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Forest ecosystem on the edge: Mapping forest fragmentation susceptibility in Tuchola Forest, Poland

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ABSTRACT

Forest ecosystems, vital for maintaining global biodiversity and ecological balance, are increasingly threatened by fragmentation. This study addresses the critical issue in the Tuchola Forest of Poland, examining the effects of natural and human factors on forest fragmentation. Our objective was to identify the most suitable dataset for monitoring forest fragmentation from 2015 to 2020, ascertain the primary drivers of fragmentation, and map the areas at high risk. Utilizing the PALSAR (25 m resolution) and Dynamic World (10 m resolution) datasets, we discovered PALSAR's enhanced ability to detect changes in forest structure, particularly evident after a significant windstorm in 2017. This dataset proved crucial in highlighting the escalating trend of forest fragmentation, reinforcing its importance for environmental monitoring and policy formulation. Our analysis identified key factors influencing fragmentation, such as proximity to croplands, tree height and age, wind speed, and vegetation water content, with areas near croplands and having younger, shorter trees being most susceptible. Employing a Weight-of-Evidence (WOE) Bayesian modeling technique, we mapped forest fragmentation susceptibility, demonstrating our methodology's effectiveness through high accuracy validation (AUC of 0.82 and Kappa Index of 0.68). Our innovative approach in mapping susceptibility to fragmentation, especially after extreme weather events, marks a pioneering contribution in Poland. This research advances the understanding of forest fragmentation dynamics and offers a scalable model for global application, emphasizing the urgent need for targeted conservation strategies to preserve the integrity of forest ecosystems amidst climatic risk and anthropogenic pressures.

1. Introduction

Forest fragmentation is a major concern in landscape ecology, significantly impacting the structure and functionality of forest ecosystems. This phenomenon not only threatens biodiversity, including wildlife habitats, water and nutrient cycles, and ecosystem resilience, but also fosters the creation of edge zones (Forman, 1996; Fischer et al., 2021). These zones escalate carbon emissions through increased tree mortality, with studies indicating that 70 % of remaining forests are within 1 km of an edge, thus highly susceptible to fragmentation's detrimental effects. These effects include a reduction in biodiversity by 13 to 75 % and impairment of ecosystem functions, notably biomass and nutrient cycles (Haddad et al., 2015; Brinck et al., 2017).

The complexity of fragmentation's impact extends to species interactions, disproportionately affecting mutualisms like pollination and seed dispersal more than antagonistic interactions. Such differential impacts necessitate a nuanced understanding of fragmentation's multifaceted effects on species persistence, distribution, and ecological interactions (Magrach et al., 2014). The scale-dependent nature of fragmentation patterns further demands a multi-scaled analytical approach, highlighting the urgency for conservation and restoration efforts to enhance landscape connectivity and mitigate extinction rates (Forman, 1996; Taubert et al., 2018; Haddad et al., 2015).

Technological advancements have revolutionized our ability to analyze forest fragmentation. Tools like FRAGSTATS, Patch Analyst for ArcGIS, and the GUIDOS Toolbox, with its Morphological Spatial Pattern Analysis (MSPA), provide sophisticated methodologies for assessing landscape connectivity and quantifying spatial heterogeneity (McGarigal, Cushman, & Ene, 2012; Rempel et al., 2012; Soille, 2003; Vogt et al., 2007; Vogt & Riitters, 2017). Yet, the effectiveness of these tools is contingent upon selecting an appropriate spatial resolution. This decision critically influences the detection and characterization of forest

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versus non-forest elements, potentially altering perceived spatial patterns significantly when comparing high (0.5 m) and low (30 m) resolution data (Wickham & Riitters, 2019). As highlighted by Fynn and Campbell (2019), the choice between coarse and fine-resolution imagery not only affects the availability and cost but also the accuracy of fragmentation metrics. Such discernment in resolution selection is essential to ensure the ecological validity of fragmentation studies, particularly in complex landscapes where the distinction between vegetation and non-vegetation can be subtle yet significant.

The study contrasts the use of PALSAR-2 Global forest/non-forest maps, utilizing SAR radar with a 25 m resolution, against Dynamic World's forest class, which employs 10 m optical Sentinel-2 imagery. This comparison aims to evaluate their respective efficacies in monitoring and analyzing forest ecosystems. PALSAR-2′s SAR radar is instrumental in providing robust measurements of forest structure and detecting disturbances under challenging climatic conditions (Atkins et al., 2023; Balling et al., 2023), while Dynamic World's use of Sentinel-2 imagery offers detailed insights into environmental changes, supporting effective management and conservation efforts (Brown et al., 2022). This comparative analysis sheds light on the strengths and limitations of SAR and optical imagery in capturing forest fragmentation dynamics, aiming to enhance our understanding of these complex processes.

Despite a considerable volume of research on forest fragmentation within Poland—encompassing historical evaluations of habitat distribution (Mazgajski et al., 2010), implications for timber resources and carbon sequestration (Budniak & Zięba, 2022), and the socio-economic drivers of forest structural changes (Żmihorski et al., 2009; Szramka & Adamowicz, 2020)—focused investigations into the Tuchola Forest Biosphere Reserve's (TFBR) vulnerability to fragmentation are notably lacking. Specifically, there have been no studies investigating the size and dynamics of edge boundaries within the TFBR, a gap this study aims to address. The devastating windstorm of 2017 accentuates the TFBR's vulnerability, emphasizing the need for focused research on its fragmentation dynamics. This study hypothesizes that storm disturbances, coupled with escalating demands for land conversion to agriculture, predominantly drive fragmentation in the TFBR.

In this research, we aim to rigorously evaluate the effectiveness of two distinct datasets—the microwave PALSAR-2 Global forest/non-forest imagery, and the optical imagery from sentinel's collection of Dynamic World, in monitoring forest fragmentation within Tuchola Forest from 2015 to 2020. Our primary objective is to ascertain which dataset provides the most accurate and detailed representation of fragmented patches during this period. Furthermore, we intend to determine the principal factors contributing to forest fragmentation, particularly focusing on the roles of wind disturbances and proximity to cropland and bareland, as identified in significant prior studies (Forzieri et al., 2020; Jung et al., 2016). Through this analysis, we aim not only to enhance our understanding of fragmentation dynamics but also to map the region's susceptibility to ongoing and future fragmentation. This research is anticipated to offer valuable insights for more effective monitoring and management of forest ecosystems, thereby contributing significantly to the discourse on forest ecology and conservation.

1.1. Study Area: Tuchola Forest, Poland

The Tuchola Forest Biosphere Reserve (TFBR), nestled within the greater Tuchola Forest in northern Poland, stands out for its exceptional biodiversity and a mix of broadleaf and coniferous forests (Nienartowicz et al., 2010). Covering an expanse of 3,195 square kilometers, (see

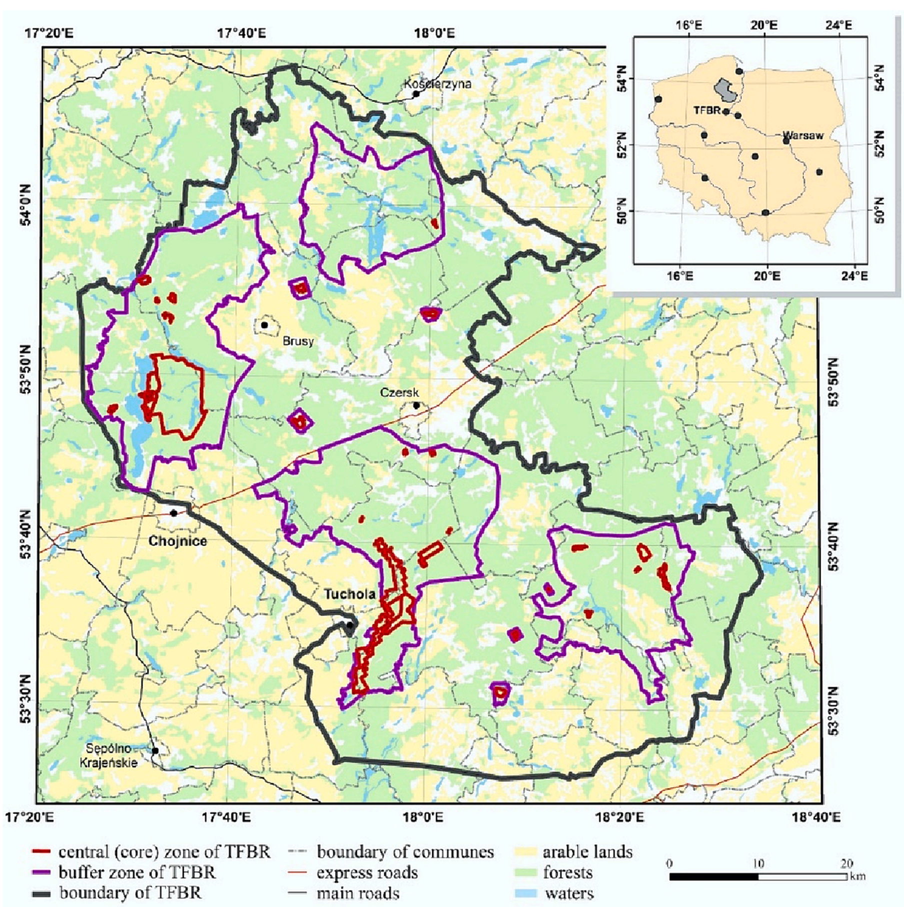

Fig. 1. The localization of the study area – Tuchola Forest Biosphere Resereve.

Fig. 1) this largely forested biosphere reserve plays a pivotal role in the UNESCO Man and Biosphere Programme, aiming at ecosystem conservation while promoting sustainable development (Nienartowicz & Kunz, 2020; Nienartowicz et al., 2010). Home to over 1,337 species of vascular plants and 1,250 phanerogams, the TFBR's ecological importance is highlighted by its rich biodiversity (Nienartowicz et al., 2010).

Historical research by Kunz (2012) indicates a significant increase in forest area within Western Pomerania, which includes the Tuchola Forest, from 16 % in 1618 to 37 % in the early 21st century. This reflects a transition from extensive deforestation due to logging and agriculture to systematic reforestation efforts since the 19th century. However, a 2017 storm notably impacted the forest's spatial structure, illustrating the dynamic nature of its landscape (Kunz, 2006; Dutt & Kunz, 2024).

The TFBR, encompassing 22 communes within two voivodeships, is recognized as Poland's most extensive UNESCO-designated biosphere reserve, predominantly covered by woodland, accounting for over 86 % of its area. It's strategically segmented into core, buffer, and transition zones, each dedicated to distinct conservation objectives and sustainable development initiatives. This zoning not only conserves a variety of ecosystems but also promotes ecological education, aligning with principles of sustainable development (Krawiec et al., 2022; Nienartowicz & Kunz, 2020).

The TFBR's landscape, shaped by its history and geological features, reflects the remnants of the ancient Tuchola Primeval Forest, with a composition that has evolved due to post-glacial climatic changes and human activities. Despite these changes, the reserve remains a sanctuary for rare and protected species, with its predominant forest types and diverse flora including a rich lichen community (Boiński, 1993; Boiński & Boińska, 2020).

Recent climatological research within the TFBR has revealed an increasing vulnerability to extreme weather events, including severe convective windstorms (Pacey et al., 2021) and whirlwinds that have caused significant forest destruction (Chojnacka-Ożga & Ożga, 2018). The 2017 windstorm, documented by Taszarek et al. (2019) and Chmielewski et al. (2020), highlights the severe impact of such climatic extremes, causing unprecedented forest damage and emphasizing the need for integrated climatic challenges into conservation strategies.

Acknowledging the historical context of deforestation and the ongoing challenges posed by climatic extremes, this study emphasizes the complex interplay between climate change and forest conservation efforts in the TFBR. The inclusion of recent climatic data and extreme weather event analyses offers a comprehensive overview, enhancing the understanding of the Tuchola Forest Biosphere Reserve's ecological dynamics and conservation priorities.

2. Data sources and processing

2.1. Rationale for time frame selection (2015–2020)

In selecting the analysis period of 2015–2020 for our study, we aimed to capture the dynamics of forest fragmentation both before and after a significant meteorological event: a derecho. A derecho is a widespread, long-lived windstorm that is associated with a band of rapidly moving showers or thunderstorms. Characterized by its intense straight-line winds, a derecho can cause substantial damage to landscapes, particularly forests, over a wide area (Chmielewski et al., 2020).

The rationale for focusing on this period is underpinned by the occurrence of one of Poland's most destructive storms on August 11, 2017. This derecho, as detailed by Chmielewski et al. (2020) and Taszarek et al. (2019), represents a catastrophic meteorological event in Poland's history. Originating as a mesoscale convective system on the border between the Czech Republic and Poland, it ravaged several provinces, causing unprecedented forest damage. Wind speeds during this event reached up to 130 km/h, and in some areas, they exceeded 150 km/h (Taszarek et al., 2019). The storm resulted in the loss of approximately 79,700 ha of forest, blocked and damaged over 1100 km of local and municipal roads, and left over 500,000 consumers without electricity (Chmielewski et al., 2020).

The period of 2015–2020 is crucial for understanding the scale of forest fragmentation attributable to such an extreme event. Prior to the derecho, the forests in Poland were already experiencing fragmentation; however, this six-year span provides a unique opportunity to quantify the magnitude of change that followed. Analyzing forest fragmentation in this timeframe not only allows for a pioneering investigation into the effects of the derecho but also offers a historic record of the fragmentation process. Such a record is invaluable in creating susceptibility maps, aiding in the prediction and management of future forest fragmentation under similar extreme events.

2.2. Remote sensing data

This study utilized a combination of synthetic aperture radar (SAR) and near-real-time (NRT) Land Use/Land Cover (LULC) datasets to assess forest/non-forest dynamics over six years, from 2015 to 2020. Two primary datasets, representing microwave and optical remote sensing technologies, were incorporated: the Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR-2) for microwave remote sensing, and the Sentinel-2 L1C collection from the Dynamic World dataset for optical remote sensing. Comprehensive forest survey data, managed by the Bureau of Geodesy and Forest Management, were obtained from the Bank Danych Lasach (Forest Data Bank, BDL). This dataset encompasses detailed information on forests administered by the State Forests National Forests Holding, acquired through the BDL portal for specific forest inspectorates within the Regional Directorates of the State Forests in Gdańsk and Toruń.

The analysis of wind speed data sourced from the European Severe Storms Laboratory (ESSL) and the European Severe Weather Database (ESWD) (Dotzek et al., 2009) involved examining reports from 2015 to 2020 on severe wind gust events. The absence of specific wind speed measurements in some ESWD reports necessitated supplementary data from ERA5 reanalyses by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2020). This supplementary data was downscaled and integrated with the ESWD reports to estimate wind speeds at relevant locations within the study area (Sulik & Kejna, 2020). The approach facilitated a detailed examination of the climatic factors influencing forest dynamics, emphasizing the impact of severe wind gusts (Taszarek et al., 2019).

2.2.1. PALSAR-2 Forest/Non-Forest map

The PALSAR-2 datasets, utilizing Synthetic Aperture Radar (SAR) technology aboard the ALOS-2 satellite, provide critical data for environmental monitoring through microwave emissions and reflections. This SAR technology captures high-quality images under all weather conditions, day and night, by leveraging L-band microwaves capable of penetrating vegetation to some extent. The global forest/non-forest map is derived from SAR imagery at a 25 m resolution, the finest resolution available for these datasets, which classifies pixels based on backscatter intensity. Pixels with strong backscatter are labeled as 'forest,' and those with low backscatter as 'non-forest,' in line with the Food and Agriculture Organization's (FAO) definition of forest. This definition includes natural forest areas larger than 0.5 ha with a canopy cover of over 10 %.

To accommodate the study period from 2015 to 2020, data from two subsets were utilized. Initially, the Global 3-class PALSAR dataset (JAXA/ALOS/PALSAR/YEARLY/FNF) covered 2015 to 2017, providing classifications of forest, non-forest, and water. Subsequently, for 2018 to 2020, the more advanced Global 4-class PALSAR-2 dataset (JAXA/ALOS/PALSAR/YEARLY/FNF4) offered detailed classifications including dense forest, non-dense forest, non-forest, and water (Shimada et al., 2014). This approach aligns with the advancements in SAR capabilities, as highlighted by Awange & Kiema (2013), to overcome typical remote sensing limitations like cloud cover and limited daylight, ensuring consistent and reliable environmental monitoring.

2.2.2. Dynamic World dataset forest cover map

In tandem with the SAR-based PALSAR-2 analysis, this study utilized the Dynamic World V1 dataset from Google Earth Engine (GOOGLE/DYNAMICWORLD/V1). Spanning from 2015 to the present, this dataset offers a near-real-time Land Use/Land Cover (LULC) classification at an unprecedented 10 m resolution (Brown et al., 2022), the highest available for such global monitoring applications. The study by Louzada et al. (2023) illustrates the effectiveness of integrating SAR with optical remote sensing data in environmental monitoring. For this study, the 'trees' band within the Dynamic World dataset was selected to identify forested areas, applying a threshold on the 'trees' probability band (greater than 0.6) to delineate forested regions from non-forest areas. This threshold was chosen based on the dataset's guidance to select pixels with high confidence in class prediction, aligning with the observed overall agreement of 73.8 % between Dynamic World model outputs and expert labels for high-confidence classes such as trees, indicating a robust delineation of forested versus non-forested areas (Brown et al., 2022). This approach enabled the examination of forest dynamics within the specified region of interest (ROI), leveraging the Dynamic World's capability to provide current and detailed LULC data, and complementing the SAR-based observations.

2.3. Analysis of forest fragmentation

Morphological Spatial Pattern Analysis (MSPA), a breakthrough in landscape ecology, offers a comprehensive approach to assessing landscape connectivity by studying the pixel arrangements (Soille, 2003; Vogt et al., 2007). The emergence of the GUIDOS Toolbox, with its user-friendly interface and broad applicability in environmental analyses, represents a further advancement in this field (Vogt & Riitters, 2017). Unlike traditional tools, GUIDOS is uniquely equipped to quantify spatial heterogeneity, a critical aspect in forest fragmentation studies, through sophisticated algorithms that provide a more nuanced understanding of fragmentation impacts.

In this study, we employed the GUIDOS Toolbox to assess forest fragmentation. This choice was motivated by the Toolbox's exceptional capability in spatial data analysis and land cover classification. Traditional methods, such as those proposed by Musick and Grover (1991) and Forman (1996), often relied on landscape-level concepts like patch-corridor-matrix or adjacency at the pixel level, which, while informative, lacked the ability to provide quantitative measures of fragmentation's degree or variation (Vogt, 2023). Moreover, these methods struggled in large-area assessments due to challenges in handling a vast number of patches and accurately representing patch sizes and shapes (Riitters et al., 2002; Heilman et al., 2002). In contrast, GUIDOS offers a robust methodology, proven in diverse research areas ranging from biodiversity impact studies to climate change effects on habitats (Rincón et al., 2022). Within this framework, fragmentation classes are defined based on the connectivity and adjacency of forest pixels, with special emphasis on categories like 'rare' and 'patchy', which indicate intense fragmentation and have significant implications for biodiversity and ecosystem health (Heilman et al., 2002). This approach not only resonates with Chavan et al. (2018) in tracking core area reduction but also aligns with Batar et al. (2021) in emphasizing the importance of understanding fragmentation drivers. Furthermore, our study leverages multi-temporal land cover data to analyze forest fragmentation, showcasing the GUIDOS Toolbox's versatility in a wide array of environmental assessments, including landslide risks and urban planning (Arrogante-Funes et al., 2021; Lin et al., 2021).

3. Predictive variables for forest fragmentation

To develop effective strategies for mitigating forest fragmentation risks, it's crucial to understand their predictive variables. Given the predominantly rural nature of the study area, this research focuses on the natural causes of fragmentation, acknowledging the limited yet not negligible human influence. The spatial representation of the ecological and geographical variables depicted in Fig. 2 serves as the basis for analyzing the factors contributing to forest fragmentation within the Tuchola Forest Biosphere Reserve (TFBR), Poland. The variables include wind speed, vegetation water content, tree age distribution, tree height, slope gradient, and distances from cropland, bare land, and roads (Fig. 2). The specific datasets from which these variables were derived are detailed in Table 1, which follows this figure. This table provides a comprehensive overview of the sources utilized for each factor.

3.1. Physical factors

Forest ecosystems' resilience and stability are significantly influenced by their physical environment. Factors such as slope angle play a crucial role in determining sunlight exposure and wind dynamics (Doane et al., 2023), which can heighten vulnerability to windthrow. The concept of forest structural diversity, which encompasses the spatial distribution of trees, species diversity, and variations in tree dimensions (size and height), is essential for understanding the impacts of wind on forest ecosystems. Forests with a higher degree of structural diversity, characterized by a mix of tree heights and species, can disrupt wind flow and potentially reduce the severity of wind damage, thereby influencing fragmentation patterns (Li et al., 2023). Furthermore, forest age and composition significantly affect fragmentation. Young and old-growth forests exhibit distinct fragmentation characteristics based on their composition and age structure, with older and taller trees, especially in conifer forests, being more susceptible to wind damage (Wulder et al., 2009). Severe wind events initiate a two-stage process of damage propagation in forests, starting with critical downward gusts and escalating as damaged areas expand (Dupont et al., 2015). Additionally, the study by Konings et al. (2021) on vegetation water content provides insights into how moisture levels impact forest resilience to environmental stressors. This comprehensive view highlights the importance of considering structural diversity and the physical factors contributing to fragmentation to enhance our understanding of forest ecosystem dynamics.

3.2. Human factors

Human activities significantly influence forest fragmentation, even in predominantly natural study areas (Haddad et al., 2015). The expansion of roads (Newman et al., 2014) and the introduction of croplands lead to land conversion and degradation, thereby disrupting forest continuity and intensifying fragmentation. Edge effects, where forests border non-forest areas, result in ecological consequences such as increased carbon emissions, as noted by Scanes (2018) and supported by findings from Haddad et al. (2015) and Mengist et al. (2022). Furthermore, Mitchell et al. (2014) explore how agricultural expansion and forest fragmentation impact ecosystem services, revealing the critical role of forest fragments in sustaining these services across agricultural landscapes. These studies collectively highlight the growing importance of addressing human factors in forest fragmentation and stress the need for managing habitat fragmentation and landscape structure to ensure the provision of multiple ecosystem services.

4. Methodology

The methodological schematic diagram depicted in Fig. 3, shows the workflow that had been carried out, it is further explained in the subsections below.

4.1. Image reclassification for fragmentation analysis

The initial step of our research entailed deriving vegetation cover

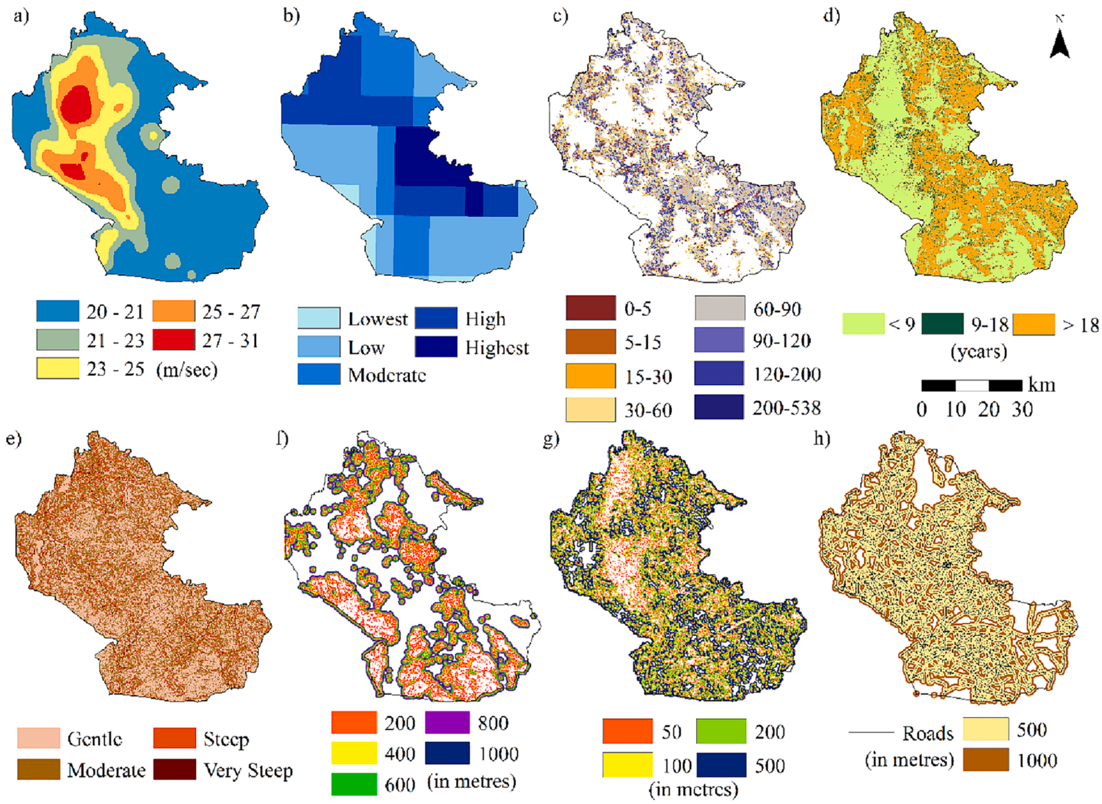

Fig. 2. Spatial representation of various ecological and geographical variables within the Tuchola Forest Biosphere Reserve (TFBR), Poland. Panels display (a) wind speed, (b) vegetation water content, (c) tree age distribution, (d) tree height, (e) slope gradient, (f) distance from cropland, (g) distance from bare land, and (h) distance from roads, derived from the different data source as mentioned in table 1.

Table 1
Data sources of predictive variables.

Factors	Source
Wind speed	ESSL, ESWD, ERA5 (ECMWF)
Vegetation water content	SMAP Enhanced L3 Radiometer Global and Polar Grid Daily 9 km EASE-Grid Soil Moisture, Version 5
Tree age	Bank Danych o Lasach (BDL) 2017
Tree height	Global Land Cover Facility, University of Maryland
Slope gradient	USGS SRTM DEM
Distance from cropland	Dynamic World image collection (2015–2020 average)
Distance from bare land	Dynamic World image collection (2015–2020 average)
Distance from roads	Global Roads Inventory Project - GRIP - version 4

maps from 2015 to 2020, as elaborated in Section 2.1. This phase utilized the PALSAR-2 Forest/Non-Forest Map in conjunction with the Dynamic World dataset, integrating Synthetic Aperture Radar (SAR) imagery analysis with near-real-time Land Use/Land Cover (LULC) data. This integration not only enhanced the accuracy of our vegetation mapping but also provided a comprehensive understanding of vegetative dynamics over the years, laying a solid foundation for our research.

Subsequently, the data from both datasets underwent a detailed reclassification into binary raster maps, a pivotal step for differentiating forest from non-forest areas. This reclassification was facilitated using Google Earth Engine (GEE), where the PALSAR-2 dataset, for the years 2015 to 2017, was reclassified with '1′ representing non-forest areas (including water bodies) and '2′ for forest areas. For data post-2017, the PALSAR data, now enriched with four bands, underwent a similar reclassification, merging Dense Forest and Non-dense Forest into a single Forest category ('2′), and Non-Forest and Water categories into a Non-Forest category ('1′). The Dynamic World dataset was also reclassified, applying a forest mask to the 'trees' band to designate forest areas as '2′ and non-forest areas as '1′, covering various land covers such as 'water', 'grass', 'flooded_vegetation', 'crops', 'shrub_and_scrub', 'built', 'bare', and 'snow_and_ice'. This methodological approach, using GEE for both datasets, enabled a nuanced analysis of different land covers, vital for accurately delineating forested from non-forested regions.

To standardize the projections and resolution, the PALSAR dataset was downloaded with a spatial resolution of 25 m and reprojected to the ETRS 1989 Transverse Mercator (EPSG:2180) coordinate system. Similarly, the Dynamic World data, with a finer scale of 10 m, was processed. Both datasets were then reclassified in GIS tools to uniform dimensions of 2550 by 2693 pixels and a cell size of 30x30 meters, ensuring consistency in spatial analysis across all images.

4.2. Forest area Density (FAD) analysis

The GUIDOS Toolbox (GTB) was pivotal in our study for analyzing forest fragmentation over six years using comprehensive datasets. Employing the Forest Area Density (FAD) function within GTB, which utilizes a per-pixel moving window technique, allowed for an assessment across variable observational scales: 7x7, 13x13, 27x27, 81x81, and 243x243 pixels. This multi-scalar analysis provided a nuanced view of forest structure and dynamics, integral to decoding ecosystem complexities (Vogt, 2023; Riitters et al., 2002, 2012a, b).

Our analysis specifically concentrated on the 'Rare' and 'Patchy' categories within the six-class categorization of Forest Area Density (FAD). These classes were chosen due to their representation of the most fragmented and disconnected forest zones. The 'Rare' class denotes areas with less than 10 % forest cover, while 'Patchy' refers to regions having 10 % to less than 40 % forest cover. The selection of these two classes was instrumental in providing evidence of forest fragmentation

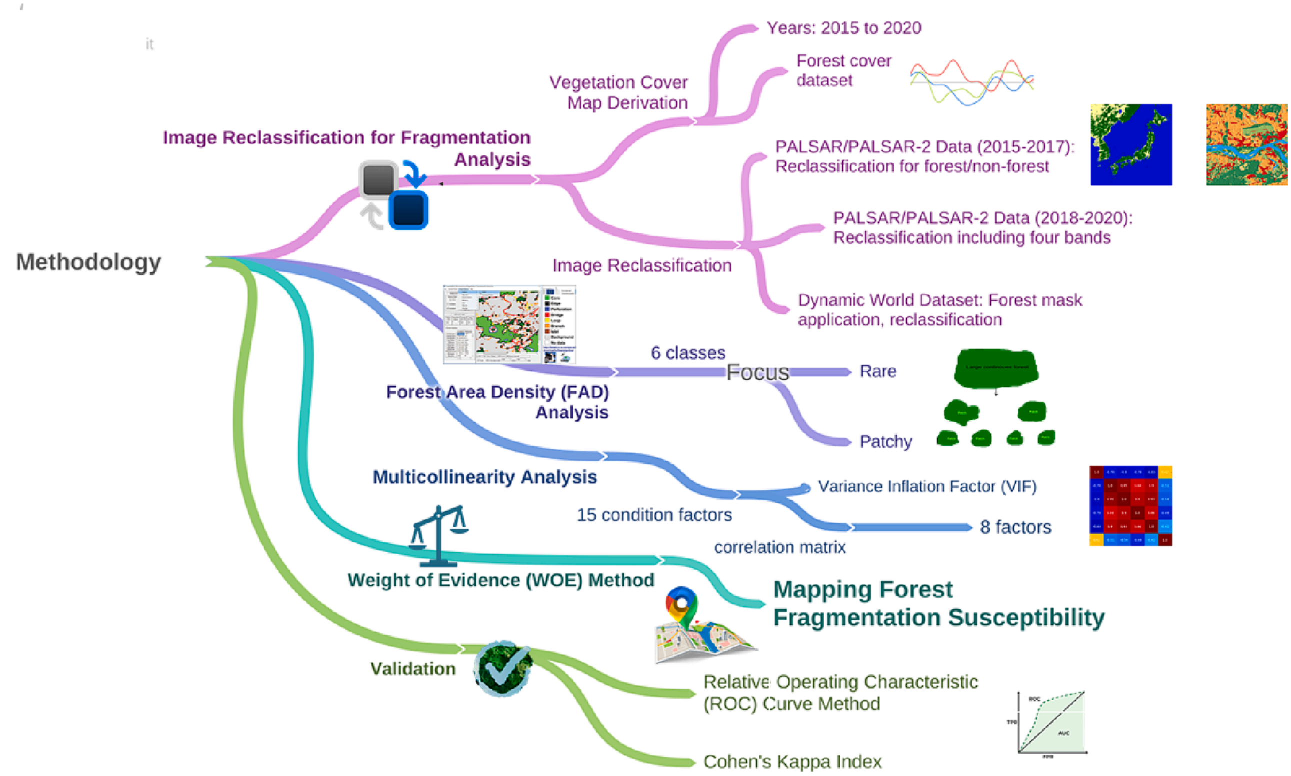

Fig. 3. Comprehensive methodological workflow. This figure presents the detailed methodological workflow employed in the study, starting from the derivation of vegetation cover maps using PALSAR-2 and Dynamic World datasets for the period 2015 to 2020. It illustrates the step-by-step process of image reclassification for forest/non-forest differentiation, forest area density (FAD) analysis focusing on 'Rare' and 'Patchy' fragmentation classes, multicollinearity analysis to refine predictive variables, and the application of the weight of evidence (WOE) method for mapping forest fragmentation susceptibility. Validation using the relative operating characteristic (ROC) curve method and Cohen's Kappa Index is included to confirm the robustness of the model.

in our model, highlighting areas significantly distanced from the core forest regions. This focus allowed for a detailed examination of the extent and impact of forest fragmentation, a key aspect of our study.

4.3. *Predictive variables through multicollinearity analysis*

In our study on forest fragmentation, we initially considered a diverse set of fifteen variables: tree species, aspect, tree age, forest type, elevation, slope, vegetation water content, soil type, tree height in 2015 and 2020, distance from road, cropland, bareland, forest, and wind speed. However, upon a detailed examination using both a Correlation Coefficient Matrix and the Variance Inflation Factor (VIF), we identified multicollinearity issues that could lead to unreliable statistical inferences, as they contravene the assumption of independent regressors (O'Brien, 2007). Notably, variables such as tree species, aspect, and forest type displayed linear relationships with other factors, indicating redundancy, and were thus excluded.

To enhance the precision of our model, we embarked on a rigorous exclusion process, following the guidelines recommended by García-Orozco et al. (2023) and incorporating fuzzy logic principles akin to those proposed by Omar et al. (2022). This refinement process resulted in the selection of eight independent factors deemed crucial for our model, as illustrated in Fig. 4: wind speed, vegetation water content, tree age, tree height in 2020, slope, distance from cropland, distance from bareland, and distance from roads. These variables were chosen due to their low correlation matrix scores and significant relevance to the fragmentation patterns observed from 2015 to 2020. During this period, numerous areas previously classified as patchy forest transitioned to bareland or cropland, pinpointing the importance of these selected factors in reflecting the current landscape conditions.

This methodical selection process bolsters the robustness of our model by mitigating multicollinearity, a crucial aspect for ensuring the validity of regression-based predictions. Our approach aligns with the best practices in ecological modeling, aimed at providing reliable data to support informed forest management and conservation strategies. The final selection of variables represents a deliberate balance between comprehensive data inclusion and statistical integrity, recognizing that each factor independently contributes to our understanding of forest fragmentation dynamics. By refining the variables, our model's predictive accuracy for areas at risk is significantly enhanced, which is vital for developing targeted conservation interventions. Our methodology showcases the adaptability required in ecological studies, ensuring that our conclusions are grounded in statistically sound practices and lay a solid foundation for ongoing and future forest management efforts.

4.4. *Construction of the forest fragmentation susceptibility map*

The methodical extraction of patchy areas, as discussed in section 4.2, was crucial for the construction of the Forest Fragmentation Susceptibility Map. This process involved correlating the eight variables detailed in Fig. 2—wind speed, vegetation water content, tree age, tree height in 2020, slope, distance from cropland, distance from bareland, and distance from roads—with these patchy zones (Fig. 7). This step was fundamental in providing an incisive investigation into the association between environmental factors and fragmentation susceptibility. By employing the weight-of-evidence approach, detailed in the subsequent section, our study precisely evaluated the susceptibility of these forested areas to fragmentation. This process enhanced our understanding of forest fragmentation dynamics, laying the groundwork for future discussions on the implications of our findings.

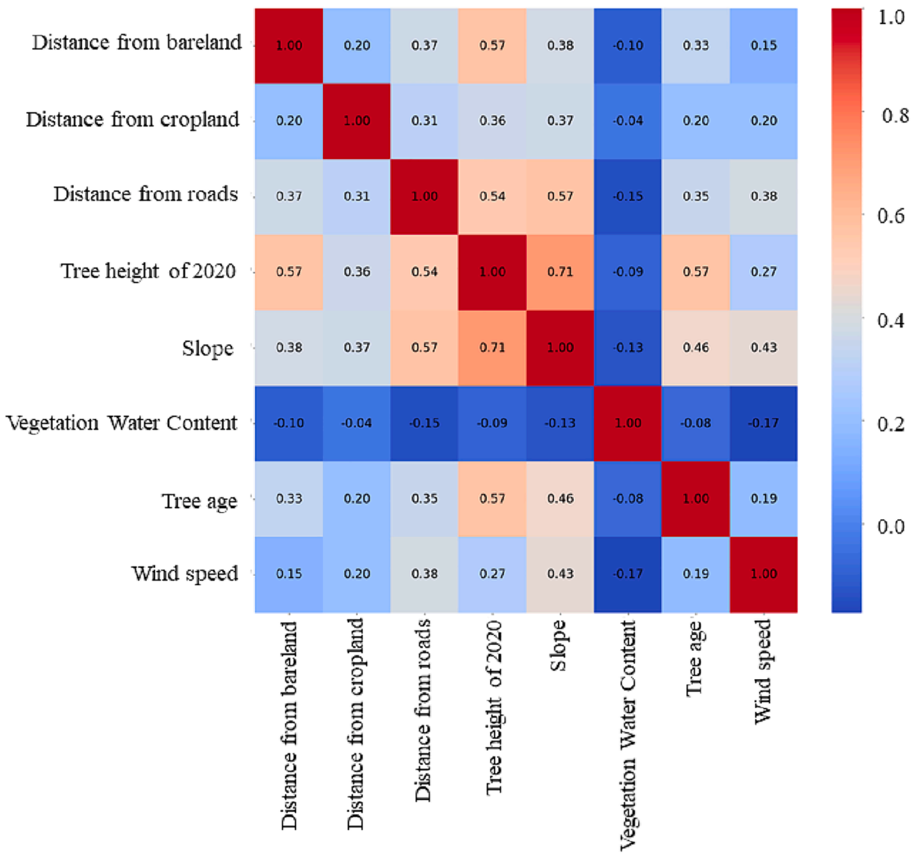

Fig. 4. Correlation matrix displaying Pearson correlation coefficients for eight predictive variables. The variables are ordered as follows: distance from bareland, distance from cropland, distance from roads, tree height of 2020, slope, vegetation water content, tree age, and wind speed. High values represent higher correlation in red and vice versa.

4.5. *Weight of evidence (WOE) method*

In our study, we utilize the Weight-of-Evidence (WOE) method, a Bayesian modeling technique, to map forest fragmentation susceptibility. This quantitative approach, initially developed in the field of mineral exploration (Bonham-Carter, 1990), has been widely applied in ecological studies due to its effectiveness in evaluating spatial associations between variables and observed phenomena.

We calculate the positive (W +) and negative weights (W −) for each variable class related to patch forests, using the method refined by Sterlacchini et al. (2011). These weights are determined using the following formulas:

$$W^{+} = \log_e\left(\frac{P(B|D)}{P(B|\overline{D})}\right)$$

$$W^{-} = \log_e\left(\frac{P(\overline{B}|D)}{P(\overline{B}|\overline{D})}\right)$$

Here, P denotes probability, B the presence of a class of patch forest predictive variable, $\overline{B}$ its absence, D the presence of a patch forest, and $\overline{D}$ the absence of a patch forest (Fan et al., 2011).

The contrast between these weights, known as the weight contrast (C), is defined as:

$$C = W^{+} - W^{-}$$

This measure reflects the spatial association strength between the variables and patch forests. To refine our analysis, we calculate the standardized weight contrast (Wstd) as the ratio of C to its standard deviation, S(C):

For the standard deviation of the weight contrast $S(C)$:

$$S(C) = \sqrt{S^2(W^{+}) + S^2(W^{-})}$$

For the variances $S^2(W^{+})$ and $S^2(W^{-})$:

$$S^2(W^{+}) = \frac{1}{N_{B\cap D}} + \frac{1}{N_{B\cap\overline{D}}}$$

$$S^2(W^{-}) = \frac{1}{N_{\overline{B}\cap D}} + \frac{1}{N_{\overline{B}\cap\overline{D}}}$$

The standardized weight contrast (Wstd) is then calculated:

$$Wstd = \frac{C}{S(C)}$$

A positive Wstd value indicates a factor's favourable influence on forest fragmentation, while a negative value suggests an unfavourable influence. A value close to zero indicates a minimal relation to forest fragmentation. Finally, the Forest Fragmentation Susceptibility Index (FFSI) is derived by summing the standardized weight contrasts (Wstd) for each variable:

$$FFSI = \sum Wstd$$

This detailed formulation of the WOE method, incorporating rigorous statistical analysis, ensures a robust approach for understanding and predicting patterns of forest fragmentation. This calculation methodology is consistent with the approach described by Batar et al. (2021). Our application aligns with the principles of objective and transparent scientific inquiry, as advocated in broader ecological studies (Dekant &

Bridges, 2016).

4.6. Validation of the forest fragmentation susceptibility map

The validation of predictive models is a fundamental step in ecological research, particularly when addressing critical issues such as forest fragmentation. Given the complexity of forest ecosystems and the multifaceted influences leading to fragmentation, our approach integrates both the Relative Operating Characteristic (ROC) curve method and Cohen's Kappa Index to offer a comprehensive evaluation of the Forest Fragmentation Susceptibility Map.

4.6.1. Validation by ROC method

To validate our forest fragmentation susceptibility map, we employed the relative operating characteristic (ROC) curve method. This standard approach evaluates model performance by analyzing the area under the curve (AUC), which assesses a classifier's overall ranking capability across all possible classification thresholds. Such a measure is crucial for comparing learning algorithms and optimizing model construction (Fawcett, 2006; Mingote et al., 2020). The ROC-AUC's utility stems from its ability to provide a single, comprehensive value representing model accuracy, with values closer to 1 indicating higher accuracy and values near 0.5 suggesting limited predictive capability (Fawcett, 2006; Batar et al., 2021).

The AUC formula for a two-class problem is:

$$AUC = \frac{\sum \text{rankings of positive samples} - \frac{n_p(n_n+1)}{2}}{n_p n_n}$$

Here, n_p and n_n represent the counts of positive and negative samples, respectively. The AUC of the ROC reflects the quality of the probabilistic model in predicting the occurrence or non-occurrence of an event (Fawcett, 2006).

4.6.2. Validation by Cohen's Kappa Index

The AUC-ROC method, while widely used, is not without its limitations, particularly in its potential to obscure model performance in specific operational contexts (Lobo et al., 2007; Vakhshoori and Zare, 2018). As such, to complement our ROC curve analysis, we conducted a confused matrix and Cohen's kappa index for validation. This statistical tool is essential for measuring the concordance between observed and predicted classifications within the forest fragmentation susceptibility map, while correcting for chance agreement (Cohen, 1960; Vakhshoori and Zare, 2018).

Cohen's Kappa (κ) is calculated to measure the agreement between two raters, adjusting for chance agreement. The formula is:

$$\kappa = \frac{P_{\text{obs}} - P_{\text{exp}}}{1 - P_{\text{exp}}}$$

where (P_{obs}) is the observed agreement among raters, and (P_{exp}) is the expected agreement by chance. Our dataset, (P_{obs}) and (P_{exp}) are derived as follows:

$$P_{\text{obs}} = \frac{TP + TN}{N}$$

$$P_{\text{exp}} = \frac{(TP + FN) \times (TP + FP) + (FP + TN) \times (FN + TN)}{N^2}$$

Here, TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively, with N being the total number of observations.

5. Results

5.1. Comparison of remote sensing datasets

The comparative analysis of PALSAR (25 m resolution) and Dynamic World (10 m resolution) datasets in mapping forest fragmentation in Tuchola Forest, Poland, from 2015 to 2020, demonstrates a clear preference for the PALSAR dataset. This is particularly evident in Fig. 5, which presents the trends in the 'Dominant' and 'Interior' classes (representing low and very low fragmentation, respectively) in both datasets. The line graphs for these classes in datasets (a) PALSAR and (b) Dynamic World reveal significant shifts post the 2017 derecho event, with the PALSAR dataset more markedly capturing the changes in forest structure. These shifts identify PALSAR's enhanced capability to detect subtle and significant alterations in the forest landscape, especially in response to sudden environmental disturbances.

Building upon these insights, Fig. 6 delves deeper into the 'Rare' (very high fragmentation) and 'Patchy' (high fragmentation) classes. Prior to 2017, the levels of fragmentation in these classes were almost negligible. However, post-2017, there was a significant rise, with the 'Rare' class in PALSAR data increasing from virtually 0 % in the years preceding 2017 to 38.68 % by 2020. Similarly, the 'Patchy' class also showed a substantial increase, rising from 7.7 % in 2017 to 30.7 % by 2020. In contrast, the Dynamic World dataset depicted these changes to a lesser extent, with the 'Rare' class peaking at 23.47 % and the 'Patchy' class at 20.32 % in 2020.

These findings, illustrated through Figs. 5 and 6 are not mere statistical variances but reflect the intrinsic capacity of the PALSAR dataset to accurately depict environmental dynamics, even during acute natural events. The implications of these results are substantial for forest conservation efforts and policy-making, highlighting the critical need for selecting appropriate remote sensing tools that can faithfully represent environmental changes.

5.2. Results of the multicollinearity analysis

Our correlation coefficient matrix, refer to Fig. 4, indicates a predominantly low to moderate interdependence among the environmental factors related to forest fragmentation. Most predictive variables show low correlation coefficients (mostly blue shades), suggesting their independence.

Particularly, "Vegetation Water Content" is the most independent variable, displaying minimal correlation with others, while "Tree age" and "Wind speed" also show low intercorrelations. Despite some moderate correlations between "Distance from cropland" and "Distance from roads" with "Tree height of 2020″ and "Slope," these are not substantial enough to indicate problematic multicollinearity. These findings affirm that the chosen variables in our model maintain their integrity for an unbiased analysis.

5.3. Rare and patchy forest fragmentation assessment

Utilizing the Forest Area Density (FAD) function within GTB using PALSAR, our analysis identified 'Rare' and 'Patchy' fragmentation classes as areas with FAD below 40 %. These classifications denote noncontinuous and extensively fragmented forest sections. Subsequent spatial analysis for the period 2015–2020 quantified these patchy forests at 175.6 km2, equating to 5.49 % of the study's total area. Over time, some of these regions have undergone further fragmentation, transitioning into bareland or cropland, thus being excluded from further analysis.

Incorporating the 2023 forest layer with a 10 m resolution allowed us to identify persistent rare and patchy forest fragments within the current forest boundaries. These areas, totaling 30.10 km^2, constitute 0.94 % of the total study region and are integral to the subsequent susceptibility analysis. The forest cover has decreased by approximately 33.23 square

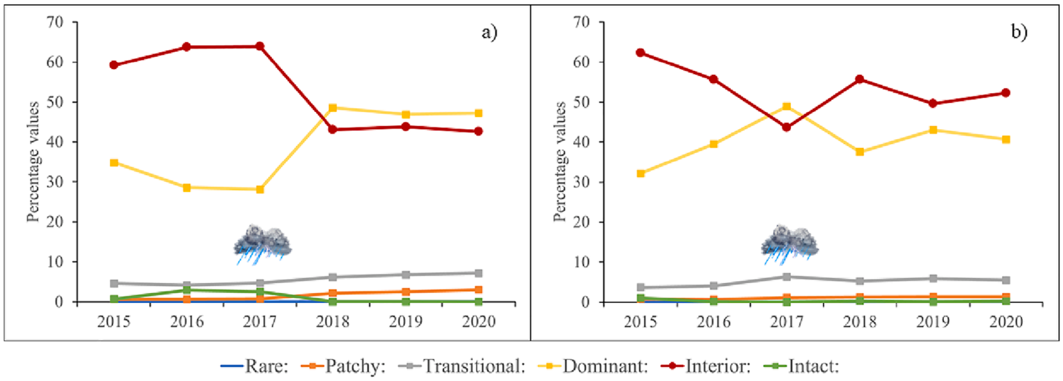

Fig. 5. FAD values through the years 2015–2020 in datasets a) Palsar b) Dynamic World.

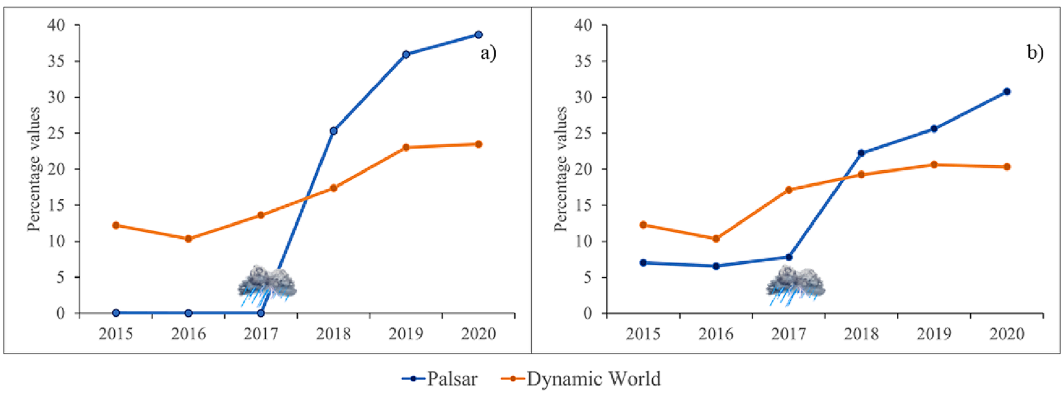

Fig. 6. FAD values in the two datasets through the years 2015–2020 for a) rare class b) patchy class.

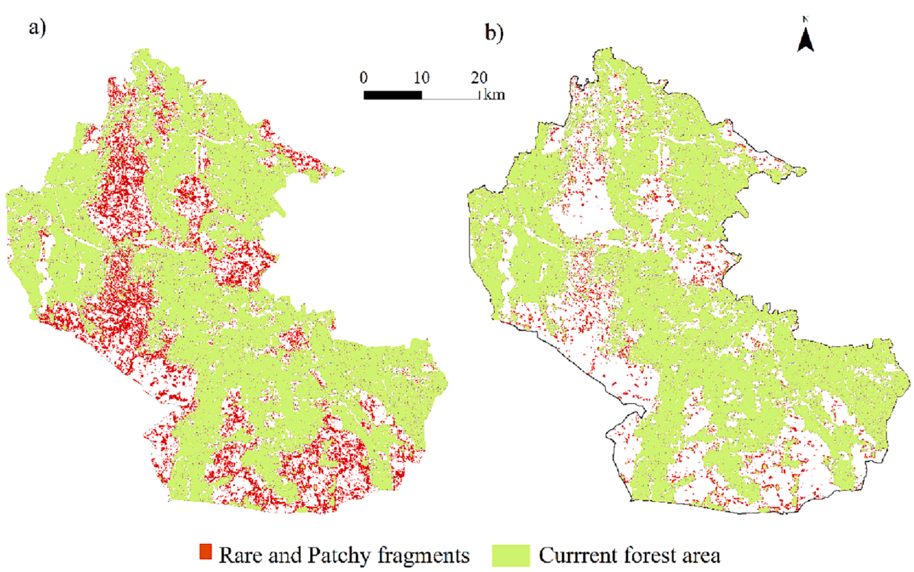

Fig. 7. Rare and patchy fragments in a) entire study region (2015–2020) and b) current forest areas of 2023.

kilometers from the year 2020 to 2023. This represents a percentage change of approximately −1.89 %, indicating a continued trend of forest fragmentation and loss within the study area. The utilization of the 2023 forest layer was pivotal in our study to understand susceptible zones in the future, focusing on the rare and patchy fragments that were present in the 2023 forest cover layer for a comprehensive analysis of the landscape's vulnerability. Fig. 7a and 7b illustrate the geographical distribution of these forests within the Tuchola Forest, showcasing the contrasts before and after the extraction process, and highlighting the changes in forest fragmentation susceptibility from the final year of the study period up until the current time.

5.4. Forest fragmentation susceptibility analysis

The forest fragmentation susceptibility map (Fig. 8) presents a detailed visualization of the areas within the Tuchola Forest that are

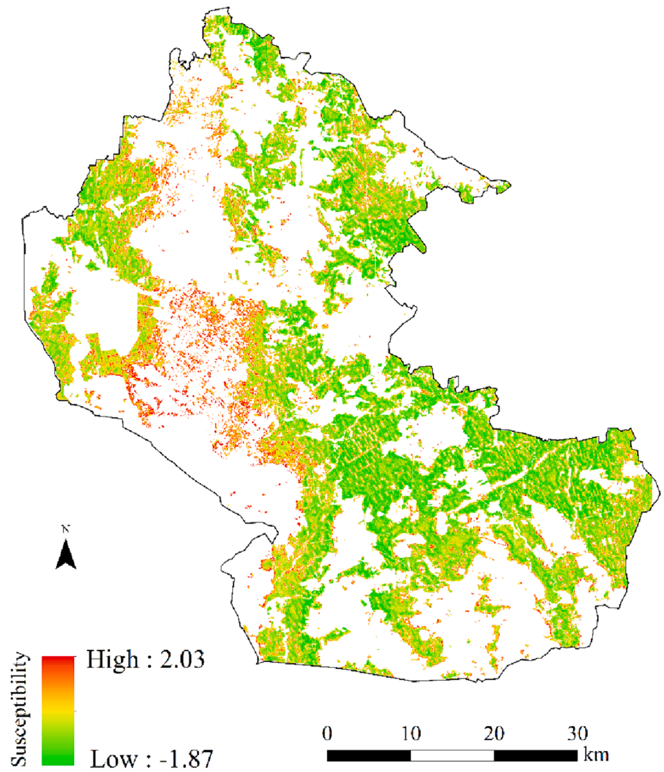

Fig. 8. Forest fragmentation susceptibility map.

particularly vulnerable to fragmentation, integrating an exhaustive analysis that takes into account a variety of predictive variables. The importance of these factors has been quantitatively assessed using the Weight of Evidence (WoE) method (Table 2), with the results indicating significant influencers on forest fragmentation susceptibility. The analysis revealed that the nearest distance from cropland, specifically within 200 m, has the most substantial positive influence on forest fragmentation susceptibility, evidenced by a WoE value of 0.54. This finding illustrates that forest areas in closer proximity to croplands are at a higher risk of fragmentation. Other significant factors contributing to increased susceptibility include the closest distances from bareland (50 m), tree height within the < 9 m range, and tree ages between 5 and 15 years, highlighting the nuanced interplay of various environmental and anthropogenic elements in forest fragmentation. Additionally, external environmental conditions such as high wind speeds (25–27 km/h) and moderate vegetation water content further exacerbate the susceptibility to fragmentation.

On the contrary, factors such as steeper slopes and greater distances from cropland and bareland correlated with reduced forest fragmentation risk. The gentlest slopes were associated with the lowest susceptibility (WoE value: −0.63), suggesting these areas are less likely to undergo fragmentation (see table 2).

Overall, the results reveal the intricate interplay between various environmental factors and their impact on forest fragmentation susceptibility. The findings from Table 1, coupled with the ROC analysis, provide a robust foundation for targeted conservation efforts aimed at mitigating the risks of further fragmentation within the Tuchola Forest landscape.

5.5. *Validation of forest fragmentation susceptibility map*

The validation of the Forest Fragmentation Susceptibility Map is further reinforced through comprehensive analyses, incorporating both the ROC curve and Cohen's Kappa Index to evaluate model performance. The ROC curve analysis, illustrated in Fig. 9, demonstrates the model's reliability in predicting susceptibility, achieving an AUC value of 0.82. This high discriminative capacity signifies the model's adeptness at distinguishing between areas susceptible and not susceptible to fragmentation.

The Cohen's Kappa calculation yielded an index of 0.68, indicating substantial agreement beyond chance. These metrics offer compelling evidence of the model's accuracy in classifying areas according to their fragmentation susceptibility, affirming the effectiveness of our methodological approach in forest conservation planning (see Table 3).

6. Discussion

6.1. *Implication of fragmentation (FAD) in different datasets*

Our comparative analysis between the PALSAR and Dynamic World datasets reveals PALSAR's superior sensitivity in detecting 'Rare' and 'Patchy' forest fragmentation post-2017, an observation echoed by Atkins et al. (2023) and Balling et al. (2023). These studies highlight the advanced radar technologies, like PALSAR, for their nuanced detection of environmental changes and shifts in forest structure, especially following significant disturbances such as the 2017 windstorm. Microwave remote sensing, as employed by PALSAR, offers distinct advantages across various environmental settings. Awange & Kiema (2013) elucidate the critical role of microwave sensing in overcoming the limitations posed by persistent cloud cover and dense vegetation, notably in tropical regions where optical remote sensing faces significant challenges. This technology's ability to penetrate vegetation canopies and function effectively under conditions of high cloud cover, such as during wet seasons, is indispensable for comprehensive fragmentation studies, particularly after severe weather events.

Furthermore, the integration of SAR and optical remote sensing methods, as demonstrated by Louzada et al. (2023), supports our findings and emphasizes the necessity of selecting the appropriate remote sensing technology tailored to specific environmental conditions and research objectives. Similarly, Meraner et al. (2020) highlight the potential of SAR-optical data fusion in removing clouds from optical imagery, using deep learning approaches to preserve the integrity of surface observations beneath cloud cover.

The effectiveness of PALSAR's microwave remote sensing in accurately capturing changes in forest structure, despite its lower resolution compared to high-resolution optical sensing from Dynamic World, demonstrates its utility in forest fragmentation analysis. This is especially relevant in post-disturbance scenarios, emphasizing the importance of choosing SAR technologies like PALSAR for forest cover and fragmentation studies. Our research not only reinforces the significance of PALSAR in forest conservation and decision-making processes but also aligns with the broader scientific consensus on the adaptability and effectiveness of SAR technology in addressing the challenges of optical remote sensing limitations.

6.2. *Influence of environmental factors on forest fragmentation susceptibility*

6.2.1. *Integrated analysis of forest fragmentation factors*

Challenging the conventional wisdom, Morreale et al. (2021) suggest that temperate forest edges may demonstrate increased growth and biomass compared to their tropical counterparts, casting new light on edge-induced vulnerability. This revelation underpins our investigation into the Tuchola Forest, where we dissect the influence of both environmental and anthropogenic factors on forest fragmentation.

Our findings highlight proximity to cropland as a significant anthropogenic influence. Forest fragments within 200 m of cropland demonstrate the highest susceptibility to fragmentation, supporting global patterns observed by Haddad et al. (2015). The role of agricultural expansion and its impact on the floristic composition at the forest-cropland interface (Ribeiro et al., 2019) calls for a nuanced approach to

Table 2
Weight of Evidence (WoE) values for forest fragmentation susceptibility factors.

Variable	Subdivision	WoE values
Distance from Cropland	200	0.54
Distance from Bareland	50	0.37
Tree height	9-18	0.36
Tree age	5-15	0.28
Wind Speed	25 - 27	0.19
Distance from Bareland	100	0.18
Vegetation Water Content	Moderate	0.16
Wind Speed	27 - 31	0.16
Slope	Steep	0.13
Tree age	0-5	0.12
Tree age	15-30	0.11
Vegetation Water Content	Low	0.09
Slope	Moderate	0.09
Vegetation Water Content	Lowest	0.08
Tree age	30-60	0.04
Wind Speed	21 - 23	0.03
Slope	Very Steep	0.03
Distance from Road	500	0.01
Tree height	0-9	0.01
Wind Speed	23 - 25	0.00
Tree age	200-538	0.00
Distance from Road	1000	-0.01
Tree age	120-200	-0.04
Vegetation Water Content	Highest	-0.07
Distance from Cropland	400	-0.10
Distance from Bareland	200	-0.18
Tree age	90-120	-0.19
Slope	Gentle	-0.19
Vegetation Water Content	High	-0.19
Tree age	60-90	-0.23
Distance from Cropland	600	-0.24
Wind Speed	20 - 21	-0.24
Distance from Cropland	1000	-0.26
Distance from Cropland	800	-0.26
Tree height	18-26	-0.33
Distance from Bareland	500	-0.41

land-use planning that considers ecological impacts. Our results from the Tuchola Forest corroborate these observations and echo similar fragmentation patterns noted by Mengist et al. (2022) across Poland, emphasizing the enduring legacy of historical land-use on present-day forest structure and biodiversity (Mazgajski et al., 2010).

Tree characteristics, notably height and age, emerged as pivotal natural factors. Our data indicates that younger forests (5–15 years) and shorter trees (less than 9 m) are more vulnerable to fragmentation. This is in line with the findings of Rodrigues et al. (2016), who observed long-term structural changes in forest canopies and the impact of anthropogenic disturbances on tree height and spatial structure. Moreover, Wulder et al. (2009) provide insight into how forest age and fragmentation are interrelated, further suggesting the influence of these factors on the ecological dynamics of forest landscapes.

Wind speed and vegetation water content are additional natural determinants of fragmentation risk. High wind speeds (25–27 km/h) and moderate water content conditions were associated with increased fragmentation risks, implying the necessity of incorporating meteorological and hydrological considerations into forest management (Konings et al., 2021; Doane et al., 2023; Li et al., 2023).

Additionally, the influence of topography on fragmentation susceptibility is accentuated by our findings. Guo et al. (2024) found that extensively burned forest patches are often located at higher elevations, while more fragmented patches tend to occur in areas with gentle slopes. Our results corroborate this pattern, suggesting that less steep slopes may facilitate the spread of fragmentation.

The interplay between forests and their topographic context is further elaborated by Doane et al. (2023), who delve into the concept of topographic roughness as a natural archive of wind events. Their work suggests that forests coevolve with their environment, with topography influencing the resilience of forests to windthrow events.

In summary, our integrated analysis of forest fragmentation factors in the Tuchola Forest emphasizes the multifaceted nature of susceptibility. It highlights the urgency of incorporating a diverse range of ecological and physical variables into forest management and conservation strategies to ensure resilience against ongoing and future environmental challenges.

6.2.2. Tree specie characteristics

In the Tuchola Forest, the composition of tree species, including the predominance of Scots pine (*Pinus sylvestris*) (82.78 %), followed by Silver birch (*Betula pendula*) (7.39 %) and English oak (*Quercus robur*) (1.29 %), suggests a landscape largely shaped by the resilience and susceptibility of these species to fragmentation (see Figure S1). Despite not being the primary factors in our correlation analysis, the species characteristics significantly contribute to the nuanced ecological dynamics of the forest. Scots pine (*Pinus sylvestris*), with its notable resilience, contrasts with the heightened vulnerability of Silver birch (*Betula*

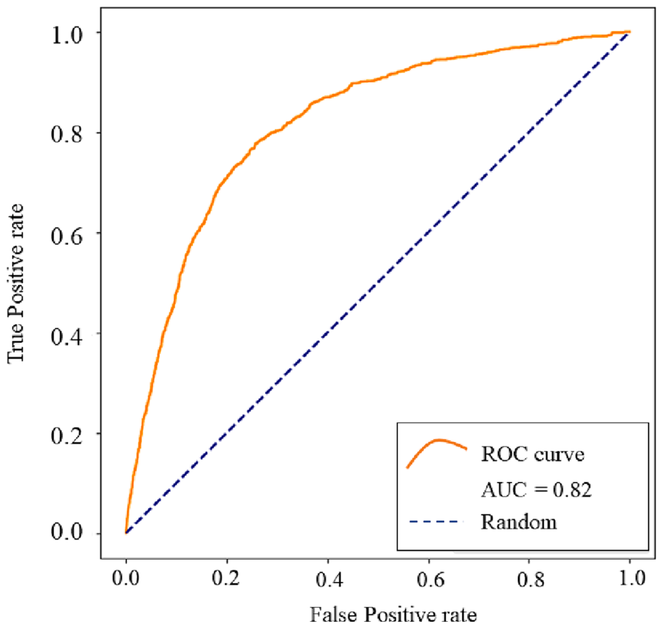

Fig. 9. The accuracy of the forest fragmentation susceptibility map.

Table 3
Summary of classification metrics for Cohen's Kappa Index.

Metric	Value
True Negative (TN)	1,494,224
False Positive (FP)	2013
False Negative (FN)	426
True Positive (TP)	2551
Cohen's Kappa Index	0.68

pendula) and English oak (*Quercus robur*) near forest edges. This distinction is crucial for understanding the intricate effects of fragmentation and is supported by the findings of Konôpka et al. (2020) and Budniak & Zięba (2022), which emphasize variable impacts on different species within Polish forests. Their findings resonate with our investigation into species-specific susceptibility and highlight importance of informed management practices tailored to the unique ecological roles and physiological needs of each species.

Pimentel et al. (2013) and Roche and Campagne (2017) advocate for an ecosystem integrity framework that incorporates both species diversity and environmental factors into forest management decisions. This approach is vital for addressing the specific needs of Scots pine (*Pinus sylvestris*), Silver birch (*Betula pendula*), and English oak (*Quercus robur*). The genetic robustness of Scots pine (Pinus sylvestris), as discussed by González-Díaz et al. (2017), may underpin its resilience, offering insights into adaptive strategies for forest conservation. Conversely, the pioneering nature of Silver birch (*Betula pendula*), highlighted by Oksanen (2021) suggests a vulnerability to edge effects that necessitates careful consideration in forest management practices. Similarly, the decline of English oak (*Quercus robur*) in altered disturbance regimes, as noted by Knoot et al. (2010), calls for a nuanced understanding of its ecological and physiological sensitivities.

Coates et al. (2018) contribute to this discourse by differentiating the effects of partial harvesting on species-specific windthrow susceptibility, particularly near forest edges. This aspect is crucial for managing fragmented landscapes, where selective interventions and the recognition of tree-level heterogeneity can influence the overall resilience of forest ecosystems to storm events.

By integrating these varied perspectives, our discussion offers a comprehensive examination of the physiological, ecological, and genetic dimensions that define the responses of Scots pine (*Pinus sylvestris*), Silver birch (*Betula pendula*), and English oak (*Quercus robur*) to fragmentation. Such a multifaceted approach is essential for developing forest management practices that are sensitive to the distinct characteristics of each species, ensuring their continued health and viability in changing environmental conditions. Through this lens, we aim to enhance the resilience of forest ecosystems, mitigating the impacts of fragmentation and promoting sustainable forest landscapes.

6.2.3. Holistic approach to forest management

Incorporating diverse factors into our model not only enhances predictive accuracy but also aligns with the ecosystem integrity framework crucial for the resilience of forests like the Tuchola Forest. This holistic approach, informed by our findings and echoed by the comprehensive analyses of forest fragmentation in Poland by Referowska-Chodak & Kornatowska (2021), stresses the importance of considering both species diversity and environmental factors in forest management strategies. The integration of development and conservation policies, as discussed by Szramka & Adamowicz (2020), becomes paramount, offering insights for anticipating high-risk fragmentation areas and emphasizing sustainable management practices that prioritize long-term ecosystem integrity and resilience.

6.3. Methodological adaptation and predictive model refinement

The refinement of variables in our study marked a pivotal transition towards an enhanced model for predicting forest fragmentation susceptibility. Initial analyses using 15 variables were fine-tuned to focus on the current vegetation state, leading to the exclusion of non-vegetated areas formerly identified as susceptible. Ground-truthing revealed that the earlier model overestimated susceptibility in areas no longer forested. Subsequent multicollinearity analysis informed the removal of highly interdependent variables such as soil type, and less impactful ones like forest type and species, as well as aspect and elevation in this relatively flat region.

A discernible shift in the susceptibility patterns was evident when comparing the previous and current maps. Where the initial model indicated heightened susceptibility at the forest edges, the refined model demonstrated more dispersed susceptibility zones, particularly in central areas with the highest wind speeds recorded between 2015 and 2020 (Fig. 2). This adaptation not only corroborated the significant role of wind in forest fragmentation but also resulted in a notable increase in model accuracy, with the ROC curve's accuracy improving from 0.64 to 0.82 which suggests an accurate and reliable model along with the Cohen's Kappa Index calculation.

The adjustment of our analytical framework, informed by empirical evidence and expert field knowledge, illustrates the dynamic nature of ecological modeling. It highlights the importance of iterative analysis and underlines the value of precise variable selection in developing models with high predictive accuracy, crucial for the formulation of effective forest management and conservation strategies.

7. Conclusion

Our study in the Tuchola Forest region not only highlights the specific challenges faced by this area but also serves as a microcosm for the broader, global imperative for adaptive forest management in the face of climate change. The heightened susceptibility of forests to windthrow events, particularly near croplands and barelands, coupled with the pivotal role of species diversity in bolstering ecosystem resilience, emphasizes the universal relevance of our findings. This global perspective reinforces the necessity of implementing adaptive management strategies worldwide to safeguard forest ecosystems against the escalating threats posed by wind disturbances and other climate change-related stressors.

Drawing on insights from Forzieri et al. (2020) regarding the increasing intensity of wind disturbances and Sanginés de Cárcer et al.

(2021) on effective post-windstorm management, our work highlights the necessity of integrating empirical data with best forestry practices. Customized strategies that consider specific forest types and site conditions are essential.

Future research should explore the balance between ecological impacts and salvage logging, incorporating climate change considerations more explicitly into forest management plans. The findings from the Joint Research Centre (JRC) on forest landscape patterns and fragmentation in Europe highlight the need for comprehensive plans addressing spatial patterns and connectivity (European Commission, Joint Research Centre (JRC), 2023; Sanginés de Cárcer et al., 2021).

In summary, our study advocates for dynamic forest management approaches that meld in-depth research, existing literature, and practical insights. Such strategies are critical to maintain the ecological integrity of forests like the Tuchola Forest, enhancing ecosystem services and ensuring resilience amidst evolving environmental challenges (Pimentel et al., 2013).

8. Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT for language polishing and editing the manuscript. After using this tool/service, the author(s) reviewed and revised the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Sanjana Dutt: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Amit Kumar Batar:** Writing – review & editing, Conceptualization, Data curation, Formal analysis, Methodology, Software, Supervision. **Sławomir Sulik:** Data curation. **Mieczysław Kunz:** Visualization, Supervision.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.111980.

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