



Higher crop rotational diversity in more simplified agricultural landscapes in Northeastern Germany

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Abstract

Context Both crop rotational diversity and landscape diversity are important for ensuring resilient agricultural production and supporting biodiversity and ecosystem services in agricultural landscapes. However, the relationship between crop rotational diversity and landscape diversity is largely understudied.

Objectives We aim to assess how crop rotational diversity is spatially organised in relation to soil, climate, and landscape diversity at a regional scale in Brandenburg, Germany.

Methods We used crop rotational richness, Shannon's diversity and evenness indices per field per

decade (i.e., crop rotational diversity) as a proxy for agricultural diversity and land use and land cover types and habitat types as proxies for landscape diversity. Soil and climate characteristics and geographical positions were used to identify potential drivers of the diversity facets. All spatial information was aggregated at 10 × 10 km resolution, and statistical associations were explored with interpretable machine learning methods.

Results Crop rotational diversity was associated negatively with landscape diversity metrics and positively with soil quality and the proportion of agricultural land use area, even after accounting for the other variables.

Conclusion Our study indicates a spatial trade-off between crop and landscape diversity (competition for space), and crop rotations are more diverse in more

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simplified landscapes that are used for agriculture with good quality of soil conditions. The respective strategies and targets should be tailored to the corresponding local and regional conditions for maintaining or enhancing both crop and landscape diversity jointly to gain their synergistic positive impacts on agricultural production and ecosystem management.

Keywords Cropping systems · Explainable artificial intelligence · Land use · Landscape heterogeneity · Multiple scales · Soil quality

Introduction

Intensive agricultural activities have contributed to the simplification of landscapes. Landscape is defined as “*area that is spatially heterogeneous in at least one factor of interest*” (Turner et al. 2001), where the “*spatially arranged entities are structurally and functionally interconnected*” (Pereponova et al. 2023). Simplified agricultural landscapes are characterised by high shares of land dedicated to agricultural production which reduces overall habitat availability and diversity, as well as containing relatively low numbers of crop types and consequently declining biodiversity (Benton et al. 2003; Landis 2017; Pretty 2018; Tschardt et al. 2005). Biodiversity and related ecosystem services play an essential role to secure the resilience of agricultural production and cultivating agricultural landscapes in line with the Sustainable Development Goals (Bullock et al. 2017; Dainese et al. 2019; Grab et al. 2018; Kovács-Hostyánszki et al. 2017; Rusch et al. 2016).

To cope with the ongoing simplification the structural and functional complexity of agricultural landscapes can be maintained or enhanced at both landscape and agricultural system levels (i.e., landscape diversity and agricultural diversity). Landscape diversity (i.e., land use diversity at a landscape level) determines biodiversity relevant to agricultural systems: bird taxonomic and functional diversity (Martínez-Núñez et al. 2023), plant species richness (Honnay et al. 2003), farmland arthropod diversity, especially regarding vegetation-dwelling taxa (Marja et al. 2022), pollinator abundance and richness (Kovács-Hostyánszki et al. 2017), and natural enemies (Chaplin-Kramer et al. 2011; Grab et al. 2018) that can regulate pests as an ecosystem service (Rusch et al.

2016). Moreover, landscape diversity can have a positive effect on yield for various crop types (Galpern et al. 2020; Nguyen et al. 2022).

In addition to landscapes, diversification can target explicitly the agricultural system. Diversification of agricultural systems can foster multiple ecosystem services in an agricultural landscape without compromising crop yield (Tamburini et al. 2020). Diversifying cropping systems, which is a large aspect of agricultural diversification, can support sustainable agricultural landscapes and resilient food production (Hufnagel et al. 2020; Rosa-Schleich et al. 2019; Tschardt et al. 2021). For example, crop diversity can be increased by targeting the spatial arrangement of different crop types within the landscape or by addressing the temporal sequence of different crop types within a field (Hufnagel et al. 2020; Kremen et al. 2012). Diverse crop rotations could increase yields (Bowles et al. 2020; Davis et al. 2012; Degani et al. 2019; Smith et al. 2023), reduce yield variability (Reckling et al. 2022), reduce weed infestation (Weisberger et al. 2019), and require fewer synthetic agrochemicals during cultivation (Davis et al. 2012; Guinet et al. 2023; Smith et al. 2023). Rotations can reduce soil erosion by up to 60% compared to continuous cropping (Hunt et al. 2019), enhance disease suppressing soil properties (Zhou et al. 2023), and soil-related ecosystem services such as decomposition could be improved (McDaniel et al. 2016).

Notably, diversifying crop rotations can also scale up the effect to the landscape level and contribute to landscape diversity by changing the spatial landscape mosaic over time and therefore should be considered as a key temporal dynamic of agricultural landscapes (Marrec et al. 2022). However, in comparison to spatial landscape aspects, the temporal diversity of cropland has been less considered within the landscape mosaic context (Marrec et al. 2022). This highlights the need to understand better how temporal crop diversity and spatial landscape diversity are related to each other, which has not been studied in the field of landscape ecology. Previous studies suggest that crop rotational diversity is spatially structured in relation to soil and climate conditions in Sweden (Sjulgård et al. 2022) and climate and farm inputs in the US (Spangler et al. 2022). Higher crop rotational diversity might be observed in more diverse landscapes because diverse landscapes can provide various and

stable ecosystem services important for several crop types such as pollination and pest control (Galpern et al. 2020; Nguyen et al. 2022). Oppositely, it is also equally possible that higher crop rotational diversity is observed in more simplified agricultural landscapes because large farms tend to manage more diverse crop rotations (Jänicke et al. 2022). Knowing these patterns and drivers is a prerequisite for improving landscape management, especially addressing both biodiversity loss and agricultural resilience and sustainability through the joint consideration of agricultural systems and the surrounding land use (Khan et al. 2023; Sietz et al. 2022; Sirami et al. 2019). Transferring existing findings from diversity research (i.e. the positive roles of the landscape in agriculture and the interaction with agricultural diversification) into practice based on synergy or trade-off dynamics may depend on geographically determined site conditions.

Our study aims to understand how crop rotational diversity is spatially organised in relation to soil, climate, and landscape diversity at a regional scale. We look at the case study region of Brandenburg in Germany, as it has a high proportion of agricultural land and does not provide optimal conditions for agriculture due to low precipitation rates and sandy soils (Gutzler et al. 2015; Ihinegbu and Ogunwumi 2021; Kipping, 2020). For the Brandenburg region, we analyse the landscape within grid cells of 10 km resolution the agricultural diversity by its crop rotational diversity per field over a 10-year period, and the landscape diversity using habitat and land use land cover (LULC) classes, as well as the suitability of the local soil quality (SQR) for arable and grassland farming, climate conditions, and geographical location. We (i) explore the links between landscape diversity, crop rotational diversity, and other influencing geographic and biophysical factors, (ii) identify the importance of predictor variables on crop rotational diversity and (iii) test how different facets of landscape diversity affect it. To address context dependency, we employ interpretable machine learning (ML) techniques in the domain of explainable artificial intelligence (xAI). They have recently gained attention in the field of agriculture to identify nonlinear, non-additive statistical associations that cannot be captured with conventional statistical methods and therefore enhance the understanding of complex ML model predictions for humans (Ryo 2022).

Materials and methods

Study region

The study region is the federal state of Brandenburg, Germany. With ca. 29,654 km² it is the fifth biggest federal state of Germany and has a population of ca. 2.5 million inhabitants (Ministerium für Landwirtschaft, Umwelt und Klimaschutz des Landes Brandenburg (MLUK), 2021). Brandenburg is characterised by a large proportion of agricultural land use, which occupies about 45% of its land surface (Amt für Statistik Berlin-Brandenburg 2022). The overall mean size of farms in Brandenburg is 242 ha, which is larger compared to the rest of Germany, where the overall mean farm size is about 63 ha (Ministerium für Landwirtschaft, Umwelt und Klimaschutz des Landes Brandenburg (MLUK), 2021). Brandenburg's field sizes have a median of 8 ha which is in comparison to former West German states like Bavaria (1.6 ha) and Lower Saxony (2.8 ha) much larger (Jänicke et al. 2022). The region of Brandenburg contains a high share of sandy and loamy soils with low water retention capacity. The long-term average annual precipitation is below 600 mm (Gutzler et al. 2015; Ihinegbu and Ogunwumi 2021; Kipping, 2020). Agricultural production is increasingly limited by water scarcity, in particular, because of frequent drought periods in spring, when the crop water demand is highest (Gutzler et al. 2015). The effects of climate change, which already have started to affect temperature and alter precipitation, entail challenges for agricultural production and yield stability.

Datasets

We collected and processed several spatial maps including crop type, habitat type, LULC type, soil, and climate conditions (Table 1).

Agricultural and landscape diversity

In this study we assessed agricultural and landscape diversity as two different levels of diversity. The agricultural diversity was represented by the crop rotational diversity. We used data from the Integrated Administration and Control System (IACS) database (MLUK) as it is the only source known to us that has been collecting field management

Table 1 List of spatial maps and variables used in this study. Data sources include crop maps by integrated administration and control system (IACS), colour-infrared biotop map (CIR2009), and corine land cover map (CLC18)

Measures	Units	Description	Original resolution	Data source
Agricultural field level				
Crop rotational richness	Absolute numbers	Mean of unique number of crop types per field from 2011–2020 per 10×10 km grid cell	1:4800, (rasterised to 100 m)	IACS (2011–2020)
Crop rotational diversity	Shannon's diversity index	Mean of the Shannon's diversity index of crop types per field from 2011–2020 per 10×10 km grid cell	1:4800, (rasterised to 100 m)	IACS (2011–2020)
Crop rotational evenness	Shannon's evenness index	Mean of the Shannon's evenness index of crop types per field from 2011–2020 per 10×10 km grid cell	1:4800, (rasterised to 100 m)	IACS (2011–2020)
Landscape level				
Habitat richness	Absolute numbers	Total number of unique habitat classes (n = 12) per 10×10 km grid cell	1:3000 (rasterised to 100 m)	CIR2009
Habitat diversity	Shannon's diversity index	Shannon's diversity index of habitat classes per 10×10 km grid cell	1:3000 (rasterised to 100 m)	CIR2009
Habitat evenness	Shannon's evenness index	Shannon's evenness index of habitat classes per 10×10 km grid cell	1:3000 (rasterised to 100 m)	CIR2009
Habitat edge density	Meters per hectare	Patchiness of habitat classes per 10×10 km grid cell	1:3000 (rasterised to 100 m)	CIR2009
Habitat mean patch size	Hectares	Average size of habitat class patches per 10×10 km grid cell	1:3000 (rasterised to 100 m)	CIR2009
LULC richness	Absolute numbers	Total number of unique land use and land cover types (LULC) (n = 44) per 10×10 km grid cell	100 m (reprojected 99.8×99.7 m)	CLC18
LULC diversity	Shannon's diversity index	Shannon's diversity index of LULC types per 10×10 km grid cell	100 m (reprojected 99.8×99.7 m)	CLC18
LULC evenness	Shannon's evenness index	Shannon's evenness index of LULC types per 10×10 km grid cell	100 m (reprojected 99.8×99.7 m)	CLC18
LULC edge density	Meters per hectare	Patchiness of LULC types per 10×10 km grid cell	100 m (reprojected 99.8×99.7 m)	CLC18
LULC mean patch size	Hectares	Average size of LULC type patches per 10×10 km grid cell	100 m (reprojected 99.8×99.7 m)	CLC18
Proportion of agricultural area	Percentage	Proportion of LULC types belonging to agricultural land use per 10×10 km grid cell	100 m (reprojected 99.8×99.7 m)	CLC18

Table 1 (continued)

Measures	Units	Description	Original resolution	Data source
Proportion of artificial surfaces	Percentage	Proportion of LULC types belonging to artificial surfaces per 10×10 km grid cell	100 m (reprojected 99.8×99.7 m)	CLC18
Others				
Soil quality rating	Points	Mean of soil quality rating (SQR) (range 0–102) for croplands per 10×10 km grid cell. The higher the rating, the better the yield potential	250 m (reprojected 259 m)	SQR by BGR
Mean precipitation	mm	Mean of annual precipitation sum in mm from 2011–2020 per 10×10 km grid cell	1000 m	DWD (2011–2020)
Mean temperature	°C	Mean of mean annual temperature in °C from 2011–2020 per 10×10 km grid cell	1000 m	DWD (2011–2020)

information for Brandenburg over many years. The IACS database is used for the management of agricultural subsidies by the Common Agricultural Policy of the European Union and contains spatial information on which crop types are cultivated per field. 206,493 field centroids were used as references and the crops reported for them were summarised into 19 important crop types and grassland classes, which correspond to the selection of Blickensdörfer et al. (2022; Table 2). After removing field centroids that contained no data, over 10 years the majority of fields contained grassland (37.83% over the total number of fields) which included permanent grassland that was not tilled and not part of arable rotations, and temporal grassland (for often 2–4 years) part of arable rotations with annual crops, followed by winter rye (10.15%), silage maize (8.34%), winter wheat (5.98%), legumes (4.04%), and oilseed rape (3.98%) (more details in supplementary material SM Fig. S1). Note that the proportion is different from the relative area. Each remaining data point represents per field one crop type from the crop classification scheme (Table 2). The diversity is assessed by computing the diversity index per field over time (2011–2020) and aggregating this information per 10×10 km grid cell by using the mean of the field data.

For the landscape level diversity, we included the number of habitat classes and the number of LULC types in a given area of 10×10 km. Habitat classes were obtained from the CIR2009 database (Landsamt für Umwelt (LfU), 2013a). Habitat type classification is based on *Flächendeckende Biotop- und Landnutzungskartierung* (BTLN) classification scheme which consists of about 2500 different individual habitat types using CIR aerial imagery (Landsamt für Umwelt (LfU), 2013b). We aggregated habitat information using twelve overarching habitat classes according to the BTLN classification scheme (SM Table S1). The habitat diversity variables can serve as an indicator of ecosystem diversity to include the aspect of biodiversity within the landscape. LULC were taken from the CORINE (Coordination of Information on the Environment) 2018 dataset (European Environment Agency (EEA), 2021). The CORINE 2018 LULC map includes a total of 44 different types (level 3) which were identified from satellite imagery data. In Brandenburg only 28 of the LULC types were present. LULC diversity indices per grid cell can be interpreted as a measure of land use diversity from a human-centred perspective. The two landscape level datasets have similarities but differ in their methodology and intended use. The respective diversity is assessed per 10×10 km grid cell.

Table 2 Crop type and grassland classes used for the calculation of the variables at the agricultural field level

Crop classes
Maize (grain)
Maize (silage, including sorghum)
Winter wheat
Winter barley
Winter rye
Winter triticale and spelt
Spring wheat, triticale and rye
Spring barley
Spring oat
Winter oilseed rape (including other Brassica)
Sugar beet (including other Beets)
Potato
Legumes (Pea, Bean, Lupin, Soybean, Lentil, Chickpea, Lucerne, and other Legumes)
Other leafy vegetables (Vegetables, Solanaceae, Vegetable Brassicaceae)
Sunflower
Onion
Carrot
Grassland (permanent and temporary)
Others (Buckwheat, Flax, Oilcrop, Hemp, other crop types and agricultural land use that are not listed)

Measuring diversity

In this study we used several indices to account for compositional and configurational aspects of diversity. Compositional diversity was assessed using the following indices: We measured the richness of types by counting the total number of different types. Shannon's diversity index (SDI) was included to represent the proportional abundance (P_i) of different types (i), where m is the total number of different types (Eq. 1) (Hesselbarth et al. 2019):

$$SDI = \sum_{i=1}^m (P_i \star \ln P_i) \quad (1)$$

Shannon's evenness (SEI) reflects the distribution of types (i) according to their overall abundance which helps to characterise if dominant types are present. Therefore, it can be considered as a measure of dominance (Eq. 2) (Hesselbarth et al. 2019):

$$SEI = \frac{-\sum_{i=1}^m (P_i \star \ln P_i)}{\ln m} \quad (2)$$

To take into account areas that are mainly dominated by human land activities we computed the

proportion of agricultural and artificial surfaces per grid cell.

Configurational aspects of the landscape diversity were measured by using the mean patch size per grid cell to reflect the overall size of the patches within a grid cell and edge density to consider for its patchiness (Eq. 3). Edge density (ED) is computed by the total edge length in meters (e_{ik}) divided by the total area (A) (Hesselbarth et al. 2019):

$$ED = \frac{\sum_{k=1}^m e_{ik}}{A} \star 1000 \quad (3)$$

Soil, climate and geographical properties

The influence of the geographical position on the diversity status was considered by including the X and Y coordinates to account for latitude and longitude. To identify further potential drivers, we collected soil quality and the climate characteristics of precipitation and temperature as they have been mentioned to be influencing factors on crop growth in other study sites (Sjulgård et al. 2022; Spangler et al. 2022).

The soil quality was assessed using the estimated yield potential for arable and grassland farming. One indicator for yield potential is the Müncheberger soil quality rating (SQR) (Bundesanstalt für Geowissenschaften und Rohstoffe (BGR), 2013). SQR is a point estimator of crop yield potential (Müller 2007). It results from a complex assessment of (i) scoring, weighting and summarizing basic soil indicators according to poor, medium and good local conditions and (ii) paring them with soil hazard indicators that can substantially limit soil properties for farming (Müller 2007). This results in an overall indicator expressing the long-term suitability of soil conditions for arable and grassland farming in terms of yield potential. The initial SQR indicator was assessed by in-field measurements (Müller 2007). The BGR adapted the indicator in a way that SQR can be assessed by aerial images (Bundesanstalt für Geowissenschaften und Rohstoffe (BGR), 2013). This leads to a soil quality map indicating soil quality with a point range from 0 to 102, while the minimal value in this study was 40 at the 10×10 km scale. The higher the SQR value the higher the yield potential of the soil.

Annual climate data for precipitation and temperature from 2011 to 2020 were provided by the German Weather Service (Deutscher Wetterdienst (DWD)). They have a resolution of 1000 m. The datasets give information about annual mean temperature in °C and annual precipitation sum in mm. We assessed the mean values as the mean of the 10×10 km grid cell per year and as the mean over 10 years.

Data preprocessing

To aggregate the individual data sets in a common format, we extracted the Brandenburg region and divided it into standardised grid cells of 10×10 km. This allowed us a comparison of $n=356$ grid cells and provided a suitable solution to consider spatial cross-scale links between field and landscape levels. Each 10×10 km grid cell includes information from each input data set in the particular 10×10 km grid cell, which was further used for calculating the required variables (for further details see Table 1). This framework makes it easy to include a diverse set of input data sets in our analysis while ensuring spatial consistency throughout the analysis. We selected a 10×10 km extent for the following analysis because

of the computational efficiency ($n=356$) while preserving the variabilities in the spatial patterns to recognise subregional differences in crop rotational diversity, landscape diversity, soil and weather variables (Fig. 1, 2). Since the fitted models regress the statistical means of the entire data, the key finding would not change even if we just changed the resolution of the spatial unit. However, it is noted that the validity of the findings is not warranted at different scales and should not be applied to explain the patterns at the finer and coarser scales. All geodata were handled and processed in R, using the packages “tidyverse” (Wickham et al. 2019), “raster” (Hijmans 2022), “rasterVis” (Perpiñán and Hijmans 2023), “sf” (Pebesma 2018), “ggspatial” (Dunnington 2023), and “cowplot” (Wilke 2020), and “landscapemetrics” (Hesselbarth et al. 2019) in R version 4.2.2 (2022–10–31 ucrt) (R Core Team 2022).

Data analysis

Correlation analysis

For data exploration, we first conducted a Pearson’s correlation analysis to test the strength and direction of relationships between each of the above-mentioned variables. We visualised our findings in a network diagram that represents correlation coefficients that are higher than 0.4 and lower than -0.4 . Each variable is represented as a node. Lines between the nodes represented for correlation coefficient by colour and width. The Pearson’s correlation results can serve to understand which variables are highly correlated with each other (multicollinearity) for interpreting the results of ML modelling. We used the R packages “PerformanceAnalytics” (Peterson and Carl 2020), “corr” (Kuhn et al. 2022), “igraph” (Csardi and Nepusz 2006), and “ggraph” (Pedersen 2022).

Machine learning application We secondly analysed the data using ML that can estimate the nonlinear, non-additive relationships (Ryo and Rillig 2017). The models assessed the link of the variables (i) crop rotational richness, (ii) crop rotational SDI, and (iii) crop rotational SEI in response to the remaining variables (Table 1).

The first step of data analysis consists of splitting the dataset randomly in training and test data sets using a common splitting ratio of 80:20 (Boehmke

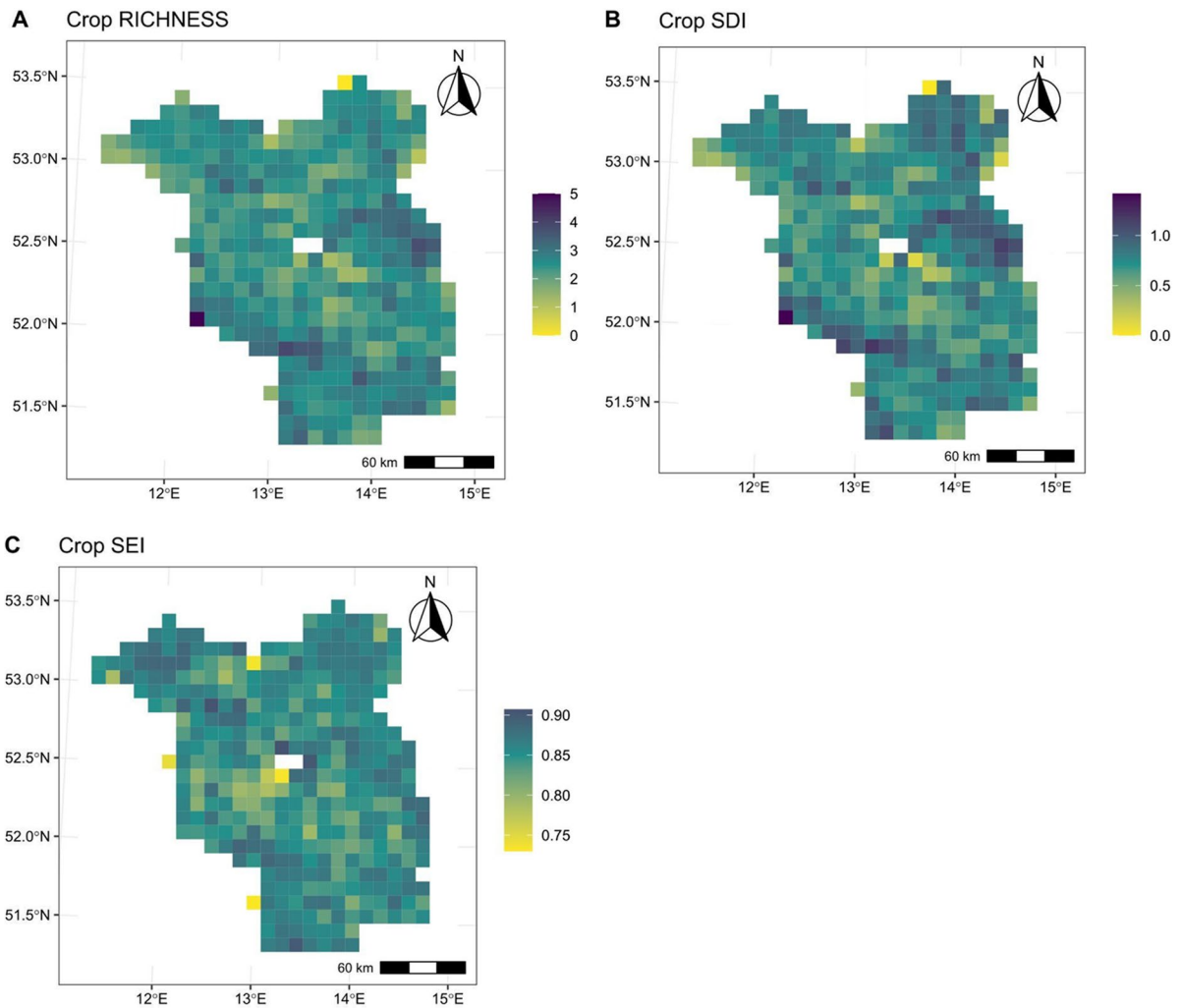


Fig. 1 Maps indicating Brandenburg's crop rotational diversity using (A) richness, (B) Shannon's diversity (SDI), and (C) Shannon's evenness (SEI) index per 10×10 km

and Greenwell 2020). This allows to train each ML model with 80% of the entire dataset ($n=284$ of 356). We created ten different training and test data sets that were used for training each model individually ten times using different random seeds to account for instability of model results pertaining to the relatively small number of data points with potential data imbalance. The training process included a resampling of the training data using fivefold cross-validation to ensure generalizability of model performances (Raschka 2020). For this, the training data was split further into five groups (folds). Then, the model was trained five times while using four ($k-1$) subsets for training the model and one subset for model

evaluation (James et al. 2022). This prevents bias by underrepresentation of particular classes and helps to select hyperparameters by estimating errors in the unseen test data (Boehmke and Greenwell 2020; James et al. 2022; Ryo 2022). Later, each model performance was evaluated by using the remaining 20% of the entire data set ($n=72$ of 356).

We compared four different ML models to find the best model: (i) linear models, (ii) decision trees, (iii) random forests (RF), and (iv) stochastic gradient boosting using the “caret” package as a meta engine (Boehmke and Greenwell 2020). Decision tree model is a simple ML model following a tree structure consisting of if-else splits (Breiman 1984; Hothorn et al.

Pearson's Correlation

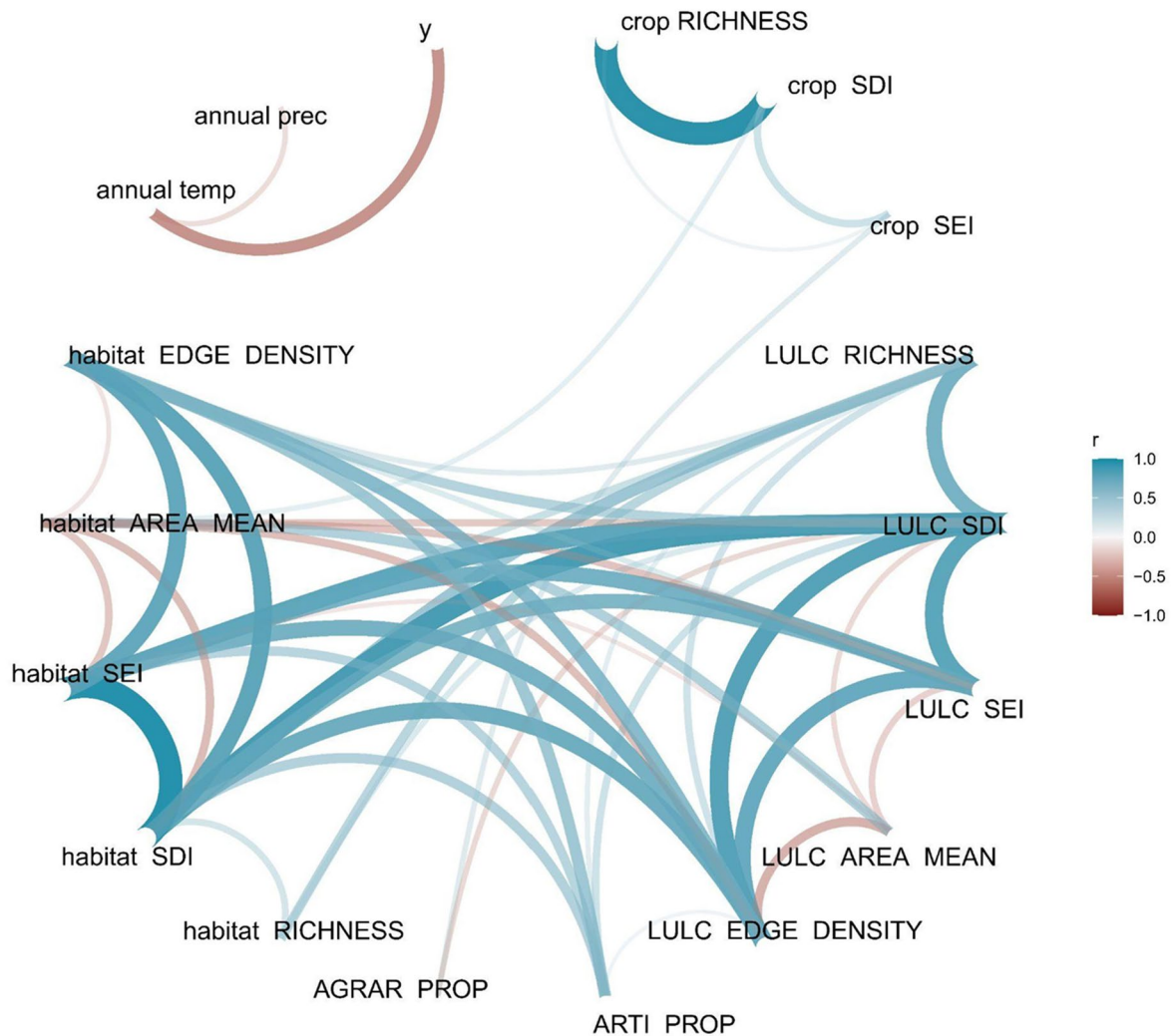


Fig. 2 Pearson's correlation coefficient network shows $|r| > 0.4$ between crop, land use land cover (LULC) and habitat diversity indices (RICHNESS, Shannon's diversity (SDI), and Shannon's evenness (SEI), mean patch size (AREA MEAN), and patchiness (EDGE DENSITY)), proportion of agricultural area (AGRAR PROP), proportion of artificial surfaces (ARTI PROP), mean annual temperature (annual temp), mean annual

precipitation sum (annual prec), and y coordinate (y). The value of the correlation coefficients determines the line appearance between the nodes (variables). Thick and bold-coloured lines indicate a strong correlation coefficient (blue=positive, red=negative), while thin, pale lines indicate a weak correlation coefficient

2006). Linear models and decision trees are relatively easy to interpret (Breiman 2001b; Ribeiro et al. 2016; Ryo 2022). In contrast, the following two ensemble models are more complex and can be considered as black-box models (Breiman 2001b; Ribeiro et al. 2016). RF is a model that combines several decision trees to obtain an overall prediction that is usually

more accurate than those from individual decision trees (Breiman 2001a). Stochastic gradient boosting also uses several decision trees but unlike RF trees are trained sequentially (Friedman 2001).

After training the models, their performances were assessed by using the test data based on R-squared value (i.e. squared correlation coefficient of predicted

and observed values). To ensure the robustness of the model performance, we repeated the training and test procedure ten times with randomization and reported the mean and standard deviations of R-squared values. After evaluating the R-squared value, we selected the model with the overall highest R-squared value for each response variable for the following analysis.

Explainable artificial intelligence analysis Subsequently, we analysed the ML models using xAI methods, which increase the understanding of the model predictions to build trust in the models (Meske and Bunde 2020; Ryo 2022; Ryo et al. 2021). These methods can be used to identify what variables were found to be most important for making predictions and how variable values are associated with the model predictions. We followed the workflow suggested by Ryo (2022) and employed post-hoc methods after the model training. First, we estimated variable importance to explain what variable from the set of given predictor variables has the highest importance for making predictions (Greenwell and Boehmke 2020; Ryo 2022). In this study, we assessed the variable importance by comparing the difference between the unpermuted baseline R-squared value and the R-squared value assessed by permuted predictor variables. Hence, the importance quantifies how much the model performance drops if the model loses the information of each predictor variable (Greenwell and Boehmke 2020; Ryo 2022). Permutations were repeated 30 times ($n_{sim}=30$) to account for model instability and the instability of importance scores was visualised using boxplots, where the thick line represents the median, the body limits the first and the third quartile, and the extended lines the smallest or highest non-outlier value. Outliers were represented using black circles. We used the R packages “caret” (Kuhn 2022), “pdp” (Greenwell 2017), “vip” (Greenwell and Boehmke 2020), “iml” (Molnar et al. 2018).

Furthermore, we created partial dependence plots (PDP) to gain insights into how a particular predictor variable is associated with the response variable (Friedman 2001; Greenwell et al. 2018; Ryo 2022). A PDP shows how a given value of the predictor variable impacts on average the model predictions. To obtain this information the predictor variable was set to a fixed value, while all other predictor variables remained unchanged and the average of predictions was taken (Greenwell et al. 2018).

Results

The crop rotational richness ranged from 1.16 to five different crop types per field over time (10 years) as a mean for each grid cell which reflects fields with continuous cropping with annual crops or permanent grassland, and diverse rotations including cereals and broad leaved crops. The crop rotational richness mean for Brandenburg was 2.5 (Fig. 1; Table S2b in Appendix). The SDI of crop rotations ranged from a minimum of 0.21 to a maximum of 1.14 with a mean of 0.74. The evenness of crop rotation measured with SEI ranged from 0.73 to 0.91 with a mean of 0.85. All diversity indices indicate higher crop rotational diversity in the middle eastern region of Brandenburg (52.5°N, 14.5°E) and in the southwestern border of Brandenburg (51.7°N, 13.2°E). Crop rotational evenness is also relatively high near the northwestern border of Brandenburg (53.2°N, 12.2°E). Minimum and maximum outliers of all crop rotational diversity indices can be found mainly at the borders of Brandenburg.

Pearson's correlation

Pearson's correlation analysis reveals the direction and strength of the relationship between the diversity variables and soil and climate conditions (Fig. 2, correlation matrix in SM Fig. S2). The similarity between habitat classes and LULC types per site could be seen by the following behaviour: LULC SDI and habitat SDI showed a strong correlation ($r=0.86$) and LULC SEI and habitat SEI were strongly correlated, too ($r=0.74$). The relationship between the different diversity indices is represented by the following Pearson's correlation: Richness and SDI were highly correlated (crop SDI and crop richness $r=0.94$; LULC SDI and LULC richness $r=0.73$). A strong correlation was revealed between SDI and SEI indices measured with LULC types and habitat classes (LULC SDI and LULC SEI $r=0.81$; habitat SDI and habitat SEI $r=0.95$). Edge density has a strong correlation with both SDI and SEI diversity indices (LULC SDI and LULC edge density $r=0.82$; LULC SEI and LULC edge density $r=0.78$; habitat SDI and habitat edge density $r=0.8$; habitat SEI and habitat edge density $r=0.79$). Finally, a strong correlation was also detected between LULC SDI and habitat SEI

($r=0.8$), LULC SEI and habitat SDI ($r=0.71$), habitat SDI and LULC edge density ($r=0.76$).

Machine learning

On average, for all response variables, the mean R-squared values of the RF models were the highest compared to those of the other models (Table 3, crop richness R-squared= 0.35 ± 0.09 ; crop SDI R-squared= 0.35 ± 0.03 ; crop SEI R-squared= 0.23 ± 0.11). For this reason, we will highlight the following xAI results based on the RF models. Additionally, based on the high correlation between crop rotational richness and crop rotational SDI, we only show the response of the SDI variable. Variable importance and PDPs of the other response variables can be found in the supplementary material (SM Fig. S3–S5).

For explaining crop rotational diversity measured with SDI, habitat patch mean size was the most important explanatory variable (median ca. 27%), followed by the proportion of agricultural area (median ca. 21%) and SQR (median ca. 14%) (Fig. 3A). For the crop rotational evenness measured with SEI, the most important variables were the proportion of agricultural area (median ca. 58%), followed by the habitat patch mean size (median ca. 11%) and SQR (median ca. 10%) (Fig. 3B).

The PDP indicated a positive nonlinear relationship between habitat patch mean size and crop rotational SDI and SEI (Fig. 4A, F). This is represented by the rapid increase in the predictions of crop rotational SDI and crop rotational SEI between a habitat patch mean size from ca. 25 to 50 hectares before the curve reaches a plateau-a-like state. Similarly, the predicted values of both crop rotational SDI and SEI are higher with an increase in the proportion of agricultural areas (Fig. 4B, G). For crop rotational SDI this positive relationship is represented by the increase of

the curve with an increase of proportion of agricultural area up to ca. 50% (Fig. 4B). For crop rotational SEI, the positive relationship is more evenly shown for the increase of proportion agricultural area up to ca. 75% (Fig. 4G).

Furthermore, a positive relationship between predicted crop rotational SDI and SEI is demonstrated by an increasing SQR value (Fig. 4C, H). For predicted crop rotational SDI the curve shows a plateauing effect when it reaches a SQR of ca. 52 points. Beyond this point, there are only minimal effects between an increase in SQR and crop rotational SDI seen (Fig. 4C). For the predicted crop rotational SEI the plateauing state is seen only from a SQR of 63 points (Fig. 4H).

The relationship between crop rotational SDI and LULC SDI shows a rather negative link with increasing LULC SDI from ca. 0.8 up to 1.7 (Fig. 4D). The relationship is less clear between crop rotational SEI and LULC SEI (Fig. 4J). The relationship between both crop rotational SDI and crop rotational SEI with LULC SEI (Fig. 4E, J) showed a similar pattern to the association between crop rotational SDI and crop rotational SEI with LULC SDI (Fig. 4D, I).

Discussion

Our analysis suggests that crop rotational diversity is higher in grid cells where soil is more fertile, the land is more dominated by agriculture, and landscape diversity is lower. A key finding was the negative relationship between crop rotational diversity and landscape diversity, potentially indicating their trade-off or competition for space. Especially the proportion of agricultural area and the habitat mean size show a strong positive effect on crop rotational diversity. In the Brandenburg region, field sizes are, due to historical reasons, relatively large compared to

Table 3 Comparison of model performance based on the estimated R-squared based on training and the observed R-squared based on the test datasets

Response	GLM		CART		RF		GBM	
	Test R2	Train R2	Test R2	Train R2	Test R2	Train R2	Test R2	Train R2
Crop richness	0.22 ± 0.06	0.22 ± 0.03	0.1 ± 0.06	0.18 ± 0.05	0.35 ± 0.09	0.34 ± 0.04	0.24 ± 0.09	0.28 ± 0.03
Crop SDI	0.28 ± 0.08	0.27 ± 0.04	0.15 ± 0.06	0.24 ± 0.04	0.35 ± 0.08	0.36 ± 0.03	0.31 ± 0.09	0.32 ± 0.03
Crop SEI	0.27 ± 0.11	0.3 ± 0.05	0.15 ± 0.09	0.2 ± 0.05	0.23 ± 0.11	0.3 ± 0.06	0.14 ± 0.08	0.24 ± 0.05

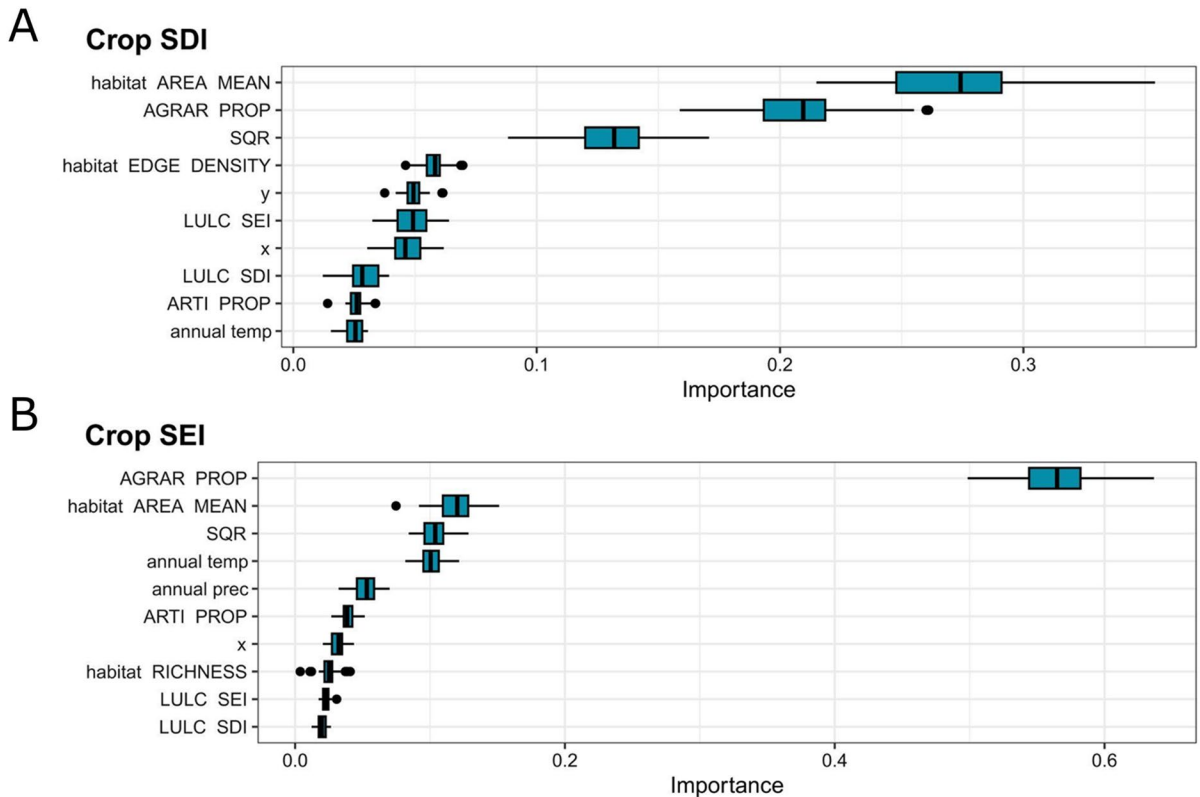


Fig. 3 Modelled importance of variables for (A) Shannon's diversity index for crop rotation (Crop SDI); and (B) Shannon's evenness index for crop rotation (Crop SEI) in Brandenburg, Germany, using random forest machine learning models with permutation variable importance. Predictor variables are land use land cover (LULC) and habitat diversity indices (RICHNESS, Shannon's diversity (SDI), and Shannon's evenness (SEI), mean patch size (AREA MEAN), and patchiness (EDGE DENSITY)), proportion of agricultural area (AGRAR

PROP), proportion of artificial surfaces (ARTI PROP), mean soil quality rating (SQR), mean annual temperature (annual temp), mean annual precipitation sum (annual prec), and x and y coordinates (y, x). The boxplot includes the median as a thick black line within the coloured body that represents the distribution between the first and third quartiles. Whiskers show the distribution of the highest and lowest non-outlier values

other parts of Germany. This can be reflected in the habitat mean patch size. Big mean patch sizes can be understood to represent homogenous or the degree of simplified landscapes, as high amounts of land belong to one only particular habitat patch. Also, the farm sizes in Brandenburg are relatively large compared to other parts and are associated with higher crop rotational diversity (Jänicke et al. 2022). Yet, our analysis cannot decompose the total agricultural area into the number of farms and farm sizes, which should be further investigated linked with the crop information per farm.

The effect of LULC diversity measured in proportional abundance SDI and evenness SEI on crop rotations is stronger seen for the crop rotation

response measured in SDI than in comparison to SEI. Given the strong positive correlation between crop rotational richness and crop rotational SDI ($r=0.94$), we can conclude that an increase in both LULC diversity indices results rather in an increase in number of crop types than their abundance over time. As higher values of LULC SDI and LULC SEI are associated with higher landscape diversity, we conclude that crop rotational diversity is higher in less diverse landscapes. However, this statement is rather plausible for the number of crop types than their temporal evenness. Overall, the relative proportion of farmland and the degree of landscape simplification are fundamental factors explaining the trade-off relationship, indicating the competition

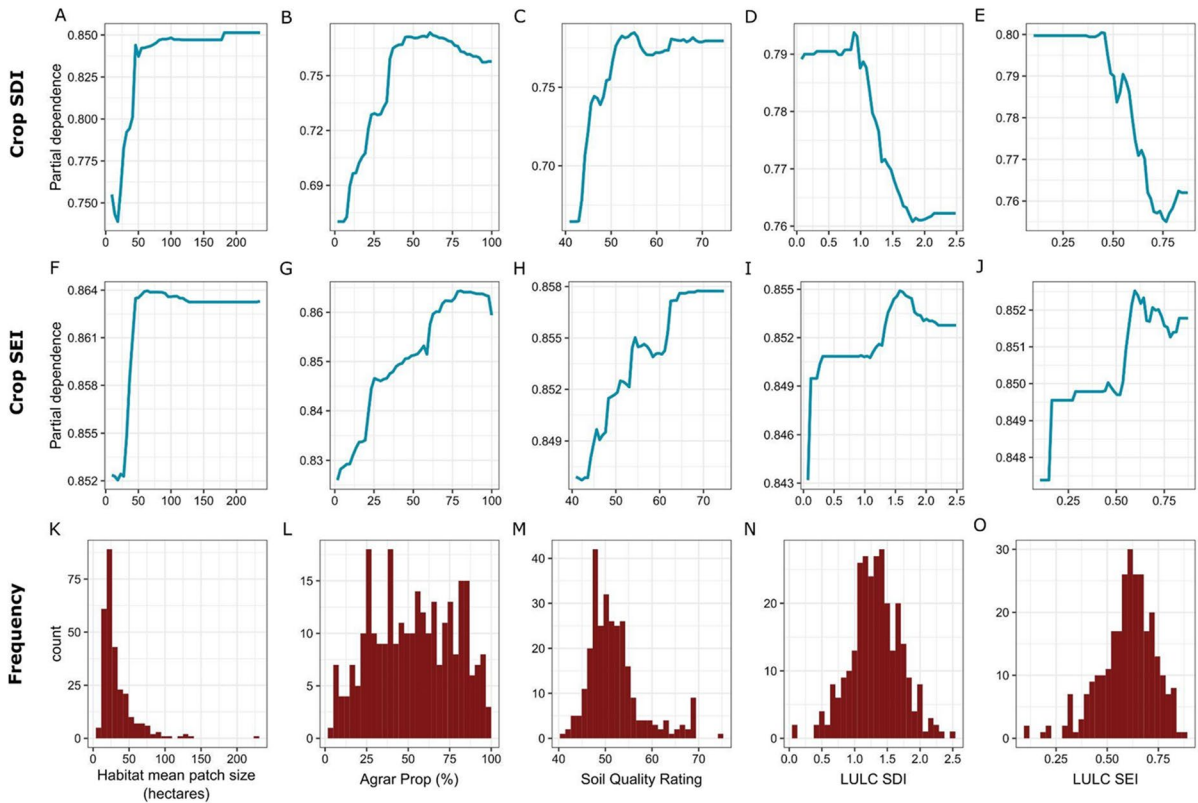


Fig. 4 Modelled relationships among crop rotational diversity (Shannon's diversity index (SDI), and Shannon's evenness index (SEI)) and landscape diversity measured in habitat patch mean size, proportion of agricultural area (Agrar Prop), land

use land cover (LULC) Shannon's diversity index (SDI) and Shannon's evenness index (SEI), and soil quality in Brandenburg, Germany, using random forest machine learning models with partial dependence plot

for limited space between agricultural and non-agricultural land use.

We showed that crop rotational diversity tends to be higher in areas with higher soil quality. The finding is in agreement with previous studies. High soil quality enables farmers to grow a diverse repertoire of crops because the soil provides suitable conditions for various crops (Rosenberg et al. 2022). In Brandenburg, it is known that better soil quality could enable to grow more crop types like e.g. winter wheat, winter barley, winter oilseed rape, rye, maize compared to poorer soil with only rye and maize (Reckling et al. 2016). This is also evident in our results, where we found that soil is particularly important up to a certain value. We can therefore conclude that soil quality acts as a limiting factor to regulate the variety of crop rotations. In contrast to other studies from the U.S. and Sweden, where they found crop rotational diversity is linked to regional and seasonal variation

in temperature (Spangler et al. 2022) and annual mean temperature (Sjulgård et al. 2022), we could not detect a strong link between the climate variables and crop rotational diversity. This could be explained by the relatively small study region that does not cover a large climatic gradient.

Knowledge about site-dependent characteristics within the landscape can help to develop policy measures and should therefore be considered as an important tool in decision-making. Sietz et al. (2022) have already developed a classification scheme for different types of agricultural land systems and associated management practices to be implemented. Following on from this, for example, regions that are particularly rich in landscape diversity should be maintained or protected and, if at all, only extensively managed at the landscape level, while medium to heavily farmed agricultural regions need to be diversified at the agricultural system level. The latter can be achieved by

supporting high crop diversity, increasing amounts of semi-natural habitats (Khan et al. 2023; Sirami et al. 2019; Tschardt et al. 2021), or adding temporal biodiversity promoting structures within the fields (e.g. flower strips) that also positively affect crop production (Albrecht et al. 2020). Additionally, increasing landscape heterogeneity, reducing field sizes and implementing diverse crop rotations have been recommended for stabilizing yields depending on the crop type and local management conditions (Nelson and Burchfield 2021; Tamburini et al. 2020; Tschardt et al. 2021). Nevertheless, we suggest that the extent of landscape and agricultural diversification depends on the local and regional conditions and requires tailored diversification or diversity conservation strategies at both levels.

Our study suggests that landscape and agricultural diversity—measured in crop rotational diversity—show a tendency to be in conflict with each other, implying the difficulty of decision-making for sustainable landscape development. While policies or management plans to increase landscape diversity often aim at conserving biodiversity and providing regulating, cultural and supporting ecosystem services, the major goal of agriculture is mainly the production of food and energy for human needs. However, it needs to be mentioned that high landscape diversity does not necessarily benefit biodiversity conservation, as this depends also on the type of habitat classes or LULC types within the landscape. Our study also showed the positive relationship between the proportion of artificial surfaces and the landscape diversity metrics. The impact of crop rotation patterns on biodiversity is worth consideration for developing sustainable agricultural landscapes. Landscape multifunctionality—which is often considered as the provisioning of a wide range of ecosystem services functions to society—is therefore an important aspect of landscape planning (Hölting et al. 2019). Different services can be achieved with different strategies and their synergy and trade-off dynamics have to be considered (Hölting et al. 2019).

As a limitation of our study, we did not take into account any functional attributes in assessing the diversity status and detailed farm management practice information. Crop sequence typologies have been analysed in Brandenburg before based on functional and structural characteristics (Jänicke et al. 2022; Stein and Steinmann 2018). Crop rotations could be

further analysed from the perspective of biodiversity conservation, as some species have been found to be stronger associated with particular crop types than others (Brandt et al. 2017; Toivonen et al. 2022). Additional drivers of diversification could be the management of fields depending on the operating farm, which can be influenced by various socio-economic factors. Adding the farmer's perspective and management characteristics into analyses is therefore another important step (Walder and Kantelhardt 2018). The distribution of socio-economic farm characteristics in the Brandenburg region can be assessed for example by integrating the farm size, farming system and management strategies, e.g. organic or conventional farming. If and how they affect agricultural diversification are expected to provide additional valuable insights into the driving forces behind diversification. Integrating the farmers' perspectives through interviews could offer a complementary perspective to the purely data-driven approach. Furthermore, small landscape elements like hedges and trees were not integrated due to the limited data availability at the spatiotemporal extent. Since these elements can impact both, biodiversity and management practices due to field geometry, it makes sense to consider them when assessing landscape diversity at a finer resolution in future studies.

Cross-scale interaction effects between local field management practices and regional conditions are currently discussed in agriculture as various studies have reported the significance of the surrounding landscape structures when implementing agricultural management practices for biodiversity conservation (Sirami et al. 2019; Tschardt et al. 2021). Agricultural diversity also takes place at different and interacting levels, from field, to farm to landscape to the entire agrifood value chain (Reckling et al. 2023). Input intensity plays another key role in supporting biodiversity which explains higher biodiversity in organic compared to conventional farming (Stein-Bachinger et al. 2022). Considering temporal diversification in agricultural landscapes by incorporating various crop rotations introduces an additional dimension to the spatial management and planning of diverse landscapes (Marrec et al. 2022; Tschardt et al. 2022). Therefore, we emphasise the need for a multi-scale perspective for enhancing diversification by combining local, regional and temporal scales. Looking at a longer time period, for example, more

than 10 years, the integration of the temporal changes in landscape diversity can also indicate long-term trends that could support planning processes.

In conclusion, crop rotational diversity presents a trade-off to the diversity of the landscape, and more specifically, crop rotational diversity tends to be associated more strongly with fertile but simplified agricultural landscapes in Brandenburg, Germany. Although our study focused on one region, it offers valuable insights into the factors and dynamics determining diversity in crop classification types and landscapes. The same study design can be implemented at much larger scales. Addressing multiple purposes of land use is important to enable biodiversity, food and energy production and other ecosystem services in a sustainable manner. Our findings serve as a basis to explore spatiotemporal cross-scale linkages that need to be explored further in future studies and with consideration of farm-scale and socio-economic factors.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors have no relevant financial or non-financial interests to disclose.

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