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Landscape metrics of the Brusy Commune before and after wind-storm: an assessment of the extent of changes based on Landsat-8 data

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Abstract. Monitoring the change in land cover in disaster-affected areas, such as forests, has become a conventional forest management practice, particularly in protected areas. Most change detection and fragmentation studies rely on single-dated satellite images even while investigating changes over a long temporal span. This study aims to move a step further to compare fragmentation before and after a derecho event that occurred in August 2017 using 23 Landsat-8 images of Brusy Commune within the Tuchola Forest Biosphere Reserve. The supervised classification was carried out in the Google Earth Engine using the machine learning algorithm of random forests within the summer months of 2017 and 2018. The high overall accuracy of 0.92 was obtained for the two images which were then analysed with landscape metrics such as mean patch size, number of patches, total edge and edge density using Patch Analyst. These landscape metrics facilitated the characterisation of landscape fragmentation at both the class and landscape levels. Shannon's Diversity Index was employed to assess heterogeneity across the landscape. The findings indicate significant fragmentation, particularly in the forest and pasture classes, with overall low diversity. This study underscores the potential for future research to employ advanced machine learning techniques and non-parametric classifiers, such as neural networks, to enhance the prediction of fragmentation across various spatial scales.

Key words:
landscape fragmentation,
landscape metrics,
LULC changes,
Landsat-8,
wind-storm,
Google Earth Engine

Introduction

The perception of forest landscapes varies significantly across different scales and is influenced by the observer's experiences and the methodological approach adopted in its study. This variability is particularly evident in remote sensing, where landscapes are interpreted through various resolutions – spatial, radiometric, spectral and temporal. These resolutions frame our understanding of the landscape's structure, dynamics and function. Natural disasters and human impacts have been consistently responsible for modifying the landscape, and it has thus become increasingly crucial to study the various changes occurring within the landscape using various remote-sensing and GIS tools on various scales (Haines-Young and Chopping 1996; Gustafson 1998; Frohn 2018; McGarigal and Cushman 2002; Vogt et al. 2007). When monitoring natural or human-induced events, change detection involves four steps: detecting the change, determining its nature, measuring its area and assessing its spatial pattern (Macleod and Congalton 1998).

Based on many remotely sensed images at various spatial resolutions and assessments of landscape metrics, researchers have been able to quantify the influence of spatial scale on landscape patterns (Kunz and Nienartowicz 2002, 2004, 2007;

Wu and Hobbs 2002; Saura 2004; Zhu et al. 2006; Gan et al. 2009). Indicators or metrics that consider the pattern, area and geometrical aspects of the landscape are used for change detection analysis (Kunz and Nienartowicz 2002). Turner et al. (2001) proposed methods for analysing landscape and forest patterns. In practice, the majority of forest fragmentation indicators are driven by either the ideas of adjacency or connectivity at the pixel level (Musick and Grover 1991). To meet requirements for the comparability of data and indicators across wide geographic regions, the input data for assessments are often derived from remote sensing and consist of land cover maps (Vogt et al. 2007).

Feng and Liu (2015) analysed raster datasets from 30 m to 330 m, at 30-m intervals, finding that landscape metrics' sensitivity to cell size varies, with some metrics significantly affected and others showing minimal sensitivity. This result is consistent with previous literature highlighting the correlation with metrics and scales (Kunz and Nienartowicz 2002; Millington et al. 2003; Uuemaa et al. 2005). Recent methodologies to analyse scale impacts have been utilised in case studies to examine scale constraints in landscape ecology (Alhamad et al. 2011; Forzieri and Catani 2011; Feng et al. 2013; Lü et al. 2013).

Forest disturbance mapping at medium resolution faced constraints until 2008, when Landsat imagery was made freely available. From a scientific perspective, the authors found it essential to not rely solely on single images from satellite sensors. Instead, they utilised a median composite of all cloud-free data for classification on Google Earth Engine (GEE). GEE is a free cloud-computing platform for satellite-data processing (Landsat, Sentinel-2, MODIS) and planetary-scale analysis (Gorelick et al. 2017). Since the first major work on the topic was published in 2013 (Hansen et al. 2013), the amount of research using GEE has risen sharply, with more than 397,000 results in Google Scholar as of April, 2024. The applications range from vegetation monitoring to land cover mapping, disaster management and agricultural applications (Kennedy et al. 2018; Mutanga and Kumar 2019; Amani et al. 2020; Orusa et al. 2023).

This research explores the suitability of Landsat's 30-m resolution for analysing landscape fragmentation, focusing on the Brusy Commune forest in northern Poland, which experienced a derecho stemming from a mesocyclone on August 11, 2017. It critically examines the impact of scale on landscape metrics and their sensitivity when employing GEE for satellite-based forest monitoring.

Materials and methods

Study area

The Brusy Commune, serving as the focal area for this study's detailed land use/land cover (LULC) changes analysis, is situated within the Chojnice Poviat of the Pomeranian Voivodeship, northern Poland (see Fig. 1). Spanning an area of 400.74 km^2, it is predominantly rural, with nearly 99% of its expanse dedicated to rural landscapes and a minor fraction (5.1 km^2) constituting the urban area of the town of Brusy. As of 2017, the commune had a population of ~14,500, resulting in a density of 36 individuals per km^2. The commune is composed of 100 settlement units, encompassing major villages, minor settlements and the urban centre of Brusy (Kunz and Nienartowicz 2023).

Within the Brusy Commune, the Przymuszewo Forest District is the predominant State Forest economic unit, encompassing 80.53% of the area, with the Czersk and Rytel Forest Districts following in contribution. Land cover/usage analysis reveals forests as the largest category, occupying 23,684 hectares or 59.1% of the commune's terrain. Agricultural spaces make up 30.4% of the land, with arable fields accounting for 20.5% of this. Water bodies, including six lakes each over 100 hectares, constitute 6.2% of the area. Built-up and transport infrastructures cover 2.1%, while areas with scattered trees and shrubbery account for roughly 0.2%. The forest landscape is mainly characterised by coniferous ecosystems, predominantly dry and fresh pine stands, with deciduous forests making up about 12% of the forestry. The average age of these forest stands is 62 years (Kunz and Nienartowicz 2023).

The Brusy Commune's forest regions are distinguished by a variety of protected areas, including the Zaborski Landscape Park located in its western sector (see Fig. 1). Within the commune boundaries, there exist eight nature reserves encompassing forest, peat bog and aquatic ecosystems, alongside 42 ecological sites.

Additionally, Brusy is among 22 communes within the Tuchola Forest Biosphere Reserve (TFBR), which was inaugurated on June 2, 2010 as part of the Man and Biosphere Programme (MaB), marking it as Poland's eleventh and largest biosphere reserve. Occupying 319,525 hectares in the country's north-west, the TFBR is predominantly forested, accounting for over 60% of its area. This significant forest cover positions the Tuchola Forest natural district as one of Poland's most extensive forested areas (Nienartowicz et al. 2010; Nienartowicz and Kunz 2018).

The Tuchola Forest Biosphere Reserve is segmented into three distinct zones: core, buffer and transit, as illustrated in Figure 1. The core zone, deemed the most critical, encompasses the "Tuchola Forest" National Park and 25 nature reserves. Following this is the buffer zone, primarily composed of four landscape parks, including the Zaborski Landscape Park, which predominantly falls within the Brusy Commune. The transit zone, the largest, extends over the territories of 22 communes (13 from the Kuyavian-Pomeranian Voivodeship and 9 from the Pomeranian Voivodeship) and the city of Tuchola, covering an area exceeding 206,000 hectares – nearly double the size of the buffer zone. This structure is a unique characteristic of the Tuchola Forest Biosphere Reserve. Nevertheless, in August 2017, the reserve, particularly within the Brusy Commune's administrative boundaries, was struck by a devastating derecho, leading to significant alterations in the landscape's structure (see figure 2)(Taszarek et al. 2019; Kunz et al. 2023).

Derecho event in Tuchola Forest Biosphere Reserve

European Severe Weather Database records 600 severe convective wind gusts annually in Poland (Dotzek et al. 2009). Such occurrences are most prevalent from May through August, with a typical peak in the late afternoon of July (Celiski-Mysaw and

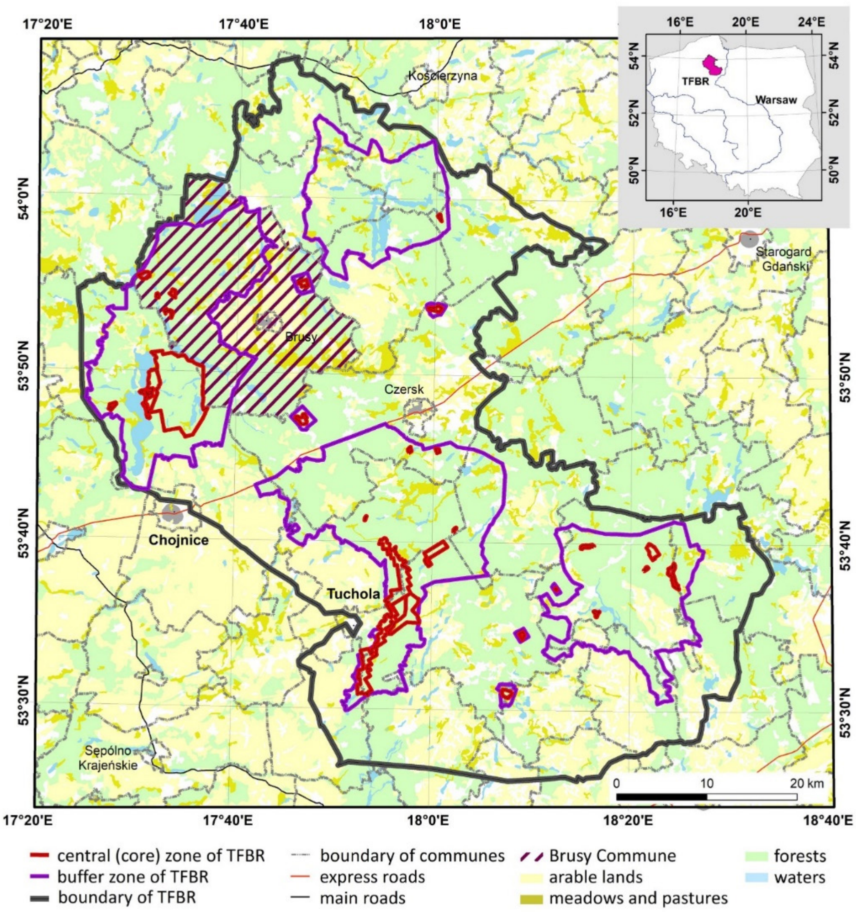

Fig. 1. Location of the Brusy Commune in the Tuchola Forest Biosphere Reserve

Palarz 2017; Taszarek et al. 2019; Sulik and Kejna 2020). These winds, capable of causing significant damage, commonly result from thunderstorm outflows and are frequently linked to supercells and mesoscale convective systems (MCS) (Zipser 1982; Doswell and Burgess 1993; Houze 1993).

Johns and Hirt (1987) were the inaugural scientists to outline the criteria for derechos, a term referring to intense downburst clusters associated with forward-propagating mesoscale convective systems (MCS) characterised by mesoscale vortices and inflow jets. According to Corfidi et al. (2016), for an event to be classified as a derecho, the damage path must maintain a width of at least 100 km and extend over a length of 650 km, predominantly driven by a mature, cold-pool MCS following the initial storm development. Annually, Poland witnesses an average of ten bow echoes and one derecho, indicative of the country's susceptibility to such severe weather phenomena. Notably, the derecho on August 11, 2017 exemplified this destructive capability, generating substantial wind damage with gusts exceeding 42 m/s (Celiski-Mysaw and Matuszko 2014; Celiski-Mysaw and Palarz 2017; Taszarek et al. 2019; Sulik and Kejna 2020).

Materials and methods

The methodological scheme has been illustrated in Figure 3 and described in detail in the following section.

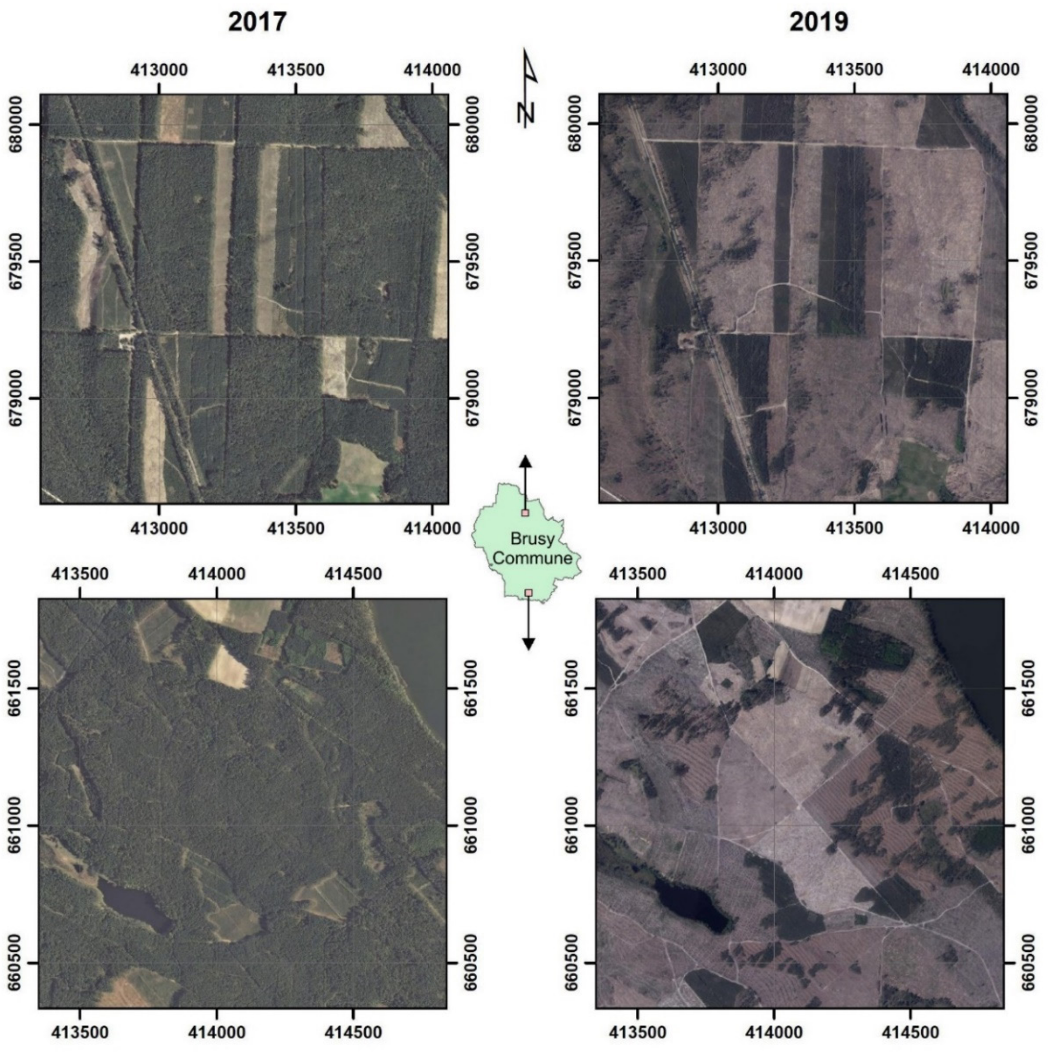

Fig. 2. Examples in aerial imageries of deforestation resulting from the derecho of August 11, 2017 (source of remote-sensing data – geoportal.gov.pl)

Satellite data

This research employed multispectral satellite imagery from the Landsat-8 Operational Land Imager (OLI), focusing on orthorectified surface reflectance data processed through Google Earth Engine (GEE) to conduct land use and land cover (LULC) classification in Brusy, North Poland, specifically during the summer period of April, May, June, and July. Landsat-8's moderate spatial resolution of 30 meters, coupled with its global reach, has facilitated its widespread adoption for various land cover delineation tasks, including the identification of agricultural lands and wetland areas, since its launch (Giri et al. 2013; Schultz et al. 2015; Gilbertson et al. 2017). For the purpose of classification, this study selected only the blue, green, red, and near-infrared (NIR) bands, given their similar Spectral Response Functions (SRF). The criteria for image selection included a cloud cover of less than 10%. The dataset comprised 10 Landsat-8 surface reflectance (SR) images collected between March 30 and July 30, 2017, as pre-disaster evidence, and 13 images from the corresponding dates in 2018 as post-disaster evidence. For each set of yearly images, a median composite was generated to represent the summer season's land cover state.

Classification method

Reference data, including both training and validation samples, were collected from Landsat imagery for the specified time frames. Reflecting the objectives of this study and the real-world conditions of the study area, six distinct land cover types were identified for sampling: water bodies, forest, damaged forest area, bare land, pastures and built-up areas. To ensure a non-biased assessment of classification accuracy, validation samples were acquired at least one week subsequent to the collection of training samples. For the purpose of training, ~1500 samples for each land cover category were compiled. Conversely, the number of validation

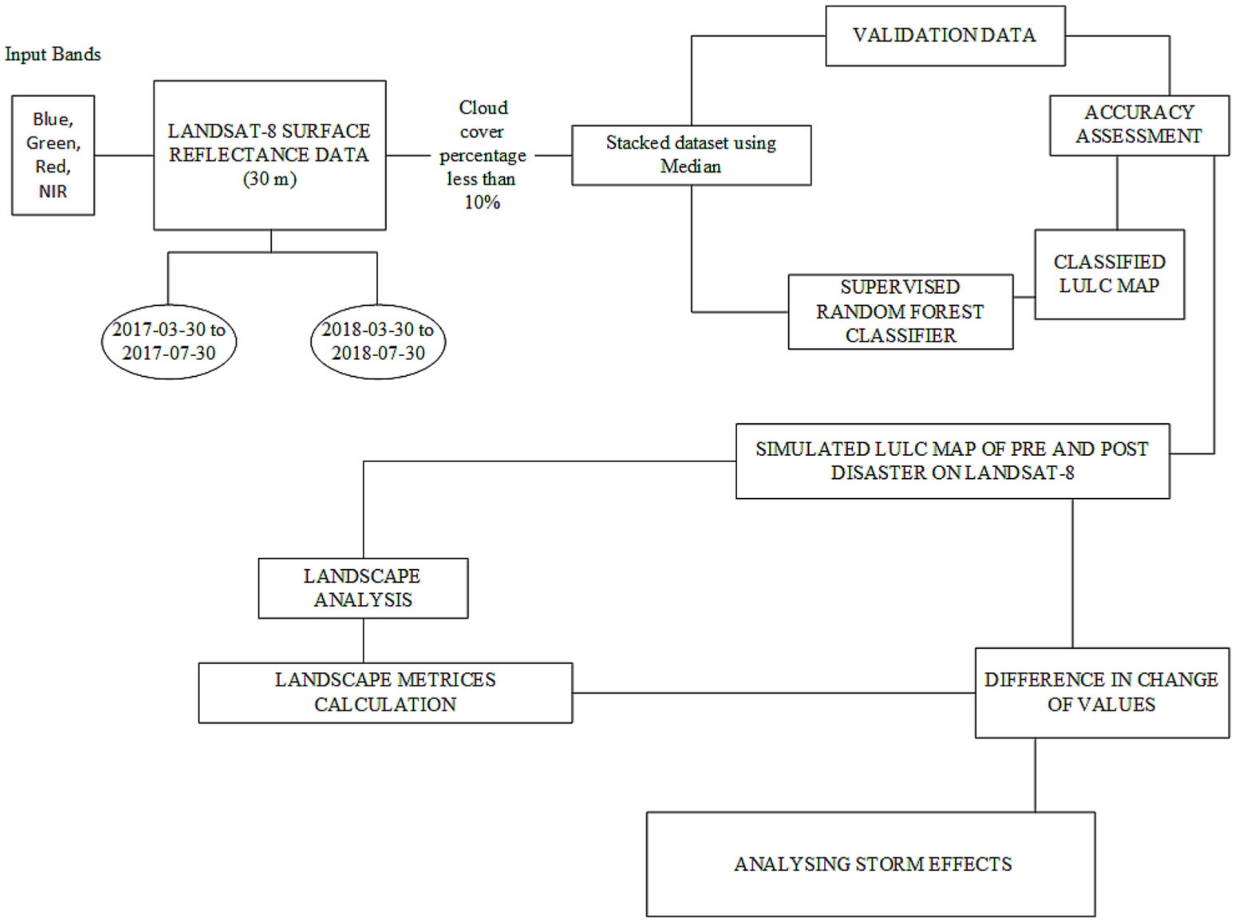

Fig. 3. Methodological scheme of work

samples was significantly lower, emphasising quality over quantity in assessing the model's performance.

Random forest classifier

In this research, the Random Forest (RF) algorithm was selected for the task of classification, recognised for its robustness in handling various satellite imagery types (Jin et al. 2019; Xu et al. 2020). Random Forest operates on the principle of Ensemble Learning, amalgamating multiple decision trees to improve the classification outcome. Each decision tree, constructed from a randomly sampled subset of the training data, contributes equally to the final decision through a process of majority voting on the classification of unlabelled samples.

Notably, the RF classifier is acclaimed for its swift training process, exceptional accuracy, resilience to outliers and resistance to overfitting, as highlighted in previous studies (Rodriguez-Galiano et al. 2012; Zhong et al. 2014). For the purposes of this study, the classifier was configured with 50 trees, a decision aimed at optimising the trade-off between computational efficiency and classification precision. All other parameters within the Google Earth Engine (GEE) framework were maintained at their default settings, ensuring a standardised approach to the classification process.

Accuracy evaluation

The evaluation of precision stands as a pivotal aspect of the classification workflow, with accuracy assessment being integral to verifying the correct categorisation of land cover types from sampled pixels (Rwanga and Ndambuki 2017). This process encompasses a variety of techniques designed to measure the thematic accuracy of land cover classifications. Among these, the confusion matrix serves as a fundamental tool, facilitating the calculation of Overall Accuracy (OA). OA is derived by dividing the number of correctly classified pixels by the total pixel count, offering a straightforward metric of classification success (Foody 2010). This measure provides a quantifiable means to assess the effectiveness of the classification algorithm in accurately identifying land cover from satellite imagery.

Landscape pattern analysis

The LULC classes can be mapped and their structural properties computed with the use of landscape ecological concepts and metrics. The authors used the term landscape metrics and indices simultaneously. Quantifying LULC patch distribution patterns and geographical analysis is crucial to understanding the direction and magnitude of landscape changes. Landscape pattern analysis can provide valuable information regarding LULC change (Zhang et al. 2011; Huang and Song 2016; Jaafari et al. 2016; Wang et al. 2018; Motlagh et al. 2020; Tariq et al. 2023; Tran et al. 2023). Forest fragmentation involves separating contiguous ecosystems into smaller sections called "patches" (Dutt and Kunz 2022). According to Forman (1995), a patch is defined as a relatively homogeneous area. The term "class" encompasses various categories of patches, including those defined by land cover/land use, habitat or vegetation types. Rutledge (2003) notes that fragmentation typically results in an increased number of patches, a reduction in the average size of these patches and an augmentation in the total length of their edges.

Fragmentation indices

Landscape indices are commonly categorised into two types: non-spatial and spatial (Gustafson 1998). Non-spatial indices quantify the composition of the landscape by measuring the classes of patches or the proportions of area they occupy. In contrast, spatial indices assess fragmentation by detailing the properties of these patches. Rutledge (2003) suggests that spatial indices are indicative of patch composition, shape and configuration. It is important to note that, strictly speaking, only patch composition is directly associated with fragmentation. However, the conventional concept of ecosystem fragmentation also encompasses the reduction of area and the additional indices previously discussed. The fundamental fragmentation landscape indices encompass composition, form and configuration. The selection of specific indices depends on authors' discretion and the metrics' applicability derived from prior studies. Composition indicators elucidate the foundational properties of fragmentation. Metrics such as the number of patches and mean patch area serve as primary measures of fragmentation (McCarigal et al. 2002). However, these metrics are inadequate in capturing fragmentation comprehensively, as it also entails considerations of patch sizes.

Shape indices gauge patch complexity, with shapes like circles or squares featuring fewer edges and more core area (Forman 1995). Fractal dimension serves as another prominent metric for assessing shape and complexity (Krummel et al. 1987; O'Neill et al. 1988; Kunz and Nienartowicz 2007).

Patch configuration indices quantify the connectivity within landscape patches (Tischendorf and Fahrig 2000). The Shannon's Diversity Index (SHDI) offers a more robust measure of abundance, while the number of patches is termed "richness" (Turner 1990). A Shannon diversity index of zero indicates uniform distribution of space among patches across the entire landscape. Traditionally, composition analysis has utilised the Shannon metric (Effati et al. 2021).

The metrics for this landscape study are listed in Table 1 and were calculated using Patch Analyst 3.1 for Esri Software based on criteria from the literature. These metrics were determined by analysis of the vector data produced from the supervised classification both at the landscape level and the class level. For the landscape-level change metrics, the authors calculated the percentage value to plot all the matrices in the same graph for better visual interpretation.

Results and discussion

LULC change analysis

Windstorms can significantly alter the landscape through mechanisms such as wind damage, precipitation and storm surge (Dutt et al. 2024). Spatial variations resulting from a recorded derecho event have been distinctly observed within these categories (Dutt and Kunz 2022). Given the capabilities of Google Earth Engine, which includes a range of machine learning techniques, it was considered advantageous to evaluate whether this application programming interface could reliably compute forest fragmentation. Accordingly, imagery

Table 1. Description and implication of metrics

Name of metrics	Definition	Implication
Number of Patches (NP)	Total number of landscape patches, if *Analyse by Landscape* is selected, or the Number of Patches for each class, if *Analyse by Class* is selected.	Describes the fragmentation of the landscape, the higher the number, the more fragmentation.
Mean Patch Size (MPS)	Mean of all patch areas belonging to class *i*.	Defines landscape composition. Diversity index and mean patch size are inversely associated (Kumar et al. 2006). As the number of classes grows, the mean patch size decreases at a landscape scale (Li et al. 2005).
Total Edge (TE)	Length of edges in the surface area; an edge is the boundary between two distinct types of land cover.	Fragmentation produces a greater edge (Rutledge 2003).
Edge Density (ED)	Total edge density index is a ratio of total edges (number of cells at patch boundary) to total area (total cells).	Total edge density represents the level of fragmentation, it begins to increase rapidly at the landscape scale, but the rate slows as the number of classes increases (Li et al. 2005) species richness is sometimes positively correlated with edge density (Kumar et al. 2006).
Area Weighted Mean Patch Fractal Dimension (AWMPFD)	Shape complexity adjusted for shape size.	Rectangles, squares, and circles have fractal dimension 1, whereas irregular shapes approach 2. Human perturbations reduce the landscape's fractal dimension.
Shannon's Diversity Index (SHDI)	Number of land cover and land use types in a landscape; when normalised, this index value ranges from 0 to 1.	A high score suggests a fairly equal proportion of land cover types. Low values signify that a single land cover category dominates.

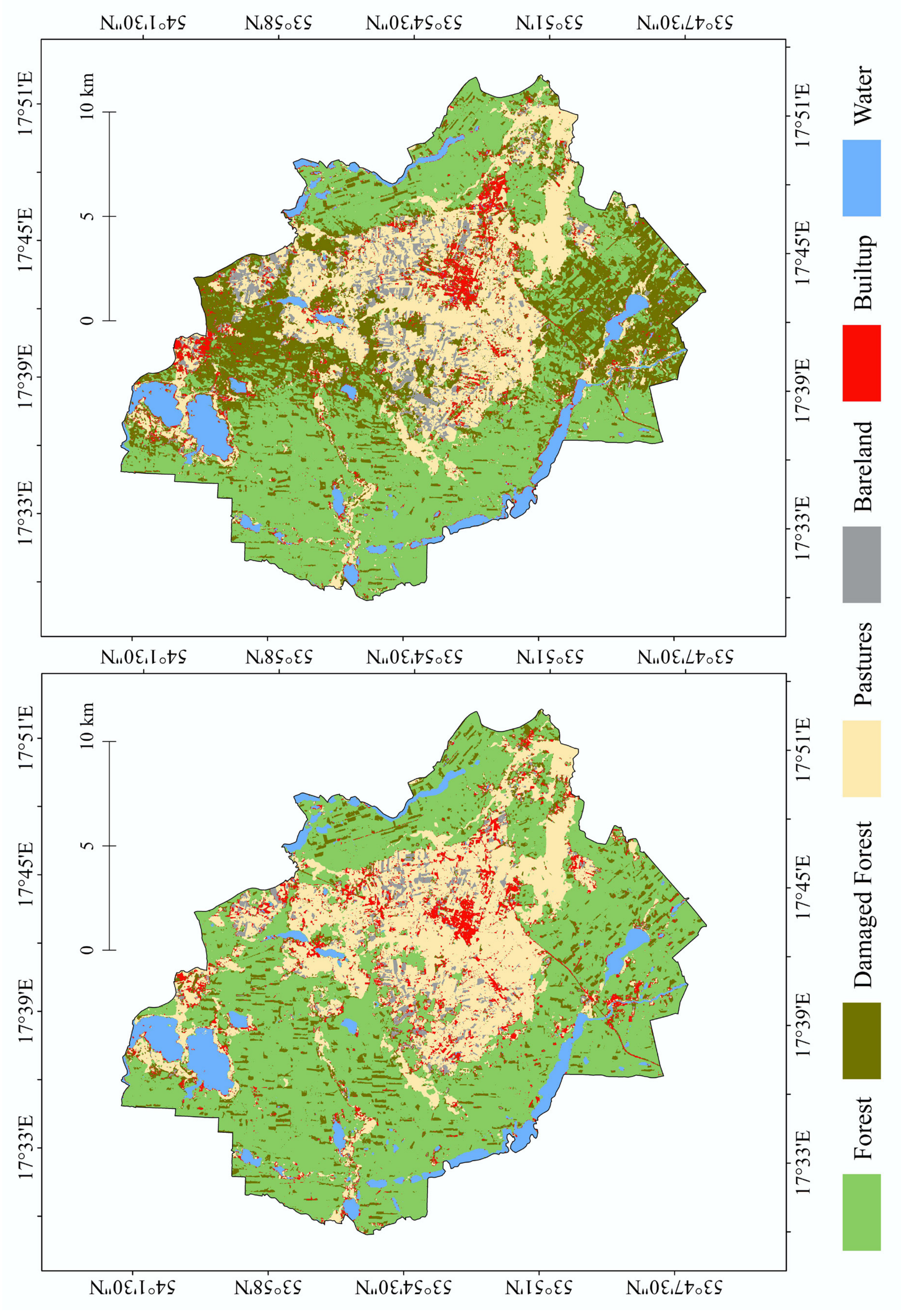

Fig. 4. Land use/land cover map of pre-disaster (left), and post-disaster (right)

from pre- (2017) and post-disaster (2018) scenarios was utilised. However, relying solely on a single database to observe these changes is inadequate for determining whether landscape metrics offer additional insights beyond conventional satellite imagery. Consequently, the authors employed supervised classification schemes to categorise Landsat images from 2017 and 2018, as illustrated in Figure 4. Post-classification, it is essential to assess and validate cartographic accuracy. Since the creation of ideal classification maps is unfeasible, a certain degree of error is anticipated. Thus, it is crucial to acknowledge the limitations imposed by user preferences, geographic regions or sensor specifications.

Figure 4 depicts land cover change trajectories in the Brusy Commune region. The trend analysis (Fig. 5A) shows a 177.52% increase in damaged forest, followed by a 79.59% increase in bare land. The forest cover decreased by 25.16%. Pastures, built-up and water had negligible change. Considering the two datasets, the predicted changes between the pre-disaster and post-disaster scenarios depict a satisfactory image of a disturbed landscape affected by windstorms.

A detailed examination of the satellite image classifications before and after the 2017 disaster, depicted in Figure 3, reveals significant vegetation loss in the north-west and south-east sections of the study area consequent to the derecho event. This data also facilitates the efficient determination of the storm's path. Notably, the region already exhibited signs of forest damage before the 2017 event, traceable to a tornado in 2012, as evidenced by the pre-disaster classified map (left) where short straight lines inside the forest patches vividly depict regions of secondary forest growth.

Errors in the classification process were noted, with omission errors present in water, pastures and bare land, while commission errors affected settlements and forests. These misclassifications, typically not expected in real-world scenarios, did not influence the water or settlement classes despite the storm events, and were thus deemed negligible by the authors. Additionally, the apparent decline in built-up areas is hypothesised to result from human classification errors, where highways and smaller settlements were likely misidentified as bare land or damaged forest.

Given the Landsat dataset's 30-m resolution, it is possible that machine learning techniques misclassified some open land as damaged forest or bare land. This scenario prompts a re-evaluation of the dataset's reliability for forest change studies and raises the question of whether higher-resolution data should be utilised for more accurate forest management analyses. These annual assessments prove crucial for identifying the impacts of recurrent events.

Fragmentation analysis at class level

According to Jiao et al. (2012), there is a significant linkage between land use and land cover (LULC) and landscape metrics. These metrics are instrumental in defining the landscape characteristics associated with LULC classes, as highlighted by Gudmann et al. (2020). Generally, the development of fragmentation indices mirrors advances in landscape ecology. This connection is succinctly captured in the title of Turner's seminal 1989 review, "Landscape Ecology: The Effect of Pattern on Process", which underscores the critical interplay between landscape patterns and ecological processes. The popularity and effectiveness of landscape pattern analysis have been enhanced by tools such as FRAGSTAT (McGarigal and Marks 1995) and Patch Analyst (Rempel et al. 1999). These tools have not only facilitated detailed measures of individual patches, classes and the entire landscape but their continued utilisation underscores their enduring relevance and utility. The analysis focuses on class-level changes across six dominant element types: damaged forest, forest, pastures, built-up area, barren land and water. Landscape metrics have yielded valuable insights into changes within the forest, particularly in terms of fragmentation, connectivity and heterogeneity. From 2017 to 2018, the total number of patches (NP) increased from 21,375 to 29,579, marking a 38.38% rise. This significant increase is partly attributable to interventions in the damaged forest landscape, where heavy equipment used for debris removal and subsequent restoration activities created numerous small, open spaces. These areas may be mistakenly identified as built-up areas in satellite imagery. Additionally, the presence of sandy surfaces and remains of devastated vegetation can further exacerbate these misclassifications.

In addition, there was a notable decrease in the mean patch size (MPS) by 30.05%, as shown in Figure 5C. This reduction, along with the results from other indicators, suggests that the landscape became increasingly fragmented during the study period. Figure 5A summarises the metrics generated for the area per land cover class at the class level, highlighting the substantial changes within the landscape. Notably, the category of damaged forest exhibited the most significant alterations. Concurrently, the MPS for pastures and forest land in Brusy also declined (Fig. 5C). This reduction in MPS occurred alongside a decrease in the total class areas (CA) (Fig. 5A) and an increase in the number of patches (NP) and edge density (ED) (Figs. 5B and 5D). These changes collectively indicate that fragmentation was most pronounced in the pastures and forest lands.

Fragmentation analysis at landscape level

Planners and policymakers often address the adverse effects of landscape fragmentation, which can arise through two primary mechanisms as identified by Burel and Baudry (2003): the reduction in the overall size of a habitat and the division of a habitat class into smaller patches. This process may also coincide with an increase in the total amount of edge, further complicating landscape integrity (Yu and Ng 2006; Dutt et al. 2024).

In this study, fragmentation was assessed using several indices, including Mean Patch Size (MPS), Number of Patches (NP), Total Edge (TE) and Edge Density (ED), as shown in Figure 6. The pre-disaster scenario exhibited a landscape where MPS was at its maximum, while TE, ED and NP were relatively low, indicating minimal fragmentation. In contrast, the post-disaster scenario showed a significant reversal in these metrics, clearly signalling increased landscape fragmentation.

Furthermore, measuring landscape heterogeneity, which encompasses patch variety and spatial complexity, is crucial for understanding landscape evolution (Burel and Baudry 2003). Despite the storm, Shannon's Diversity Index (SHDI), calculated to assess heterogeneity, showed no significant changes between pre- (1.64) and post-disaster (1.62) scenarios, as presented in Figure 6. This stability suggests that no substantial shifts in land cover types occurred within the short study period. The similar

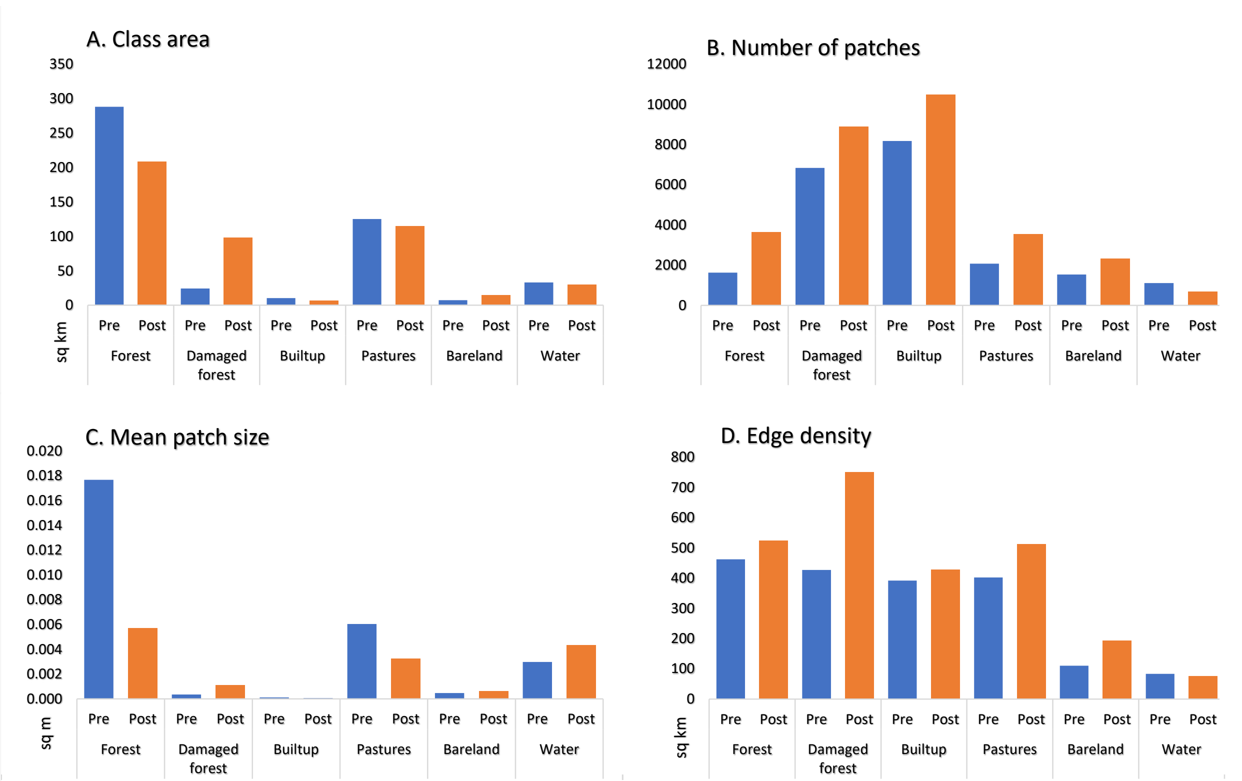

Fig. 5. Selected landscape indices: A. class area (CA), B. number of patches (NP), C. mean patch size (MPS), and D. edge density (ED)

values of this index imply that while the structural dominance of land cover categories changed, it did not significantly impact overall diversity.

In general, the areas that remained forested despite the storm event are located at a considerable distance from roads and settlements, as well as from pastures (Fig. 4). This shows that there are many complex and interconnected processes behind recent land cover change.

Conclusion

The patterns found in the landscape as a result of our research show a direct relationship between land use and land cover. Within the research area, forests are generally located at a distance from human populations, roads, and pastures. This configuration may indicate the vulnerability of vegetation that remains closer to open lands and built-up structures, a finding consistent with what Dutt et al. (2024) identified in their study on forest fragmentation susceptibility. The methods employed within the study combine satellite images with landscape metrics, allowing us to assess and analyse changes in land use patterns in the study region. The utilisation of machine learning ensemble methods of stacked images covering the entire summer season of 2017 and 2018 with relevant metrics enables a deep investigation of dynamic landscapes that would have otherwise appeared static using single-date land cover analysis approaches. Although remote sensing is increasingly used to research land cover change (Feng et al. 2013; Gilbertson et al. 2017; Gin et al. 2019), few studies relate land cover change trajectories using multiple-dated imageries with landscape patterns.

The alleged lack of interpretability of numerous landscape metrics has always been a key issue (Haines-Young and Chopping 1996) in estimating which metrics are the most appropriate to which type of landscape and spatial resolution. Although this technique has also been applied to imagery with a medium resolution, the objective has remained the same: to investigate an area of interest and gather information about the texture of an image. The methodologies utilised here provide information on forest disturbance in the study area; spatial analysis of forest fragmentation at the class and landscape levels; land cover-change analysis through the incorporation of data from multiple images; and comparison of spatial patterns before and after the storm event. It is also worth noting that medium-resolution Landsat data are sufficient to determine forest fragmentation in this region.

This research blends environmental sciences and landscape ecology with remote sensing, GIS and machine learning techniques bringing us a step

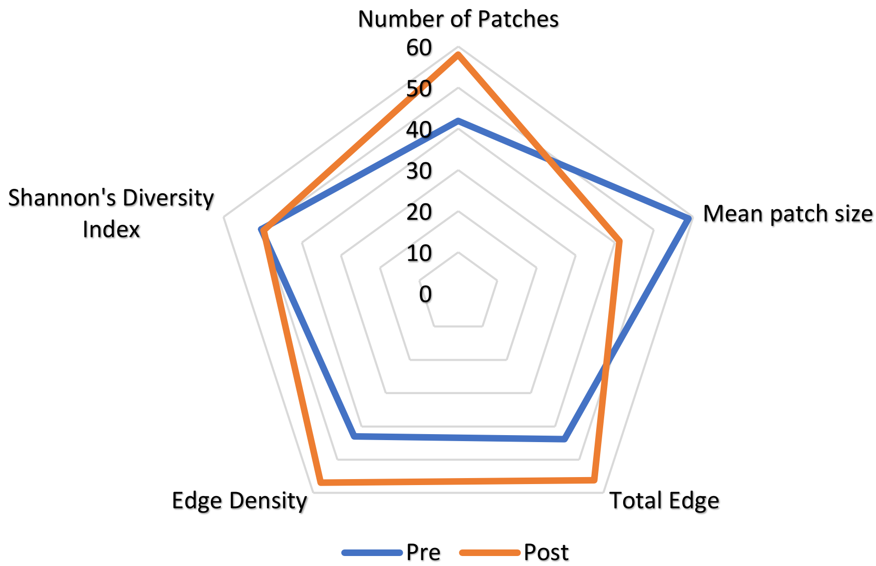

Fig. 6. Fragmentation and diversity analysis at landscape level

forward from the past forest disturbance studies. Further integration of methodologies and interpretations across disciplines is required if we are to fully comprehend and consequently mitigate the effects of global and local change on the environment.

Future studies should: (1) look into non-parametric classifiers like neural networks and decision trees that might improve LULC classification accuracy; (2) analyse specified landscape metrics using more scales, such as 4 m, 10 m, 90 m, 250 m, 500 m and 1000 m; (3) establish the scale influence on surface processes and LULC changes; (4) assess LULC changes at different spatial and temporal scales using efficient feature algorithms from various types of sensors; and (5) further integrate GIS and remote sensing and expert systems in detecting, visualising and monitoring LULC changes in disturbed forest environments.

Disclosure statement

No potential conflict of interest was reported by the authors.

Author contributions

Study design: SD, MK; data collection: SD, MK; statistical analysis: SD; result interpretation: SD, MK; manuscript preparation: SD, MK; literature review: SD, MK.

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