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Predicting old-growth structures in temperate small-scale private forests using landscape data

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Abstract

Key message Old-growth forest structures in small-scale private forests are strongly shaped by landscape context and can be reliably predicted using freely available spatial data. Remnant forest patches within mixed cultural landscapes act as important reservoirs and connectivity elements for forest biodiversity and should be prioritized in conservation and management planning.

Context Many forest species of high conservation concern depend on old-growth structures, which are often rare in contemporary production forests. In small-scale private forests, these structures are fostered by inactive owners and influenced by parcel topography.

Aims We attempt to quantify the abundance of old-growth structures in small-scale private forests in Lower Saxony, Germany. Landscape-related predictors are employed to model spatial distribution patterns.

Methods The *Parcel Index of Conservation Attributes* (PICA) was calculated from forest structural data and modeled using a gradient boosting tree model. Independent survey data was used to evaluate its performance externally. The predictions are shown in the form of a spatial distribution map.

Results The prediction identified parcels with a high abundance of old-growth structures. These were mostly found outside of large, more intensively managed forest regions and consisted of stands rich in broadleaf trees situated in semi-open, mixed-use cultural landscapes.

Conclusion Predictions about the spatial distribution of valuable habitats can be made using freely available landscape-scale data. Verifying these predictions using small samples increases the trustworthiness of the model. Forest patches in fragmented agricultural landscapes can act as islands of old-growth structures. These patches are vital for rare forest species and must be urgently protected.

Keywords Biodiversity hotspots, Forest management, Forest ownership, Predictive modeling, Machine learning, Fragmented cultural landscapes

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1 Introduction

The biodiversity of European forests largely consists of species groups that depend on old-growth structures, which are mainly found in unmanaged, mature forests. Examples include bryophytes, lichens, saproxylic fungi and beetles, as well as bats and birds (Blasi et al. 2010; Rigo et al. 2024; Storch et al. 2023). Forests that are rich in old-growth structures are recognized as supporting a variety of forest ecosystem services and providing diverse habitats for forest species (Storch et al. 2018; Wagenaar et al. 2025; Zeller et al. 2023).

Old-growth structures include lying or standing deadwood (Henneberg et al. 2025), old trees approaching the end of their lives (Gilhen-Baker et al. 2022), high biomass pools, structural variation in tree sizes and canopy layers (Bauhus et al. 2009), and tree-related microhabitats (Martin et al. 2022). These structures are rare in production forests, which are typically managed with relatively short rotation periods (Barredo et al. 2021). Primary forests without anthropogenic influences have virtually disappeared from most of Europe (Sabatini et al. 2018). However, old-growth structures can develop in secondary forests if they are left undisturbed (Barredo et al. 2021), or if they are managed in a semi-natural way (Bauhus et al. 2009). But these structures take long periods of time to develop.

In Germany, large forest holdings under public or private ownership are primarily managed by professionals, while small properties often undergo more irregular management. Small-scale private forest parcels—cadastral units owned by individuals—of up to 20 ha account for 22.8% of Germany's total forested area (Thünen Institute 2022a). Systematic forestry is often not possible in the economies of small-scale private forests. Individual owners who do not depend on income from wood sales often pursue non-economic objectives, such as preserving natural or cultural values, or even non-management (Husa and Kosenius 2021; Tiebel et al. 2024). This behavior increases the likelihood of old-growth structures developing and persisting in such forests (Johann and Schaich 2016). However, their long-term protection is not reliably guaranteed Svensson et al. 2025).

The continuous retention of old-growth structures, i.e., ecological or habitat continuity, is essential for the long-term survival of specialized forest species (Wysocki et al. 2025). This emphasizes the crucial role of forest management that is aware of old-growth structures, which hinges on precise spatial data (Barredo et al. 2021). Targeted outreach and policy instruments, such as protection legislation, incentives or conservation contracts (Demant et al. 2020), can safeguard such structures in private forests, but decision makers are in need of dependable spatial distribution data to implement these measures effectively.

Spatial data on old-growth habitats and the biodiversity that depends on them is usually unavailable due to the diverse ownership and the non-professionalized nature of small-scale private forests. This lack of actionable data presents a major research gap in the understanding of small-scale private forest structures and biodiversity (Thompson et al. 2022). A landscape-scale inventory of old-growth structures would be transformative, as it would allow decision makers to pinpoint their conservation actions. Precise and complete maps of old-growth forest structures could serve as a valuable substitute to field surveys of old-growth biodiversity (Martin et al. 2022), which are often prohibitively costly (Juutinen and Mönkkönen 2004).

As old-growth structures can manifest in a variety of ways, it is challenging to compare the nature conservation value of different small-scale private forest parcels. Therefore, a numerical index that takes various old-growth structures into account would be useful for assessing the spatial distribution of high-conservation-value structures among small-scale private forest parcels, especially at a landscape scale. In the present study, we propose a numerical index we call the *Parcel Index of Conservation Attributes* (PICA). PICA considers various forest structural variables known to be associated with old-growth forest biodiversity, including living and dead wood volumes and the number of large trees (Blasi et al. 2010; Storch et al. 2023).

Similar to other indices of structural characteristics (Di Filippo et al. 2017; Meyer et al. 2021; Reich et al. 2022), PICA can be calculated directly from field data obtained through forest structure surveys. However, for PICA to be useful at a landscape scale, it is preferable to model PICA values using data that is more easily accessible. In a previous study (Hansen et al. 2023), we identified predictors of old-growth forest structures in small-scale private forests. This study showed that old-growth structures were notably influenced by the landscape parameters of the forest parcels. The most important predictors were slope, distance to a road, ancient forest land and forest fragmentation metrics. These results suggested a method of predicting the abundance of old-growth forest structures in private forest parcels, substituting the need for comprehensive forest surveys with the ability to draw on already existing, blanket-coverage open landscape data. The final model should be able to produce a prediction map showing the spatial distribution of old-growth structures in small-scale forest parcels, as expressed by PICA values, at the landscape scale.

Specifically, our study addresses the following research questions:

- Can the *Parcel Index of Conservation Attributes* (PICA) be used to accurately quantify the abundance of valuable old-growth structures in small-scale private forests?
- To what extent are old-growth structures influenced by the landscape parameters of the individual forest parcels?
- What can be inferred from a spatial distribution model that predicts PICA values, and accordingly the abundance of old-growth structures, on the landscape scale?

2 Methods

2.1 Overview of the study design

Field data was collected on 78 small-scale private forest parcels in northwest Germany, and stored in a training dataset together with landscape data from open sources. A model m_1 was then trained using this dataset to predict PICA values. A control sample of 48 small-scale private forest parcels was surveyed to generate an independent testing dataset, which allowed for an external evaluation of the model's performance. Finally, a second predictive model m_2 was trained using both datasets to produce a raster-based prediction of PICA values in the study area (Fig. 1).

2.2 Study area

Fieldwork was conducted in the Lower Saxon Hills, a 14,228 km^2 geographic region consisting of two contiguous areas in the German federal state of Lower Saxony (Fig. 2). The region's private forest owners are subject to homogeneous legal and administrative conditions. Thirty-three percent of the region is forested, primarily with European beech (*Fagus sylvatica* L., 39%), which dominates the natural vegetation. Other common tree species include Norway spruce (*Picea abies* (L.) H. Karst., 18%), oaks (*Quercus robur* L. and *Q. petraea* (Matt.) Liebl., 12%), sycamore maple (*Acer pseudoplatanus* L.), wild cherry (*Prunus avium* L.), birch (*Betula pendula* Roth), hornbeam (*Carpinus betulus* L.), Scots pine (*Pinus sylvestris* L.), and Douglas fir (*Pseudotsuga menziesii* (Mirbel) Franco) (ML 2024). Private forests in the region account for 45% of the forested area. Nineteen percent of the private forest area is divided into small-scale private forests with a maximum size of 5 ha (ML 2024). The distribution of forest property is comparable to that of many other European countries (Schmithüsen and Hirsch 2010; UNECE and FAO 2020). The bedrock in the Lower Saxon Hills consists primarily of Mesozoic limestone and sandstone, partly with a Quaternary loess cover, and occasionally evaporite (gypsum karst) (LBEG 2022). The region's climate is oceanic to humid continental (Köppen classifications Cfb and Dfb), but it has experienced rising temperatures and more erratic precipitation patterns in recent years. The 2024 annual mean temperature on the parcels we studied ranged from 10.0 to 11.7 °C, and the 2024 annual precipitation ranged from 744 to 1249 mm (DWD 2025a, b). Drought, elevated temperatures, and accompanying tree pests have impacted both conifer and broadleaf trees, rendering forestry in the study area highly vulnerable (George et al. 2022; Knutzen et al. 2025; Senf et al. 2020).

2.3 Study site selection and field work

Members of three local private forest owner associations who participated in a large-scale questionnaire survey in the Lower Saxon Hills region (Hansen et al. 2023, 2025; Tiebel et al. 2021) and had provided contact information were asked for information about the exact location of their property. Eighty-eight owners of small-scale private forest parcels in the study area responded to this call, and 78 of them provided useful geographic information about their forest parcels. The 78 small-scale private forest parcels (sizes between 0.14 and 3.73 ha, average size: 1.16 ha) were visited during a first field campaign in 2021. Forest parcels exhibited a wide structural variety, ranging from deforested former conifer plantations to old broadleaf forests that have not undergone active management for several decades. On the sites, data on forest structure, management, and biotopes was collected. This resulted in the training dataset, d_{train} (Figs. 1 and 2). A model m_1 trained with this dataset was used to identify an additional set of 48 small-scale private forest parcels (see Section 2.6) in the study area (sizes between 0.15 and 2.31 ha, average size: 0.65 ha). A second field campaign was conducted in 2022 and 2023 to collect data on these parcels for external model evaluation, resulting in the test dataset, d_{test} (Figs. 1 and 2).

On each of the 126 small-scale private forest parcels, forest structural data was collected in one or several 500 m^2 circular plots ($r = 12.62$ m), according to Meyer and Fricke (2018). One plot was chosen for parcels smaller than 1.5 ha, two for parcels larger than 1.5 but smaller than 3 ha, and three for parcels of at least 3 ha. For single-plot parcels, parcel centroids were chosen as plot centers, allowing some flexibility for parcels with concave shapes. If a parcel had multiple plots, the plots were placed using repelling buffers in the geographic information system to maximize the distance from one another and from the parcel borders. We aggregated all plot data surveyed on multi-plot parcels by taking the mean. This removed within-parcel resolution but allowed us to treat these parcels the same way we treated parcels with a single plot. Additionally, estimation bias was lower on these parcels. Within each plot, all living or dead standing trees with a diameter at breast height

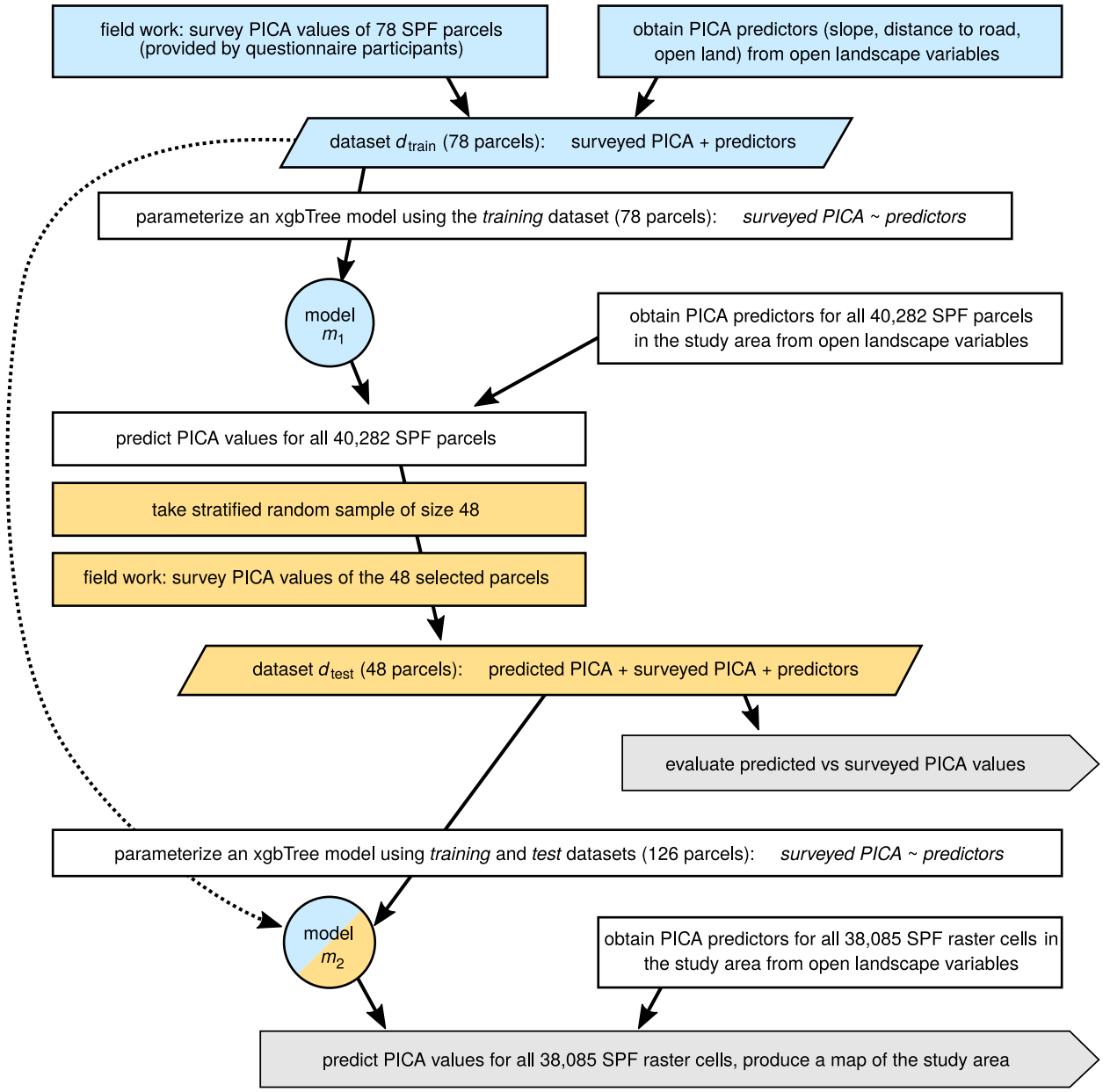

Fig. 1 Flow chart of the study design. Blue color denotes elements related to the training dataset d_{train} (78 small-scale private forest parcels). Orange color denotes elements related to the testing dataset d_{test} (48 small-scale private forest parcels). Datasets shown as parallelograms, prediction models (xgbTree) shown as circles. Black arrows denote flow paths. Gray arrow boxes symbolize the primary outcomes of the overall design

(dbh, at 1.3 m) of at least 7 cm were recorded, along with their dbh and species. For each tree species, we grouped measured diameters into three classes and, from each class, selected three trees (when available) for height measurements ($n \leq 9$ total) using a handheld laser rangefinder (LTI TruPulse 360B). These data were used to fit individual Näslund height curves (Mehtätalo et al. 2015) for each tree species and each plot, which allowed us to interpolate the heights of unmeasured trees. Tree volume was calculated from dbh and height, using species-specific form factors. When surveying deadwood, we inventoried stumps with a diameter of at least 7 cm. We recorded their diameter and height and classified them as conifer or broadleaf. Deadwood lying on the ground was inventoried if its diameter was at least 20 cm at the thicker end. The length and diameter at both ends were

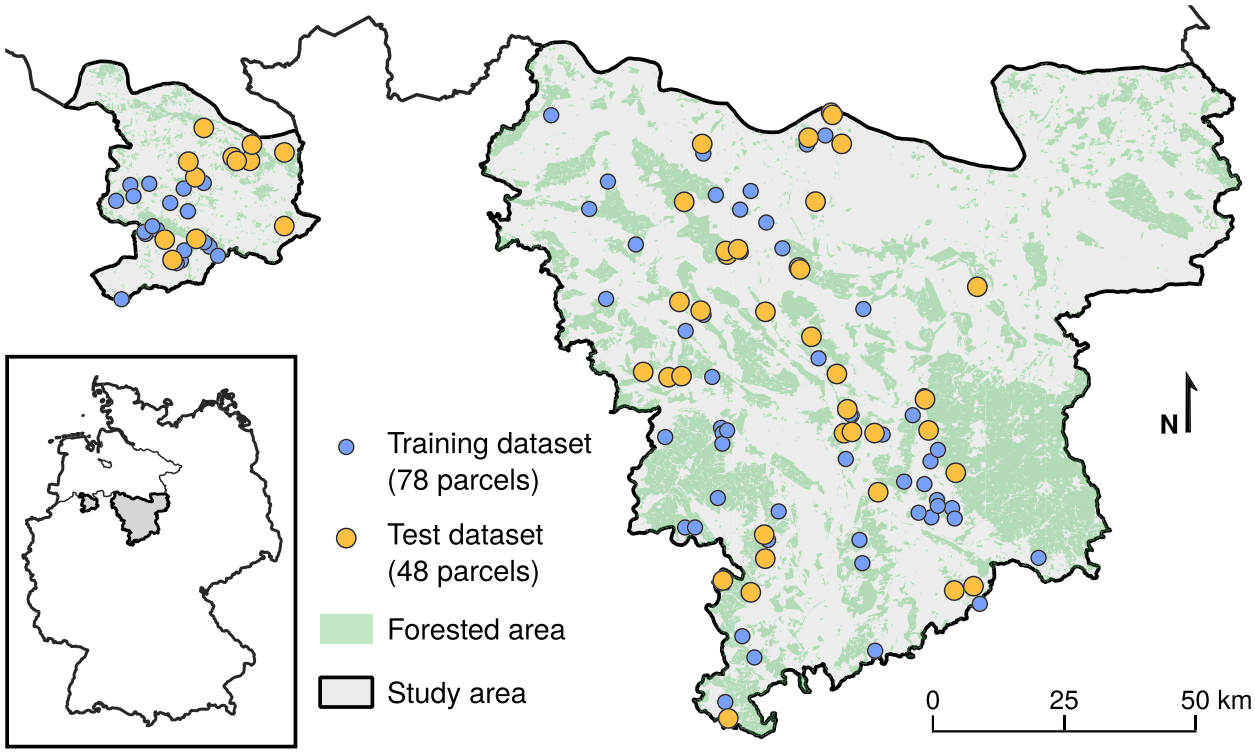

Fig. 2 Map of the study area, the Lower Saxon Hills (14,228 km^2). Forest parcels in the training dataset d_{train} (small blue data points) were provided by owners who participated in a questionnaire. Parcels in the test dataset d_{test} (larger orange data points) were selected by a stratified random sampling process, see Section 2.6

recorded, and each object was classified as either conifer or broadleaf, and as either of anthropogenic (showing saw marks) or natural origin. The volume of large objects, such as complete fallen trees, was calculated as it was for standing trees. The same was done for dead standing trees. All lying objects were recorded as if cut off at the plot border. The volume of harvested wood for each stump was calculated by first extrapolating the stump's diameter to dbh using a uniform tapering value of 1 cm/m. Then, the appropriate height curve and standard form factor were applied. Thus, the harvested wood volumes are the integral of the wood volume taken from the forest over the stump persistence time. These different wood volumes were used to calculate the Forest Management Index (ForMI) (Kahl and Bauhus 2014). We treated tree species planted outside their natural range, e.g., *Picea abies* (Norway spruce), as non-native. Several data were recorded not only in the plots, but also throughout the entire forest parcel. In this way, we recorded the occurrence of standing trees, whether living or dead, with a dbh of at least 50 cm throughout the entire parcel. Large-tree density was recorded at the parcel scale because these trees are rare, spatially clustered, and often absent from 500 m^2 plots. To evaluate the effects of parcel area, we examined the relationship between parcel size and large-tree density using Spearman's rank correlation coefficient. We also identified the three most important biotope types in terms of surface area (Drachenfels 2021). We assigned numerical "biotope values" to all biotope types present on the parcels (ranging from 0 = low to 24 = high), following the German federal regulation on avoiding and compensating for interventions in nature and landscapes (BKompV 2020; see Hansen et al. 2023). These numbers describe the standardized ecological value of biotope types, and favor old-growth and native forest types. We aggregated all biotope type values from a parcel, assigning weights based on the spatial extent of each biotope type. We used Wilcoxon rank sum tests to check for differences in structural data between the d_{train} and d_{test} datasets. Descriptive statistics of landscape parameters and field data are shown in Table 1.

2.4 Parcel Index of Conservation Attributes (PICA)

In the following, we define the *Parcel Index of Conservation Attributes* (PICA). This index attempts to quantify the abundance of old-growth structures on a forest parcel. PICA considers variables closely related to slowly-evolving and valuable old-growth habitat structures, that have been shown to be driven by the landscape parameters of the forest parcels (Hansen et al. 2023; see

Table 1 Descriptive statistics of data collected in the field; PICA values; and predictors (landscape parameters) for data sets d_{train} and d_{test}. Results of Wilcoxon rank sum tests are given as p-values. Significantly different means are marked [a/b]

Variable	Dataset	Mean	SD	Min	Median	Max
Broadleaf living volume in m^3 ha^{-1}	d_{train}	210	228	0	116	877
(*p*-value: 0.270)	d_{test}	247	218	0	230	853
Broadleaf deadwood volume in m^3 ha^{-1}	d_{train}	11.2 [a]	21.9	0	3.03	124
(*p*-value: 0.042)	d_{test}	23.3 [b]	39.4	0	7.51	175
ForMI	d_{train}	0.462	0.292	0	0.402	0.984
(*p*-value: 0.156)	d_{test}	0.382	0.327	0	0.391	0.987
Biotope type value	d_{train}	14.3	4.18	6	13.0	23
(*p*-value: 0.193)	d_{test}	15.3	4.31	9	14.9	23
Trees at least 50 cm dbh per ha	d_{train}	18.4	30.5	0	4.39	163
(*p*-value: 0.113)	d_{test}	30.9	40.0	0	10.5	144
PICA value	d_{train}	0.436	0.226	0.078	0.436	0.905
(*p*-value: 0.090)	d_{test}	0.520	0.250	0.078	0.587	0.973
Slope in degree	d_{train}	7.8	5.8	0.1	6.3	27.9
(*p*-value: 0.558)	d_{test}	8.8	6.7	0.3	7.0	24.4
Broadleaf forest ($n=0, y=1$)	d_{train}	0.538	0.502	0	1	1
(*p*-value: 0.100)	d_{test}	0.688	0.468	0	1	1
Distance to road in m	d_{train}	373	280	24	303	1146
(*p*-value: 0.110)	d_{test}	562	479	32	435	1752
Open land in 200 m radius	d_{train}	0.398 [a]	0.336	0	0.376	1
(*p*-value: 0.023)	d_{test}	0.290 [b]	0.320	0	0.233	1
Open land in 2 km radius	d_{train}	0.541	0.190	0.048	0.564	0.814
(*p*-value: 0.612)	d_{test}	0.531	0.182	0.101	0.575	0.809

also Section 2.5). The components of PICA include: (*a*) amount of living broadleaf wood; (*b*) amount of deadwood, particularly from broadleaf tree species; (*c*) low management intensity; (*d*) occurrences of rare, valuable biotopes; and (*e*) density of large-diameter trees. This choice was motivated by rapid applicability in common settings. Forest structural data that is standardly gathered in the field is mostly sufficient to calculate the index components. We chose to use the density of large-diameter trees (ρ_{ldtree}) on the parcels as one of the five individual components rather than the density of microhabitats or habitat-bearing trees (Larrieu et al. 2018). Surveying tree diameters is much more efficient than surveying microhabitats. Large-diameter trees are likely to already have microhabitats or develop them in the future (Kozák et al. 2023; Torres-García et al. 2024).

While (*a*), (*b*), and (*c*) were calculated from plot data, (*d*) and (*e*) were measured on the whole forest parcel. PICA values are unitless numbers ranging from 0 to 1, and the index is calculated as the mean of five components, each of which also ranges from 0 to 1. The forest structural parameters that define these components are as follows: (*a*) the volume of living broadleaf trees ($V_{\text{livingBrl}}$) given in m^3 ha^{-1}; (*b*) the volume of broadleaf deadwood (V_{deadBrl}) given in m^3 ha^{-1}; (*c*) the forest management intensity index (ForMI), defined to range from 0 to 3 by Kahl and Bauhus (2014), which uses standard inventory data of trees and deadwood to assess management intensity during the last 30–40 years of a stand; (*d*) biotope values ranging from 0 to 24 according to BKompV (2020); and (*e*) the density of large-diameter trees (ρ_{ldtree}), given in ha^{-1}. Since these five components do not fall within the range of 0 to 1, we applied transformations similar to those described by Storch et al. (2023). Biotope values were divided by 24. We considered high management intensities to be detrimental to old-growth structures and therefore subtracted the ForMI index values divided by three from one. To bring the broadleaf living volumes, broadleaf dead volumes, and habitat trees densities into the interval [0, 1], we used a saturation function s_h with the following properties: (*a*) $s_h(0)=0$; (*b*) $s_h(h)=0.5$; (*c*) $\lim_{x\to\infty} s_h(x)=1$. A standard logistic function with an additional parameter h that satisfies these constraints is given by:

Table 2 Values of the *h* parameter for the different PICA components. Occurrences of old-growth structures close to *h* correspond to PICA component scores of 0.5

PICA component	Value of *h* chosen	Rationale
Broadleaf living volume	250 m^3 ha^{-1}	The average in our dataset is 224 m^3 ha^{-1}, median 158 m^3 ha^{-1}. Average for all private forest sizes in Lower Saxony is 148 m^3 ha^{-1}, for small-scale private forests 174 m^3 ha^{-1} (Thünen Institute 2022b)
Broadleaf deadwood volume	20 m^3 ha^{-1}	The average in our dataset is 16.1 m^3 ha^{-1}, median 6.0 m^3 ha^{-1}. The average for all private forest sizes in Lower Saxony is 8.1 m^3 ha^{-1}, and 11.5 m^3 ha^{-1} for small-scale private forests (Thünen Institute 2022c)
Density of large-diameter trees	5 ha^{-1}	The average in our dataset is 22.9 ha^{-1}, median 5.8 ha^{-1}. Lower Saxony recommendation for minimal density in Natura 2000 areas is 6 ha^{-1} (ML and MU, 2019), For forests older than 100 years, Hesse state forest service recommends 10 ha^{-1}, and 15 ha^{-1} in Natura 2000 reserves (HMUKLV 2022)

$$s_h(x)=\frac{2}{1+e^{-ln(3)\frac{x}{h}}}-1$$

The value of *h* was chosen individually for each PICA component (broadleaf living volume, broadleaf dead volume, and density of large-diameter trees) according to the corresponding averages in our dataset and statewide inventory data (see Table 2). For example, consider the amount of broadleaf living volume, for which we chose $h=250$ m^3. Parcels with a broadleaf volume of 250 m^3 will receive a score of 0.5 on the broadleaf volume PICA component scale. The PICA value for an individual forest parcel is calculated as:

$$\mathrm{PICA}=\frac{1}{5}\left[s_{250}\left(V_{\mathrm{livingBrl}}\right)+s_{20}\left(V_{\mathrm{deadBrl}}\right)+\left(1-\frac{\mathrm{ForMI}}{3}\right)+\frac{\mathrm{biotopeValue}}{24}+s_5\left(\rho_{\mathrm{ldtree}}\right)\right]$$

2.5 Landscape-related predictor variables

Based on previous results (Hansen et al. 2023), we selected five landscape parameters of small-scale private forest parcels that have been shown to significantly influence our response variables, i.e., the components of PICA. The selected predictors were (*1*) terrain slope, calculated from a digital elevation model (variable *slope*) (GeoBasis-DE/LGLN 2025); (*2*) parcel status as broadleaf or conifer forest (variable *broadleaf*), sampled from CORINE land cover data (Copernicus Land Monitoring Service 2018) at the parcel centroid; (*3*) the parcel's distance to the nearest paved road (variable *distance to road*), calculated using a road network map (OpenStreetMap contributors 2022); (*4*) the amount of open land within a 200 m radius of the parcel (variable *openland 200 m*); and (*5*) the amount of open land within a 2 km radius of the parcel (variable *openland 2 km*). The last two calculations were also based on CORINE land cover data (Copernicus Land Monitoring Service 2018). We decided on discarding the variables *parcel size*, *elevation*, *water availability*, and *nutrient availability*. While *parcel size* had to be removed for data licensing reasons (see Section 2.6), the other three variables had no influence on the relevant response variables. As we did not have clearance to disclose all small-scale private forest parcel geometries in the study area, polygon data were converted to raster data with a resolution of 100 m × 100 m to make study area-wide predictions. For prediction purposes, these raster cells were treated in the same manner as the land tenure parcels. Geospatial data were analyzed using QGIS 3.42 (QGIS Development Team 2025) and R 4.4.3 (R Core Team 2025).

2.6 Modeling and model evaluation

When evaluating a prediction model, it is possible to restrict oneself to an internal evaluation, using procedures such as cross-validation to extract as much information as possible from a limited data set. However, to determine whether a prediction model can generalize to new and different situations, a form of external validation is necessary (Ramspek et al. 2021). The dataset used to train a model may be biased; in our case, for example, it consists of owner-provided forest parcels. To address this issue, we employed a random sampling process to identify new, unseen forest parcels that may differ structurally from the training dataset. During external evaluation, we tested the model's predictions on these new parcels against independently surveyed ground truth. This allowed us to better understand the model's ability to generalize to new cases. Although costly, an external evaluation can greatly benefit the selection of a prediction model. It can assess generalizability to new data and detect overfitting, thus supporting the model's robustness and increasing trust in its predictions (Bowman and Robitaille 2005; Pearce and Ferrier 2000).

After completing the first field campaign to survey forest structural variables in the d_{train} dataset, we calculated

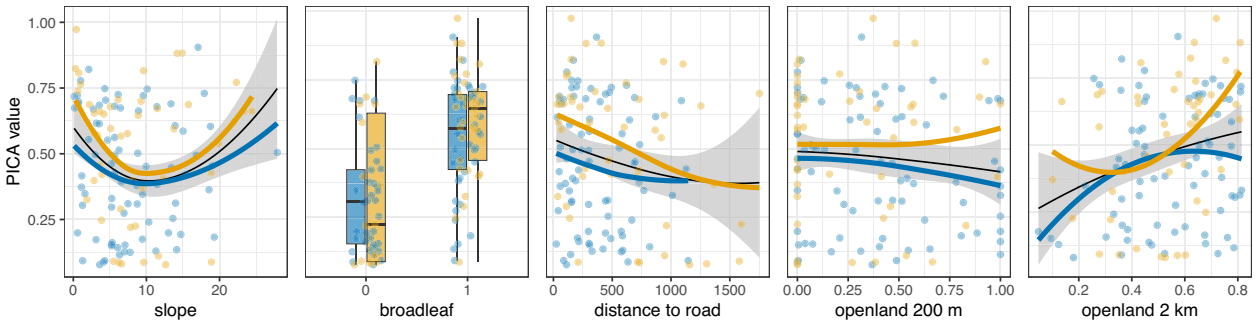

Fig. 3 Scatter plots of the PICA values of datasets d_{train} (blue) and d_{test} (orange) against each of the five predictors. For the binary predictor *broadleaf*, boxplots are shown. For the other predictors, smoothing curves (LOESS) are given for d_{train} and d_{test}, while the black curve represents the response for the combined dataset of $d_{train} \cup d_{test}$. Confidence intervals (95%) are shown for the latter

PICA values (see Section 2.4) and landscape variables (see Section 2.5) for each of the 78 parcels. A gradient boosting tree (xgbTree) model m_1 (Chen and Guestrin 2016) was trained to predict the response variable (PICA values) from the predictors (the landscape variables), using manual fine-tuning of hyperparameters to achieve the best mean absolute error (Willmott and Matsuura 2005). Internal evaluation was performed using fivefold cross-validation, repeated five times (Hastie et al. 2017; Yates et al. 2023). Model m_1 was then used to predict PICA values for all 40,282 known private forest parcels of ≤ 4 ha size in the study area (Hansen et al. 2026). This threshold was chosen to avoid extrapolating beyond the parcel sizes in the training set d_{train}, which ranged from 0.142 ha to 3.805 ha. A stratified random sample of size 48 was taken from all these small-scale private forest parcels by randomly selecting 12 parcels from each predicted PICA quartile. This sampling method aimed to capture the PICA range in the study area, as opposed to random sampling, and differed from the sampling method used for d_{train}, thus providing a suitable foundation for the external evaluation (Ramspek et al. 2021). The 48 new parcels were surveyed on-site during our second field campaign, using the same methodology that was used before (see Section 2.3). PICA values were calculated from the components. The resulting data constituted the d_{test} dataset, which was used for the external evaluation of model m_1 (Fig. 1). In order to perform predictions using as much information as possible from the available data, a second gradient boosting tree model, m_2, was parameterized using the union of the d_{train} and d_{test} datasets (i.e., 126 small-scale private forest parcels), again employing repeated fivefold cross-validation. Hyperparameters were carried over from m_1 to prevent overfitting to the data. We expected m_2 to perform as well as model m_1 and to make better use of the available data. Our decision to use gradient boosting tree models was supported by several factors. We encountered nonlinearities in the responses early on, as seen in the slope response in Fig. 3. Like random forest models, gradient boosting tree models allow for high interpretability, for example by providing variable importance measures. Additionally, machine learning algorithms such as XGBoost are top performers for predicting tabular data (Grinsztajn et al. 2022; Januschowski et al. 2022). These algorithms can handle missing values, which could be important in situations involving incomplete surveys or missing landscape data.

A map showing all small-scale private forest parcels in the study area could not be released for licensing reasons. This prevented the use of parcel size as a predictor. Therefore, we assessed variable importance in model m_2 and used it to perform a rasterized (100 m × 100 m) prediction of PICA values for all 38,085 raster cells in the study area containing known small-scale private forest parcels (Hansen et al. 2026).

3 Results

3.1 First field campaign: dataset d_{train}

The broadleaf living volumes on the 78 d_{train} parcels ranged from 0 to 877 $m^3\ ha^{-1}$ (see Table 1), with an average of 210 $m^3\ ha^{-1}$ (SD = 228 $m^3\ ha^{-1}$). Very large living broadleaf volumes were rare in the dataset, with 75% of the parcels having values below 350 $m^3\ ha^{-1}$. Broadleaf deadwood volumes (from natural and anthropogenic origins combined) also varied greatly, ranging from 0 to 124 $m^3\ ha^{-1}$. However, the average of 11.2 $m^3\ ha^{-1}$ (SD = 21.9 $m^3\ ha^{-1}$) was rather low, and was surpassed by only around 25% of parcels. Forest management intensity was captured by the ForMI index. Management intensities were distributed approximately uniformly in our dataset. The biotope types we encountered scored between six and 23 biotope value points, with an average of 14.3. The lowest values were assigned to young plantations of non-native tree species, such as Douglas fir, while the highest values were given to old oak and beech stands. Sampling of large-diameter trees took

Table 3 Spearman correlation matrix of predictors

		Slope	Broadleaf *y/n*	Distance to road	Openland 200 m
d_{train}	Slope	1.000			
	Broadleaf	−0.023	1.000		
	Distance to road	0.033	−0.103	1.000	
	Openland 200 m	0.219	−0.323	−0.014	1.000
	Openland 2 km	−0.013	0.112	0.028	0.348
$d_{train} \cup d_{test}$	Slope	1.000			
	Broadleaf	−0.088	1.000		
	Distance to road	0.066	−0.150	1.000	
	Openland 200 m	0.163	−0.291	−0.164	1.000
	Openland 2 km	−0.030	0.135	−0.151	0.388

place throughout each small-scale private forest parcel. While such trees were absent or rare on most parcels (none were found on around a third of all parcels), 10% of the parcels had more than 50 trees per hectare with a diameter of at least 50 cm. In general, larger parcels tended to have slightly fewer large trees per hectare, but the effect size was small (Spearman's $\rho = -0.179$). PICA values were calculated from these numbers for the d_{train} dataset. These values were distributed uniformly between 0.078 and 0.905, with a mean and median of 0.436. The five landscape-related predictors were calculated from freely accessible sources (see Section 2.5). PICA values plotted against these predictors are shown in Fig. 3 (blue data points and curves, see also Section 3.3 for a closer characterization).

3.2 The first model m_1

Before training the model that will predict PICA values, we checked the landscape-related predictors (*slope*, *broadleaf*, *distance to road*, *openland 200 m*, *openland 2 km*) for multicollinearity by computing variance inflation factors (VIF). VIF values were very moderate, with a maximum of 1.49. Spearman correlation between the predictors was also low, with a maximum absolute value of 0.384 (see Table 3). The predictors were considered sufficiently unrelated and were all included in the subsequent analyses. Model m_1 was trained for lowest mean absolute error (MAE) using the d_{train} data. Some hyperparameters of the xgbTree model were manually tuned for low MAE: The maximum tree depth (*max_depth*) was set to three. The minimum sum of instance weights needed in a child node for a split (*min_child_weight*) was left at one, the default. The learning rate (*eta*) was set to 0.03. The minimum loss reduction (*gamma*) was set to zero. The subsample ratio of columns (*colsample_bytree*) was set to one. The subsample ratio of the training instances (*subsample*) was set to 0.8. The number of boosting rounds (*nrounds*) was set to 100.

PICA values in the dataset showed a standard deviation of 0.226, while the model achieved an MAE of 0.093 (root mean square error (RMSE) of 0.114), which represented 41.2% of the outcome standard deviation. The model's R^2 was 0.857, see the "training" results in Fig. 4. It is worth noting here that this high performance is due to the fact that model m_1 was asked to predict data that it was trained on. Regarding the variable importance (*vi*, a numerical value between 0 = lowest and 100 = highest importance) of the predictors, we found that model m_1 favored the *broadleaf* predictor the most ($vi = 100$). *Distance to road* ($vi = 79$), *slope* ($vi = 60$), and *openland 200 m* ($vi = 44$) were also important predictors, whereas *openland 2 km* ($vi = 0$) did not contribute to the model's predictions. Model m_1 was used to predict preliminary PICA values for 40,282 small-scale private forest parcels in the study area.

3.3 Second field campaign: dataset d_{test}, PICA values and predictors

The 48 small-scale private forest parcels in the d_{test} dataset showed slightly higher amounts of living broadleaf volume, with mean and median values of 247 $m^3\ ha^{-1}$ and 230 $m^3\ ha^{-1}$, respectively (see Table 1). The overall range (0 to 853 $m^3\ ha^{-1}$) was comparable to the d_{train} dataset. Broadleaf deadwood was significantly more prevalent (Wilcoxon rank sum test, $p = 0.042$), with an average of 23.3 $m^3\ ha^{-1}$, ranging from 0 to 175 $m^3\ ha^{-1}$. Forest management intensity in the d_{test} dataset was slightly lower, averaging 0.382. The biotope type values encountered on the new parcels were slightly higher than those in the training set, ranging from 9 to 23 and averaging 15.3. The density of large-diameter trees on the d_{test} parcels was slightly higher,

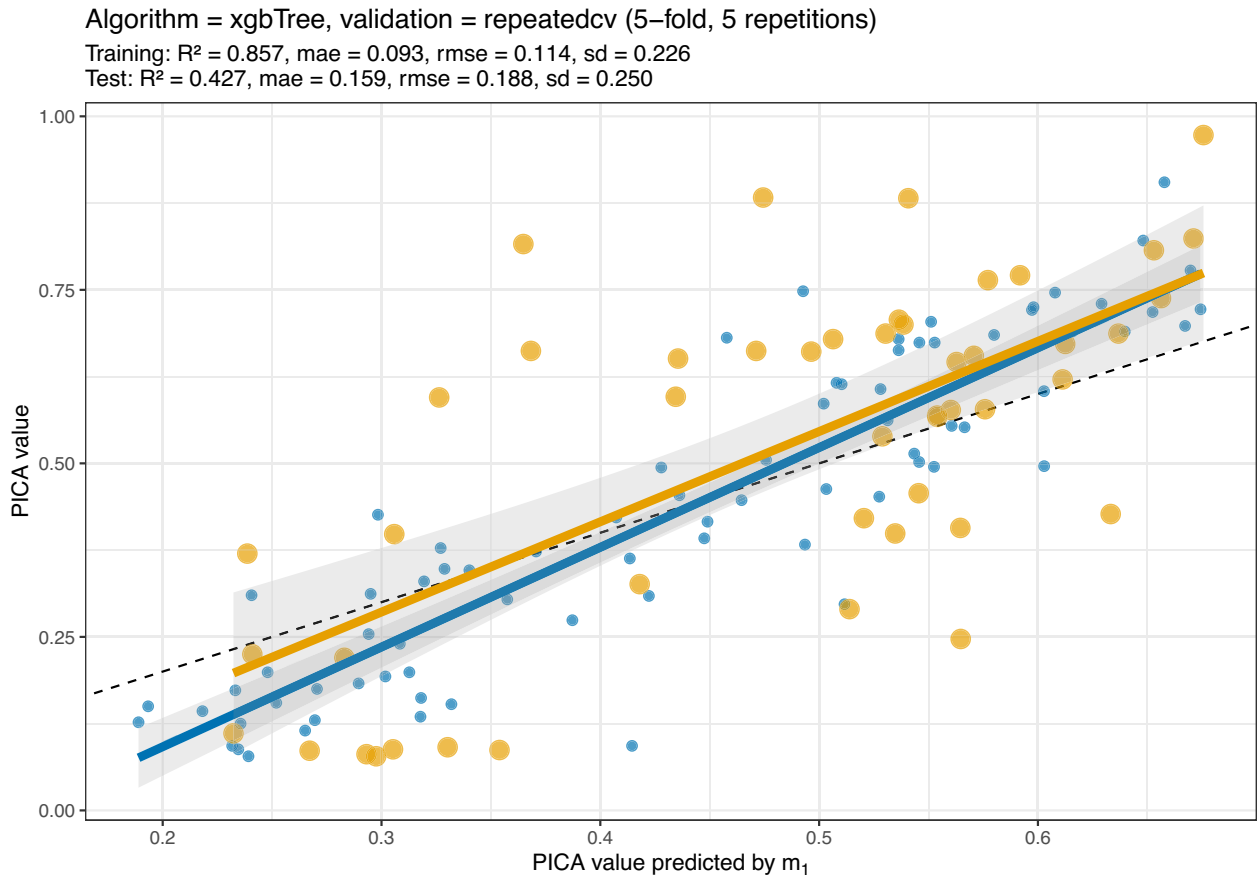

Fig. 4 Calibration plot for model m_1. Shown are predictions for the training dataset d_{train} (small blue data points, blue regression line), and the result of the external evaluation with the test dataset d_{test} (big orange data points, orange regression line). The dashed line indicates a perfect fit. Confidence intervals are 95%

with an average of 30.9 ha^{-1}. PICA values calculated from these components were slightly higher on average (0.520), though not significantly different from the d_{train} dataset (Wilcoxon $p = 0.090$, bootstrapped (p1 − p2) PICA mean difference of − 0.085 with 95% percentile confidence interval of − 0.172 to 0.001, using 5000 replicates). The new data points appear in orange in Fig. 3, along with their accompanying smoothing curves. Black curves indicate a fit for the union of datasets d_{train} and d_{test} ($d_{train} \cup d_{test}$) and are equipped with 95% confidence bands. For both d_{train} and d_{test}, lying in a broadleaf forest was clearly associated with higher PICA values. *Slope* and *distance to road* showed tighter bands for smaller predictor values, as did *openland 200 m*. *Slope* showed hump-shaped curves for both datasets. Higher PICA values were observed on parcels with low or high slopes and lower PICA values for intermediate slopes. *Distance to road* exhibited a negative influence on PICA values, which was more pronounced in dataset d_{test}. *Openland 200 m* exhibited a slightly negative influence; however, large *openland 200 m* values showed an anomaly in the d_{test} dataset. LOESS regression for *openland 2 km* was inconclusive, showing opposite directional hump-shaped curves between the datasets. Though the relation of PICA values and *openland 2 km* was overall positive, it showed looser confidence bands. This was also the only case in which the d_{train} and d_{test} data (blue and orange curves) differed considerably.

3.4 Model evaluation

The most important test for our model was the external evaluation (Ramspek et al. 2021), in which we compared the predicted PICA values for the new forest parcel set, d_{test}, with the actual PICA values calculated from the field-measured component variables. The result is shown visually in the calibration plot in Fig. 4. In this plot, the actually measured PICA values are plotted against the PICA values predicted by model m_1. The blue data points correspond to parcels in the d_{train} dataset. Since these parcels were used to train the model, the blue data points scatter closely around the dashed line representing perfect predictions. Accordingly, the model achieved a low mean absolute error and a high R^2 value on the training

data. The predictions for the test dataset d_{test} (orange data points) deviated more from the dashed line than in the case of d_{train}, resulting in a higher mean absolute error of 0.159 during external evaluation (with a root mean squared error of 0.188). This was still 36.4% below the standard deviation (0.250) of the actual, field-measured PICA values in d_{test}. The R^2 value was 0.427, indicating an adequate fit of model m_1 to the test dataset d_{test}. The model generalizes relatively well, while overfitting some training patterns. The prediction errors are substantially smaller than the PICA standard deviation for both models; therefore, the predictions are informative, even though their absolute values carry uncertainty. Retraining model m_2 on the full dataset did not change the model errors. However, some of the variability in the data (visible in Fig. 3) remains unexplained by the model.

3.5 Updated model m_2 and predictions for the study area

To make predictions for the small-scale private forest parcels within the study area, we retrained a second gradient boosting tree model, m_2, using the union ($d_{train} \cup d_{test}$) of the datasets d_{train} and d_{test} to predict PICA values from the landscape-related predictor variables. We carried over the hyperparameter tuning that was optimized in model m_1. Regarding the variable importance (*vi*) of the predictors, we found that, similarly to model m_1, model m_2 favored the predictor *broadleaf* the most (*vi* = 100). *Distance to road* (*vi* = 68), *slope* (*vi* = 62), and *openland 200 m* (*vi* = 47) were also important predictors. *Openland 2 km* (*vi* = 0) did not contribute to the predictions. PICA values in $d_{train} \cup d_{test}$ showed a standard deviation of 0.238. The MAE of model m_2 was 0.099, with an RMSE of 0.121. This represented 41.6% of the outcome standard deviation. The R^2 value was 0.740. Note that this denotes a good model fit to the training data.

Since model m_2 was trained on a larger dataset ($d_{train} \cup d_{test}$) than model m_1, it was preferred for making final predictions of PICA values for all small-scale private forest parcels in the study area. We used model m_2 to calculate PICA value predictions for all small-scale private forest raster cells (100 m × 100 m) in the study area (Hansen et al. 2026). In total, we identified 38,085 small-scale private forest cells, amounting to 9.6% of the total forested area (ML 2024). Predicted PICA values ranged from 0.170 to 0.774, with an average of 0.460 (SD = 0.140) and a median of 0.501. Ninety-five percent of the cells scored lower than 0.675.

The top five percent of parcels with the highest PICA values are highlighted in Fig. 5. These top PICA raster cells appeared to be rare in large, contiguous forested areas. To determine if this difference was significant, we calculated the area of the surrounding contiguous forest polygon (OpenStreetMap contributors 2022) for each raster cell centroid. The mean contiguous forest area around the raster cells with in the top 5% (PICA values larger than 0.675) was 272 ha (SD = 534 ha), with a median area of 84.9 ha. For the remaining 95% of raster cells, the mean contiguous forest area around the cells was 1223 ha (SD = 1979 ha), with a median area of 342 ha. The difference of the means was − 951 ha. A Wilcoxon rank sum test confirmed that the top 5% PICA raster cells were significantly different from the remaining 95% of the small-scale private forest raster cells ($p < 0.0001$) when the size of the surrounding contiguous forest area was considered. Given the large number of raster cells, we quantified the effect size of the observed difference using bootstrapped (5000 replicates) 95% confidence intervals for the means. The interval for the mean surrounding forest area of the top 5% raster cells was [248 to 297 ha]. For the remaining 95% of raster cells, it was [1203 to 1243 ha], and [− 982 to − 920 ha] for the difference of the means.

4 Discussion

Old-growth structures are vital habitats for a multitude of rare forest species. Their protection often hinges on the availability of precise geographical data, which is lacking in small-scale private forests due to the low organization and difficult reachability of forest owners. Our research was guided by the aims of (*1*) developing an index that represents old-growth structure abundance on small-scale forest parcels; (*2*) investigating the effects of known predictors of such structures on the index; and (*3*) compiling a model that is able to predict stand-specific index values throughout the study area. We proposed a multi-component *Parcel Index of Conservation Attributes*, PICA, that captured main old-growth structures on the land parcel level. Variables that were known to have an influence on these structures, such as slope, broadleaf status, distance to road, and the vicinity of open land, were shown to be valid predictors of PICA index values.

4.1 On the response of PICA values to predictor variables

We identified multiple informative relationships between five predictors—*slope*, *broadleaf* (0/1 value given by the CORINE broadleaf status of the parcel), *distance to road*, *openland 200 m* (percentage of open land in a 200 m vicinity of the parcel), *openland 2 km* (dito, for the 2 km vicinity)—and the PICA index value of a parcel.

The slope predictor showed a peculiar hump-shaped influence on PICA values, with medium slopes corresponding to low PICA values, while high and low slopes corresponded to high PICA values. In hilly, densely populated areas, such as the study area in Lower Saxony, larger managed forest areas are often confined to medium-sloped hillsides (Mann et al. 2023). Very steep

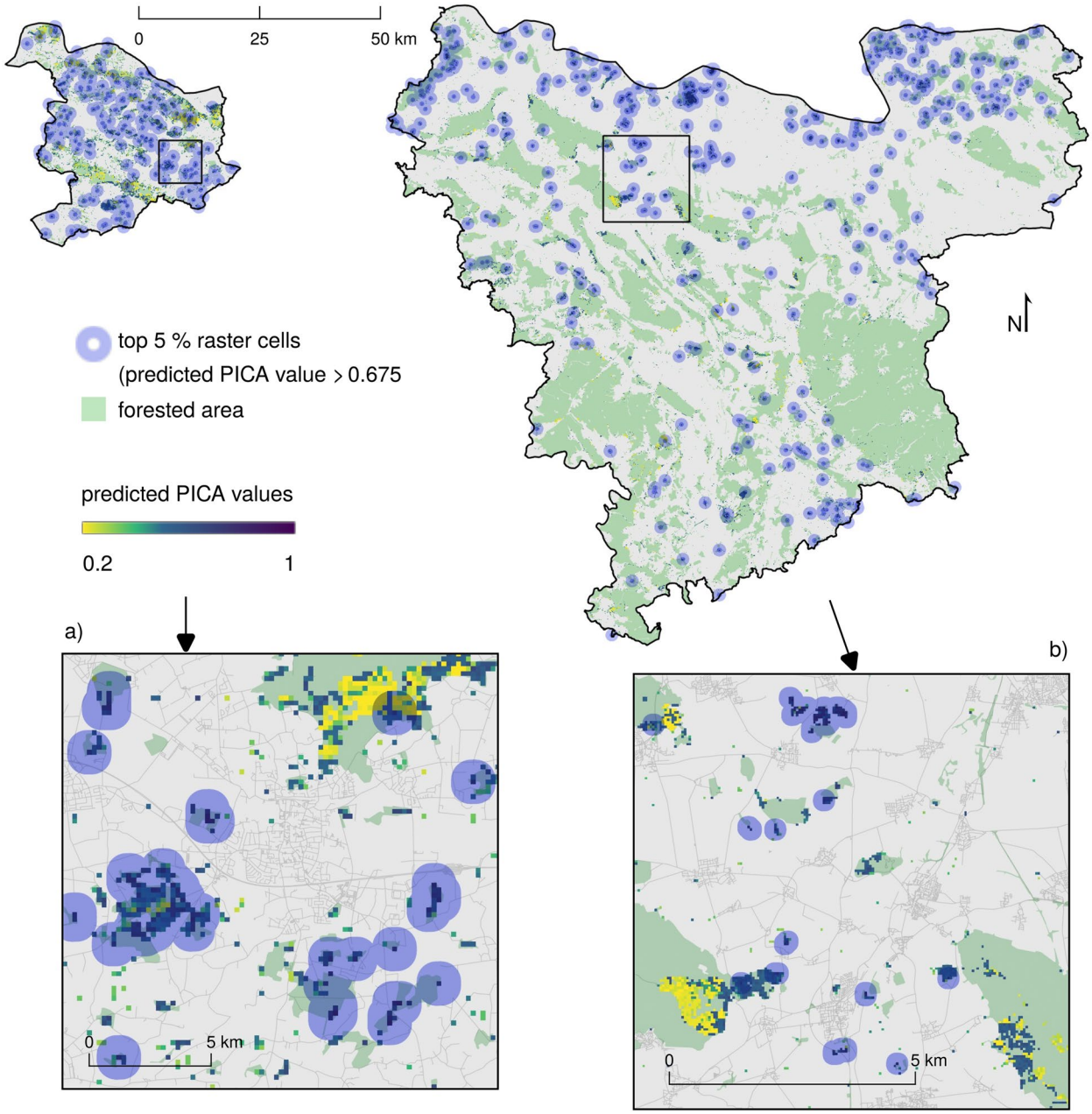

Fig. 5 Map of the Lower Saxon Hills region showing forest cover in green and PICA values as predicted by model m_2, raster cell size is 100 m × 100 m. The positions of the top 5% of raster cells with the highest PICA values are highlighted with a blue circle. Detail maps (**a**) and (**b**) enlarge example regions and illustrate rastered PICA predictions

terrain is not ideally suited for profitable timber production and is often neglected as a result (Bujoczek et al. 2021; Engel 2019). Consequently, small-scale private forest parcels on very steep terrain almost certainly experience a lack of management: Trees can grow to high ages surpassing common harvest maturity and develop high diameters and wood volumes, which increases the PICA components of living broadleaf volume and density of large-diameter trees. Deadwood is often left on these inaccessible parcels due to deficient infrastructure, which directly increases the deadwood PICA component. Conversely, flat terrain often has fertile soil that is used for agriculture. In such landscapes, forest areas often have an insular character and, if managed at all (Engel 2019), are dedicated to producing valuable hardwoods, such as oak, using a long-term selection cutting system, featuring

Fig. 6 **a** Borders between forest and agricultural land tend to be clearly defined, with boundary trees of insular forest patches often exempt from wood harvesting. **b** Such boundary trees are prone to developing a multitude of microhabitats. **c** A lack of awareness of valuable structures in private forests can lead to increased logging if the market situation changes. **d** A future-proof protection of old-growth habitats is an ongoing task. Efforts to conserve old-growth structures like large-diameter trees at the border as well as in the interior of forest parcels need to be supplemented with measures to ensure the replenishment of old-growth structures

high-diameter broadleaf trees. Forests influenced by groundwater or perched water with azonal natural vegetation such as oaks, hornbeam, and alders, are also confined to flat areas and provide habitats for rare and specialized forest species (Drachenfels 2021). In addition to high wood volumes and diameters, both forest types are recognized as highly valuable in BKompV (2020) and receive high biotope values that further increase PICA values. We found that broadleaf sites (according to the CORINE dataset, Copernicus Land Monitoring Service 2018) strongly influenced the PICA values, which was to be expected, since two of the index's components (broadleaf living and deadwood volume) depend on broadleaf trees. These findings together suggest that low PICA values correspond to large, conventionally managed regions of conifer forests. This is also supported by the behavior of the distance to road curve (Fig. 3). In the study area, higher distances to the next paved road are almost exclusively found in larger hill ranges (OpenStreetMap contributors 2022), whereas the remaining areas are more densely populated and have a denser road network. Land cover data asserts that these hills are predominantly stocked with conifer species, thus the effects of greater distance from roads and low broadleaf coverage reinforce each other and negatively influence PICA values in these areas.

4.2 Old-growth forest structures in mixed cultural landscapes

We found that old-growth structures of high nature conservation value were disproportionately common in isolated and remnant private forest patches within mixed-use landscapes, rather than in parcels embedded within large closed forest areas. Using the surrounding contiguous forest area as our metric, the top 5% of parcels in terms of conservation value (i.e., those with the highest PICA values) occurred, on average, in contiguous forests of barely 300 ha, whereas this metric for the remaining 95% was over 1200 ha. This pattern suggests that small remnant forest patches in a heterogeneous landscape matrix often retain or accumulate old-growth structural features (see Fig. 6). Previous research has highlighted the significant conservation value of insular "oases" of old, structure-rich forest patches within agricultural landscapes (Orłowski and Nowak 2007).

While forest interiors typically host a higher proportion of forest specialists (Hofmeister et al. 2016; Wulf and Kolk 2014) and provide more effective heatwave buffering, forest edges exhibit higher total species richness, greater biomass of large-diameter stemwood, more tree-related microhabitats, and higher levels of tree

regeneration (Bobiec et al. 2018; Orłowski and Nowak 2007). Therefore, the conservation value of remnant forest patches under private ownership depends heavily on the size, shape, and landscape context of the patches. Maintaining old-growth forest structures in small, highly edge-dominated patches is essential for conserving forest specialist taxa, whereas these patches may also increase overall richness through generalists. Both the interiors and edges of these patches contribute complementary ecosystem services (see Fig. 6).

Despite providing essential ecosystem services (Decocq et al. 2016), small forest patches in mixed landscapes often receive little attention from conservation stakeholders (Valdés et al. 2020). Currently, they have no strict conservation status, which makes them vulnerable to the owners' will (Stolz and Riedel 2018). Due to their small size, these forest patches are additionally often considered less important for specialized species (Varela et al. 2018). However, research has shown that they can provide varied habitat conditions that benefit forest specialist species, especially when the parcels are ancient woodlands (Buse 2012; Wulf and Kolk 2014). Mature forest patches serve as vital habitats for forest species and should be prioritized in conservation planning (Buse 2012; Russo et al. 2023; Stolz and Riedel 2018; Valdés et al. 2015; Wulf and Kolk 2014).

4.3 Assessment of the model framework and research desiderata

The proposed index PICA, its components, and the predictors we analyzed should be regarded as a flexible framework, open to adaption based on local conditions, data availability, and funding for fieldwork. The described model is calibrated to our datasets, which include low altitude ranges, very small parcel sizes, and a limited set of tree species assemblages. We recommend recalibrating it using a local dataset before deploying it in markedly different regions. In the same spirit, it might be beneficial to adjust the saturation functions that map PICA components to the valid range. They relied on choosing an individual parameter, h, for each component to define the threshold at which the saturation function reaches 0.5. The selected h values reflected the average values in our survey results and similar thresholds in German nature conservation legislation (see Table 2). These thresholds can be modified when transferring the methodology to other regions.

There is strong and ongoing evidence of the correlation between old-growth structures and the occurrence of forest species of particular conservation concern (Storch et al. 2023; Wagenaar et al. 2025; Zeller et al. 2023; Zumr et al. 2023). However, comparing actual and predicted PICA values with specific biodiversity data could further strengthen this connection. Special structures with significant conservation value, such as remnants of former coppice management or forest bogs (Leuschner and Ellenberg 2017), are outside the scope of PICA. Focusing on individual old-growth forest species or groups would require defining specialized indices to capture these species' particular habitat preferences (Lachat and Bütler 2009). If a dependency on landscape variables could be established, then extrapolation to the landscape scale would also be possible in these cases.

It could be beneficial to include additional possible predictors of old-growth structures and to examine their impact. Possible candidates include parcel size, stand age, time since the last harvest (if available), soil characteristics, protection status, as well as the variable area of surrounding contiguous forest as developed in Section 3.5. On the other hand, it might be possible to reduce the number of open land variables by identifying a single variable that can still explain enough variance in the input data.

Concerning the performance of the models, the calibration plot (Fig. 4) shows a slight overestimation of low PICA values and a similarly slight underestimation of high PICA values. This regression toward the mean could result from limited sample coverage at the extremes, or from the fact that the index consists of five different components describing partially disparate aspects of the land parcel. Stratified sampling, as was done for the test data set d_{test}, is advisable for the analysis of future forest parcel pools. Because the forest parcels in our sample were often very small, we sampled only a limited number of plots per parcel. To reduce potential sampling bias, we drew from a relatively large and diverse set of small-scale private forest stands. Nevertheless, predictive performance deteriorates near the extremes of the predictor ranges. For instance, our data has limited representation of very high slope or very large distance to road values. Predictions at the extremes should be treated with caution and validated in the field.

Small forest parcels of high conservation value are heavily influenced by edge effects. Although the negative effects of fragmentation on biodiversity are often overreported (Riva et al. 2024), these effects may actually reflect an influx of generalist species rather than the persistence of old-growth forest specialists (Vanneste et al. 2024). Further, focused research could provide insights into the roles of edges and interiors of small, isolated forest patches, and could further improve predictive modeling.

4.4 Practical relevance for conservation management and decision makers

Rare and endangered forest biodiversity depends on structures characteristic of old-growth forests that are

scarce in today's production forests. Small remnants of ancient woodlands persist in mixed landscapes, but are often overlooked and underprotected. There is an urgent need to protect such parcels (Valdés et al. 2020), as they provide vital habitat for a multitude of species of conservation concern (Proesmans et al. 2019; Winiger et al. 2023), and can function as biodiversity refugia and stepping stones in an unfavorable background matrix (Buse 2012; Liira and Paal 2013). We have shown that old-growth forest structures can be predicted using freely available landscape data, thus demonstrating a roadmap to minimize the costs and efforts associated with biodiversity surveys and extensive forest structural surveys. We propose conducting low-intensity fieldwork to record forest structures at selected sites and using modeling techniques to gain insights into the landscape-wide distribution of forest parcels of high conservation value. Our findings on the spatial distribution of valuable small forest patches in mixed cultural landscapes align with those of previous studies (Decocq et al. 2016; Proesmans et al. 2019; Valdés et al. 2020). Creating a prediction map of conservation values for a given region allows decision-makers to design targeted actions to ensure the retention and continuous provision of old-growth structures in small, private forests. Recent market incentives and policy decisions support higher management intensities (Eriksson et al. 2024; Lerink et al. 2023), even in small-scale private forests that were shielded from intensive management in the past due to owner inactivity. However, this poses a substantial risk to vulnerable structures of conservation concern that are harder to find in professionally managed forests. Cautious management or even refraining from forest management allows old-growth structures to develop and persist (Larrieu et al. 2026) and is essential for safeguarding rare and endangered forest species.

5 Conclusion

Many forest species of high conservation concern depend on special structures related to the old-growth character of forest stands. These structures thrive under low management intensity and are rarely found in intensively managed production forests, except when actively promoted. We developed the *Parcel Index of Conservation Attributes* (PICA) as a tool that allows for a precise quantification of the abundance of old-growth structures in temperate small-scale private forests. Based on findings that the structures captured by this index are influenced by the topography of forest parcels, we developed a model that predicts PICA values on the landscape scale using freely available landscape data. We used a comprehensive model using field data to calculate predictions in the form of a map, highlighting the spatial distribution of valuable old-growth structures in the small-scale private forests of our study area. Landscape planners and decision makers are encouraged to use this tool to pinpoint target areas for conservation efforts in the future. A distribution analysis revealed that the forest stands of highest conservation concern are situated outside larger forested areas, underscoring the importance of forest remnants in agricultural landscapes. These small forest oases have been shown to provide a multitude of ecosystem services at a high intensity per area, to secure carbon retention, and to serve as retreats and stepping stones for forest biodiversity. The continuous conservation and interlinkage of these forest patches should be a high priority for decision makers, and our model can support them by providing reliable spatial information about the location of parcels of high conservation value.

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Authors' contributions
P.H.: writing—original draft, visualization, methodology, formal analysis, conceptualization. M.T: writing—review and editing, investigation. T.P.: writing—review and editing, investigation, funding acquisition. A.M.: writing—review and editing, investigation, funding acquisition.

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Data availability
All research data used in the scope of this article, as well as the prediction of PICA values across the entire study are, is available at Zenodo (Hansen et al. 2026). DEM data for Lower Saxony are publicly available (GeoBasis-DE/LGLN 2025). A road network was extracted from OpenStreetMap (OpenStreetMap contributors 2022). Forest type and open land status were taken from CORINE data (Copernicus Land Monitoring Service 2018). We used the following non-free data sources: Cadastral data were provided by NW-FVA, Göttingen, Germany. Data on forest ownership in Lower Saxony were provided by the Chamber of Agriculture in Lower Saxony (LWK). Restrictions apply to the availability of these data, which were used under license for the current study, and are not publicly available. Data are however available from the authors upon reasonable request and with permission of NW-FVA and LWK, respectively.

Declarations

Competing interests
The authors declare no competing interests.

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