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Research Paper

Temporal and spatial crop diversity are related and affected by farm and landscape configurations

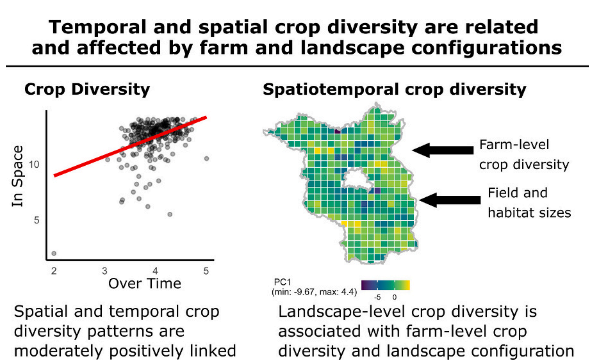
Josepha Schiller [a,b], Clemens Jänicke [c,d,e], Moritz Reckling [a,f], Masahiro Ryo [a,b,*]

[a] Leibniz Centre for Agricultural Landscape Research (ZALF), Eberswalder Str. 84, 15374 Müncheberg, Germany
[b] Brandenburg University of Technology Cottbus–Senftenberg, Platz der Deutschen Einheit 1, 03046 Cottbus, Germany
[c] Leibniz Institute of Agricultural Development in Transitions Economies (IAMO), 06120 Halle (Saale), Germany
[d] Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany
[e] Integrative Research Institute on Transformations of Human-Environment Systems (IRI THESys), Humboldt Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany
[f] Department of Crop Production Ecology, Swedish University of Agricultural Sciences (SLU), Uppsala, Sweden

HIGHLIGHTS

- Crop diversity patterns studied on >5500 farms using interpretable Machine Learning.
- Spatial and temporal crop diversity are moderately positively linked.
- Farm-level crop diversity is linked to landscape-level crop diversity.
- Higher crop diversity in simplified landscapes with high farm-level crop diversity.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT

Numerous studies underscore the importance of temporal and spatial diversification in cropping systems for enhancing agricultural resilience under growing uncertainty.

OBJECTIVE: Although positive effects of crop diversification have been widely reported, the factors influencing temporal and spatial crop diversity remain largely unknown.

METHODS: We address this gap by analyzing spatiotemporal crop diversity patterns across more than 5500 farms with up to 170,000 fields in Germany, and associating them with farm, edaphic, topographic, and landscape attributes. Using Pearson's correlation, principal component analysis, and interpretable machine learning, we assess links between spatial and temporal crop diversity and identify predictors.

RESULTS AND CONCLUSIONS

Landscapes with high spatial diversity also tend to have higher temporal diversity, indicating moderate positive links ($r = 0.41$ and 0.49). Crop diversity was expressed along two gradients: overall diversity in time and space (explaining 58.9% variance) and a contrast between higher spatial or temporal diversity (explaining 21.6%

* Corresponding author at: Leibniz Centre for Agricultural Landscape Research (ZALF), Eberswalder Str. 84, 15374 Müncheberg, Germany.
E-mail address: Masahiro.Ryo@zalf.de (M. Ryo).

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variance). Farm-level diversity strongly predicted both gradients (mean variable importance $R^2 \approx 0.47$ and ≈ 0.14). Higher spatial diversity was also linked with an increasing number of farms, while higher temporal diversity was linked with decreasing landscape configuration.

SIGNIFICANCE: Our study indicates that at the landscape level, there is a co-occurrence between more diverse crop rotations and more diverse crop mosaics, explained by the number of farms, farm crop portfolio, and landscape configurations. Future studies should cover a broader geographic extent across Europe to confirm the generalizability of our findings to understand how agricultural diversity is shaped in space and time.

1. Introduction

Agricultural practices have negative impacts on the environment, affecting limited resources like land and water, introducing agrochemicals, and emitting greenhouse gases (Campbell et al., 2017; Kremen et al., 2012; Springmann et al., 2018). At the same time, global environmental change adds growing uncertainty to productivity (Zurek et al., 2022). Hence, to ensure stable production in the long term, agricultural systems must develop ecological, economic, and social resilience (Hertel et al., 2021).

The diversification of cropping systems across scales in time and space is a promising approach for enhancing the resilience of agricultural systems (Arndt and Helming, 2025; Jones et al., 2021; Kremen and Miles, 2012; Priyadarshana et al., 2024; Rosa-Schleich et al., 2019; Tamburini et al., 2020). Temporal crop diversity can be defined through diverse crop rotations at the field level, where different crop types are grown subsequently (Arndt and Helming, 2025). Previous studies have shown that more diverse crop rotations can result in more stable and/or higher yields (Bowles et al., 2020; Degani et al., 2019; Smith et al., 2023; Yang et al., 2024) even under harsh climatic conditions (Gaudin et al., 2015; Marini et al., 2020). Furthermore, it can increase soil fertility (Davis et al., 2012; Smith et al., 2023; Yang et al., 2024), reduce soil erosion (Hunt et al., 2019), and enhance pest and weed control (Weisberger et al., 2019; Zhou et al., 2023). Spatial crop diversity can be defined through spatial heterogeneity of crop mosaics within landscapes (Priyadarshana et al., 2024; Sirami et al., 2019). This refers to the spatial distribution of crops across a geographic area, ranging from field-level crop diversification (e.g., intercropping) to broader landscapes, national levels, and beyond. A comprehensive meta-analysis of 122 studies confirmed the overall positive effects of spatial crop diversity on invertebrate, vertebrate, and pollinator biodiversity (Priyadarshana et al., 2024), while the effects depend on context (Bosem Baillod et al., 2017; Khan et al., 2023; Q. Yang et al., 2025). Moreover, spatial crop diversity has been linked to increased yields (Burchfield et al., 2019) and national food stability (Renard et al., 2023; Renard and Tilman, 2019). Together, these findings suggest that crop diversity at both temporal and spatial scales provides complementary benefits for the environment and the agricultural system.

Although many studies have demonstrated the positive effects of diversifying cropping systems, empirical investigations on what explains the geographical distribution patterns of temporal and spatial crop diversity are usually done independently. Understanding both diversity patterns is important because each can provide distinct agronomic and ecological benefits (e.g., Burchfield et al., 2019; Renard and Tilman, 2019; Yang et al., 2024; Zhou et al., 2023). For instance, one can expect that if both spatial and temporal crop diversity are high in the landscape, temporal diversity can enhance local stabilized production, e.g., via the enhancement of crop growth as previous crop type affects nutrient availability, breaking pest cycle, and maintaining soil health. Spatial diversity is the consequence of collective field management at the regional scale, offering ecological benefits and agricultural production stability at a larger scale. From an ecological perspective, spatially diverse but temporally stable landscapes can offer slow-changing habitats for animals and plants that need stable yet diverse resources (e.g., specialists). Temporally diverse but spatially homogeneous landscapes indicate high synchronization across fields, which may be beneficial for generalists who can adapt to habitats with changing available resources dynamically year by year. Therefore, different spatiotemporal diversity types can indicate different agroecological benefits and dynamics, characterizing the uniqueness of the whole agricultural diversity in the region.

A logical assumption is to expect a positive link between temporal and spatial crop diversity at a large scale, including dozens of fields, as asynchronous crop rotations across different fields will lead to a mosaic-like crop pattern at the landscape scale. Yet, we found only one study from the US that investigated the connection between temporal and spatial crop diversity quantitatively, which revealed a positive relationship at the scale of a typical US farm (Aramburu Merlos and Hijmans, 2020). This positive relationship implies that regions with higher spatial crop diversity tend to have higher temporal crop diversity and vice versa due to asynchrony across fields and farms. Such co-occurrence can have implications for farming and ecology, by combining productivity benefits with more diverse crop habitats that support biodiversity at the larger scale. However, whether this relationship can be found within a large-scale agricultural landscape and what factors influence the spatial and temporal patterns of crop diversity are largely unknown. If they are linked, they could be targeted by joint policy measures; if not, addressing temporal and spatial crop diversity would require independent policy measures. By filling this gap, this study provides empirical ground for understanding the links between spatial and temporal crop diversity and its mediating factors. It aims to provide guidance for diversity-oriented landscape management by identifying regions with differing levels of crop diversity and enhancing or limiting factors.

We hypothesize that there is a positive link between spatial and temporal diversity in a large agricultural dominated region in Germany. The scale dependency of observations from the US indicates that farm characteristics play an important role in mediating this relationship (Aramburu Merlos and Hijmans, 2020). Indeed, larger farms in Germany have been associated with higher temporal crop diversity (Jänicke et al., 2022). Consequently, we hypothesize that various factors including edaphic and environmental conditions affect crop diversity, but particularly, farm size plays a role in driving spatiotemporal crop diversity in Germany. Farms serve as a unit of decision-making for crop type, rotation, and spatial arrangement, which is affected by political incentives or financial support as well as environmental conditions (Schaak et al., 2023). Understanding how farm characteristics shape crop diversity at both the field and landscape levels is essential for designing targeted crop diversification strategies to strengthen the resilience of agricultural systems at a large spatial scale.

The objective of the present study is to analyze spatiotemporal crop diversity in Brandenburg, Germany. We aim to identify how spatial and temporal crop diversity is interconnected and linked with farm attributes and landscape conditions. We assess temporal crop diversity per field over 10 years and spatial crop diversity within the landscape of 10 $\times$ 10 km grid cells ($n = 293$). As potential influencing factors, we include the mean size of fields, annual crop and livestock diversity at the farm level, field numbers per farm, farm sizes, and conventional or organic management strategy. Furthermore, we assess the impacts of the landscape complexity and conditions, such as soil quality and slope, based on the findings by Schiller et al. (2024). Nonlinear relationships were investigated using machine learning (ML).

2. Materials and methods

2.1. Data

2.1.1. Study region

The study region covers the federal state of Brandenburg with about 29,000 km^2 in the northeastern part of Germany (Fig. 1). It is characterized by ca. 50% land use for agricultural purposes, with 76% arable land and 23% permanent grassland (Ministerium für Landwirtschaft, Umwelt und Klimaschutz des Landes Brandenburg (MLUK), 2021). The average size of farms in Brandenburg is 242 ha, which is bigger than the overall mean farm size in Germany with 62 ha (Bundesministerium für Ernährung and und Landwirtschaft (BMEL), 2022). Also, the mean field size in Brandenburg is ca. 8 ha, which is larger than that in the western (2.8 ha) or southern (1.6 ha) German regions (Jänicke et al., 2022). The share of organic farmland was 18% in 2024 (Ministerium für Land- und Ernährungswirtschaft, Umwelt und Verbraucherschutz (MLEUV), 2025).

The soils in Brandenburg are characterized by a high proportion of light sandy soils (Landesamt für Umwelt (LfU), 2024), making agricultural production difficult, especially under harsh climate conditions (Bundesanstalt für Geowissenschaften und Rohstoffe (BGR), 2013). The altitude in Brandenburg ranges between 30 and 50 m above sea level, with fluctuations between around 0.5 m and 200 m above sea level (Landesamt für Bergbau, Geologie und Rohstoffe Brandenburg, 2010). Brandenburg has an average annual temperature of 10 °C (Laenderdaten.info, 2024b) and an average annual precipitation sum of 558 mm (Deutscher Wetterdienst (DWD), 2019), which is lower than the Germany-wide precipitation sum (ca. 700 mm) (Laenderdaten.info, 2024a)).

2.1.2. Agricultural land use

The Integrated Administration and Control System (IACS) represents a great data source for analyzing agricultural land use in Germany (Uthes et al., 2020), as it contains land use information for all fields for which an agricultural business applied for subsidies of the European Common Agricultural Policy (CAP). This information is gathered in the Geo-Spatial Application (GSA), a subelement of the IACS that farmers use to declare the main crops they grow and the main agricultural measures they apply to each field (Leonhardt et al., 2024). Via these measures, it is possible to derive information on organic and conventional management of the fields. Additionally, the IACS contains information on all subsidies paid out for husbandry in an animal-based application system, representing another important aspect of agricultural land use. The crop information is published annually as an anonymized vector dataset on the Geoportal Brandenburg website (Landesvermessung und Geobasisinformation Brandenburg (LGB), 2025). As the anonymized data do not include information about individual farms, such as farm size and animal husbandry, as well as on the agricultural measures applied to each field, we requested GSA data with a unique farm identifier and the missing information from the agricultural ministry Ministerium für Landwirtschaft, Umwelt und Klimaschutz

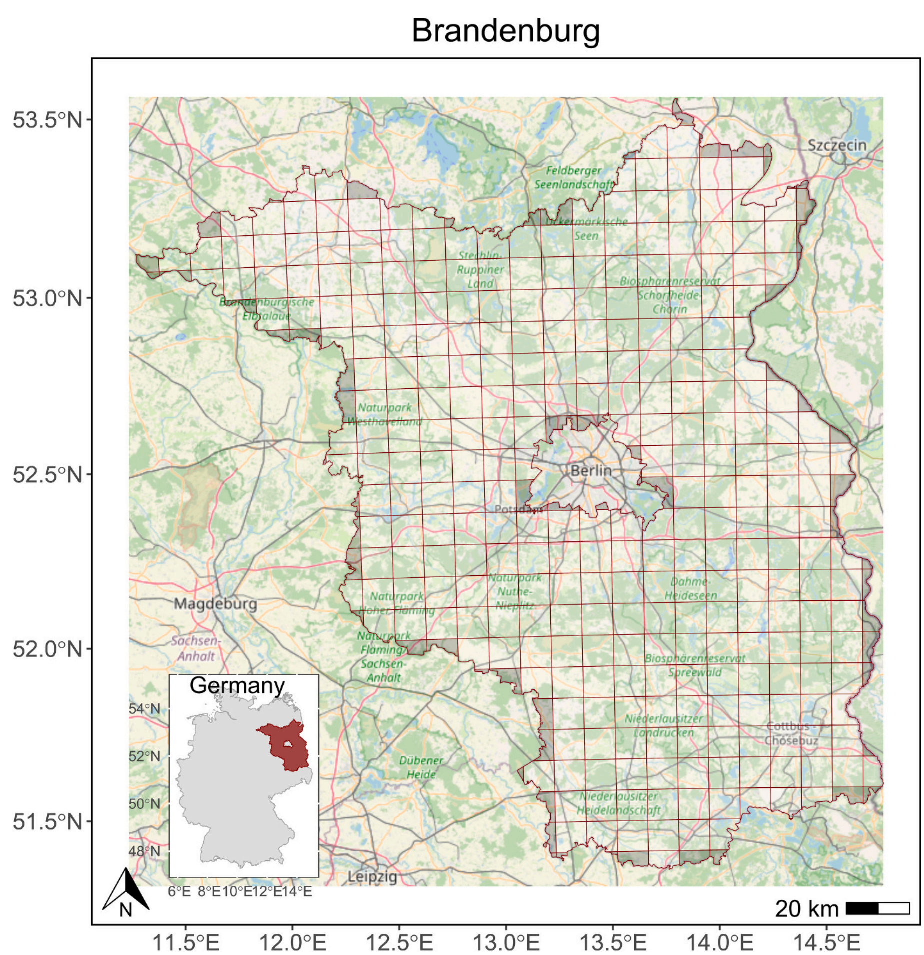

Fig. 1. Overview of the case study region: map of the case study region Brandenburg, Germany, showing 10 × 10 km grid cells in red line colors, gray field grids were classified as boundary grids and removed. Germany and Brandenburg shape maps were created using data from GADM (2018) and the Brandenburg base map using data from OpenStreetMap (OpenStreetMap contributors, 2025). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(MLUK) des Landes Brandenburg, 2021 to assign georeferenced fields and livestock data to individual farms.

We used a ten-year period of IACS datasets from 2011 to 2020 to assess agricultural land use, farm type, and farm attributes. This included information on more than 5500 farms and more than 150,000 fields per year (Table 1). First, we aggregated the land use information per field into 14 crop classes based on Jänicke et al. (2022); (see Table 2, yearly crop distribution in Table A.1). Furthermore, we used farm management data to identify whether farms have livestock or practice organic farming. Livestock information included cattle, sheep, poultry, and pig farming. Finally, we used the farm identifier to calculate more farm attributes such as the farm size, the number of fields per farm, and the number of crop and/or livestock types managed per farm. We removed all fields with less than 0.3 ha, as these are not eligible for CAP subsidies.

2.1.3. Habitat and land cover map

We integrated the landscape structural complexity using the habitat and land cover maps ("CIR2009") of the state of Brandenburg (Landesamt für Umwelt (LfU), 2013a). The CIR2009 dataset is based on up to 2500 classes of habitat and land cover types according to *Flächendeckende Biotop- und Landnutzungskartierung* (BTLN) (Landesamt für Umwelt (LfU), 2013b, 2013a) and comprises color-infrared (CIR) aerial images from 2009 which were homogenized into the corresponding classes. In this study, we aggregated the classes into 12 overarching habitat and land cover types (Table A.2).

2.1.4. Soil quality rating and topography

The soil yield potential map ("SQR1000" Ackerbauliches Ertragspotential der Böden in Deutschland) estimates the soil quality in Germany for arable farming, particularly for cereal crops (Bundesanstalt für Geowissenschaften und Rohstoffe (BGR), 2013). The yield potential ranges on a point scale between 1 and 102, with increasing values indicating higher yield potential. Brandenburg's average SQR score of ca. 51 (Table A.3) is lower than the German average of 61 (Bundesanstalt für Geowissenschaften und Rohstoffe (BGR), 2013). The SQR is derived from an adapted method of the Müncheberg soil yield potential according to Müller (2007), where the yield potential is based on the evaluation of eight basic indicators and four hazard indicators. The topography data were derived from the German "DGM1000" digital elevation model (GeoBasis-DE/BKG, 2021). We calculated the difference between the highest and lowest points within a grid cell as a proxy for slope to integrate the effect of varying topography.

2.2. Data processing

2.2.1. Grid cells

We defined a grid cell of size 10 × 10 km to include the joint effects of several farms. All data points from one of the above variables that fell into a grid cell were aggregated into a single representative value. This means all field and farm information is aggregated to the landscape level. This approach reduced pseudo-replication for fields that belong to the same farm and region. Furthermore, we removed grid cells close to the Brandenburg border if less than 50% area within the grid cell belonged to the Brandenburg state (Fig. 1). Detailed processing information can be found in Table 3, and the variable distributions in Table A.3. We generated the study grid map (Fig. 1) using the R packages "basemap" (Schwalb-Willmann, 2024), "ggspatial" (Dunnington, 2023), and "sf" (Pebesma, 2018). Germany and Brandenburg boundary maps were derived from GADM (2018).

Table 1
Annual number of farms, fields, and mean sizes (in hectares) in Brandenburg derived from Integrated Administration and Control System (IACS) data.

Year	Number of farms	Farm size mean (ha)	Number of fields
2011	5642	228.79	152,169
2012	5600	232.04	151,640
2013	5550	233.75	150,131
2014	5539	232.18	149,399
2015	5638	223.50	152,726
2016	5639	227.00	153,264
2017	5609	233.60	154,618
2018	6030	220.51	159,164
2019	6047	219.75	162,820
2020	6079	218.83	169,966

2.3. Measuring diversity

2.3.1. Field level: temporal crop diversity

We assessed temporal crop diversity using the following diversity metrics. Crop richness was defined as the number of distinct crop classes reported per field from 2011 to 2020 (10 years). Additionally, Shannon's diversity index (SDI; Eq. (1)) was calculated as follows:

$$SDI = -\sum_{i=1}^{m} (P_i * lnP_i) \tag{1}$$

where P_i is the proportional abundance of a distinct type (i) and where m is the total number of distinct types (Hesselbarth et al., 2019). We also computed Shannon's evenness index (SEI; Eq. (2)) to assess whether the diversity was dominated by certain crop classes (Hesselbarth et al., 2019):

$$SEI = SDI/lnm \tag{2}$$

Because of varying field shapes over the 10 years, we used the field centroids from 2020 as reference areas and determined which crops were reported at this point in previous years. We removed fields with more than 3 years of missing data and fields with more than 5 multiannual crops because we assumed that these areas were not part of an active crop rotation. The centroids were also used to assign each field to a single grid cell to avoid duplication of fields if the total field extent fell into more than one grid cell. We averaged all observations present within a 10 × 10 km grid cell to one representative value per diversity metric.

2.3.2. Farm level: farm attributes

We included farm-level attributes from the IACS data, such as the total farm size, the annual crop diversity per farm (farm-level crop SDI), and, if available, livestock diversity per farm (farm-level livestock diversity) (Tacconi et al., 2022). Those obtain only one value per variable per grid cell, and we averaged those variables across all farms present within a 10 × 10 km grid cell. Furthermore, we counted the total number of farms per grid cell and assessed the proportions of livestock and organic farms.

2.3.3. 2.2.3 Landscape level: Spatial crop diversity and landscape complexity

At the landscape level, we evaluated spatial crop diversity by calculating crop diversity metrics in space, i.e., crop richness, SDI, and SEI, using the distinct crop types that were present within a 10 × 10 km grid cell. First, we calculated each metric for every grid cell for each year (2011–2020) and then averaged the metrics over the 10 years for each grid cell. Furthermore, we computed an artificial variable indicating the theoretical average area per crop type within each grid cell (Eq. (3)).

$$Theoretical\ area\ per\ crop = Area\ under\ agricultural\ production / Crop\ Richness \tag{3}$$

Additionally, for each grid cell, we assessed landscape complexity by computing the habitat richness and SDI as indicators of landscape composition using distinct habitat types. The mean size of habitats (habitat size mean) and their edge density (*ED*) are indicators of landscape configuration per grid cell. *ED* is calculated by dividing the total edge length in meters (e_{ik}) by the total area (A) (Eq. (4)) (Hesselbarth

Table 2
Crop classification.

Arable Grass
Legumes, extensive (incl. Clover, green manure)
Legumes, intensive (incl. Peas, beans, and lupine)
Maize
Multiannual use (incl. Grassland, fallow, perennials and others)
Potato
Spring Cereals
Sugar Beet
Triticale
Minor crops (incl. Vegetables, sunflower, herbs, and other)
Winter Barley
Winter Rapeseed
Winter Rye
Winter Wheat

et al., 2019):

$$ED = \left(\sum_{k=1}^{m} e_{ik} \Big/ A\right) * 1000 \tag{4}$$

2.4. Data analyses

2.4.1. Principal component analysis: spatiotemporal crop diversity

A principal component analysis (PCA) was conducted to generate variables indicating temporal and spatial crop diversity with a joint metric. We used temporal crop diversity and spatial crop diversity per grid cell and measured each in terms of richness, SDI, and SEI as inputs for the PCA. First, we normalized the input variables, second, transformed them into a covariance matrix, and finally applied PCA using the princomp() function from the R package "FactoMineR"(Husson et al., 2013).

2.4.2. Correlation analysis

To explore the strength and directions of linear relationships between variables, we performed Pearson's correlation analysis (Fig. A.1). We visualized the coefficients as a network plot (Fig. A.2), with line thickness indicating strength and color indicating the direction of relationships between variables. Variable pairs with absolute Pearson's coefficients above $|r| = 0.7$ were considered highly correlated and were not included together as predictor variables in machine learning to reduce multicollinearity. We kept the following variables: x and y coordinates, farm-level crop diversity measured in SDI, farm-level livestock diversity measured in SDI, number of farms, share of farms with livestock management, share of farms with organic farming, farm size mean, habitat richness, habitat edge density, habitat size mean, SQR, slope, ha per crop, field size mean (Table B.1.). Yet, we removed the following variables: spatial crop diversity measured in richness and SDI, temporal crop diversity measured in richness and SDI, area under agricultural management, and share of area under organic management. This decision was based on the following rules: (1) PC1 and PC2 already include information about temporal and spatial crop diversity and therefore showed high correlation with the crop diversity metrics. (2) Richness and Shannon's diversity are related metrics and were also highly correlated (Fig. A.1). The resulting variable combinations used for model training are listed in Table B.1. We generated the network plot using the ggraph() function from the R packages "PerformanceAnalytics" (Peterson and Carl, 2020), "corrr" (Kuhn et al., 2022), "igraph" (Csardi and Nepusz, 2006), and "ggraph" (Pedersen, 2022).

2.4.3. Machine learning

For ML prediction, the dataset was randomly split into training (70%, $n = 205$) and test (30%, $n = 88$) data. We trained models using generalized linear regression (LM), decision trees (DT), random forest (RF), and stochastic gradient boosting (GB) with the R package "caret" (Boehmke and Greenwell, 2020). The models used predictor sets based on the correlation analyses, in which the highly correlated variable pairs ($|r| > 0.7$) were not used together (see Section 2.3.2; Table B.1). LM approximates linear relationships between predictors and response, whereas DTs follow an if-else-split tree structure (Breiman, 1984; Hothorn et al., 2006). RF and GB are both tree ensemble models that combine multiple DTs to improve model accuracy. In particular, RF employs bagging (multiple DTs are trained at the same time with different subsets and predictions consisting of averaging several DT outputs (Breiman, 2001)), and GB employs boosting (a DT is sequentially corrected based on the error of the previous one (Friedman, 2001)).

Overall, we trained six models using different response variables to assess what factors influence crop diversity. For two of these, the response variables represent a combined measure of spatiotemporal crop diversity (PC1 and PC2), whereas the remaining four models were trained to test spatial and temporal crop diversity independently. The latter ones' response variables included temporal crop diversity measured in SDI and richness and spatial crop diversity measured SDI and richness (a detailed description of predictor and response variable combinations is provided in Table B.1). We applied 5-fold cross-validation to the training data set to optimize the hyperparameters and avoid overfitting (James et al., 2022; Raschka, 2020). In this approach, the training data were split iteratively (k-1) into five subsets (folds); in each iteration, four folds were used to train the model, and the remaining fold was used to validate its performance, and hyperparameters were selected to increase the model's performance (James et al., 2022; Raschka, 2020). During cross-validation, the mean squared error (MSE) was used as an indicator to select the best-performing models.

Afterwards, we evaluated the final model performance on the remaining 30% test data set, reporting R^2 to quantify test performance, which indicates the extent to which the variance in the dependent variable can be explained by the model's predictor variables. It is computed as the squared Pearson's correlation coefficient. The machine learning applications followed the methodological steps of Ryo (2022). To improve the robustness of the ML application, we executed 10 iterations of the training and test splits randomly. Each split was used for training and testing an independent model, resulting in 40 unique models per response variable (10 iterations × 4 algorithms × 6 response variables = 240 model trials in total; but only the best performing model for each response variable was chosen as the final model).

2.4.4. Post-hoc explainability

To address the accuracy-interpretability trade-off, we applied post-hoc methods as part of interpretable machine learning. LM and DT are considered relatively easy to interpret due to their open algorithmic structure, but RF and GB are considered more complex models given their algorithmic structures, which are too complex for human comprehension (Gunning and Aha, 2019; Rudin, 2019).

We selected the best performing models according to their test set R^2 values and first computed the permutation variable importance scores (with 30 permutations, nsim = 30) to draw variable importance plots (VIPs) using the function vip() from the "vip" R package (Greenwell and Boehmke, 2020). The plots show the median model performance decrease and interquartile ranges when each variable is permuted. Second, we generated partial dependence plots (PDP) to visualize how changes in key predictor variables affect the model predictions (Friedman, 2001; Greenwell et al., 2018; Ryo, 2022). To do so, a key predictor variable was artificially fixed to a specific value, but the other variable values remained unchanged. We utilized the R packages "pdp" using the partial() function (Greenwell, 2017) and "iml" (Molnar et al., 2018).

The PCA and machine learning analysis code, together with the spatiotemporal crop diversity dataset containing the PCA principal components, are available on Zenodo (https://doi.org/10.5281/zenodo.17084000).

Table 3
Overview of data and variables used in this study: data derived from Integrated Administration and Control System (IACS), color-infrared biotope map (CIR2009), soil quality rating (SQR1000), and Digital Geländemodell (DGM1000).

Variable	Metric	Description	Data source (original resolution)
Field level			
Temporal crop diversity	Richness	Number of distinct crop classes per field over 10 years averaged per 10 × 10 km grid cells	IACS 2011–2020 (1:2400)
	Shannon's H	Shannon's diversity index of crop classes per field over 10 years averaged per 10 × 10 km grid cells	IACS 2011–2020 (1:2400)
	Shannon's evenness	Shannon's evenness index of crop classes per field over 10 years averaged per 10 × 10 km grid cells	IACS 2011–2020 (1:2400)
Field size mean	Hectares	Mean size of fields averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
Farm level			
Farm size mean	Hectares	Mean size of farms averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
Number of fields	Count	Number of fields per 10 × 10 km grid cells averaged over 10 years	IACS 2011–2020 (1:2400)
Farm-level crop diversity	Richness	Number of distinct crop classes per farm averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
	Shannon's H	Shannon's diversity index of distinct crop classes per farm averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
	Shannon's evenness	Shannon's evenness index of distinct crop classes per farm averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
Farm-level livestock diversity	Richness	Number of distinct livestock types (cattle, hogs, poultry, sheep) per farm averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
	Shannon's H	Shannon's diversity index of distinct livestock types (cattle, hogs, poultry, sheep) per farm averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
	Shannon's evenness	Shannon's evenness index of distinct livestock (cattle, hogs, poultry, sheep) types per farm averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
	% livestock farms	Proportion of farms with livestock production management (cattle, hogs, poultry, sheep) averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
Farm type	% organically managed farms	Proportion of farms with organic field management averaged per 10 × 10 km grid cells and over 10 years	IACS 2011–2020 (1:2400)
Landscape level			
Number of farms	Count	Number of farms per 10 × 10 km grid cells averaged over 10 years	IACS 2011–2020 (1:2400)
Spatial crop diversity	Richness	Number of distinct crop classes per 10 × 10 km grid cells averaged over 10 years	IACS 2011–2020 (1:2400)
	Shannon's H	Shannon's diversity index of crop classes per 10 × 10 km grid cells averaged over 10 years	IACS 2011–2020 (1:2400)
	Shannon's evenness	Shannon's evenness index of crop classes per 10 × 10 km grid cells averaged over 10 years	IACS 2011–2020 (1:2400)
	Theoretical area per crop	Area under agricultural land use divided by the crop richness	IACS 2011–2020 (1:2400)
Soil	SQR	mean soil quality rating per 10 × 10 km grid cells	SQR1000 (250 m; reprojected 259 m)
Landscape composition	Richness	Number of distinct habitat and land cover classes per 10 × 10 km grid cells	CIR2009 (1:300, rasterized to 100 m)
	Shannon's H	Shannon's diversity index of distinct habitat and land cover classes per 10 × 10 km grid cells	CIR2009 (1:300; rasterized to 100 m)
Landscape configuration	Mean patch size	Mean size of habitat and land cover patches per 10 × 10 km grid cells	CIR2009 (1:300; rasterized to 100 m)
	Edge density	Edge density of habitat and land cover patches per 10 × 10 km grid cells	CIR2009 (1:300; rasterized to 100 m)
Slope	Elevation range	Difference between maximum and minimum elevation per 10 × 10 km grid cells	DGM1000 (1000 m)

3. Results

3.1. Spatial and temporal crop diversity

The temporal crop richness per 10 × 10 km grid cell, measured over 10 years, ranged from a minimum of 2 to a maximum of 5 crops per field (Table A.3). The mean and median richness were both approximately 4 crops per field (Table A.3). The temporal crop SDI ranged from ca. 0.7 to 1.4, with both the mean and median ca. 1.2 (Table A.3). The spatial crop richness within the 10 × 10 km grid cells ranged from 2 to 14 crops, with an average of approximately 12 crops and a median of approximately 13 crops (Table A.3). The spatial crop SDI varied from 0.2 to 2.3, with a mean value of 1.7 and a median value of ca. 1.8 (Table A.3).

The PCA analysis was performed using temporal and spatial crop diversity metrics, each measured in richness, SDI, and SEI. This resulted in two principal components: Principal Component 1 (PC1), accounting for 58.9% of the total variance, and Principal Component 2 (PC2), accounting for an additional 21.6% (Fig. 2a). The PC1 scores ranged from −9.7 to 4.4, with a mean of 0 and a median of 0.1, and the PC2 scores ranged from −3.2 to 4.9, with both the mean and median at around 0 (Fig. 3, Table A.3). Together, these principal components explained 80.5% of the variability in the input variables, ensuring robust dimensionality reduction.

The loadings indicate that PC1 represents an aggregated measure of spatiotemporal crop diversity, with positive scores corresponding to higher levels of temporal and spatial crop diversity metrics. This is represented by all diversity metric vectors pointing toward positive PC1 (Fig. 2a). Thus, PC1 can be interpreted as a proxy for general crop diversity. In practice, this translates to higher PC1 scores per grid, indicating higher overall crop diversity as a combination of both temporal and spatial crop diversity (Fig. 2a, 3a). Complementary, PC2 separates whether diversity patterns are dominated by spatial crop diversity patterns (negative PC2 scores) or temporal crop diversity patterns (positive PC2 scores). This means that grids with high positive PC2 scores tend to have fields with relatively diverse crop rotations over time but a relatively more homogenous crop arrangement (spatial crop diversity). In contrast, grids with low negative PC2 scores tend to have many different crops (high spatial crop diversity), but relatively simpler or shorter crop rotations (temporal crop diversity). This interpretation is grounded in the loadings, as all spatial crop diversity metrics load toward decreasing (more negative) PC2 values, while the temporal diversity metrics load toward increasing (more positive) PC2 values. Therefore, negative PC2 scores indicate relatively higher spatial crop diversity, whereas positive scores suggest higher temporal crop diversity (Fig. 2a, 3b).

Based on both PC axes, one can interpret how diverse the crops are in general (PC1) in the area as well as the relative strength of temporal vs spatial diversity (PC2). The orientation of diversity variable vectors indicates spatial crop diversity vectors at a 50° to 90° angle to temporal crop diversity vectors. This indicates a moderate positive correlation between temporal and spatial crop diversity, as supported by a Pearson's correlation coefficient of 0.41 between richness and 0.49 between SDI variables (Fig. 2b, c). Notably, a positive or negative PC2 score does not imply that the complementary crop diversity scale (time vs. space) is necessarily low; rather, the scores are based on a combination of original variables and refer to the tendency of a data point toward either spatial or temporal diversity.

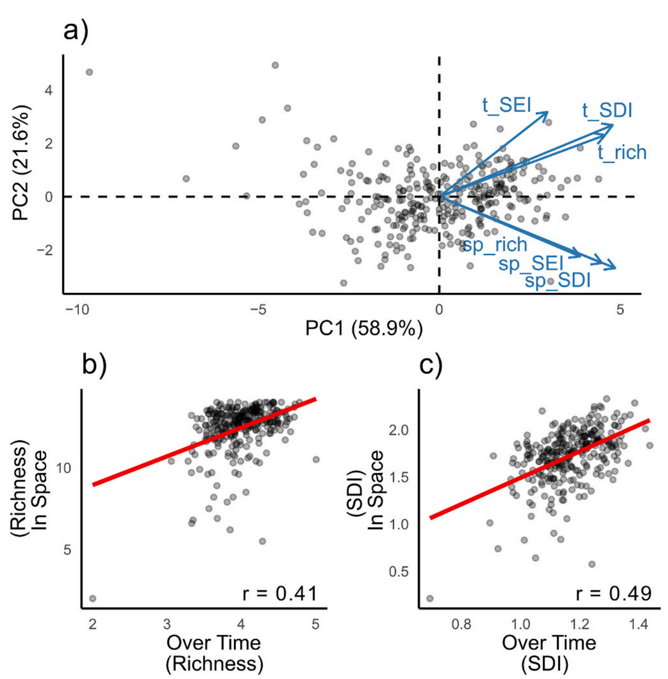

Fig. 2. PCA biplot and Pearson's correlation analysis: a) PCA biplot showing the distribution of data points per 10 × 10 km grid cell (gray dots) based on crop diversity metrics in the space defined by principal components (PC) PC1 and PC2, blue arrows represent loading of diversity variables in time (t_) and space (sp_) measured as richness (rich), Shannon's diversity (SDI), and Shannon's evenness (SEI); b-c) Pearson's correlation between temporal and spatial crop diversity, measured in b) richness and c) SDI, red lines indicate linear relationships between time and space. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Machine learning analysis to identify influencing factors of diversity

3.2.1. Overall model performance

A comparison of the models using four algorithmic structures showed that, overall, RF and LM outperformed DT and GB (Table B.2). The performance measured in R^2 differed between response variables. General crop diversity (PC1) achieved the highest R^2 of 0.44 (± 0.06) when RF was used, whereas PC2 LM showed the best performance, with $R^2 = 0.1$ (± 0.05). Spatial crop diversity had the best performance when LM was used for predicting spatial crop SDI, with $R^2 = 0.59$ (± 0.09), and when RF was used for spatial crop richness, with $R^2 = 0.46$ (± 0.07). For temporal crop diversity, the best performance was achieved for predicting temporal crop richness, with RF $R^2 = 0.18$ (± 0.06) and temporal crop SDI with RF $R^2 = 0.23$ (± 0.06). The results indicate that spatial diversity is more predictable than temporal diversity.

3.2.2. Variable importance in linear regression and random forest model

To identify the key important predictor variables, we generated permutation-based variable importance scores for LM and RF models, as they showed the overall highest performance. The predictor variables were ranked according to the performance drop after permutation, where higher importance scores indicate more important variables (Fig. 4, B.1, B.2).

The general crop diversity (PC1) was most affected by farm-scale crop diversity, with a median R^2 performance contribution of ≈0.47 in RF and ≈0.39 in LM (Fig. 4a, B.1). In the RF models, the field size mean was the second most important variable (≈0.16), and the habitat size mean was the third most important variable (≈0.06, Fig. 4a). In contrast, in the LM models, the number of farms ranked second (≈0.13), and the field size mean ranked third (≈0.11, Fig. B.1b). PC2, which described relatively higher spatial or temporal crop diversity, was impacted the most by farm-level crop SDI in RF (≈0.14) and LM (≈0.16) (Fig. 4b, B.1d). In the RF models, the second most important variable was slope (0.05) and SQR mean (0.04). In the LM models, PC2 was also affected by habitat edge density (≈0.06) and proportion of organic farms (≈0.05).

In the models that predict temporal crop diversity, temporal crop richness was most affected by the spatial crop SDI (RF ≈ 0.49, LM ≈ 0.25) (Fig. B.1e, f). Furthermore, in the RF models, among the three most important variables were habitat size mean (≈0.09), and farm-level crop SDI (≈0.06) (Fig. B.1e). In contrast, in the LM models, the second most important variables were the east-west gradient (x coordinate) (≈0.03) and the proportion of organic farms (≈0.02) (Fig. B.1f). Additionally, temporal crop SDI was most impacted in RF models by spatial crop SDI (≈0.15), field size mean (≈0.06), and habitat size mean (≈0.05) (Fig. B.2 g). The temporal crop SDI LM models were most affected by spatial crop SDI (≈0.26), proportion of organic farms (≈0.04), and habitat edge density (≈0.2) (Fig. B.2 h).

Regarding spatial crop diversity, spatial crop richness was most affected by farm-level crop SDI (LM ≈ 0.2, RF ≈ 0.1), number of farms (RF ≈ 0.51, LM ≈ 0.17), and temporal crop SDI (LM ≈ 0.12; RF ≈ 0.09) (Fig. B.2i, j). The spatial crop SDI was most affected by farm-level crop SDI (RF ≈ 0.6; LM ≈ 0.55), and temporal crop SDI (RF ≈ 0.09; LM ≈ 0.1). LM and RF models differed in ranking either field size mean (LM ≈ 0.09) and slope (RF ≈ 0.03) within the three most important variables (Fig. B.2 k, l).

3.2.3. Partial dependence plots

We generated PDPs using RF models to visualize the nonlinear relationships between key predictor variables and response variables (Fig. 5, B.3) according to their variable importance scores. The general crop diversity (PC1) indicates a positive relationship with farm-level crop SDI. In particular, increasing farm-level crop SDI from ≈0.7 to ≈1.4 led to increasing PC1 values from ≈ − 2 to ≈1, indicating an

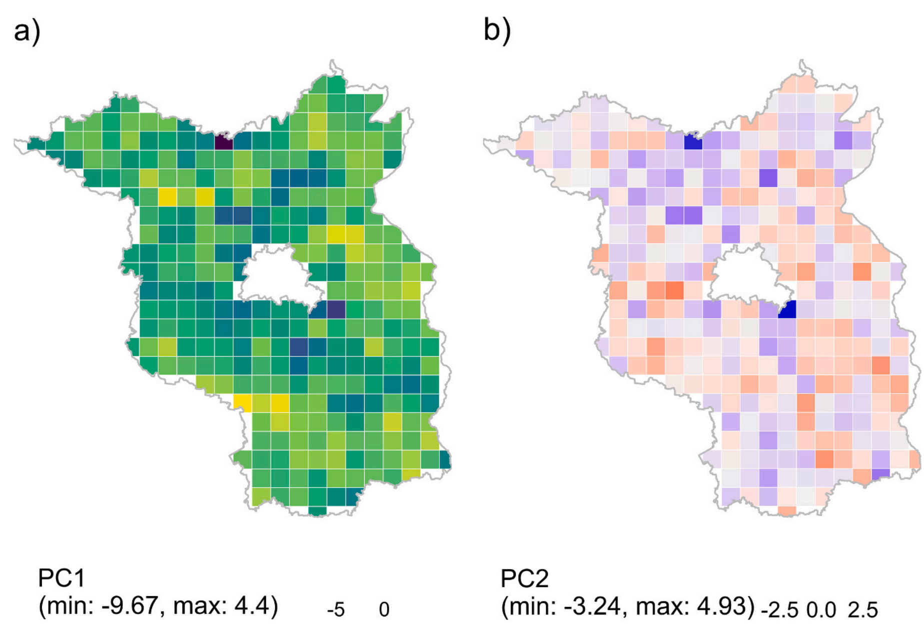

Fig. 3. Spatial distribution of principal components (PC): a) PC1 and b) PC2 of crop diversity across 10 × 10 km grid cells in Brandenburg, Germany; a) PC1 reflects overall crop diversity, with higher values for the more diverse crop types in time and space; b) PC2 indicates the relative strength of temporal (positive PC2) and spatial (negative PC2) diversity aspects.

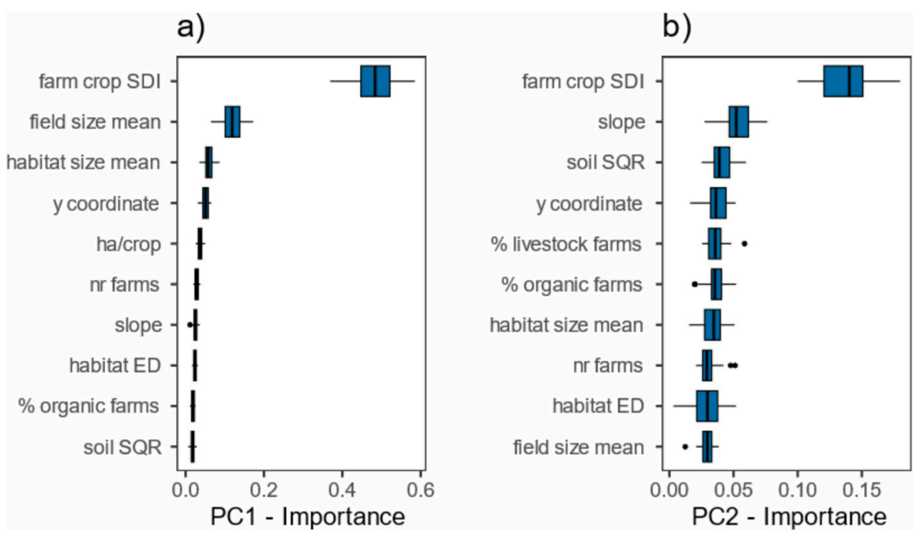

Fig. 4. Variable importance ranking based on permutation variable importance scores from random forest models predicting the principal components (PC) PC1 (a) and PC2 (b); SDI = Shannon's diversity, nr = number, ED = edge density, SQR = soil quality rating.

increase in crop diversity of more than 20% (Fig. 5a). Additionally, the relationships between field size mean and PC1 (Fig. 5b) and habitat size mean and PC1 (Fig. 5c) show that increasing field and habitat size means positively affected general crop diversity, as reflected by PC1; PC1 plateaued at around 0.8 when the habitat size mean was around 50 ha and PC1 plateaued at around 0.25 when field size mean was around 13 ha.

The PC2, which distinguishes between higher temporal or spatial crop diversity, indicates an overall negative relationship between PC2 and farm-level crop diversity and slope (Fig. 5d,e). In particular, when the farm-level crop SDI was less than 0.9, PC2 values were positive, which indicates relatively higher temporal crop diversity. With increasing farm-level crop SDI to ca. 1.5, the PC2 value decreased to about −0.4, indicating higher spatial crop diversity (Fig. 5d). The slope was associated with negative PC2 values, which corresponds with higher spatial crop diversity than temporal crop diversity (Fig. 5e). Soil quality was also associated with negative PC2 values (Fig. 5f), indicating that soil quality is more strongly associated with spatial crop diversity than with temporal crop diversity.

4. Discussion

Understanding temporal and spatial crop diversity patterns and their influencing factors is essential for fostering agricultural diversification. In our case study, we hypothesized that (i) spatial and temporal diversity are positively linked and (ii) that this relationship is influenced by various factors, especially farm size. By jointly analyzing temporal and spatial crop diversity and their influencing factors across >55,000 farms and 170,000 fields at the landscape scale, our study extends previous farm-scale work and provides new evidence on how farm-level crop diversity, the number of farms, and field size and habitat size are linked to crop diversification patterns in large-scale farming systems.

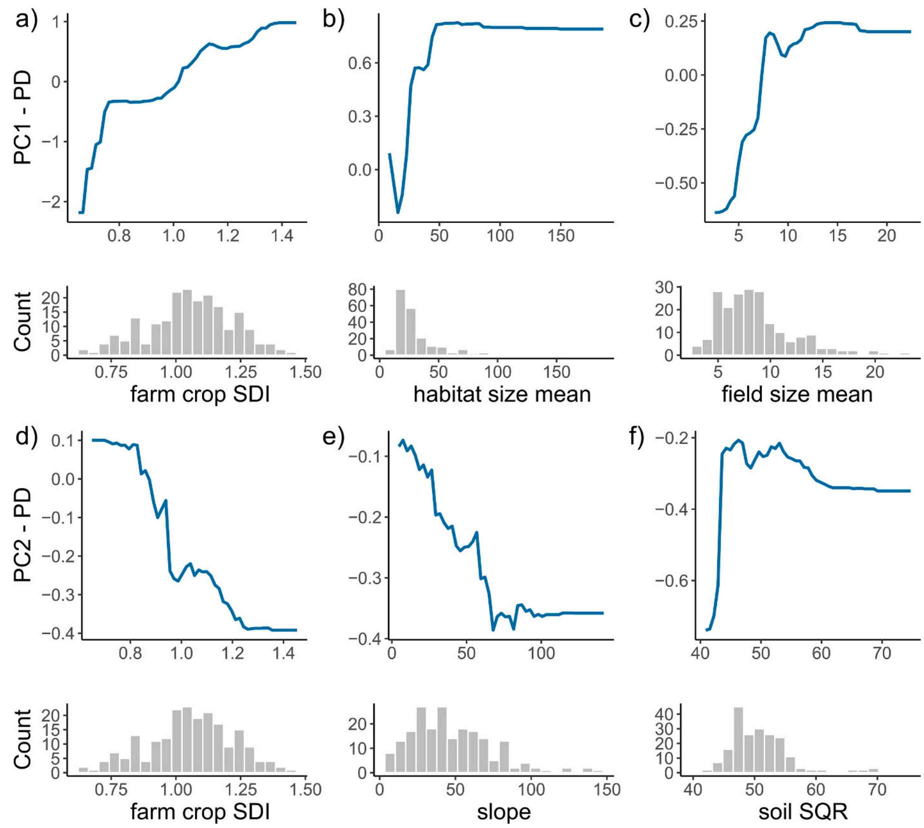

Fig. 5. Partial dependence (PD) plots from random forest models showing modeled associations between the key predictor variables and principal components (PC) PC1 (a-c) and PC2 (d-f); gray histograms below each PD plot indicate the distributions of the respective predictor variables across 10 × 10 km grid cells; SDI = Shannon's diversity, SQR = soil quality rating.

4.1. Link between spatial and temporal crop diversity

Our results confirm our first hypothesis and indicate a positive relationship between temporal and spatial crop diversity (Fig. 2). This relationship becomes evident by a moderate linear relationship between spatial and temporal crop diversity (Fig. 2) and by high variable importance scores when temporal crop diversity was used to predict spatial crop diversity and vice versa (Fig. B.1, B.2). Our findings are in line with those of Aramburu Merlos and Hijmans (2020), who observed a strong relationship between temporal and spatial crop diversity at scales comparable to farm levels in the US. Our results indicate that, in Brandenburg, the temporal crop diversity (crop rotations) is higher in regions where there is also higher spatial crop diversity and vice versa. Hence, crop diversity shows a synergistic interaction between time and space. This can be explained by the fact that crop rotations are implemented across many fields of a farm, resulting in higher diversity of crops spatially.

4.2. Farm-level crop diversity drives spatiotemporal crop diversity across landscapes

Our results suggest a positive link between farm-level crop diversity and spatial and temporal crop diversity (referred to as general crop diversity), which is represented by the PC1 variable, in 10 × 10 km landscapes (Fig. 4a, 5a). Therefore, we can assume that farm-level crop diversity is an important variable for describing general crop diversity within landscapes. To identify important variables for predicting the spatial or temporal crop diversity, we interpreted the model for predicting PC2. In this context, we observed that higher farm-level crop diversity was particularly associated with higher spatial crop diversity (negative PC2) within 10 × 10 km landscapes (Fig. 5d, B.3). To verify this interpretation of PC2, we conducted an additional analysis focusing exclusively on spatial crop diversity. This revealed that, in addition to farm-level crop diversity, the number of farms was even more strongly positively associated with higher spatial crop richness at the landscape level (Fig. B.2i). These results highlight that different facets of crop diversity, e.g., general or spatial, can be influenced by different farm-level characteristics.

While farm-level crop diversity was the most important variable for predicting general crop diversity (PC1), spatial crop diversity at the landscape level was shaped by a combination of the number of farms and farm-level crop decisions. For example, a single farm may select spatial crop arrangements based on the practiced crop rotation, farm type (conventional, organic, arable, and/or livestock-oriented), or farm-specific preferences (Jänicke et al., 2022; Klebl et al., 2023; Schaak et al., 2023). If one farm manages a large area, this means that this landscape diversity pattern is determined by the decision of a single farmer. In contrast, if multiple farms manage the same total area, we expect that each farmer decides on a partly unique spatial crop arrangement based on the factors mentioned before. To some extent, the spatial arrangements are expected to be similar or differ across farms. Such variation can accumulate at the landscape level, resulting in a complementary spatial mix of crops. Hence, the variation in crop types among farms can enhance spatial crop diversity at the landscape level, which implies that in our case study region, Brandenburg, landscapes dominated by a single farm could show less spatial crop diversity than landscapes with many farms that jointly manage a similar area.

Our machine learning models did not confirm our second hypothesis regarding a positive link between farm size and spatial or temporal crop diversity, but we observed a positive link between temporal crop diversity and field size. However, the exploratory correlation analysis revealed a positive Pearson correlation between farm size and farm-level crop diversity ($r = 0.43$; Fig. A.1, A.2). Since farm-level crop diversity was identified as the most important variable for explaining spatiotemporal crop diversity across landscapes, this suggests that larger farms could indirectly promote higher crop diversity, as they tend to manage more and bigger fields (Jänicke et al., 2024).

A positive relationship between farm size and temporal crop diversity has been observed in Germany (Jänicke et al., 2022), and a positive relationship between farm size and spatial crop diversity has been reported in Sweden (Schaak et al., 2023). One explanation for this link could be that bigger farms have better access to financial and material resources, including a higher workforce (Jänicke et al., 2022; Tacconi et al., 2023), which enables more diverse crop rotations that are spread and timely decoupled across multiple fields.

Additionally, we suspect that larger farms face more heterogeneous landscape conditions, e.g., varying soil conditions, due to their larger geographical distribution, which affects individual field management and leads to more diverse cropping patterns. In contrast, a global meta-study covering 51 regions, mainly from other parts of the world, emphasized that smaller farms tend to have higher yields and have greater crop diversity and biodiversity overall, but have to rely on family labor, whereas larger farms can benefit from mechanization (Ricciardi et al., 2021). This raises the question of whether the positive link between farm size and crop diversity at the farm level in Germany leads to increased yields and therefore enhanced economic resilience on larger farms and whether this differs from links observed in other regions.

One could argue that farms are key drivers of agricultural landscapes, influencing crop diversity at both the field and landscape levels. As the primary decision-making unit for field management, by implementing diverse crop rotation farms shape temporal crop diversity patterns. Moreover, because farms manage multiple fields, it is expected that the crop rotation patterns at multiple fields are asynchronously staggered over time, which increases spatial crop diversity across the landscape at any given time (Aramburu Merlos and Hijmans, 2020). Our finding of a positive link between temporal and spatial crop diversity linked to higher farm-level crop diversity underlines these synergistic spatiotemporal interactions. Therefore, farm management not only drives field-level patterns but also alters spatiotemporal changes in landscape compositions and configurations (Marrec et al., 2022).

To account for those fluctuations in biodiversity conservation, Marrec et al. (2022) proposed regional-level planning of agricultural landscapes to coordinate farm management decisions, ensuring continuous habitat availability and connectivity for species. This approach takes into account that farm management shapes both crop patterns and resource availability at the field and landscape levels, thereby affecting the ecological resilience of agricultural systems.

4.3. Increased predictive performance for spatial crop diversity over temporal crop diversity

Overall, our results showed a higher predictive performance for explaining spatial crop diversity than temporal crop diversity (Table B.2). This can be explained by the fact that most of our predictors capture relatively stable structural and environmental conditions (e.g., field size, habitat configuration, number of farms), which are more directly related to the spatial crop mosaic than to interannual rotation decisions at the farm level. Temporal crop diversity can be shaped by crop rotation patterns depending on historical management practices at fields, agronomic crop rotation rules, including also minor crops and cover crops, as well as market dynamics (Palka et al., 2026), which we did not include in our study. This can also explain why we observed overall negative links between a predictor variable and the PC2 variable (Fig. 5d-f). The positive relationship between a predictor variable and PC2 does not imply that there is no link with temporal crop diversity. It rather indicates that links with spatial diversity were relatively stronger than those with temporal diversity. Therefore, we decided to test both diversity scales independently of each other to confirm the influential factors associated with the respective scales.

4.4. Field size mean and habitat size mean explain temporal crop diversity

Our results show that temporal crop diversity was positively linked with field size means (related to our second hypothesis) and habitat size means per grid cell. This suggests that in our study region, farmers tend to cultivate more diverse crop rotations in areas with relatively larger fields than in those with relatively smaller fields. This is in line with Schiller et al. (2024), who found higher temporal crop diversity in agricultural-dominated and simplified areas. For example, in landscapes with larger fields, management could be dominated mainly by annual crops, which can be supported by large machines requiring relatively lower labor investment (Roschewitz et al., 2005). In contrast, areas with small field sizes could be less dominated by agricultural land use and/or more cultivated with perennials or continuous cropping of cereals and maize. Although we observed a positive relationship between the field size mean and temporal crop diversity, how this is associated with the land use intensity, e.g., pesticide use, in this area needs further investigation (Roschewitz et al., 2005).

Our results are relevant for the debate about decreasing field sizes, which translates into increasing landscape configuration. Several studies have reported the positive effects of smaller field sizes on biodiversity (e.g., Fahrig et al., 2015; Hass et al., 2018; Sirami et al., 2019; Wesemeyer et al., 2023). However, our study indicates a synergy between higher field sizes and higher temporal crop diversity, which results in a trade-off for reducing field size. Wesemeyer et al. (2023) showed that by decreasing field sizes and adjusting woody species in Brandenburg by 5%, both bird biodiversity and agricultural net returns will be enhanced. Notably, the feasibility of reducing field size means—e.g., < 6 ha, as suggested by Sirami et al. (2019)—will likely be dependent on the target region. For example, in Brandenburg and other states in the Eastern part of Germany, farms have historically grown larger fields compared to the south of Germany (Jänicke et al., 2024). Therefore, while we observed a higher temporal crop diversity in areas with overall higher field size means and habitat size means in Brandenburg, how this is associated with biodiversity conservation measures, such as seminatural habitats or functional crop diversity, and whether this link can be transferred to more distant regions, like in southern Germany, needs to be further investigated. Our findings are specific to Brandenburg, a region characterized by large-scale farming with comparatively large fields and farms and very low to moderate soil conditions. In comparison, farming structures in southern Germany or other parts of Europe are small-scale (Bundesministerium für Ernährung and und Landwirtschaft (BMEL), 2022; Eurostat, 2022). Smaller farms can lead to smaller field sizes and higher edge density in landscapes but not necessarily a higher temporal or spatial diversity as few major crops dominate farming. Consequently, the transferability of our findings is limited, and they should be interpreted in the context of Brandenburg's landscape characteristics. Future work could therefore test whether the relationships between diversity, temporal and spatial crop diversity patterns, and their influencing factors also hold for small-scale farming and under different landscape conditions.

4.5. Future directions: toward biodiversity-friendly and high-yielding agricultural landscapes

The ecological benefits of agricultural diversification are still under debate. On the one hand, the potential of increasing landscape complexity to support biodiversity is most effective in landscapes that are neither too simple nor too complex (intermediate landscape-complexity hypothesis) (Tscharntke et al., 2012). Furthermore, enhancing landscape complexity should consider the negative effects of landscape fragmentation when (crop) habitats become too small (heterogeneity trade-off hypothesis) (Khan et al., 2023). Also, Sirami et al. (2019) observed that increasing crop diversity benefited biodiversity only in areas where seminatural habitat cover was >11%. On the other hand, Schiller et al. (2024) identified that temporal crop diversity was higher when soil quality reached a certain threshold, highlighting poor soil quality as a limiting factor for temporal crop diversity.

A framework that considers the context-dependency of agricultural landscapes and gives suggestions for agricultural practices based on the current state of land use was published by Sietz et al. (2022). For example, they suggest that diversifying cropping systems is a recommended practice under "intensive agricultural production and low farmland biodiversity" and "intermediate agricultural production and farmland biodiversity". In relation to our study, this translates to enhancing crop diversity in intermediate complex landscapes with at least 11% seminatural habitats and medium fertile soils (SQR ca. 50). Additionally, it has to be considered that input intensity (fertilization, pesticide application) has been shown to be more relevant for biodiversity than field size alone (Stein-Bachinger et al., 2022), and organic farming supports biodiversity (Sanders et al., 2025), even in large fields.

4.6. Limitations

Our study did not account for the identity of crops and habitats within the measured diversity, nor did it explore how differing classification schemes impact the diversity values. Yet, both the diversity composition based on identity and how the identities are defined, e.g., using total diversity vs. functional diversity, are important to consider when interpreting diversity values and their effects. For example, when the effect of crop diversity on yield volatility was tested in Germany, the results identified that the share of barley and wheat is more important for reducing yield volatility than overall crop diversity is (Ahrends et al., 2024). Similarly, Bosem Baillod et al. (2017) showed that the positive effects of crop diversity on pest control were mediated by the share of present aphid host habitat cover. Moreover, Schaak et al. (2023) observed that using different classification schemes, such as functional or related diversity, can lead to diverging diversity metrics. For example, grouping individual crops into "cereals", "winter cereals", or "spring cereals" can reduce the observed diversity. While this study focused primarily on analyzing the spatiotemporal links of crop diversity and its influencing factors, future work can expand our research by tailoring the classification scheme to specific research objectives, e.g., yields or biodiversity implications. These schemes can further depend on the target group, e.g., bird or soil biodiversity. In this sense, diversity metrics should not be treated as fixed entities but rather as context-dependent constructs that require adjustment according to the ecological or agronomic outcome of interest (cf. Ahrends et al., 2024; Bosem Baillod et al., 2017).

We intended to understand how the large, landscape-scale (i.e., 10 × 10 km) differences can be explained. All data points from one of the above variables that fell into a grid cell were aggregated into a single representative value. This means all field and farm information is aggregated to the landscape level. This approach reduced the concern about pseudo-replication and hierarchical structuring of the data. We also accounted for latitude and longitude information in a nonlinear, non-additive manner, which can address spatial structuring and autocorrelation among neighbouring cells to some extent. Yet, we admit that this analytical approach has room for improvement. For instance, it would be possible to employ a mixed-effect model to account for the hierarchical structure of the data if we analyzed the field-level variability by constraining field information to the same farm. In this case, the method can account for farm-specific unobserved features. However, identifying key factors at the field level was out of our scope, and this approach could not have considered several factors, like the number of farms, which we identified as a key factor. This complementary analysis can be done in future studies.

This aggregation also brings further limitations. While the benefit is to approximate the average effect of multiple farms within landscapes, it loses information about individual farm attributes. Furthermore, the 10 × 10 km scale may be too coarse to account for diversity aspects that are relevant to small organisms like invertebrates, as their distribution ranges are narrower (> 0.5 km^2) (Priyadarshana et al., 2024). Consequently, finding a suitable grid cell size can vary depending on the research question. In addition, we addressed multicollinearity in the predictor variables by excluding highly correlated variable pairs ($|r| > 0.7$), rather than applying more advanced approaches for handling collinearity. This ensured that the set of predictors used for the analyses did not contain strongly collinear variables. Nevertheless, our findings reflect landscape-wide trends beyond the individual farm level, which confirms spatiotemporal crop diversity patterns that have been observed in other regions (Aramburu Merlos and Hijmans, 2020). It is also worth testing the same approach for a large spatiotemporal extent or other biogeoclimatic regions.

5. Conclusion

The present study found a positive linkage between temporal and spatial crop diversity across more than 5500 farms in Brandenburg, Germany, and tested its link with various attributes and surrounding landscape conditions. The results showed that farm-level crop diversity is positively associated with both spatial and temporal crop diversity. More specifically, higher crop diversity at the field and landscape levels is positively associated with higher crop diversity at the farm level in more simplified landscapes, which are characterized by large field and habitat mean sizes. This pattern suggests that farm-level crop diversity plays a key role in temporal and spatial crop diversity in structurally simplified landscapes, which can guide diversity-oriented management and policy design. Our findings, therefore, extend previous farm-scale studies by providing a spatiotemporal landscape perspective on crop diversification and its main influencing factors in large-scale farming systems. We contribute to a mechanistic understanding of cross-level and cross-scale effects within agricultural landscapes.

CRediT authorship contribution statement

Josepha Schiller: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Clemens Jänicke:** Writing – review & editing, Data curation. **Moritz Reckling:** Writing – review & editing. **Masahiro Ryo:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI ChatGPT Plus to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2026.104685.

Data availability

The PCA and machine learning code and the spatiotemporal crop diversity dataset, including the PCA components, are openly available on Zenodo (https://doi.org/10.5281/zenodo.17084000).

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