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Characterising Agricultural Landscapes using Landscape Metrics and Cluster Analysis in Brandenburg, Germany

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Abstract

An increasing demand for agricultural products within the past years has led to increasing agricultural intensification. Various agricultural compositions and landscape configurations can have different impacts on the provision of ecosystem services. The EU follows the aim of supporting and developing sustainable food production systems. We use the plot-based data provided by the Integrated Administration and Control System (IACS) to identify different types of agricultural landscapes and their spatial distribution in Brandenburg, Germany. By calculating a set of landscape metrics to characterise agricultural land use, we were able to identify six types of agricultural landscapes by a Two-Step cluster analysis for a hexagonal grid. Thereby, the majority of Brandenburg is covered by agriculture characterised by high share of cropland but different degrees of fragmentation. By providing a framework using landscape metrics derived from IACS data, the approach of clustering to identify typologies is highly transferable to other regions within the EU and may provide an important asset for offering new units of analysis for a better tailored environmental and agricultural planning depending on the local to regional characteristics.

Keywords:

agricultural land use pattern, agricultural intensification, landscape metrics, cluster analysis

1 Introduction

European agricultural landscapes have featured considerable changes towards intensification and marginalization of areas, and these major trends are expected to continue in the future (Lüker-Jans, Simmering, & Otte, 2016; Rounsevell, Annetts, Audsley, Mayr, & Reginster, 2003). We define agricultural landscapes as the result of land uses and management in an area following the definition of Kizos and Koulouri (2006). These landscapes provide ecological functions, e.g. habitat provision; economic functions, e.g. income generation; and cultural functions, e.g. landscape aesthetics. According to Lüker-Jans et al. (2016), marginal agricultural landscapes are characterised by unfavourable biophysical conditions, such as steep slopes, shallow and/or poor soils, and inferior accessibility. They often show increased biodiversity and habitat richness due to low intensities of cultivation, crop and grassland rotation and small-parcelled mosaics. Conversely, intensive agriculture often goes along with larger field sizes, lower heterogeneity in habitat structure, and more monoculture (Ruiz-Martinez, Marraccini, Debolini, & Bonari, 2016). Thus, intensification is frequently associated with a decrease in biodiversity and negative effects on the environment, i.e. soils and water quality (Thomson et al., 2019). A sustainable pathway is needed for maximising agricultural production and particularly achieving future food security while at the same time 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). The European Common Agricultural Policy (CAP), the major policy instrument driving agricultural land use in Europe, aims to support the sustainable management of natural resources such as water, soil and air and to contribute to the protection of biodiversity, enhance ecosystem services and preserve habitats and landscapes (European Union, 2019).

In the past decades, landscape metrics have been successfully applied to characterise and compare (agricultural) landscapes across space and time in a quantitative manner (Uuemaa, Mander, & Marja, 2013). Typically, number, size, shape and arrangement of patches of different land-use/land cover types are used quantify landscape structure, composition and dynamics. Lately, metrics have also been used as proxies for characterising agricultural land use intensity, e.g. area under cultivation, mean patch size and Shannon's Diversity Index (Schlesinger and Drescher 2018). In contrast, others have analysed inputs, such as labour, capital or management practices, and outputs, such as yields (Shriar, 2000) or the dependence on industrial goods, e.g. machinery and fertilizer (Temme & Verburg, 2011; Zasada et al., 2013) to characterise agricultural land use intensity. However, these studies face the problem of data availability and are therefore often restricted to small areas and selected farms. A promising dataset to achieve area-wide characterization by different types of agricultural landscapes comes from the Integrated Administration and Control System (IACS, in German: Invekos). In recent years, initial studies successfully used this dataset that is derived from the subsidy-payments to the farmers to analyse agricultural land use change (Lüker-Jans et al., 2016; Tomlinson, Dragosits, Levy, Thomson, & Moxley, 2018) and farm-level agriculture characterization (Lomba et al., 2017; Uthes, Kelly, & König, 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 study of Brandenburg, Germany. While landscape metrics are most frequently applied to grids and administrative areas, we use hexagons. They have shown to better capture spatially continuous phenomena such as agricultural landscapes because of their spatial smoothing effect towards the edges of the hexagons (Birch, Oom, & Beecham, 2007; Schindler, Poirazidis, & Wrbka, 2008). The outcomes of this study may provide an important asset for providing new units of analysis for better-tailored environmental and agricultural policies depending on the local to regional characteristics.

2 Material and Methods

2.1 Study Area

We focus on the state of Brandenburg, which is located in the northeast of Germany covering 29.640 km² of which 45% are used for agriculture (Figure 1). Ongoing pressure on agricultural land to convert into residential land is observed in the suburban areas of Berlin, while an increasing demand for regional food production can also be observed. At the same time, Gutzler et al. (2015) anticipate an increased use of cropland for renewable energy production. Farms in Brandenburg are comparatively large, around 240 ha, four times the German average (Gutzler et al., 2015). In addition, general low soil quality with almost two-thirds being sandy and sandy-loamy soils, low rainfall at only 591 mm/year and a high technological level characterise the agricultural land use. Compared to other German states, Brandenburg shows a relatively high share of organic agriculture (12 % of agricultural area) that is further increasing in recent years (Ministerium für Landwirtschaft, Umwelt und Klimaschutz [MLUK], 2019).

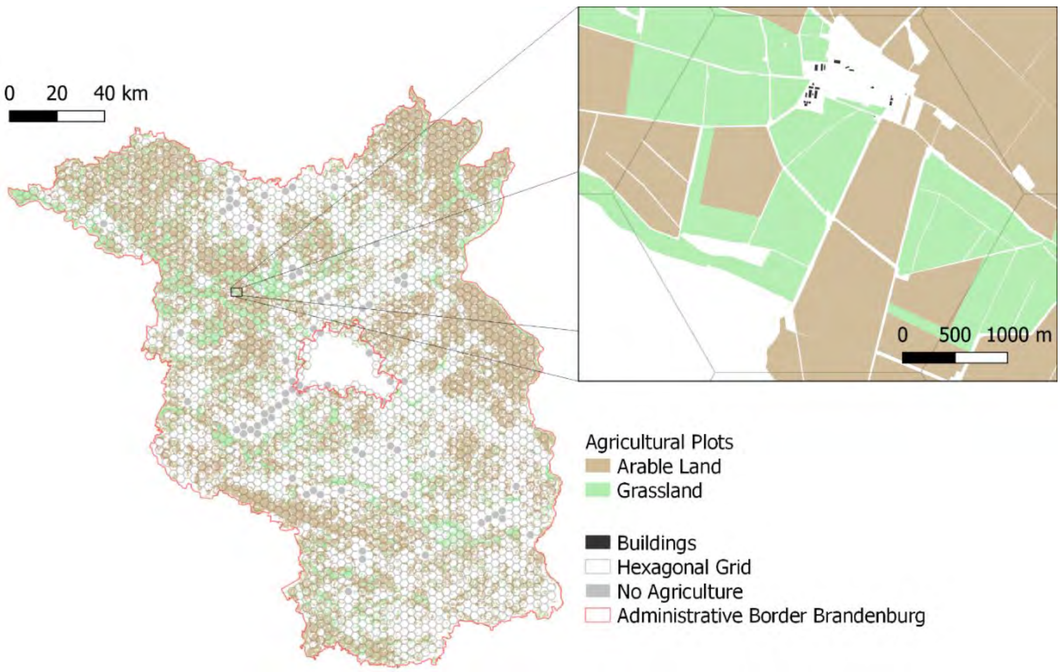

Figure 1: Agricultural land use and hexagons grid outline of the state of Brandenburg, Germany.

2.2 Data

We used plot-based information on cultivation for Brandenburg agriculture in 2018 (reported for 31.5.2018) provided by the Integrated Administration and Control System (IACS). We selected and reclassified the data into the categories: grassland, cropland, and maize as a single crop. We also derive the plot sizes and edges and if a plot is managed conventionally or organically. In addition, we use Open Street Map (OSM) data on buildings and soil quality data that captures the yield potential (Bundesanstalt für Geowissenschaften und Rohstoffe, 2014).

2.3 Methods

We created a hexagonal grid with a cell size of 10 km² (N = 2836; 178 were deleted because of missing data). The size of the cells captured the landscape level and the spatial configuration of plots within. We selected the following indicators to assess different types of agricultural landscapes based on a literature review: soil quality (values from 0-100), number of buildings (N), edge density (calculated as share of total hexagon area, in km/10km²), median plot size (ha), organic share of total agricultural area (%), maize share of total agricultural (%), cropland share (%), Shannon Diversity Index, share agriculture of total area (%) and mean distance to settlements (km). 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. (2013), the expansion of maize is expected to be on par with intensification of crop production. We calculated the respective indicator values for the year of 2018 for the hexagons. To reduce redundancies in the datasets we calculated Spearman's correlation coefficients (Lausch & Herzog, 2002) and dropped those indicators with a correlation of 0,4 or more, i.e. share of agriculture, Shannon's Diversity Index, distance to settlements. We then applied a cluster analysis on the remaining 7 indicators: number of buildings, soil quality, median plot size, edge density and share of cropland, maize and organic agriculture. The Two-Step clustering offers the advantage automatic determination of the optimum number of clusters and was originally developed for large datasets by Chiu, Fang, Chen, Wang, and Jeris (2001). For validation of the cluster number, the model fit was evaluated by the silhouette coefficient, which is a measure of cohesion and separation of clusters. A value above 0,2 thereby indicated a fair quality of clusters (Tkaczynski, 2017).

To measure spatial autocorrelation for the categorical cluster values, we calculated the join count (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

We identified 6 different types of agricultural landscapes in Brandenburg: 1 Peri-urban, 2 High Fragmentation, 3 Low Fragmentation, 4 High Intensity, 5 Low Intensity (marginal grasslands), 6 Organic Production (see Table 1). The Two-Step clustering for these 6 clusters returned the best results with relatively low Bayesian Information Criterion (BIC) values (7894,076) and distance measure is the highest (1,546). A The silhouette measure of cluster cohesion and separation indicates a fair quality (0,3) for these 6 clusters.

Table 1: Centroid of clusters with indication of lowest (green) and highest (red) values

	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

More specifically, the identified types of agricultural landscapes can be characterised as the following:

Cluster 1 (**Peri-Urban**: 5,8 % of all clusters, N = 149) can be described as the peri-urban agriculture cluster mainly characterised by very high mean numbers of 3206 buildings (Table 1). Hence, mean share of agricultural area is lowest amongst the clusters with a calculated average of 24,5 %. Consequently, edge density is also relatively low (mean 5,0 km/10 km²). With the lowest average median plot size (3,0 ha) plots in this cluster tend to be smaller than plots in other clusters. Share of maize and cropland in general tend to be lower than in the other clusters. Additionally, the areas of this cluster are characterised by lower soil quality (49,4) in terms of yield potential.

Cluster 2 (**High Fragmentation**: 36,1 % of all clusters, N = 933) characteristics are that of high fragmentation and high mean of agriculture share (66,0 %). Cropland share in general and particularly share of maize is relatively high.

On the contrary, **Cluster 3** (**Low Fragmentation**: 22,4 % of all clusters, N = 579) is characterized by low fragmentation of the agricultural landscape explained by a low mean agriculture share of 25,5 %. Furthermore, it shows a high share of cropland, relatively high soil quality and low edge density. The landscape is generally not characterised by agriculture, but other land covers 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 share of cropland (93,7 %) and maize (20,5 %).

Cluster 5 (**Low Intensity**: 15,6 % of all clusters, N = 404) mainly represents marginal grasslands with a mean agriculture share of 44,5 %. The low soil quality (47,2) leads to plots mainly used for grassland (low share of cropland = 35,7). Compared to other clusters (except 6) grassland is thereby 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 %.

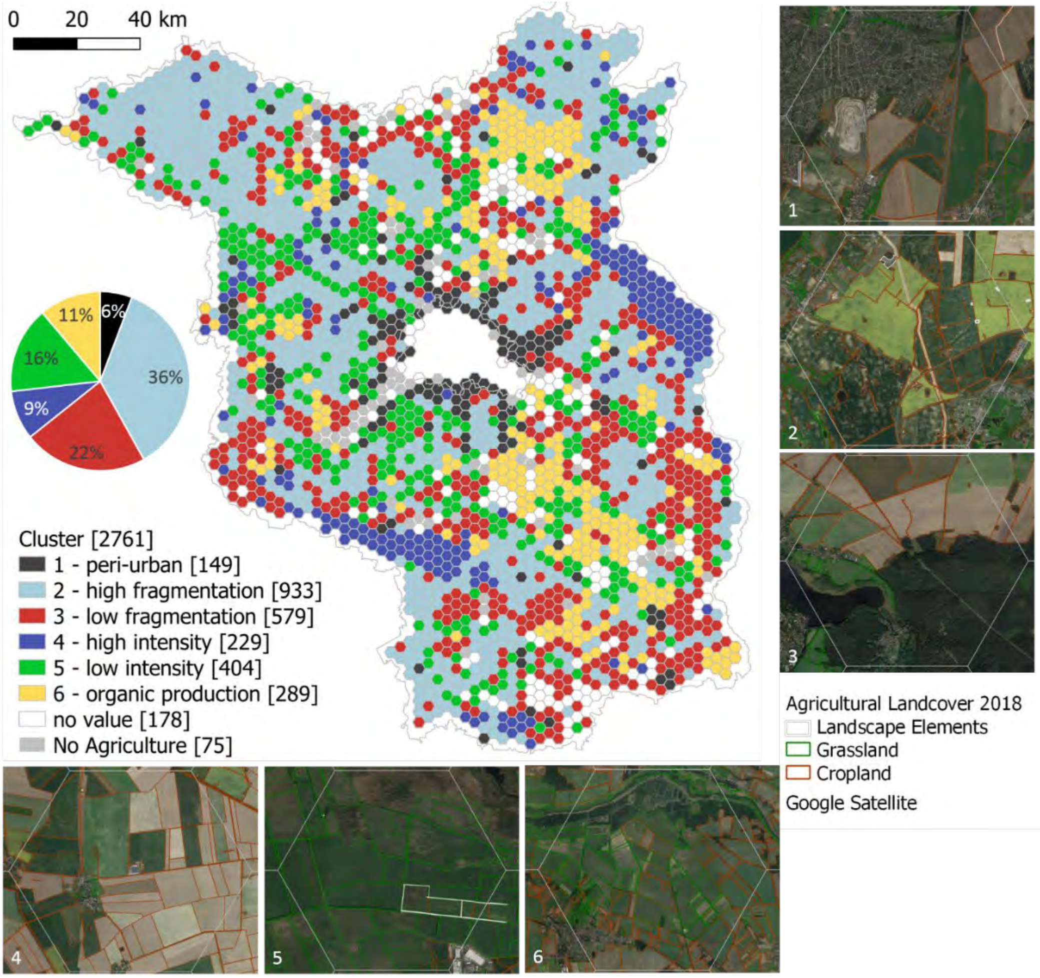

Figure 2: Map and exemplary satellite imagery (Google) of Agricultural Land Use clusters in Brandenburg 2018

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 production' might be that it occurs often in nature preserves under stringent conditions (Venghaus & 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 & 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.

4 Discussion

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). Our types thereby also include information on composition, diversity and intensity based on a plot-based analysis instead of representing a single indicator (e.g. soil quality). They can help to understand the agricultural landscape structure in Brandenburg and identify regions where monitoring and specified support measures are necessary.

Typologies of Brandenburg's agriculture have been created mainly through farmer decisions with reference to renewable energy production (Venghaus & Acosta, 2018). Thereby the farmer is the decision-making "designer" of agricultural landscapes whereby we used landscape metrics as input for typologising agriculture. Consistent with Lüker-Jans et al. (2016) using k-means clustering, we identified similar agricultural types focused on cropland share with maize as a particular crop. In contrast to our hexagons providing a smooth surface allowing the unambiguous definition of neighbourhoods for the study area, they analyze metrics on a municipal level which provides higher variance in shape and size than grid-based analysis. In general, landscape metrics prove to be an adequate tool for analysing configuration and composition of landscapes. 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. Other studies have used remote sensing, e.g. to identify patchiness of the agricultural landscape (Weissteiner, García-Feced, & Paracchini, 2016). The analysis on a finer spatial scale could enable the possibility of investigating finer landscape structures and, additionally, changes in e.g. agricultural composition. A common problem in ecological analysis of spatial indicators is scale. Scale dependence can be addressed by sensitivity analysis via up- and downscaling the grid cell size and can be applied in further studies. Oberlack et al. (2019) emphasised that archetypes can help tailor intensification strategies to particular contexts. Additionally, to increase the quality of the "archetypes", Eisenack et al. (2019) proposed a framework to merge quantitative and qualitative approaches. However, 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 thereby the high possibility of transferability to other study regions.

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 high spatial clustering of high intensity 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 is, according to Thomson et al. (2019), a fundamental connection between the diverse array of relevant disciplines at the plant to field level and can inform national and global decision making. Future work will focus on relations of these different types with land price development, ownership patterns and trade-offs for example between food and energy production.

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References

Bichler, B., & Häring, A. M. (2003). Die räumliche Verteilung des ökologischen Landbaus in Deutschland und ihre Bestimmungsgründe. Retrieved from https://orgprints.org/5046/1/5046-02OE469-uni-hohenheim-2003-raeuml-verteilg.pdf

Birch, C. P.D., Oom, S. P., & Beecham, J. A. (2007). Rectangular and hexagonal grids used for observation, experiment and simulation in ecology. *Ecological Modelling*, *206*(3-4), 347–359. https://doi.org/10.1016/j.ecolmodel.2007.03.041

Bundesanstalt für Geowissenschaften und Rohstoffe (2014). Ackerbauliches Ertragspotential der Böden in Deutschland. Retrieved from https://www.bgr.bund.de/DE/Themen/Boden/Ressourcenbewertung/Ertragspotential/Ertragspotential_node.html

Chiu, T., Fang, D., Chen, J., Wang, Y., & Jeris, C. (2001). *A robust and scalable clustering algorithm for mixed type attributes in large database environment*. Retrieved from KDD '01: Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining website: http://dl.acm.org/citation.cfm?id=502549

Eisenack, K., Villamayor-Tomas, S., Epstein, G., Kimmich, C., Magliocca, N., Manuel-Navarrete, D., . . . Sietz, D. (2019). Design and quality criteria for archetype analysis. *Ecology and Society*, *24*(3). https://doi.org/10.5751/ES-10855-240306

European Union (2019). THE POST-2020 COMMON AGRICULTURAL POLICY: ENVIRONMENTAL BENEFITS AND SIMPLIFICATION. Retrieved from https://ec.europa.eu/info/sites/info/files/food-farming-fisheries/key_policies/documents/cap-post-2020-environ-benefits-simplification_en.pdf

Fachagentur Nachwachsende Rohstoffe e. V. (2013). *Biogas an introduction*. Retrieved from https://mediathek.fnr.de/media/downloadable/files/samples/b/r/brosch.biogas-2013-en-web-pdf.pdf

Gutzler, C., Helming, K., Balla, D., Dannowski, R., Deumlich, D., Glemnitz, M., . . . Zander, P. (2015). Agricultural land use changes – a scenario-based sustainability impact assessment for Brandenburg, Germany. *Ecological Indicators*, *48*, 505–517. https://doi.org/10.1016/j.ecolind.2014.09.004

Kizos, T., & Koulouri, M. (2006). Agricultural landscape dynamics in the Mediterranean: Lesvos (Greece) case study using evidence from the last three centuries. *Environmental Science & Policy*, *9*(4), 330–342. https://doi.org/10.1016/j.envsci.2006.02.002

Landesamt für Ländliche Entwicklung, Landwirtschaft und Flurneuordnung (2016). Datensammlung für die betriebswirtschaftliche Bewertung landwirtschaftlicher Produktionsverfahren im Land Brandenburg. Retrieved from https://lelf.brandenburg.de/media_fast/4055/Datensammlung%202016_web.pdf

Lausch, A., & Herzog, F. (2002). Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability. *Ecological Indicators*, *2*(1), 3–15. https://doi.org/10.1016/S1470-160X(02)00053-5

Lomba, A., Strohbach, M., Jerrentrup, J. S., Dauber, J., Klimek, S., & McCracken, D. I. (2017). Making the best of both worlds: Can high-resolution agricultural administrative data support the assessment of High Nature Value farmlands across Europe? *Ecological Indicators*, *72*, 118–130. https://doi.org/10.1016/j.ecolind.2016.08.008

Lüker-Jans, N., Simmering, D., & Otte, A. (2016). Analysing Data of the Integrated Administration and Control System (IACS) to Detect Patterns of Agricultural Land-Use Change at Municipality Level. *Landscape Online*, *48*, 1–24. https://doi.org/10.3097/LO.201648

Ministerium für Landwirtschaft, Umwelt und Klimaschutz (2019). Massnahmeprogramm Oekologische Produktion. Retrieved from https://mluk.brandenburg.de/sixcms/media.php/9/Massnahmeprogramm_Oekologische_Produktion.pdf

Oberlack, C., Sietz, D., Bürgi Bonanomi, E., Bremond, A. de, Dell'Angelo, J., Eisenack, K., . . . Villamayor-Tomas, S. (2019). Archetype analysis in sustainability research: meanings, motivations, and evidence-based policy making. *Ecology and Society*, *24*(2). https://doi.org/10.5751/ES-10747-240226

Rounsevell, M.D.A., Annetts, J.E., Audsley, E., Mayr, T., & Reginster, I. (2003). Modelling the spatial distribution of agricultural land use at the regional scale. *Agriculture, Ecosystems & Environment*, *95*(2-3), 465–479. https://doi.org/10.1016/S0167-8809(02)00217-7

Ruiz-Martinez, I., Marraccini, E., Debolini, M., & Bonari, E. (2016). *Indicators of agricultural intensity and intensification: A review of the literature*. Retrieved from https://hal.archives-ouvertes.fr/hal-01277628/document

Schaller, L., Targetti, S., Villanueva, A. J., Zasada, I., Kantelhardt, J., Arriaza, M., . . . Viaggi, D. (2018). Agricultural landscapes, ecosystem services and regional competitiveness—Assessing drivers and mechanisms in nine European case study areas. *Land Use Policy*, *76*, 735–745. https://doi.org/10.1016/j.landusepol.2018.03.001

Schindler, S., Poirazidis, K., & Wrbka, T. (2008). Towards a core set of landscape metrics for biodiversity assessments: A case study from Dadia National Park, Greece. *Ecological Indicators*, *8*(5), 502–514. https://doi.org/10.1016/j.ecolind.2007.06.001

Schmidtner, E., Lippert, C., Engler, B., Häring, A. M., Aurbacher, J., & Dabbert, S. (2012). Spatial distribution of organic farming in Germany: does neighbourhood matter? *European Review of Agricultural Economics*, *39*(4), 661–683. https://doi.org/10.1093/erae/jbr047

Shriar, A. J. (2000). Agricultural intensity and its measurement in frontier regions. *Agroforestry Systems*, *49*(3), 301–318. https://doi.org/10.1023/A:1006316131781

Temme, A.J.A.M., & Verburg, P. H. [P. H.] (2011). Mapping and modelling of changes in agricultural intensity in Europe. *Agriculture, Ecosystems & Environment*, *140*(1), 46–56. https://doi.org/10.1016/j.agee.2010.11.010

Thomson, A. M. [Allison M.], Ellis, E. C., Grau, H. R., Kuemmerle, T., Meyfroidt, P., Ramankutty, N., & Zeleke, G. (2019). Sustainable intensification in land systems: trade-offs, scales, and contexts. *Current Opinion in Environmental Sustainability*, *38*, 37–43. https://doi.org/10.1016/j.cosust.2019.04.011

Thünen Institut (2014). Der Thünen Agraratlas. Retrieved from https://www.thuenen.de/de/infrastruktur/thuenen-atlas-und-geoinformation/thuenen-atlas/

Tkaczynski, A. (2017). Segmentation Using Two-Step Cluster Analysis. In T. Dietrich, S. Rundle-Thiele, & K. Kubacki (Eds.), *Segmentation in Social Marketing: Process, Methods and Application* (pp. 109–125). Singapore: Springer Singapore; Imprint: Springer. https://doi.org/10.1007/978-981-10-1835-0_8

Tomlinson, S. J., Dragosits, U., Levy, P. E., Thomson, A. M. [Amanda M.], & Moxley, J. (2018). Quantifying gross vs. Net agricultural land use change in Great Britain using the Integrated Administration and Control System. *The Science of the Total Environment*, *628-629*, 1234–1248. https://doi.org/10.1016/j.scitotenv.2018.02.067

Uthes, S., Kelly, E., & König, H. J. (2020). Farm-level indicators for crop and landscape diversity derived from agricultural beneficiaries data. *Ecological Indicators*, *108*, 105725. https://doi.org/10.1016/j.ecolind.2019.105725

Uuemaa, E., Mander, Ü., & Marja, R. (2013). Trends in the use of landscape spatial metrics as landscape indicators: A review. *Ecological Indicators*, *28*, 100–106. https://doi.org/10.1016/j.ecolind.2012.07.018

Venghaus, S., & Acosta, L. (2018). To produce or not to produce: an analysis of bioenergy and crop production decisions based on farmer typologies in Brandenburg, Germany. *Regional Environmental Change*, *18*(2), 521–532. https://doi.org/10.1007/s10113-017-1226-1

Weissteiner, C. J., García-Feced, C., & Paracchini, M. L. (2016). A new view on EU agricultural landscapes: Quantifying patchiness to assess farmland heterogeneity. *Ecological Indicators*, *61*, 317–327. https://doi.org/10.1016/j.ecolind.2015.09.032

Zasada, I., Loibl, W., Berges, R., Steinnocher, K., Köstl, M., Piorr, A., & Werner, A. (2013). Rural–urban Regions: A Spatial Approach to Define Urban–Rural Relationships in Europe. In K. Nilsson (Ed.), *Peri-urban futures: Scenarios and models for land use change in Europe* (pp. 45–68). Heidelberg: Springer. https://doi.org/10.1007/978-3-642-30529-0_3