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Modeling of Habitat Suitability Using Remote Sensing and Spatio-Temporal Imprecise In Situ Data on the Example of Red Deer

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Abstract: This paper presents a streamlined approach to describing potential habitats for red deer (*Cervus elaphus*) in situations where in situ data collected through observations and monitoring are absent or insufficient. The main objectives of this study were as follows: (a) to minimize the negative effects of limited in situ data; (b) to identify landscape features with a functional relationship between habitat quality and landscape structure; and (c) to use imprecise in situ data for statistical analyses to specify these relationships. The test area was located in the eastern part of Mecklenburg-Western Pomeriania (Germany). For this area, remotely sensed forest maps were used to determine landscape metrics as independent variables. Dichotomous habitat suitability was determined based on hunting distances over a five-year period. Ecological and biological habitat requirements of red deer were derived from suitable landscape measures, which served as model inputs. Correlation analysis identified the most relevant independent landscape metrics. Logistic regression then tested various metric combinations at both class and landscape levels to assess habitat suitability. Within the model variants, the contagion index, edge density, and percentage of forested area showed the largest relative impact on habitat suitability. The approach can also be applied to other mammals, provided there are appropriate structural preferences and empirical data on habitat suitability.

Keywords: habitat; modeling; red deer; *Cervus elaphus*; remote sensing; GIS; in situ; ground-truth; landscape metrics; landscape structure; logistic regression; Landsat

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1. Introduction

In times when humans are exerting increasing influence on natural ecosystems, the protection of biodiversity requires a thorough understanding of the habitat requirements of wild animals. Worldwide, landscapes are increasingly the result of intensive interaction between natural processes and human land use [1]. Factors such as climate change, ongoing urbanization, and industrial agriculture have profoundly altered the structure of biotopes [2,3]. These dynamic changes present a scientific challenge in developing reliable methods of assessing habitat quality. Modeling habitat suitability for wildlife is an essential component of modern nature conservation and landscape management strategies. In particular, large mammals such as red deer (*Cervus elaphus*) require careful habitat identification and analysis to consider both their ecological needs and the often-competing interests of forestry, agriculture, and hunting [4,5]. The increasing fragmentation of natural habitats due to human activities is one of the major challenges for maintaining healthy red deer populations as it significantly influences the animals' movement patterns, behavior, and habitat selection [6,7]. Several studies have shown links between structural and ecological interactions and ecosystem quality for plants and animals at different spatial and temporal scales [8]. However, although these interactions are understood, the available data for assessing a site's species are often inadequate [8]. One reason for this limitation is often restricted access to the site-specific in situ data required for assessing habitat quality, along with the availability of species-specific data. To address the lack of such data, suggested assessing individual population status by integrating various types of information. While some studies show that dominant species can control vegetation development, it is likely that dominant herbivores and carnivores in Central Europe exert similar influence on their habitats. Landscape structure can thus be viewed as an indicator of both natural and anthropogenic patterns and processes at the landscape level [9,10]. Extracting information to support decisions and actions for sustainable resource protection—where sustainable land use is integrated with economic considerations—requires clear and comprehensible information for evaluating the respective land use. This operationalization can be achieved by calculating landscape structure indicators or landscape metrics, which serve as indicators for detecting environmental changes [11,12].

A monitoring system for estimating biodiversity and habitat quality requires area-wide, up-to-date data; representative quantitative indicators; a data processing chain, models for deriving indicators; and an evaluation system. Combining different data sources is essential for identifying optimal sampling strategies. To adequately represent the complexity of dynamic systems, various monitoring strategies must be integrated for data collection [13].

Traditional approaches to habitat modeling are often based on field data collected through telemetry studies, direct observations, or extensive fieldwork. These methods provide valuable insights but are mostly limited to small geographic areas and involve significant financial and logistical hurdles [14,15]. To address this challenge, the use of in situ data, such as hunting bag statistics, has recently emerged as a cost-effective alternative. Hunting data, which provide information on population distribution and density, are increasingly used as an indicator of habitat preferences, especially in combination with remote sensing data to enable large-scale modeling [16,17].

However, one of the major research gaps is the question of how reliable in situ data such as hunting bag statistics actually are in reflecting habitat preferences, especially when combined with medium-resolution remote sensing data. Studies show that although these data provide useful information at the landscape level, they are often not detailed enough to accurately reflect local habitat preferences [18,19]. Despite the increasing availability of remote sensing data, the integration of these data into wildlife habitat modeling has not yet been sufficiently researched, especially in highly fragmented and heterogeneous landscapes, as is relevant for red deer [20]. Therefore, we test the data via a streamlined modeling approach.

Another key challenge in modeling habitat suitability for red deer is the consideration of different spatial scales. The habitat selection of red deer is influenced by both large-scale landscape structures and microhabitats. Studies have shown that fragmentation, forest edge density, and the mixing of forest and open land are crucial factors for the habitat use and movement behavior of red deer [21,22]. These dynamic interactions between landscape structure and habitat use are particularly relevant in areas with high human activity, where red deer are often forced to use less optimal habitats [23]. In most parts of Germany, red deer are restricted to designated core areas. Additionally, red deer primarily retreat to the forest due to hunting pressure, despite being essentially an open-land animal. These factors should be considered in the model evaluation process.

Another important aspect that has been insufficiently studied so far is the seasonal variability of habitat use. Red deer often follow the so-called "green wave", a seasonal migration that aims to always have access to the most nutrient-rich food sources [4]. This aspect has often been neglected in habitat modeling, although considering seasonal changes is essential for a complete understanding of habitat selection [24].

Therefore, the objectives of this study are as follows: (a) to predict potential habitats for red deer (*Cervus elaphus*) in eastern Mecklenburg-Western Pomerania based on landscape structure; (b) to mitigate the issue of insufficient habitat (in situ) data by converting hunting bag statistics into a proxy for habitat suitability; (c) to develop a streamlined habitat model by integrating various data sources, including remote sensing data, hunting bag statistics, deer-related landscape structure analysis, and statistical modeling; (d) to identify structural landscape properties that influence deer habitat quality and demonstrate how remote sensing and in situ proxy data can be integrated to explore relationships between habitat quality and landscape structure; and (e) to produce habitat suitability maps for land use planning and landscape management.

2. Materials and Methods

The basic idea of our approach to modeling red deer habitats is to distinguish between preferred and less-preferred habitats using landscape structural characteristics (landscape metrics) as independent variables. For this purpose, a suitable dichotomous classification procedure was developed using proxy habitat suitability data as the target variable and suitable landscape metrics based on classified remote sensing data as independent variables. An overview of this approach is shown in Figure 1, and the integrated data and quantified metrics are shown in Tables A1 and A2.

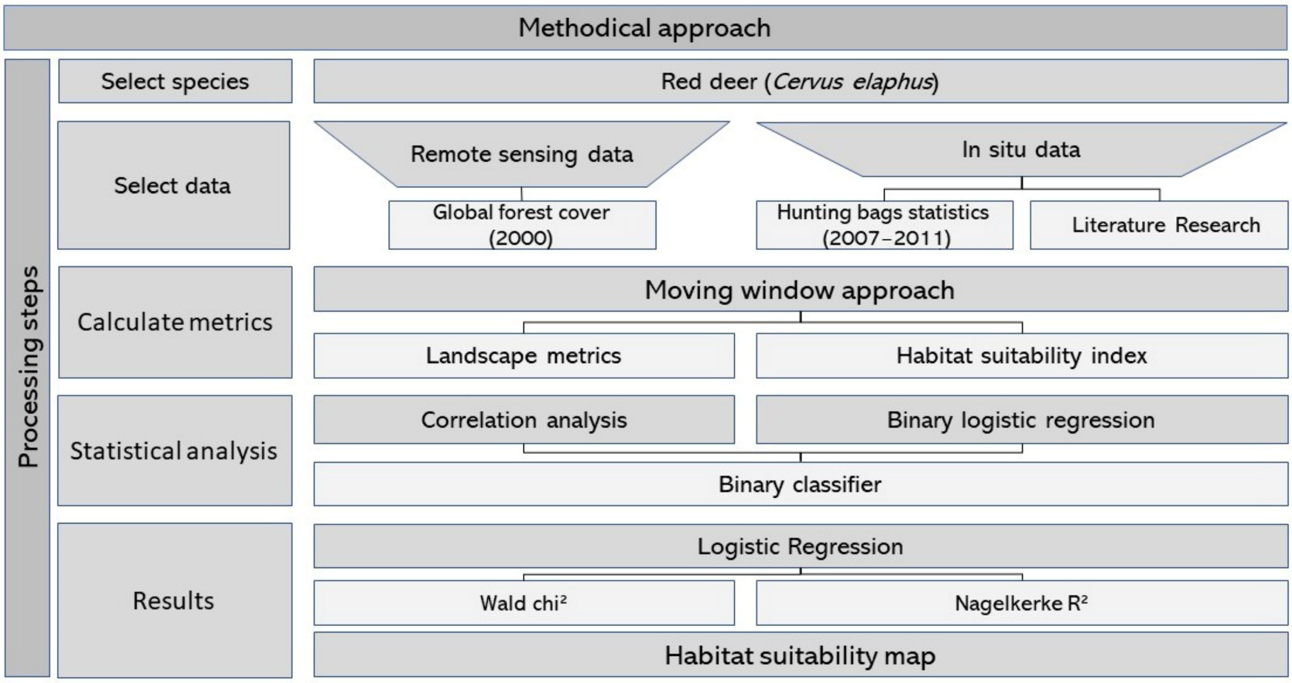

Figure 1. Processing chain for the methodical approach for modeling and predicting red deer habitat suitability for the test site Mecklenburg-Western Pomerania, Germany.

2.1. Content Background

Currently, red deer is one of the largest wildlife species in Central Europe [25–27]. There are approximately 210,000 red deer in Germany and 21,000 in Mecklenburg-Western Pomerania, with abundance ranging from 0.2 to 10 or more animals per km^2 [28]. The species is controversial in society due to long-standing conflicts of interest between forestry, hunting, and nature conservation [29]. Red deer are an important game species but also have a negative impact on forest regeneration [30]. Currently, hunters play a major role in determining their distribution in Mecklenburg-Vorpommern [31]. In contrast to the German states, red deer in Mecklenburg-Western Pomerania are free to choose their habitat [32], which strongly influences their distribution. The rural structure, climatic conditions, abundant food supply, and low human population density of Mecklenburg-Vorpommern favors the maintenance of preferred red deer habitats. The preferred habitat of red deer is a large, coherent landscape with a mosaic of forest habitats and open areas [33–35]. The habitat requirements of red deer, as found in various literature sources, are summarized in Table 1. The particular challenge in modeling wildlife, e.g., red deer habitats, is to combine these very different and detailed requirements as an appropriate means of access to spatially available data sources.

Table 1. Red deer habitat preferences derived from literature (modified after [36]).

Red Deer (*Cervus elaphus*)				
Class **Mammals**	**Order** **Even-Toed Ungulates**	**Family** **Cervidae**	**Genus** **Red Deer**	**Population Size in Germany** **approx 210,000 Individuals**
Ecological Influencing Habitat Factors				**Reference**
General character: Ruminant animals, regurgitates food in remasticate to aid in digestion.				[34]
Europe habitat regions: Temperate; terrestrial.				[25,37]
Habitat features (usual residence): Forested areas, grasslands, agricultural fields, bog land.				[33–35]
Elevation: 0–2500 m a.s.l.				[34]
Food habitats: Herbivore, intermediate; feeding on mixed diet of browse and graze; primary food sources: grasses, herbs, leaves, tree fruits (i.e., acorn, bark), field fruits (i.e., maize, potato); and in winter: needles of conifers trees, grass, shrubs, shoots of trees.				[34,38]
Main home range components: Food, cover, water, space.				[39]
Home range size (influencing factors): Official reed deer districts, seasonal changes, food supply, sex, age.				[40,41]
Habitat area: Male, 2400 ha; female, 1300 ha (Nationalpark "Vorpommersche Boddenlandschaft").				[40,42]

2.2. Study Area

The study area covers the eastern part of the federal state of Mecklenburg-Western Pomerania in northeastern Germany. This is due to the availability of habitats with representative distribution data for red deer, collected by the state. It extends approximately 172 km from north to south and 170 km from east to west. The majority of land use is agricultural (62.5%), followed by woodland (24.1%), settlements and transportation infrastructure (8%), and water (6%), including 1700 lakes [28]. Forested areas are embedded in gently rolling lowlands. The forested areas are mostly distributed in rather small patches with long forest edges. Agricultural fields are often interspersed with "kettle holes", which are rich in woodland. These provide shelter, forage, and resting places for deer, especially in winter [41]. Commonly grown crops such as winter cereals, maize, and oilseed rape are valuable food sources.

2.3. Data Basis

2.3.1. Remote Sensing Data

Our approach is based on the remote sensing-based Forest Cover Map product, which captured tree canopy cover for the year 2000 [43]. This value-added product is based on Landsat 7 ETM+ data. The Landsat satellite family is part of one of the longest historical remote sensing missions from 1978 to the present. Although the Landsat-based global forest cover is certainly not the most accurate data source for Germany, the easy availability of Landsat data and derived products at no cost would allow analogous studies for other areas and times with a quasi-automatic process line. For the present study, the global tree canopy cover for the year 2000 was used to calculate landscape metrics and to identify the habitat preferences of red deer. The use of forest cover data from the year 2000 is not considered a relevant uncertainty factor, as the rather large-scale forest open land structure considered for these studies did not change significantly between 2000 and the time interval of the hunting data from 2007–2011.

2.3.2. In Situ Data

Comprehensive and reliable explicit in situ red deer data (measured by telemetry, radio tagging, or camera trapping) to derive a classifier are not currently available. Therefore, it was necessary to derive them from other indirect data sources. For this purpose, governmentally collected data (hunting bags) of red deer for Mecklenburg-Western Pomerania from 2007–2011 were used as a proxy. The hunting bag data were provided by the Ministry of Agriculture and Environment of Mecklenburg-Western Pomerania via the Thünen Institute for Forest Ecosystems in Eberswalde [28]. The general assumption behind using hunting bags is that a high rate of hunting success rate in a certain area indicates a high deer density and thus preferred habitats [44].

Data pre-processing included spatial regionalization and harmonization of the data. To this end, hunting bag data were linked to a specific municipality of Mecklenburg-Western Pomerania and then predicted per km^2 for all the hunting seasons from 2007 to 2011. Finally, the data were merged with the geographic municipality dataset (VG250; scale of 1:250,000) of Mecklenburg-Western Pomerania [45]. The final dataset contains the number of hunted individuals per km^2 in the considered hunting period and ranges from 0 to 4.05 hunted deer/km^2/year. It should be noted that hunting bags were not available for all municipalities. Figure 2 visualizes the hunting data processed in this way.

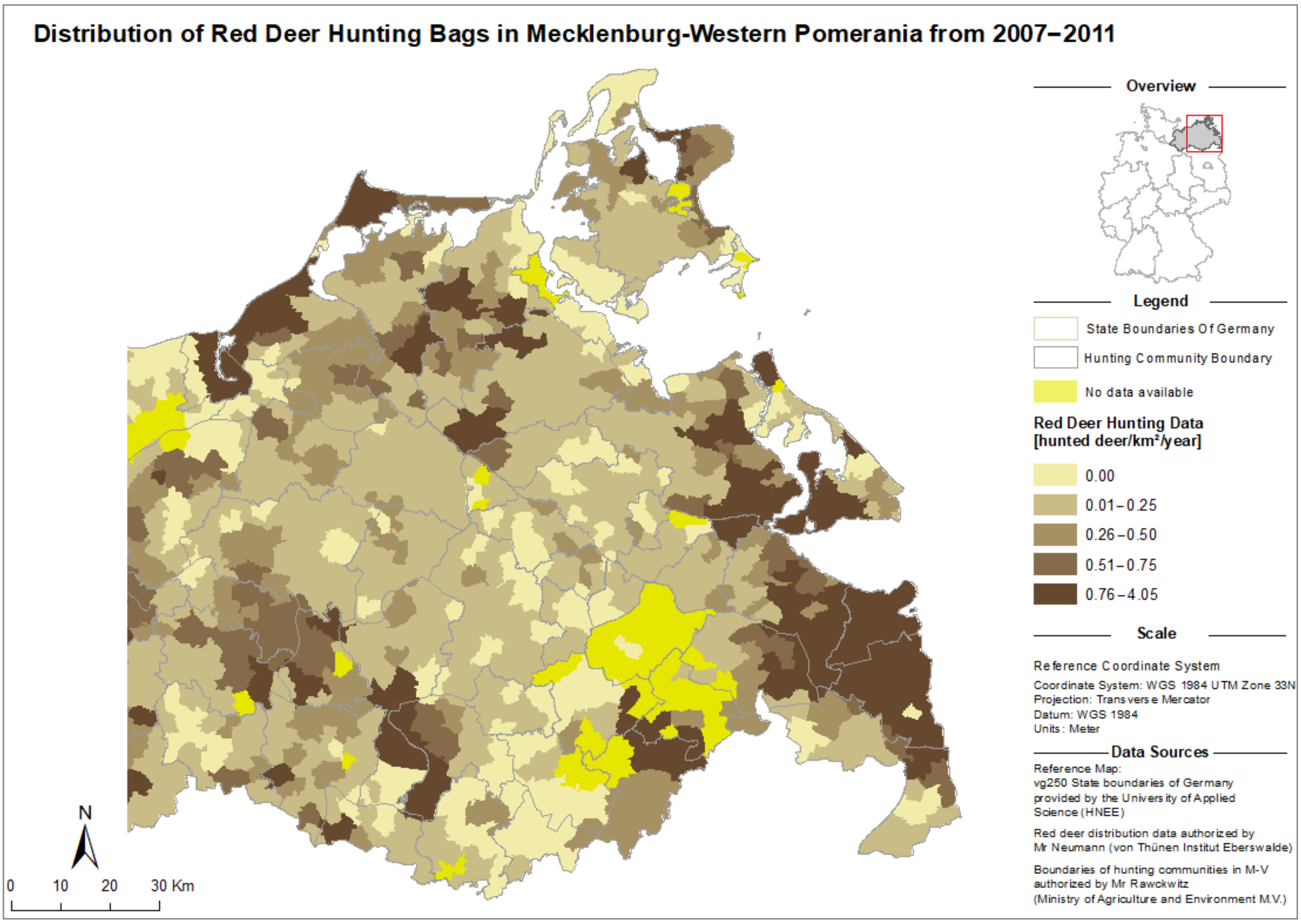

Figure 2. Distribution of red deer hunting bags in Mecklenburg-Western Pomerania, Germany (total numbers of individuals hunted from 2007 to 2011 [hunted red deer/km^2/year]).

2.4. Model Development

2.4.1. Data Processing

For further data processing, the study area was covered with a vector grid (fishnet) containing 171 rows and 173 columns with a cell size of 1 km × 1 km. The target resolution of 1 km was chosen in view of the spatial requirements of the red deer (see Table 1) and the size of the study area. This spatial environment was the setting for all of the subsequent processing of geospatial data, either as a vector grid or as a corresponding raster layer.

As the analogous hunting bag data were available within the municipal boundaries and not for all municipalities, they were adjusted to the target resolution, and data gaps were filled via spatial interpolation using moving window technology [46]. First, an overlay of hunt data and the fishnet was created. Moving window technology was applied to the target area data with an analysis window of 5 km × 5 km using the mean values to produce the final comprehensive habitat index map (Figure 1). Application of the moving window algorithm simultaneously smoothed adjacent individual values and filled in missing values (Figure 3). This avoids unnaturally sharp transitions in habitat quality between immediately adjacent cells. The interpolated values are interpreted as predicted relative habitat suitability values, with larger values indicating more-preferred habitats and smaller values indicating less-preferred habitats. The original global forest cover was interpolated analogously in the spatial extent, location, and resolution of the vector grid.

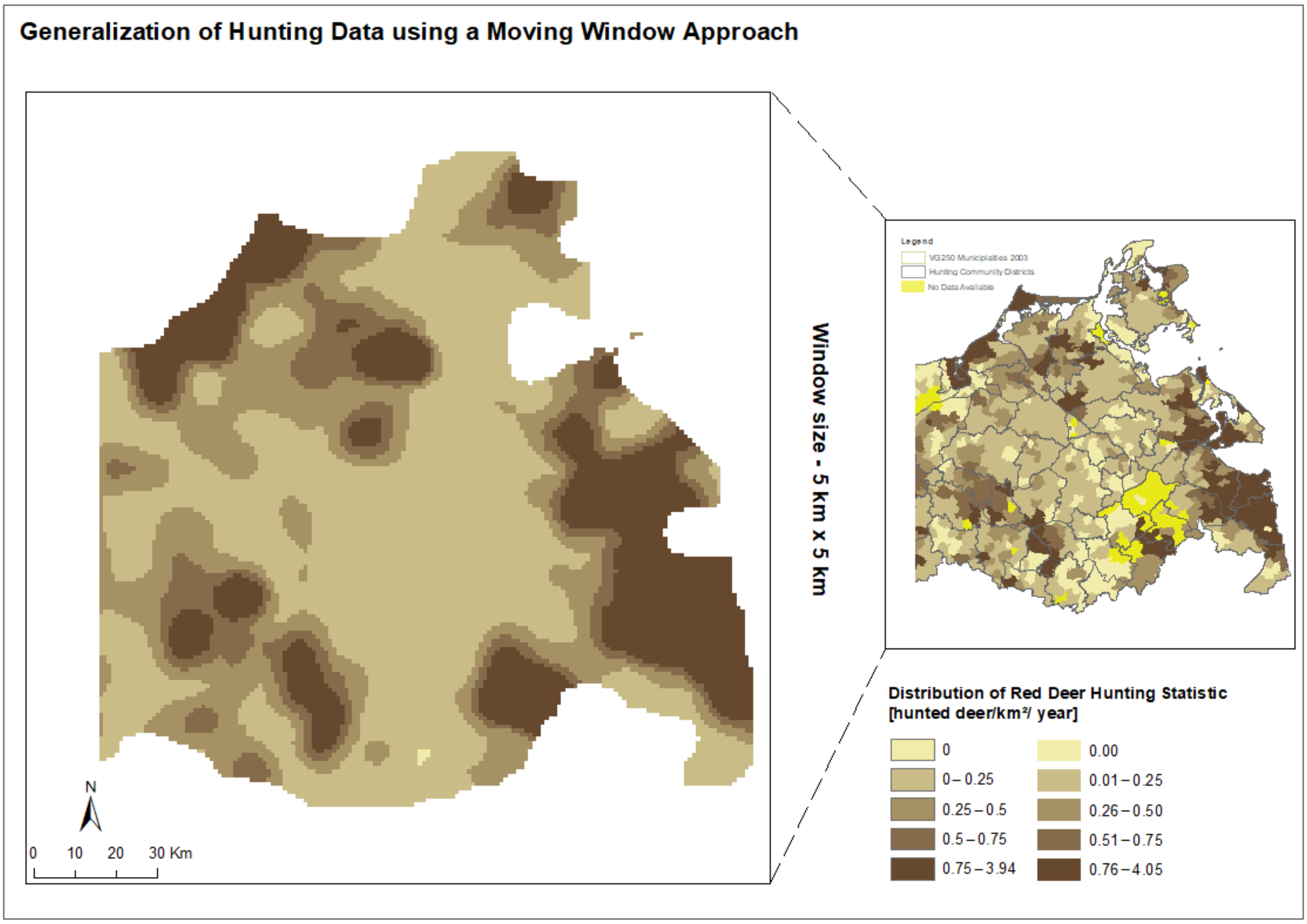

Figure 3. Generalization the distribution of empirical red deer hunting data in Mecklenburg-Western Pomerania, Germany, with a 5 km × 5 km moving window (total number of red deer hunted from 2007 to 2011 [hunted deer/km^2/year]).

2.4.2. Landscape Metrics

The known ecological and biological habitat requirements of red deer (Table 1) were used to identify an initial set of landscape metrics to serve as numerical inputs to the subsequent statistical model (habitat classifier) (Figure 1). Both class- and landscape-level metrics were considered to account for local and regional aspects of landscape structure. Rank correlation analysis was used to identify the landscape metrics that were most highly correlated with hypothesized habitat quality. This eventually reduced the total number of considered landscape metrics to six significant ones, three each at landscape and class level. The landscape-level metrics considered include the following: (1) area-weighted mean radius of gyration (GYRATE_AM), which measures the continuity of the patches; (2) the contagion index (CONTAG), which indicates the aggregation of patches; and (3) effective mesh size (MESH), which measures the percentage of cell adjacencies of patches within one class. Among the class level metrics considered, there are the following: (4) edge density (ED), which is the total length of all edge segments per hectare for the considered landscape; (5) percentage of landscape (PLAND), which informs of the dominance of a certain patch type; and (6) mean shape index (SHAPE_MN), which is a patch-level shape index averaged over all patches in the landscape (see Table A2). The selection of these indices allows for a transparent interpretation in terms of red deer structural habitat preferences and potential practical habitat management. All calculated metrics were based on the binary forest and non-forest information of the global forest cover image. This means that exactly two different class levels are considered. Corresponding landscape metrics were assigned to each 1 km $\times$ 1 km cell of the study area.

Landscape structure analyses were performed using FRGASTATS v4.2. software [47], and subsequent statistical analyses were performed using IBM SPSS Statistics (version 22). For more information on calculating the respective structural metrics, see McGarigal and Marks [47].

2.4.3. Statistical Modeling

The statistical classifier used was the binary logistic regression. Logistic regression is less demanding on the data than discriminant analysis or the other statistical classifiers. Both continuous and discrete data can be used as independent variables. However, there is a risk that multicollinearity of the inputs may affect the classification results in the long term [48]. Multicollinearity occurs when input variables are correlated with each other. In our model variants, therefore, only the least mutually correlated landscape metrics were used as inputs to the logistic regression. In the case of two or more potential inputs, those with the best interpretability of red deer habitat requirements were selected as independent variables.

Overlaying the study area with a 1 km $\times$ 1 km vector grid resulted in a total of 29,583 cases. From the total dataset, sorted by the estimated habitat suitability derived from the hunting bags, the lower and upper quartiles were then selected to create a new dichotomous target variable called the habitat suitability index. This clearly distinguishes between "preferred" habitats, coded 1, and "less-preferred" habitats, coded 0. As a significant proportion of the cells are located outside of the study area, the actual number of cases used for the statistical modeling was reduced to 5779.

To develop the final statistical model, four logistic regression models (variants 1–4) were tested using the previously created dichotomous target variable and various combinations of landscape metrics at both class and landscape levels as independent variables: (1) metrics from the landscape level only; (2) metrics from class level only; (3) metrics from both the landscape and the class level; and (4) a final reduced model containing only the most influential standardized metrics. The final result was a classifier that covered both local and landscape effects with a limited set of landscape metrics at both class and landscape level; additionally, it allowed for a clear interpretation of the input effects in relation to the known ecological requirements of red deer. The goodness-of-fit of the logistic regression functions was assessed using the Nagelkerke R^2 value and the Hosmer–Lemeshow statistics (especially when comparing model variants). When evaluating the statistical results, it is important not only to compare the goodness-of-fit of the model variants but also to determine the relative impact of each input. Therefore, the statistical significance of individual regression coefficients was tested using the *p*-value of the Wald chi^2 statistic. To assess not only the statistical significance of individual inputs but also their actual impact, particularly in model variants 3 and 4, standardized regression coefficients were calculated.

3. Results

3.1. Selection of Different Input Metrics and Reporting of Intermediate Results

The results for four all four variants (1–4) are presented, showing for each of the independent input metrics-associated regression coefficient (B) the Wald chi^2 statistics of the regression coefficients and their associated *p*-values. For all four models, the *p*-values of the regression coefficients are <0.05 = 5%, indicating statistical significance at the 5% level of error, and the overall classification success is expressed by the overall classification rate for each model.

3.2. Model Variant 1

Model variant 1 (Table 2) shows an overall classification rate of 63.7%; the Nagelkerke R^2 statistics is rather low, with a value of 0.101. The value of the Hosmer–Lemeshow statistics has a value of 96.950. The binary classification was better at predicting the "less preferred" habitats than the "preferred habitats" (68.1% versus 58.8%).

Table 2. Landscape-level input metrics and test statistics of the binary logistic regression model variant 1 for the evaluation of habitat suitability for the test area, Mecklenburg-Western Pomerania, Germany. The indicators were derived via the Forest Cover Map product based on Landsat 7 ETM+ data for the year 2000.

Binary Logistic Regression—Model Variant 1				
Input Metrics	**B**	**Wald Statistics**	***p*-Value of Wald Statistics**	**Exp(B)**
CONTAG	−0.005	15.684	0.000	0.995
MESH	−0.001	42.549	0.000	0.999
GYRATE_AM	−0.002	24.592	0.000	0.998
Constant	3.546	108.777	0.000	34.691

All regression coefficients of model variant 1 have a negative sign, which results in Exp(B) values < 1.0, thus indicating an inverse trend between increasing metric values and the probability of predicting preferred habitat suitability. The structural characteristics of the landscape expressed by CONTAG (aggregation of patches), MESH (relative patch structure), and GYRATE_AM (continuity of patches) have a significant influence on red deer habitat suitability.

3.3. Model Variant 2

Model variant 2 (Table 3) shows an overall classification rate of 68.4%, the Nagelkerke R^2 statistics shows a value of 0.183, and the Hosmer–Lemeshow goodness-of-fit reaches a value of 190.577. The binary classification was better at predicting the "less preferred" habitats than the "preferred habitats" (79.4% versus 58%).

The overall classification success and both goodness-of-fit statistics are better than for variant 1. The regression coefficients for SHAPE_MN with a value of 0.797 and for PLAND with a value of 0.033 are positive, thus indicating a parallel trend between the structural characteristics expressed by these metrics and the prediction of habitat suitability. The regression coefficient for ED is negative, with a value of −0.084, thus indicating an opposite trend between prediction of habitat suitability and edge density.

Table 3. Class-level input metrics and test statistics of the binary logistic regression model variant 2 for the evaluation of habitat suitability for the test area, Mecklenburg-Western Pomerania, Germany. The indicators were derived via the Forest Cover Map product based on Landsat 7 ETM+ data for the year 2000.

Binary Logistic Regression—Model Variant 2				
Input Metrics	**B**	**Wald Statistics**	***p*-Value of Wald Statistics**	**Exp(B)**
SHAPE_MN	0.797	26.819	0.000	2.219
ED	−0.084	38.346	0.000	0.919
PLAND	0.033	376.419	0.000	1.033
Constant	−1.480	105.326	0.000	0.228

3.4. Model Variant 3

Model variant 3 (Table 4) achieves an overall classification rate of 71.4%, the Nagelkerke R^2 statistics shows a value of 0.241, and the Hosmer–Lemeshow goodness-of-fit reaches a value of 88.352. Both "less preferred" and "preferred habitats" are predicted with slightly different success rates (74.3% vs. 68.6%).

Table 4. Landscape- and class-level input metrics and test statistics of the binary logistic regression model variant 3 for the evaluation of habitat suitability for the test area. Mecklenburg-Western Pomerania, Germany. The indicators were derived via the Forest Cover Map product based on Landsat 7 ETM+ data for the year 2000.

Binary Logistic Regression—Model Variant 3				
Input Metrics	**B**	**Wald Statistics**	***p*-Value of Wald Statistics**	**Exp(B)**
SHAPE	1.351	58.803	0.000	3.863
ED	0.023	137.761	0.000	0.799
PLAND	−0.224	194.256	0.000	1.023
CONATAG	−0.043	78.489	0.000	0.958
MESH	−0.004	13.278	0.000	1.002
GYRATE_AM	0.002	48.226	0.000	0.996
Constant	2.493	37.235	0.000	12.102

The overall classification success is better than for variants 1 and 2, indicating that the inclusion of more-detailed structural information obviously leads to a better prediction result. All six metrics contribute substantially to the classification success, although the regression coefficients for PLAND (−0.224), CONTAG (−0.043), and the MESH (−0.004) are negative, thus indicating an opposite trend between changed metric values and the predicted habitat suitability. The results of this model variant seems reasonable, as it considers structural properties at the landscape level (i.e., on a larger ecological scale) and the class level (i.e., on a smaller ecological scale) to be important.

3.5. Deriving the Final Suitability Model

To select the predictor variables for variant 4, we used the three most influential inputs from model variant 3 (Table 4). The actual effect of a factor cannot be deduced from statistical significance alone. Therefore, the aim was to give equal consideration to statistical significance, relative effect, and transparent interpretation when selecting the input metrics for the logistic regression model. Model variant 3 showed that the combination of metrics on class and landscape level gives the best classification result. However, the interpretation of the six different, partly opposite effects is not entirely clear. To simplify the model and thus facilitate an easier interpretation, the regression coefficients of model variant 3 were standardized according to the method proposed by Table 5 below.

Table 5. Landscape- and class-level input metrics and test statistics of the binary logistic regression model (regression coefficients) of model variant 3 for the evaluation of habitat suitability for the test area, Mecklenburg-Western Pomerania, Germany. The indicators were derived via the Forest Cover Map product based on Landsat 7 ETM+ data for the year 2000.

Binary Logistic Regression—Model Variant 3		
Input Variable	**Unstandardized Regression Coefficient**	**Standardized Regression Coefficient**
CONTAG	−0.043	−0.266
MESH	0.002	0.143
GYRATE	−0.004	−0.099
ED	−0.224	−0.156
SHAPE	1.351	0.091
PLAND	0.023	0.143

The inputs with the largest relative effect are the landscape-level metrics CONTAG and MESH and the class level metrics ED and PLAND. The CONTAG index has the largest relative effect, with a value of −0.266, followed by ED for the forest class, with a value of −0.156. MESH and PLAND have the same value of 0.143, both containing information on the share of forest area. For ease of understanding, PLAND is preferred to MESH as the input for a model with three input metrics on either the class or landscape level (variant 4).

3.6. Model Variant 4

The overall classification success of model variant 4 reaches 68.8%, which is slightly lower than the success of model variant 3, but importantly, here, only three input variables were used compared to the previous six. The Nagelkerke R^2 statistics shows a value of 0.199; the Hosmer–Lemeshow goodness-of-fit statistics reaches a value of 70.525. The rate of “preferred habitats” (67%) is close to the rate of 68.6% in model variant 3. This leads to the conclusion that preferred habitats can be predicted with almost the same accuracy but with fewer input variables.

Table 6 provides a comparison of the unstandardized and standardized regression coefficients. It shows that the rank or importance of the variables changes but not their overall effect. The CONTAG index increases from −0.027 to −0.166. Here, it has the greatest relative importance but works in the opposite direction. It measures the extent to which land cover types are aggregated or clumped. LAND is the least significant, with a value of 0.026 for the unstandardized coefficient, but the second most important, with a value of 0.164 for the standardized coefficient for the overall classification. In contrast, the ED index decreases in its relative importance from −0.092 to −0.065.

Table 6. Landscape- and class-level input metrics and final test statistics of the binary logistic regression model of model variant 3 for the importance of the variables for the test area, Mecklenburg-Western Pomerania, Germany. The indicators were derived via the Forest Cover Map product based on Landsat 7 ETM+ data for the year 2000.

Binary Logistic Regression—Model Variant 4					
	B	**Wald Statistic**	***p*-Value of Wald Chi-Square Statistics**	**Exp(B)**	**Standardized Regression Coefficient**
CONATG	−0.027	121.284	0.000	0.974	−0.166
ED	−0.092	37.445	0.000	0.912	−0.065
PLAND	0.026	379.739	0.000	1.027	0.164
Constant	0.719	13.620	0.000	2.052	

The predicted values were used and exported to a GIS (Figure 4), where the distribution of "preferred" habitats is highlighted in light green, the "less preferred" habitats are color-coded in yellow, and both are shown together with the forest cover map.

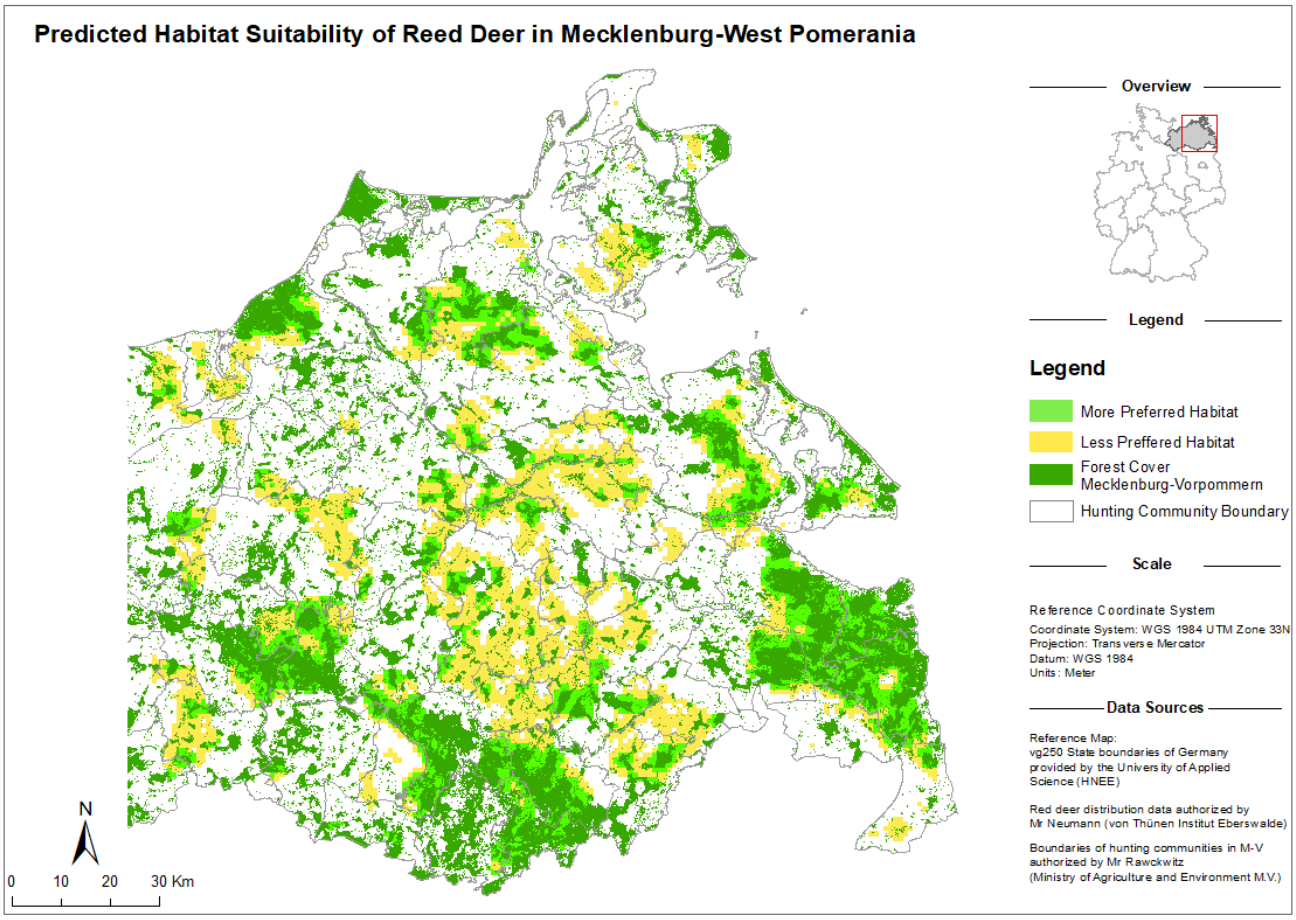

Figure 4. Predicted habitat suitability for red deer in Mecklenburg-Western Pomerania, Germany, based on binary logistic regression modeling and the importance of the variables (CONTAG, ED, PLAND).

4. Discussion

The results of the study on habitat modeling for red deer in Mecklenburg-Western Pomerania provide valuable insights acquired by combining remote sensing data, landscape metrics, and spatial and temporal inexact in situ data—in this case, hunting bag statistics. This study represents an important approach to enabling predictive modeling despite limited in situ data.

4.1. Discussion on the Importance of Proxy Data for Habitat Use Modeling

The integration of hunting data as proxy for habitat suitability has proven to be an effective method of predicting the potential habitat preferences of red deer in the absence of direct observation data. This is supported by the study by Chassagneux et al. [16], which shows that hunting pressure and anthropogenic disturbance significantly influence the movement behavior of red deer. This study showed that habitat suitability is lower in areas with high hunting pressure, indicating that proxy data can function as a valid and cost-effective alternative to expensive telemetry studies.

Another example is the work of Alves et al. [39], which uses methods such as scat and track counting to determine the habitat use of red deer. They confirm that indirect methods can provide valuable information on habitat preferences, especially in areas that are difficult to access.

4.2. Discussion on the Role of Remote Sensing

A key finding of this study is that remote sensing data provide an effective basis for modeling large-scale mammalian habitats [18]. Despite the relatively coarse resolution of the Landsat 7 ETM+ data (30 m), significant landscape patterns in the habitat use of red deer could be identified. This highlights that remote sensing, even at medium resolution, in combination with appropriate landscape metrics, can provide valuable information for understanding animal behavior and habitat selection. For example, in a study by Oeser et al. [49], the habitat dynamics of red deer and roe deer in Central Western Europe were investigated using similar remote sensing techniques, with Landsat data being used to analyze forest disturbance. The approach of combining low-resolution remote sensing data with hunting or telemetry data is considered a valuable approach by several authors, especially in regions with limited direct observation data. Furthermore, the study by Kwong et al. [19] shows that remote sensing data combined with landscape metrics can provide a robust basis for habitat modeling.

4.3. Discussion on Model Performance

Four different model variants were tested in the study, which differ in their combination of different metrics. Interestingly, model variant 3, which combined metrics at both the landscape and class level, showed the highest prediction accuracy (71.4%). This shows the importance of considering habitat structures at both the local and regional levels to fully understand red deer behavior. In contrast, the simplified model variant 4, with only three of the most influential metrics, achieved a prediction accuracy of 68.8%. This shows that it is possible to reduce the number of variables without significantly losing model accuracy. This reduction has the advantage that the model is easier to interpret and the most important factors determining habitat selection can more easily be identified. Particularly noteworthy is the importance of the contact index (CONTAG), which was identified as one of the most important predictors in both models. Its negative influence underlines the red deer's preference for heterogeneous landscapes.

4.4. Discussion on Landscape Structures

The modeling was based on various landscape metrics, which were calculated at both the class level (e.g., forest cover, edge density) and the landscape level (e.g., contagion index (CONTAG), gyration radius (GYRATE_AM)). The importance of these metrics reflects the structural preferences of the red deer.

The contact index, which measures the aggregation of landscape elements, has a negative influence on habitat preference. This could indicate that red deer prefer heterogeneous landscapes with a mixture of forest and open land areas over heavily aggregated forest areas. Edge density, a measure of the length of forest edges, also had a significant influence on habitat use. Red deer frequently use forest edges as a transition between cover and grazing, which explains the high relevance of this measure for habitat modeling. Landscape structure—in particular, the fragmentation of forest areas and the spatial arrangement of forest and open land—plays a central role in the habitat use of red deer. Studies show that red deer have complex interactions with their environment, with landscape structure having a significant influence on their movement patterns, resource use, and choice of retreat areas.

The results of this study clearly show that the index describing the connectivity of forest areas (CONTAG), the index describing fragmentation (MESH), and edge density (ED) are significant predictors of red deer habitat suitability. These metrics are consistent with the results of Walter et al. [7], which show that the size of the home range of red deer is highly dependent on landscape composition and configuration. In more fragmented landscapes, the freedom of movement of red deer is restricted, which, in turn, leads to lower habitat suitability. Bevanda et al. [6] emphasize that fragmentation of forest areas significantly increases the size of red deer home ranges as they are forced to travel greater distances to find sufficient food and cover. In more fragmented landscapes, red deer are less able to find their preferred habitats, which can affect their fitness and survival.

Sigrist et al. [22] point out that fragmentation not only reduces food availability but also the ability to seek shelter from predators and human disturbance. In fragmented landscapes with high edge lengths, red deer are more exposed, which means that they have to adapt their behavior more often by moving to less suitable areas.

Studies such as those by Oeser et al. [49] and Walter et al. [7] show that red deer are able to use resources efficiently in well-connected landscapes, while also having smaller, better-defined home ranges. Connectivity allows red deer to move freely between feeding and shelter areas, increasing their fitness and survival, especially during challenging seasons such as winter. Furthermore, Wu et al. [50] and Sun et al. [51] show that factors such as proximity to water sources, the degree of cover provided by shrubs, and distance to roads and villages are crucial for the habitat preferences of red deer.

The present results also show that human activities, especially habitat fragmentation by agriculture and infrastructure, have a significant impact on habitat use. The negative effects of fragmentation on habitat suitability observed in this study are consistent with the results of Dechen Quinn et al. [52], who found that white-tailed deer have smaller home ranges in more fragmented landscapes. This highlights the importance of maintaining contiguous forest patches for the long-term survival of red deer populations. Walter et al. [7] also emphasize that deer require larger home ranges in more fragmented areas to access the resources they need. These findings are particularly relevant for landscape management in Mecklenburg-Vorpommern, where fragmentation caused by human activities is widespread.

4.5. Discussion on Seasonal Dynamics and Phenology

A very important result of this study is its calculation of seasonal habitat use dynamics. As Mysterud et al. [4] and Sigrist et al. [22] show, red deer follow the "green wave" to maximize access to nutrient-rich food during the growing season. This is particularly relevant in fragmented areas where the availability of high-quality forage is subject to seasonal fluctuations. The present study shows that seasonal variability in vegetation is a crucial factor for habitat suitability, underlining the importance of a dynamic consideration of habitat preferences. These findings are critical for management, particularly with regard to the effects of climate change on vegetation patterns and availability.

5. Management Implications

The findings on the influence of landscape structure on red deer habitat use have important implications for wildlife management. They suggest that maintaining contiguous forest patches and reducing fragmentation are key strategies for improving habitat quality for red deer.

Bevanda et al. [6] and Mysterud et al. [4] emphasize that management strategies should aim to create corridors between fragments to improve connectivity and promote the movement of red deer.

To minimize the negative influence of hunting pressure on red deer populations, sustainable hunting management plans should be implemented. This includes regulating hunting seasons to take into account reproductive cycles and introducing quotas to avoid overhunting. According to Jarnemo et al. [40], heavily hunted populations tend to retreat into remote, inaccessible areas. Better-coordinated hunting management could help prevent the displacement of red deer from high-quality habitat and keep the population at a healthy level.

A crucial factor in supporting the red deer is protecting key habitats such as dense forests, wetlands, and wooded areas at higher elevations. These areas provide the red deer with food and shelter from human disturbance. One way to protect these key habitats is to establish buffer zones around them, where human activities such as agriculture, forestry, and recreation are restricted. According to Oeser et al. [49], such buffer zones are particularly important for minimizing the impact of disturbance while providing the red deer with the cover and security they need for reproduction and survival.

6. Conclusions

This study shows that combining remote sensing data and proxy data, such as hunting bag statistics, is an effective way to model the habitat use of red deer in areas with limited in situ data. The application of landscape metrics has shown that even data with a low resolution, such as those from Landsat 7, can provide sufficient results. The importance of landscape structure was emphasized by the analysis of metrics such as the contagion index and edge density. These indices have a significant influence on habitat suitability and confirm the red deer's preference for heterogeneous, unfragmented landscapes. The seasonal dynamics of vegetation—in particular, the availability of food resources—play a crucial role in the habitat selection of red deer. This highlights the need to consider seasonal and phenological changes in future management strategies. The integration of hunting data as a proxy variable showed that this method is very reliable for identifying preferred and less-preferred habitats. Hunting data could therefore be a cost-effective alternative to direct telemetry studies, especially in regions that are difficult to access. These research results suggest that the preservation of unfragmented forest areas and the creation of corridors between habitat fragments are crucial for the long-term survival of red deer populations. Landscape fragmentation has been shown to have a negative impact on the animals' freedom of movement and resource use.

Future studies should further explore the use of modern technologies such as high-resolution remote sensing data to improve habitat modeling and better capture dynamic changes in the landscape. The results of this work can be transferred to other large mammals with similar ecological requirements.

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Appendix A

Table A1. Overview of the data used in this study for the region of Mecklenburg-Western Pomerania, Germany.

Dataset	Spatial Resolution	Temporal Resolution [Year]	Reference/Link
Forest Cover Map product based on Landsat 7 ETM+ data	30 × 30 m	2000	[43]
Geographic municipality dataset VG250 AKTIS, Federal Agency for Cartography and Geodesy	1:250,000	2007	[45]
Hunting data	• High deer density and preferred habitats. • Number of hunted individuals per km^2.	2007/08–2011/12	[28]

Table A2. Derived landscape metrics for the quantification of landscape structure from Landsat 7 ETM+ data based on Fragsats V. 4.2. (For more information, see Mc Garigal and Marks, [47].)

Landscape Metrics	Abbreviation	Landscape/Class Level of Quantification	Description
Area-weighted mean radius of gyration	(GYRATE_AM)	Landscape-level	Measures the continuity of patches
Contagion index	(CONTAG)	Landscape-level	Indicates the aggregation of patches
Effective mesh size	(MESH)	Landscape-level	Measures the percentage of cell adjacencies of patches within one class
Edge density	(ED)	Class-level	The total length of all edge segments per hectare for the considered landscape
Percentage of landscape	(PLAND)	Class-level	Informs about the dominance of a certain patch type
Mean shape index	(SHAPE_MN)	Class -level	Patch-level shape index averaged over all patches in the landscape

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