, higher uncertainties in yields and thus fear of lower income and high dependence on subsidies (Best, 2006). Best (2006) confirms that organic farms have higher shares of grassland. The share of organic agriculture shows high spatial clustering with a global Moran's I of 0.56. We find areas with high percentage of organic farming have lower median plot sizes, which is in line with the studies of Best (2006) and Caporali et al. (2003). Moreover, edge density tends to be higher in areas with a high share of organic farming and a low share of maize. Edge density represents the composition of plots, and shapes without strictly rectangular plots show higher edge density values. From this, we infer that such shapes might increase agricultural landscape diversity, in line with Uthes et al. (2020). Edges might operate as zones for ecologically valuable elements, like hedges or tree rows. The share of these landscape elements (Figure 4) is generally low in relation to the total agricultural area due to the chosen landscape scale. However, they perform a number of functions, such as serving as windbreaks, modifying the microclimate and assisting in soil retention and water purification (Stoate et al., 2009).

Figure 3 – Indicator maps of the number of buildings, mean distance to settlements (km), mean SQR (points), agricultural share (% of grid cell area), median plot size (ha) and edge density (m/10 km²) in 2018

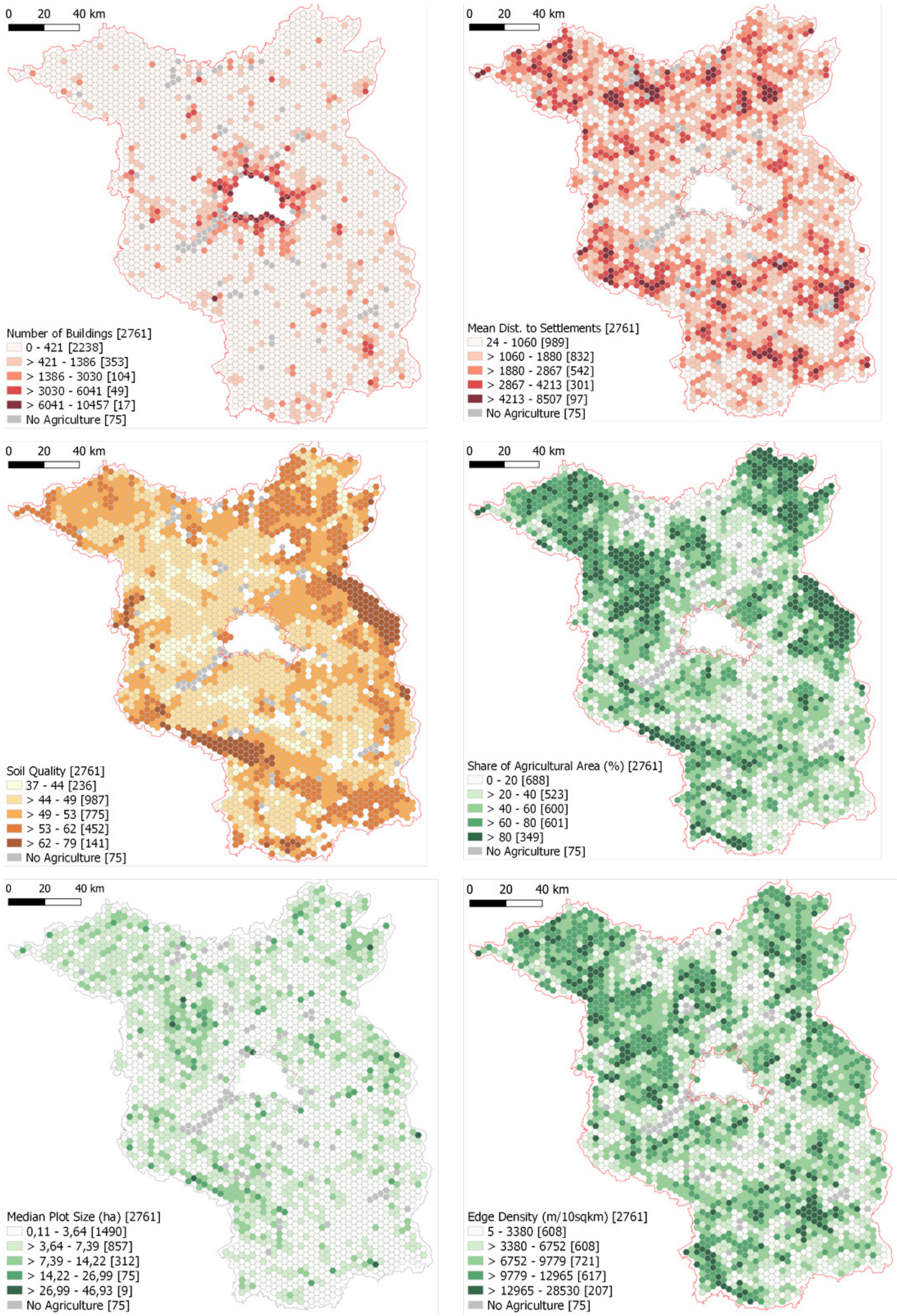
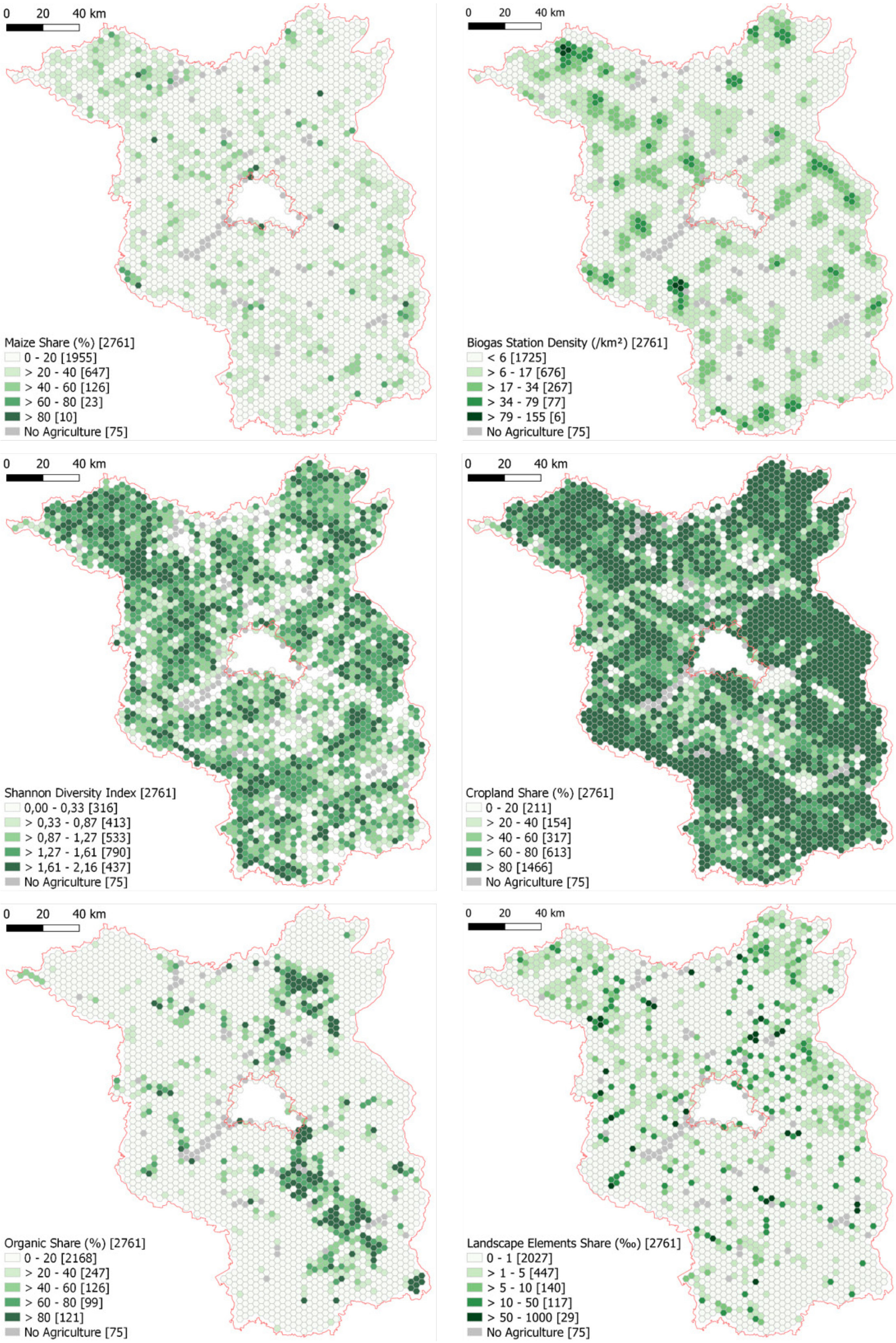


Figure 4 – Maps of agricultural Indicators, including share of maize (%), biogas station density (N/km²), SDI and share of cropland, organic agriculture and maize (% of total agricultural area) in 2018



Furthermore, they enhance landscape diversity and connectivity; are explicitly acknowledged as important cultural features; and have recreational, aesthetical and heritage value (van der Zanden et al., 2016). The ecological value of certain plot sizes could depend on the agricultural use; according to Crist and Peters (2014), larger and older plots of grassland could support, for example, higher insect species biodiversity than smaller plots. Moreover, they can store a higher amount of carbon dioxide (Yang et al., 2019). However, cropland plots are often cultivated with monocultures and thus are less beneficial for ecological richness if not separated with elements such as hedge rows. However, the SDI, as an indicator of agrobiodiversity, is not necessarily higher in areas with a high share of organic farming. The higher the index value, the more crops are cultivated within the cell (Figure 4). The SDI shows a Moran's I of 0.37.

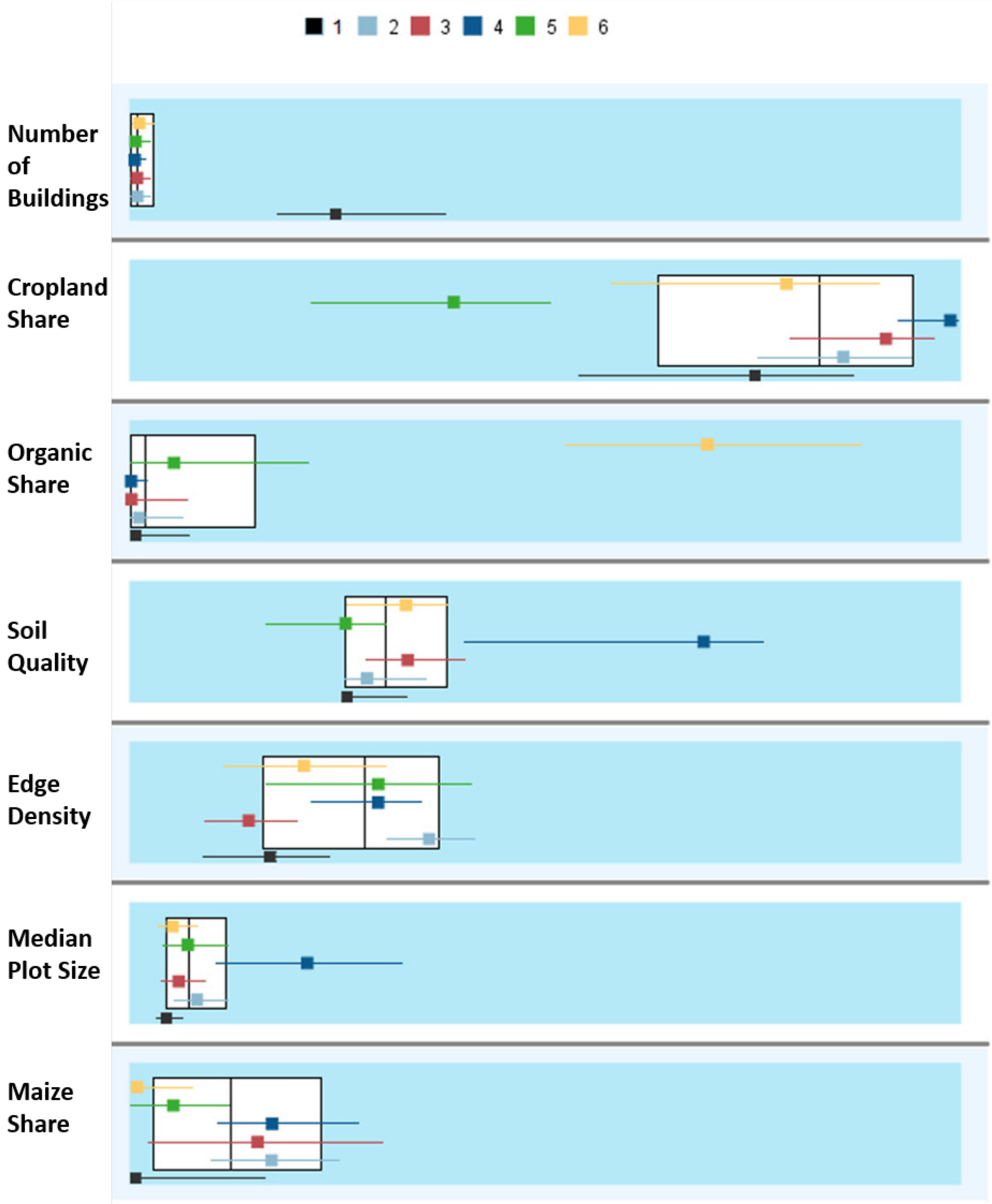
3.2 Types of Agricultural Landscapes

We identified six different types of agricultural landscapes in Brandenburg: peri-urban, high fragmentation, low fragmentation, high intensity, low intensity (marginal grasslands) and organic production (Table 1). The two-step clustering analysis returned the most optimal results with a cluster number of six, with relatively low BIC value of 7 894.076 and the highest distance measure of 1.546 (Annex 1). The silhouette measure of cluster cohesion and separation indicates that these six clusters have fair quality (0.3).

Table 1 - Centroid of clusters with the lowest (green) and highest (red) values

	Cluster centroid						
Cluster	**Soil Quality**	**Number of Buildings**	**Edge Density (km/ 10km²)**	**Median Plot Size (ha)**	**Organic Share (%)**	**Maize Share (%)**	**Cropland Share (%)**
1 – Peri-urban	49.4	3206.2	5.0	3.0	7.6	10.1	68.9
2 – High fragmentation	49.4	194.7	10.4	4.4	5.1	18.4	83.7
3 – Low fragmentation	51.3	197.4	4.1	3.5	5.3	19.3	86.7
4 – High intensity	62.8	173.9	7.9	11.2	3.2	20.5	93.7
5 – Low intensity	47.2	207.8	8.3	4.5	12.9	7.2	35.7
6 – Organic production	50.4	244.6	6.3	3.2	68.9	4.8	72.1
Combined	50.8	374.8	7.7	4.6	13.5	15.1	75.6

Figure 5 - Cluster comparison of input variable centroids



The identified types of agricultural landscapes can be characterised as follows (the mean values of clusters are shown in Table 1 and Figure 5):

Cluster 1 ('peri-urban': 5.8 % of all clusters, N = 149) can be described as the peri-urban agriculture cluster, which is mainly characterised by a high mean number of buildings (3 206) and the lowest mean share of agricultural area (24.5 %). Consequently, edge density is relatively low (mean: 5.0 km/10 km^2). The lowest average median plot size (3.0 ha) in this cluster is smaller than in other clusters. Additionally, the shares of maize and cropland tend to be lower than in the other clusters, and areas of this cluster are characterised by lower soil quality (49.4).

Cluster 2 ('high fragmentation': 36.1 % of all clusters, N = 933) shows high fragmentation and a high mean of agriculture share (66.0 %). The cropland share (83.7 %) in general and the share of maize (18.4 %) in particular are relatively high.

Cluster 3 ('low fragmentation': 22.4 % of all clusters, N = 579) is characterised by low fragmentation of the agricultural landscape and a low mean agriculture share (25.5 %) but a high share of cropland, relatively high soil quality and low edge density. In general, the landscape is not dominated by agriculture, but other types of land cover, such as water or forest.

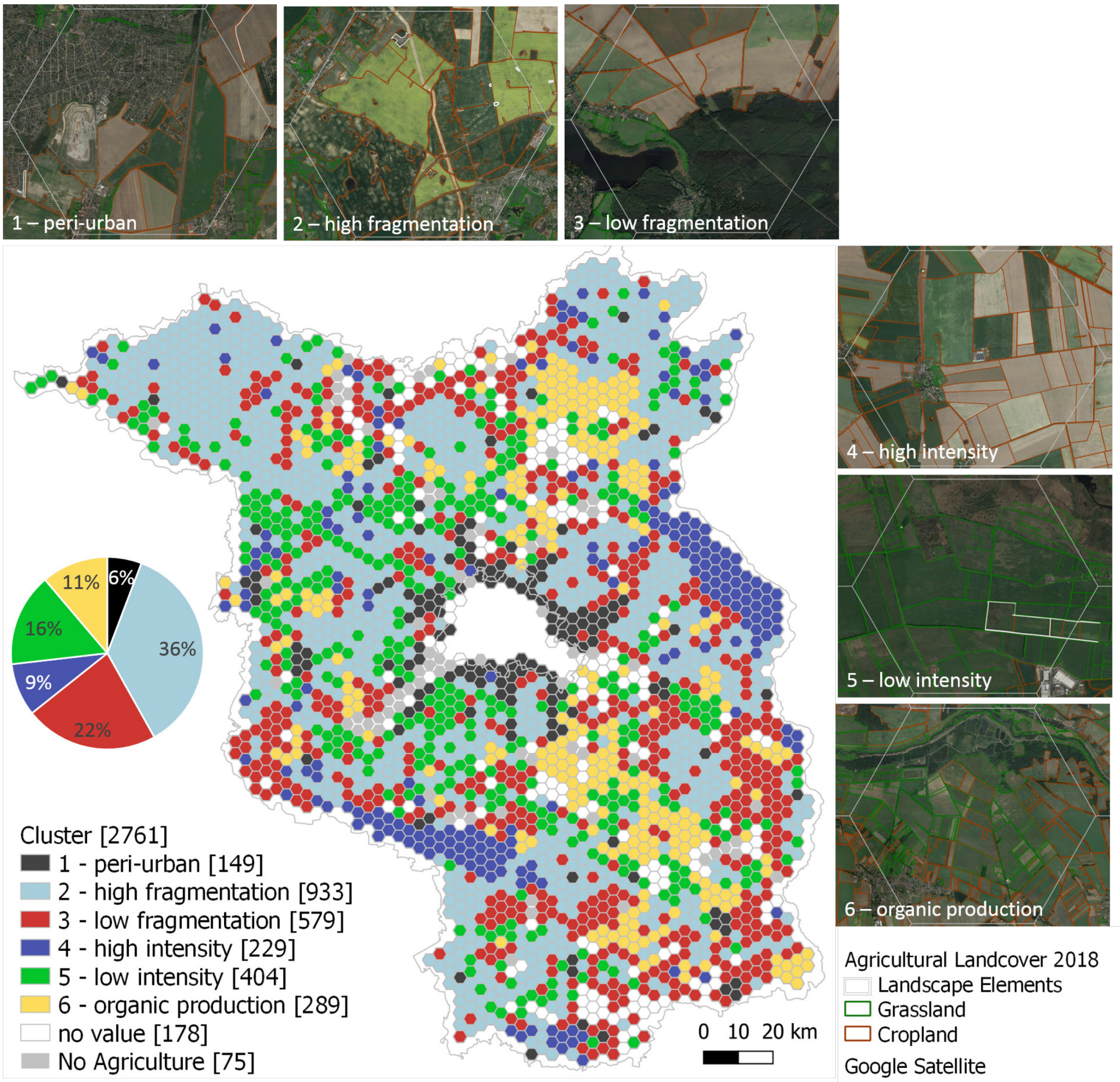
Cluster 4 ('high intensity': 8.9 % of all clusters, N = 229) shows the highest mean agriculture share (66.3 %) as well as high-quality soil (62.8). It is characterised by large plot sizes (11.2 ha) with large shares of cropland (93.7 %) and maize (20.5 %).

Cluster 5 ('low intensity': 15.6 % of all clusters, N = 404) mainly includes marginal grasslands, with a mean agriculture share of 44.5 %. The low soil quality (47.2) is interpreted as the reason why plots are mainly used for grassland. There is a low share of cropland (35.7 %). In contrast to other clusters (except Cluster 6), grassland is often managed organically (mean organic share = 12.9 %).

Cluster 6 ('organic production': 11.2 % of all clusters, N = 289) represents organic farming. It is characterised by a low share of cropland and maize, smaller median plot sizes (3.2 ha) and a mean agricultural share of 32.5 %.

The map in Figure 6 shows the spatial distribution of clusters in Brandenburg. For the join count, $p > 0.01$, and thus cells with only one or two total neighbouring hexagons are excluded. We identified a high positive spatial autocorrelation for the high intensity (N = 98) and organic production (N = 95) clusters. This means that one agricultural landscape type is located next to another agricultural landscape of the same type. The spatial clustering of high intensity agriculture that we find in our results may be attributed to the underlying spatial clustering of high soil quality. One reason for spatial clustering of organic agriculture might be that it occurs often in nature preserves under stringent conditions (Venghaus and Acosta, 2018). In contrast to other studies and literature, we could not find significantly higher soil qualities in areas under organic production. Other influencing factors could be operational determinants, for example the share of grassland which is higher in our organic production type than in other clusters (Bichler and Häring, 2003). Another reason the potential agglomeration effect of organic agriculture (Schmidtner et al., 2012). In contrast, the low fragmentation (N = 34) and low intensity (N = 43) clusters do not show a high degree of spatial autocorrelation and are distributed across the state. The peri-urban (N = 54) and high fragmentation (N = 71) clusters show medium spatial autocorrelation and are mostly randomly spatially distributed whereby the peri-urban cells are concentrated around Berlin.

Figure 6 – Map of agricultural landscape types in Brandenburg, Germany, from 2018 with exemplary satellite imagery for each type (Google)



This paper focuses on the methodological suitability of landscape metrics as an input for cluster analysis within a hexagonal grid. One of the advantages of using IACS data is the potential to transfer the approach to other study regions in which similar monitoring data are available. Our results complement information on agricultural landscapes, such as the agro-ecological zones of Brandenburg (*Landbaugebiete*), that have been given a suitability rating for crop production (*Ackerzahl*; Landesamt für Ländliche Entwicklung, Landwirtschaft und Flurneuordnung, 2016) and the maps available in the Thünen Atlas, including the distribution of crop types or grassland on a municipal scale (Thünen Institut, 2014). Based on a plot-based analysis, we add new information to the existing data regarding composition, diversity and intensity. Our approach is innovative because it integrates different indicators into a new land use typology, which is considered an improvement over the use of single indicators (e.g. soil quality). The newly provided information improves the understanding of the agricultural landscape structure in Brandenburg and helps to identify regions where monitoring and specified support measures may be required.

Earlier typologies of Brandenburg's agriculture have been based mainly on farmers' decisions and referenced renewable energy production (Venghaus and Acosta, 2018). In this approach, the farmer, based on the decisions that he makes, is the 'designer' of agricultural landscapes. In contrast, we used landscape metrics as inputs for typologising agriculture. Lüker-Jans et al. (2016) emphasise that 'intensive land use is connected to landscapes with rather favourable site conditions for arable cultivation like relatively flat and fertile land', which corresponds with our findings, particularly for clusters 'low fragmentation' and 'high intensity'. Consistent with Lüker-Jans et al. (2016), using k-means clustering, we identified similar agricultural types based on cropland share, with maize as a focal crop. However, in contrast to our hexagons, which provide a smooth, homogeneous surface that enables unambiguous definition of neighbourhoods for the study area, Lüker-Jans et al. (2016) analyse metrics on a municipal level, which results in higher variance in shape and size than grid-based analysis. In general, landscape metrics have been proven to be an adequate tool for analysing the configuration and composition of landscapes.

3.3 Limitations

Similar to Lomba et al. (2017), Uthes et al. (2020) and Lüker-Jans et al. (2016), we were able to show the potential of IACS data for analysing agricultural land use. Future backing through remote sensing data, such as crop type mapping (Griffiths et al., 2018), crop yield mapping (Lobell et al., 2015) or landscape pattern analysis (Weissteiner et al., 2016), would increase the potential for this approach to be applied to areas in which frequent land-use monitoring is not available. Analysis on a finer spatial scale could include finer landscape structures and provide a suitable basis for analysing changes in, for example, agricultural composition over time. In this study, we did not consider the temporal dimension of land use. Applying our proposed method to different time slices would make it possible to address changes in the set of indicators and the resulting clustering. This would reveal processes that occur in the agricultural landscape and could help identify how changes in boundary conditions would impact the composition of a landscape. In Brandenburg, two prominent examples of such processes are the increase of maize in the crop portfolio and monocultures and the construction of biogas plants in direct response to implementation of the Act on Granting Priority to Renewable Energy Sources in 2000 (Federal Environmental Ministry, 2000). We hypothesise that such development would be revealed by an analysis with multiple time slices of IACS data.

A common problem in ecological analyses of spatial indicators is scale. Scale dependence can be addressed by performing a sensitivity analysis of grid cell size, and can be applied in further studies. However, landscape metrics have proven to be a suitable tool for landscape analysis, even though there are limitations when it comes to up- and downscaling of the generated results (Schlesinger and Drescher, 2018). Oberlack et al. (2019) emphasised that archetypes can help tailor intensification strategies to particular contexts. Additionally, to increase the quality of archetypes, Eisenack et al. (2019) proposed a framework to merge quantitative and qualitative approaches, which is beyond the scope of this study.

4 Conclusions

Our findings reveal six different types of agricultural landscapes and their respective spatial patterns. We conclude that Brandenburg is characterised by highly fragmented agriculture and a high degree of spatial clustering of intensive agriculture and organic production. The chosen landscape metrics derived from IACS data have proven to be adequate for improving the understanding of agricultural landscapes, and they are suitable for measuring agricultural intensity and diversity in terms of plot composition and configuration at the EU level since IACS data are available across the EU. Our paper proposes an approach at the landscape level, which, according to Thomson et al. (2019), provides a fundamental connection between the diverse array of relevant socio-economic and biophysical conditions and processes and can inform national—and even global—decision-making.

In addition to performing spatio-temporal analysis, future work should address the relations between different typologies of agricultural landscapes and land price development, ownership patterns and trade-offs, for example between food and energy production.

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6 Annex

Annex 1 – Automatic clustering.
Six clusters show a relatively low BIC and high distance measures.

# of Clusters	BIC	BIC change[a]	Relations of BIC changes[b]	Relations of distance measures[c]
1	12639.288			
2	10915.973	−1723.315	1.000	1.269
3	9581.095	−1334.878	0.775	1.664
4	8822.853	−758.241	0.440	1.349
5	8289.365	−533.488	0.310	1.274
6	7894.076	−395.289	0.229	1.546
7	7677.336	−216.740	0.126	1.074
8	7483.168	−194.168	0.113	1.086
9	7313.045	−170.124	0.099	1.069
10	7160.902	−152.143	0.088	1.273
11	7065.035	−95.867	0.056	1.206
12	7004.337	−60.698	0.035	1.188
13	6970.704	−33.633	0.020	1.024
14	6940.408	−30.297	0.018	1.041
15	6915.647	−24.760	0.014	1.285

a. The changes were based on the previous number of clusters in the table.

b. The change rates are relative to the change in the two cluster solutions.

c. The distance measurements are based on comparison of the current number of clusters with the previous number of clusters.