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Forest Science and Technology

ISSN: 2158-0103 (Print) 2158-0715 (Online) Journal homepage: www.tandfonline.com/journals/tfst20

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To cite this article: Henzulkifli Rahman, Lilik Budi Prasetyo & Hendra Gunawan (03 Aug 2026): The Relationship between Forest Fragmentation and the Case of Human-Tiger Conflict in the Maninjau Nature Reserve Landscape, Indonesia, Forest Science and Technology, DOI: 10.1080/21580103.2026.2708129

To link to this article: https://doi.org/10.1080/21580103.2026.2708129

Published online: 03 Aug 2026.

FOREST SCIENCE AND TECHNOLOGY
https://doi.org/10.1080/21580103.2026.2708129

RESEARCH ARTICLE

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The Relationship between Forest Fragmentation and the Case of Human-Tiger Conflict in the Maninjau Nature Reserve Landscape, Indonesia

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ABSTRACT
Forest fragmentation caused by land use changes has been linked to human-wildlife conflict. However, a clear understanding of how landscape configuration influences conflict incidents remains limited. In Sumatra, studies on human-tiger conflict (HTC) have mainly focused on broad indicators such as forest cover loss or distance to settlements. This has created a gap in understanding how detailed forest fragmentation features influence conflict patterns. This study aims to fill that gap by examining the relationship between spatiotemporal changes in forest fragmentation and HTC occurrences within the Maninjau Nature Reserve Landscape in West Sumatra. We analyzed forest fragmentation dynamics from 2005 to 2024 using fragmentation analysis tools and landscape metrics derived from land-cover data, subsequently correlating these metrics with the spatial distribution of 47 confirmed HTC incidents. Our results show a significant 62% reduction in large core forest areas, concomitant with an increase in perforated and edge-dominated forest typologies. The majority of HTC incidents occurred outside intact core forest, predominantly in agricultural and plantation areas adjacent to forest edges. Edge density exhibited the strongest and most consistent positive correlation with HTC density (ρ = 0.31). This suggests that expanding human-forest interfaces elevates the risk of encounters, even when overall fragmentation metrics show a decline due to landscape homogenization. Our findings highlight that spatial configuration, rather than sheer forest loss, significantly influences HTC patterns. By establishing Edge Density as a robust indicator of conflict risk, this study provides actionable insights for land use planning, particularly in prioritizing edge-buffer management and targeting interventions in high-risk zones. Integrating these fragmentation metrics into conservation planning is essential for mitigating human-tiger conflicts while sustaining ecological connectivity in a fragmented tropical landscape.

ARTICLE HISTORY
Received 12 November 2025
Revised 14 July 2026
Accepted 20 July 2026

KEYWORDS
Forest Fragmentation; Habitat Connectivity; Landscape Configuration; Human-Tiger Conflict; Edge Effect

1. Introduction

Forest fragmentation is generally considered a major cause of ecosystem disruption. Reports show that biodiversity losses range from about 13% to 75%. This varies depending on the spatial scale, taxonomic group, and overall landscape context (Haddad et al., 2015; Ma et al., 2023). Fragmentation is not an isolated event; it results from changes in land use driven by agriculture, urban development, and construction. These activities turn continuous forests into non-forested areas (Cayuela et al., 2006; Jha et al., 2005; Liu et al., 2019; Pinto et al., 2023). This suggests a correlation between human activity and forest fragmentation (Romanillos et al., 2024). Once fragmentation occurs, edge effects increase, isolation between habitat patches grows, and the entire landscape pattern changes. This makes fragmentation a significant threat to nature and the organisms living there (Fischer & Lindenmayer, 2007; Taubert et al., 2018). Fragmentation is also recognized as a key factor in human-wildlife conflicts, especially conflicts involving humans and tigers (Zhang et al., 2022). By reducing habitat connectivity and constraining wildlife movement, fragmentation increases spatial overlap between human activities and large carnivores. In tiger landscapes, forest fragmentation, declines in prey availability, and overlapping resource use between humans and tigers have consistently been identified as key factors contributing to conflict (Acharya et al., 2017; Ma et al., 2024; Malviya & Krishnamurthy, 2022).

The ways by which forest fragmentation causes greater conflict between humans and wildlife may be illustrated using two different approaches to landscape ecology: the compositional approach and the

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configurational approach (Nad et al., 2022; Bautista et al., 2023). The compositional approach involves the changes in the total amount and the size distribution of patches within a given landscape, wherein the decrease in core forest patches causes larger species to migrate to human settlements in search of food and territory (Khosravi et al., 2024). In contrast, configurational impacts consist of altering the pattern of the habitat in relation to other uses, such as increasing edge density, creating perforations in contiguous forests, and reducing connectivity among forest fragments (Movasaghi et al., 2025). The creation of configurational impacts increases the likelihood of encounters by increasing the length of the interface between forests and human activities, and by establishing corridors that funnel animals into agricultural lands and settlements. While composition and configuration may be highly correlated in fragmented landscapes, separating the two factors is necessary for predicting conflict risk and mitigating encounters. Recent research has shown that configuration-based metrics, especially edge density and landscape complexity, tend to perform better than habitat loss in predicting predation incidents involving large carnivores such as bears, leopards, and tigers (Bautista et al., 2023; Khosravi et al., 2024).

In Indonesia, HTC represents a chronic conservation and socio-ecological challenge, particularly on the island of Sumatra, where nearly all major conservation landscapes report recurring annual conflict incidents (Lubis et al., 2020; Patana et al., 2023; Pusparini et al., 2018). Large-scale deforestation amounting to 72,905.3 hectares between 2006 to 2012, combined with major linear infrastructure such as the 2,700-kilometer Trans-Sumatra Toll Road, has accelerated landscape fragmentation and resulted in Sumatran tiger populations being confined to at least 27 increasingly isolated forest patches (Wibisono et al., 2009; Wibisono & Pusparini, 2010). Several studies suggest that such landscape transformations increase the likelihood of tigers moving into human-dominated areas, thereby elevating the risk of future human-tiger conflict (Poor et al., 2019; Sloan et al., 2019; Sulistiyono et al., 2015; Wibisono & Pusparini, 2010). Field data from various landscapes confirm the above connection. For example, over a period of 13 years, 228 cases of HTC events have been identified in the areas of the Kerinci Seblat National Park and Bukit Barisan Selatan National Park (Struebig et al., 2018). In Aceh Province, between 2017 and 2019, according to reporting, 49% of human-tiger conflicts were related to cattle depredation and 39% to sightings of tigers (Figel et al., 2023). Over ten years, 148 conflict cases were recorded across the entire Leuser Ecosystem (Lubis et al., 2020).

West Sumatra Province has one of the highest HTC incidences in Sumatra, with 137 documented cases between 2005-2023 (Wati, 2021; Nurhamida, 2024; Rahman et al., 2022). During the same period, the province experienced substantial forest loss, approximately 139,590 hectares, between 2011 and 2021, predominantly around conservation areas and their buffer zones (Baittri, 2022). This signifies that the forest in the vicinity of the conserved sites is subject to increased fragmentation and expansion in the area of the human-tiger interaction zone, and thus, its functional capacity declines (Wati, 2021). The conversion of 202 ha of adjacent forest into plantations and farmland in 2014 changed the structure of the landscape by creating additional patches of isolated land (Ritonga et al., 2023). Such structural changes are thought to have contributed to the perpetuation and increase in cases of HTC, including those recorded in 2018.

Although research on the ecology of the Sumatran tiger has expanded substantially, encompassing population estimation, analyses of human-tiger conflict characteristics, habitat suitability modelling, and conservation status assessments (Linkie et al., 2003; Neo et al., 2023; Nyhus & Tilson, 2004; Struebig et al., 2018; Wibisono et al., 2009). Even though these studies have contributed greatly to our knowledge about the ecology of tigers and HTC patterns, they have considered the state of the habitat in fairly crude ways, such as the existence of forest cover or proximity to settlements. This has resulted in it becoming hard to separate out the independent influence of landscape composition (decreasing patch sizes, core habitat area loss) from landscape configuration (increasing edge density, shape complexity, landscape isolation) on the nature of conflict. For instance, decreasing patch size (compositional influence) can lead to increased roaming behavior by tigers, while increasing edge density (configurational influence) can result in more frequent encounters without necessarily reducing home ranges. As a result, there is a lack of studies that have explored the link between fragmentation characteristics and the density of human-tiger conflict events. The problem with existing research methods is that they fail to provide a multivariate fragmentation approach, which would be able to assess the impact of the fine-grained landscape structure on tigers' mobility patterns, availability of prey, and likelihood of meeting people. Considering that fragmentation not only results in the loss of habitat but also in changes in its spatial organization, spatial metrics become indispensable for investigating the role of fragmentation in HTC (Altunel et al., 2021; Nad et al., 2022; Movasaghi et al., 2025).

The combination of multiple landscape indices, patch size, shape, and spatial configuration has been shown to improve the precision of fragmentation analysis and provides a more robust basis for linking landscape structure to conflict occurrence. However, such integrative spatial analyses remain underrepresented in HTC studies in Sumatra, representing a critical gap in both theory-driven and applied conservation research.

The objectives of this study are therefore to (1) identify typologies of human-tiger conflict (HTC) using secondary data and official news sources, (2) analyze forest fragmentation patterns to capture multitemporal changes in key landscape metrics, and (3) examine the relationship between forest fragmentation characteristics and the spatial HTC density by integrating land cover-based fragmentation analysis with historical conflict records.

This study is especially valuable since it does not consider forest fragmentation as a context of conflict but treats it as a factor influencing the process, thereby helping to develop measures that may prevent future cases of human-tiger conflict. By examining the connection between landscape modification processes and conflict development, this work can help incorporate ecology into spatial planning to preserve the population of Sumatran tigers. This underscores the importance of a spatial approach to both HTC mitigation and biodiversity protection (Kholis et al., 2017). The findings of this study provide a critical foundation for designing landscape-level interventions that balance human land use with large carnivore persistence.

2. Materials and Methods

2.1. Study Area

The study area is situated in the western part of Sumatra Island, a known portion of the historical distribution range of tigers (*Panthera tigris sumatrae*) natural range (Luskin et al., 2017). The study landscape is focused on the Maninjau Nature Reserve conservation area, which continues to function as an important habitat for the Sumatran tiger. Geographically, the landscape is located within the coordinate range of 99°56′55″E-100°26′2″ and 0°0′28″S-0°28′41″S, covering a 2,810 km^2 area with an elevation gradient of 0 - >1000 m dpl (BPS, 2025; Takarina et al., 2023). In terms of the administrative region, this research area is in Agam Regency and bordered by Padang Pariaman Regency and Pasaman Regency (Figure 1).

The Maninjau Nature Reserve is characterized by a tropical climate, with an average annual rainfall of approximately 5,508 mm yr^{-1} and a predominantly hilly-to-steep topography (BPS, 2024). Primary and secondary tropical rainforests dominate vegetation cover within the reserve, whereas the surrounding areas consist of a heterogeneous mosaic of land uses, including agroforestry systems, aquaculture, plantations, agricultural lands, and human settlements (Wojewódka-Przybył et al., 2024).

Human activities surrounding the Maninjau Nature Reserve are relatively intensive, as evidenced by the presence of settlements, agricultural expansion, oil palm plantations, and road networks encircling the conservation area (Safitri et al., 2023). These human-modified areas are closely associated with livestock grazing, dryland agriculture, and high levels of daily human mobility in and around the conservation landscape (Antomi et al., 2016). The study boundary was delineated using an Area of Interest (AOI) approach by integrating historical spatial data on human-tiger conflict (HTC) occurrences. Consequently, the study area was defined around conflict hotspots that are predominantly influenced by human activities in the vicinity of the reserve.

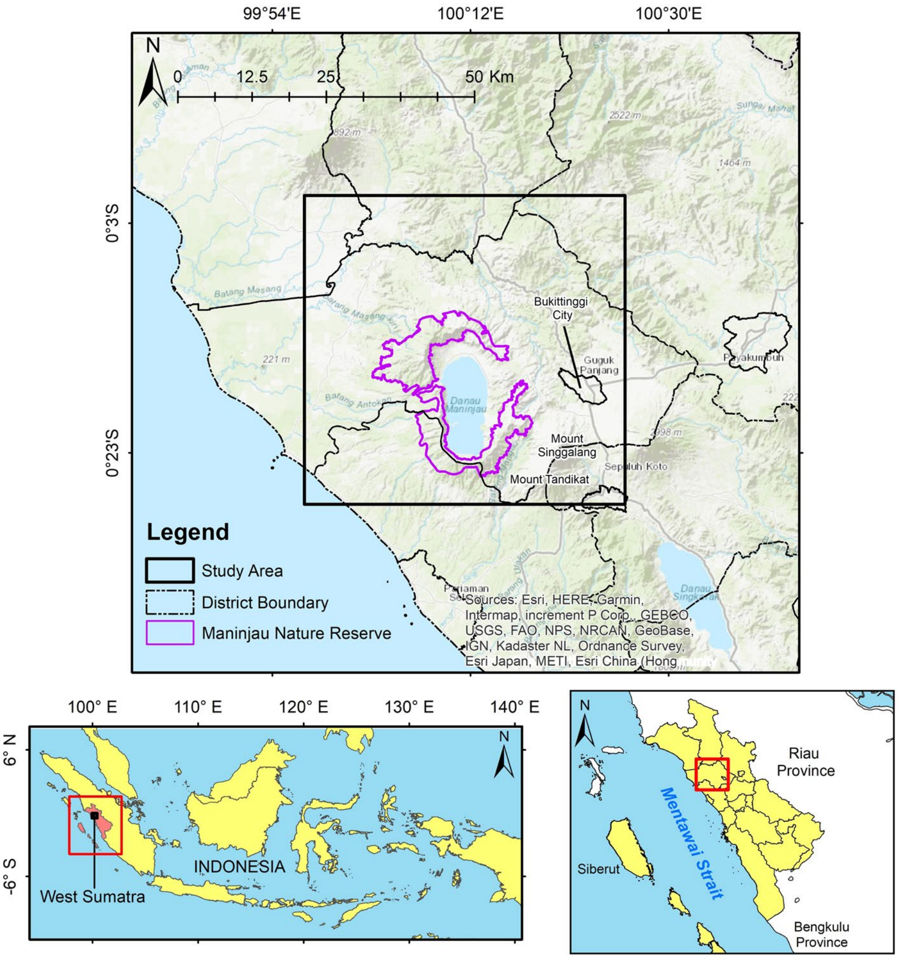

Figure 1. Study Area.

2.2. Data Collection

We utilized Level-2 Landsat 5 Enhanced Thematic Mapper Plus (ETM+) satellite imagery from 2005 and Level-2 Landsat 8 Operational Land Imager (OLI) imagery from 2024, both with a spatial resolution of 30 meters (Path 127, Row 060). Both datasets were selected to represent landscape conditions before and after a period of intensified land cover change and increasing human-tiger conflict in the study area, as well as to capture changes in forest fragmentation over an approximately two-decade time span. The selection of these two reference years was based on documented expansions of plantation and agricultural lands that began around 2005 in areas surrounding the conservation landscape and continued through 2024 (Azzakia & Frananda, 2025).

Landsat satellite imagery was obtained from the official archive of the United States Geological Survey (USGS) via the Earth Explorer platform (https://earthexplorer.usgs.gov/). Image downloading and initial preprocessing were conducted using the Google Earth Engine Platform (GEE), which was employed to filter imagery based on cloud cover, select scenes with optimal radiometric quality, and generate cloud-minimized natural color (Red-Green-Blue) composite images for each observation year (Basheer et al., 2022). The Level-2 products used had already undergone radiometric and atmospheric corrections, making them suitable for land cover classification without additional preprocessing. The processed imagery was subsequently exported from GEE in GeoTIFF format and further analyzed in QGIS v.3.42.1. All spatial datasets were standardized to the Universal Transverse Mercator (UTM) Zone 47S projection to ensure spatial consistency throughout the subsequent analytical procedures.

We also gathered information related to HTC events between 2005 and 2024, which includes several types of conflicts, such as attacks on domestic animals (cattle, goats, and buffalo), attacks on household pets (dogs), sightings of tigers around plantations and residential areas, and attacks on human beings. Spatial data on HTC event locations were sourced from the West Sumatra Provincial Office of the Natural Resources Conservation Agency (BKSDA) and past literature (Wati, 2021; Ritonga et al., 2023; Nurhamida, 2024; Kholis, 2025). These datasets consist of information about the geographical location of each event (collected via handheld GPS by BKSDA officers during the confirmation of each event), dates of the events, and management actions.

Validation of data and assessment of spatial accuracy: In order to enhance the reliability of the spatial coordinates of conflict locations, a multi-step validation process was applied. Firstly, all the spatial coordinates of conflicts were checked against official BKSDA conflict reports, that contain field observations as well as photographs (in many cases) of the conflict sites. Secondly, for those conflicts for which the accuracy of coordinates was in doubt (for instance, in the case when coordinates were estimated as village centroids), additional validation was performed using Google Earth Pro satellite images to verify the land cover type and distance from the forests. Thirdly, in order to provide missing information on typologies of conflicts and post-conflict actions, official news sources were used. However, news reports were considered only as sources of typologies of conflicts and narratives, but not as sources for spatial coordinates, since the accuracy of such coordinates cannot be guaranteed. Finally, conflicts were compared across several sources, and conflicts with conflicting location information were excluded from analysis.

Data source (primary fieldwork vs. secondary compilation): In this study, the data on the conflict incidents that have been analyzed were obtained solely from secondary sources (BKSDA documentation and previous publications). No primary fieldwork was carried out to obtain locations of HTC incident data since this paper aims to analyze the past trend of conflict incidents in the span of 19 years. Nevertheless, the first author visited the Maninjau Nature Reserve landscape in 2023 and 2024 to validate the land cover classification as well as the condition of the local landscape, but no primary data on the conflict incidents were collected during these field visits. From the data collected through secondary sources, there is a total of 65 incidents of HTC recorded. However, due to the lack of year information in some data (n = 12) and the discrepancy of spatial coordinates in some other data (n = 6), these incomplete data were excluded from further analysis. Thus, a total of 47 HTC conflict incidents (n = 47) were considered valid for use in this study.

2.3.1. Land Cover Change Detection and Accuracy Assessment

The imagery was then processed using the Random Forest algorithm to generate multi-temporal land cover classifications within the QGIS environment, employing the Semi-Automatic Classification Plugin (SACP) (Meli Fokeng et al., 2020). The literature indicates that Random Forest provides consistent results and good accuracy in land cover classification applications (Ambarwulan et al., 2023). The standard land cover accuracy categories used in this study follow the classification applied in the research by (Gunathilaka & Fernando, 2022; Rwanga & Ndambuki, 2017). Land cover was categorized into eight classes with assigned numeric codes: 1) Primary Forest, 2) Secondary Forest, 3) Water Body, 4) Cropland, 5) Bare Land, 6) Built-up Area, 7) Plantation, and 8) Paddy Field (Table 1).

The training samples and validation samples were extracted using a combination of high-resolution image interpretation (Google Earth Pro) and ground truth verification, which involved the use of ROIs to capture representative pixels. The random forest model was trained using 500 decision trees (ntree = 500), which were selected to achieve model stability based on existing recommendations (Belgiu & Drăgu, 2016). The reflectance bands of the satellite data were the input parameters, whereas natural color composites (Red-Green-Blue) were used to assist in identifying the

Table 1. Land Cover Classes Used.

No	Land Cover	Description
1	Primary Forest	Thriving forests can be lowland forests, mountains, and hills, or highland tropical rainforests with tight canopies.
2	Secondary Forest	Forests that develop in lowland forests, mountains, and hills, or highland tropical forests that have experienced human intervention.
3	Water Body	Waters, including seas, lakes, and rivers
4	Crop Land	Dryland farming with seasonal crops
5	Bare Land	Land without cover is both natural and semi-natural
6	Build Up Area	Land used for residential and human activity purposes
7	Plantation Land	Agricultural land without crop rotation, such as mixed plantations, oil palm, and annual crops
8	Paddy Field	Flooded or watered agricultural areas

features in the two temporal datasets. After obtaining the samples, they were randomly divided into two groups for training (70%) and validation (30%) based on existing best practices in land cover change studies (Maxwell et al., 2018; Mellor et al., 2015).

Land cover change was identified through the overlaying of the output raster maps resulting from the land cover classifications done for the years 2005 and 2024. To measure the magnitude and direction of land cover change, a land cover transition matrix was developed to measure the change between the land cover categories (Boussema et al., 2023). This procedure was implemented in RStudio using the *raster* and *terra* packages, which facilitate multitemporal raster overlay operations and the systematic extraction of pixel-level change information.

An accuracy assessment was conducted to evaluate the reliability of the land cover classification using a confusion matrix approach. Classification performance was quantified using the Kappa Coefficient (KC), User's Accuracy (UA), and Overall Accuracy (OA). This analysis is done using the RStudio software together with the ggplot2 and caret packages to create pixel-based error matrices (Çelik & Altunel, 2025; Roy et al., 2025). The accuracy evaluation metrics were calculated using the following equations (Zafar et al., 2024):

$$OA = \frac{\sum_{i=1}^{n} x_{ii}}{N}$$

$$UA = \frac{x_{ii}}{\sum_{j=1}^{n} x_{ij}}$$

$$K = \frac{N\sum x_{ii} - \sum\left(x_{i+}x_{+i}\right)}{N^2 - \sum\left(x_{i+}x_{+i}\right)}$$

Where x_{ii} represents the number of correctly classified pixels for class i, N denotes the total number of pixels, $\sum_{j=1}^{n} x_{ij}$ is the total number of pixels classified into class i, x_{i+} is the total number of pixels in row i, and x_{+i} represents the total number of pixels in column i of the confusion matrix. Land cover classification accuracy was considered acceptable when the Kappa Coefficient exceeded ≥0.80/80%, which is commonly categorized as a high level of agreement and deemed suitable for subsequent spatial and landscape analyses (Al-Dousari et al., 2023).

2.3.2. Creation of Human-Tiger Conflict Typology

Based on the characteristics of conflicts, a typology was developed to classify human-tiger conflict (HTC) events into four types. This classification system included livestock depredation (cattle, buffalo, goats), attack on domestic animals, human injury/death, tiger removal/mortality, and unclassified (no data). This typology allows for comparison with previous HTC studies, and aids interpretation of spatial patterns of conflict (Nyhus & Tilson, 2004; Lubis et al., 2020). HTC location coordinates were converted into shapefile format using QGIS. This was supplemented with post-conflict mitigation response data and, where required, reconstructed through systematic searches of official news sources. The records were then organized and coded numerically to allow for consistency in analysis. The resulting dataset was imported into RStudio and visualized using *ggplot2* to depict conflict typologies. HTC locations were overlaid with the 2024 land cover map to examine land cover conditions at conflicts (R Core Team, 2023).

2.3.3. Forest Fragmentation Analysis

The analysis of forest fragmentation (FF) was conducted using the Fragmentation Analysis Tool version 2.0 (FAT) from the University of Connecticut (Gu et al., 2021; Vogt et al., 2007). This tool utilizes a classification system that categorizes landscapes into distinct areas, including patch, perforated, edge, and core areas (Randhawa et al., 2024). The fragmentation classes under the FAT v2.0 classification scheme are defined as follows patch: small and fragmented patches of forests surrounded by non-forest land cover, and represent the least intact and most disjunctive fragments of forests in the study region. Perforated forest areas with holes within their interiors, implying early fragmentation where interior forests are being lost from inside the fragments. Edge forest areas within a certain distance (in this case 100 m) from a non-forest edge are subjected to microclimatic changes and higher accessibility to humans. Core Area forests within the interior of edges, which are further sub-classified according to size thresholds to reflect their functional value for tiger habitat utilization. The initial step involved assigning numeric codes to land cover data: a value of 2 was given to forested land cover (i.e., primary and secondary forests), and a value of 1 was assigned to non-forest land cover types (including water bodies, plantations, rice fields, bare land, shrubland, and built-up areas).

Subsequently, a reclassification was performed using the Reclassify tool to generate a new binary raster (GeoTIFF format) containing two classes: forest (value = 2) and non-forest (value = 1), which was then input into FAT v2.0. The FF classification produced six categories of output including patch, perforated, edge, small core area (<250 acres/101 ha), medium core area (250-500 acres/101-202 ha), and large core area (>500 acres/202 ha), employing an edge width of 100 meters (Biswas et al., 2023; Shimrah et al., 2022). These core area categories are consistent with the standardized classification system applied in FAT v 2.0, based on ecological principles concerning minimum requirements of habitat area for forest-dependent species. The 250-acre (101 ha) threshold value of small core areas reflects the minimum area necessary for maintaining interior conditions of the forest independent of the edge effects while the threshold value of 500 acres (202 ha) for large core areas has been used previously in fragmentation studies to recognize functionally connected habitat patches that can sustain viable wildlife population (Vogt et al., 2007; Randhawa et al., 2024). These values are widely recognized within landscape fragmentation studies and are suitable for the current study, considering the movement ecology of Sumatran tigers that require extensive habitat. The *GeoTIFF* output from the FF analysis was then converted into vector format to facilitate area calculations (in hectares) for each FF class using the Calculate Geometry function. For further analysis, the data were imported into RStudio and Microsoft Excel to generate histograms, graphs, and tabulated summaries of each FF class area. Forest fragmentation change (FFC) analysis was conducted by comparing multi-temporal FF datasets from 2005 and 2024. These datasets were overlaid using RStudio to determine changes in the spatial extent of each FF class. The overlay formula used in the FFC analysis followed the method described by Hussain et al. (2024) and Thiam et al. (2022), as outlined below:

$$\Delta FFC = FF_x - FF_y$$

Where ΔFFC refers to Forest Fragmentation Changes. FF_x represents the forest fragmentation data in year x and FF_y refers to forest fragmentation data in year y. This approach utilized the difference between the FF and FF_Y values, termed ΔFFC, to identify patterns of forest loss and succession.

To quantify fragmentation patterns, we employed a landscape metrics-based approach, which is a reliable method for quantifying landscape structure through a systematic and organized workflow. This method combines raster land cover data assigned numerical codes in a shapefile grid to capture the spatial variability of fragmentation patterns within the study area. The analysis was conducted in RStudio using the *landscapemetrics, terra, raster,* and *sf* packages (Hesselbarth et al., 2019). The multi-temporal land cover raster data were reclassified into two classes: forest (primary and secondary forest = 1) and non-forest (built-up areas, shrubland, plantations, water bodies, bare land, and rice fields = 0). The reclassification was using the Reclassify tool, and the resulting raster files were saved in GeoTIFF format with a UTM Zone 47S projection. Subsequently, the landscape metrics analysis was conducted using a grid/pixel size of 2 km. The grid size was based on the average daily movement of Sumatran tigers, which is approximately 1.8 ± 1.4 and 3.5 ± 2.5 km/day (Kurniawan, 2012; Priatna, 2012).

Five indices were used in the study, including Number of Patches (NP), Landscape Shape Index (LSI), Largest Patch Index (LPI), Edge Density (ED), and Patch Density (PD) (Table 2). These indices were selected based on their relevance by Acharya. (2018) and Sharma et al. (2020), which emphasized that forest fragmentation is a key driver of human-tiger conflict (HTC), though its influence may vary across species and regions. As tiger habitats continue to shrink, individuals are increasingly confined to fragmented landscapes, often leading to direct encounters with human activity. Therefore, the selected landscape metrics are essential to describe the fragmentation patterns relevant to understanding and mitigating the HTC case.

Table 2. Landscape metrics used in the study

Landscape Metrics	Formula	Definition	Description and Unit Value
Number of Patches (NP)	$NP = N$	Number of patches in each landscape grid	Higher NP indicates forest fragmentation, 0 ≥ 1
Landscape Shape Index (LSI)	$LSI = \frac{0{,}25\sum_{k-1}^{m} e'_{ik}}{\sqrt{A}}$	The total length of the edges is adjusted to the size of the landscape, representing the complexity of the shape of the patch in the grid	Higher LSI values indicate more complex landscapes with random or irregular edges, LSI > 1
Largest Patch Index (LPI)	$LPI = \frac{\max(a_{ij})}{A}(100)$	The proportion of the total area of the landscape occupied by the largest patch, expressed as a percentage in the grid	Higher the LPI, indicates that the grid is dominated by patches, 0 < LPI ≤100
Edge Density (ED)	$ED = \frac{\sum_{k=1}^{m} e_{ik}}{A}(10.000)$	The edge length of the grid is divided by the total area of the landscape, displaying the edge density	A high ED value indicates a high edge density and looks more fragmented, ED ≥ 0, infinite value, ED = 0 if there are no edges on the landscape grid
Patch Density (PD)	$PD = \frac{n_i}{A}(10.000)(100)$	The number of patches in the grid divided by the area of the landscape displays the patch density per grid	A high PD value indicates a high level of patch density and represents a more fragmented landscape, PD > 0

(NP, N = total number of patches in the landscape), (LSI, *e'ik* = total length (m^2) in the landscape between fragment types *i* and *k*; involves the entire boundary of the landscape as well as some or all of the background edge segments involved with class *i*, *A* = total landscape area (m^2)), (LPI, *aij* = area (m^2) patch *ij*, *A* = total landscape area (m^2)), (ED, *e'ik* = total length (m^2) in the landscape between fragment types *i* and *k*; involves the entire landscape boundary as well as some or all of the background edge segments involved with class *i*, *A* = total landscape area (m^2)), (PD, *ni* = patch number in a class *i* type patch landscape, *A* = total landscape area (m^2)) (McGarical et al., 1995).

Edge-related indices (ED, LSI) have been identified as indicators of forest–human interfaces where conflict is likely to occur. Conversely, NP, LPI, and PD are significant in terms of capturing patch structure and habitat suitability for tigers (Kanagaraj et al., 2011; Sunarto et al., 2012). The alteration in landscape metrics was determined through the calculation of the following equation:

$$\Delta LMC = LM_X - LM_y$$

where ΔLMC refers to the change in landscape metrics, LM_X represents the landscape index in 2024, and LM_Y represents the corresponding index in 2005.

2.3.4. Relationship Between Forest Fragmentation and Human-Tiger Conflict (HTC)

The relationship between forest fragmentation metrics and HTC density was analysed using the Kernel Density Estimation (KDE) in QGIS, based on historical conflict shapefiles. The kernel density estimation (KDE) method was applied following (Warren & Silverman, 1987; Silverman, 2018; Govorov et al., 2025), and is expressed as:

$$\widehat{f}_h(s) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{s - S_i}{h}\right)$$

where s notes the target location with spatial coordinates within a defined analysis extent, and S_i represents the input point, assumed to be randomly and independently distributed, corresponding to the locations of human-tiger conflict incidents. The function $K(.)$ is a second-order, two-dimensional kernel function centered at zero and radially symmetric, as implemented in the fixed-kernel density algorithm in QGIS. The parameter n indicates the total number of input points, while h represents the kernel bandwidth, determined by the specified search radius and uniformly applied in all directions. Outside the defined analysis extent, density estimates are set to zero in accordance with the KDE implementation in QGIS.

The final HTC dataset comprised only 47 conflict incidents (n = 47); this sample size is commonly encountered in spatial studies of human-tiger conflict that involve rare and opportunistic events, particularly for threatened large carnivores such as the Sumatran tiger. Conflict records are inherently sparse, spatially uneven, and influenced by detection limitations and reporting bias, especially within and around conservation areas (Treves et al., 2009). The objectives was not to perform population-scale inference, but rather to map out relative spatial patterns and examine the relationship between forest fragmentation and the density of conflict occurrences. A more exploratory strategy is generally seen as suitable, and it is frequently applied in landscape ecology work (Hesselbarth et al., 2024). Figure 2 illustrates the research workflow, encompassing data collection, data analysis, and the generation of research outputs.

Before selecting the appropriate correlation test, a normality test was conducted using the Shapiro-Wilk method, given that the sample size of HTC cases was less than 50 (n = 47) (Razali & Wah, 2011). The purpose of this test was to determine whether the data were normally distributed, thereby informing the choice of subsequent statistical tests. Data were considered normally distributed if the $p\text{-}value > 0.05$ (accept H_0, reject H_1). Conversely, $p\text{-}value < 0.05$ indicated non-normal distribution (reject H_0, accept H_1) for each variable. Based on the normality test results, all variables showed non-normal distribution, as indicated by p-values (≤ 0.05). Therefore, non-parametric statistical

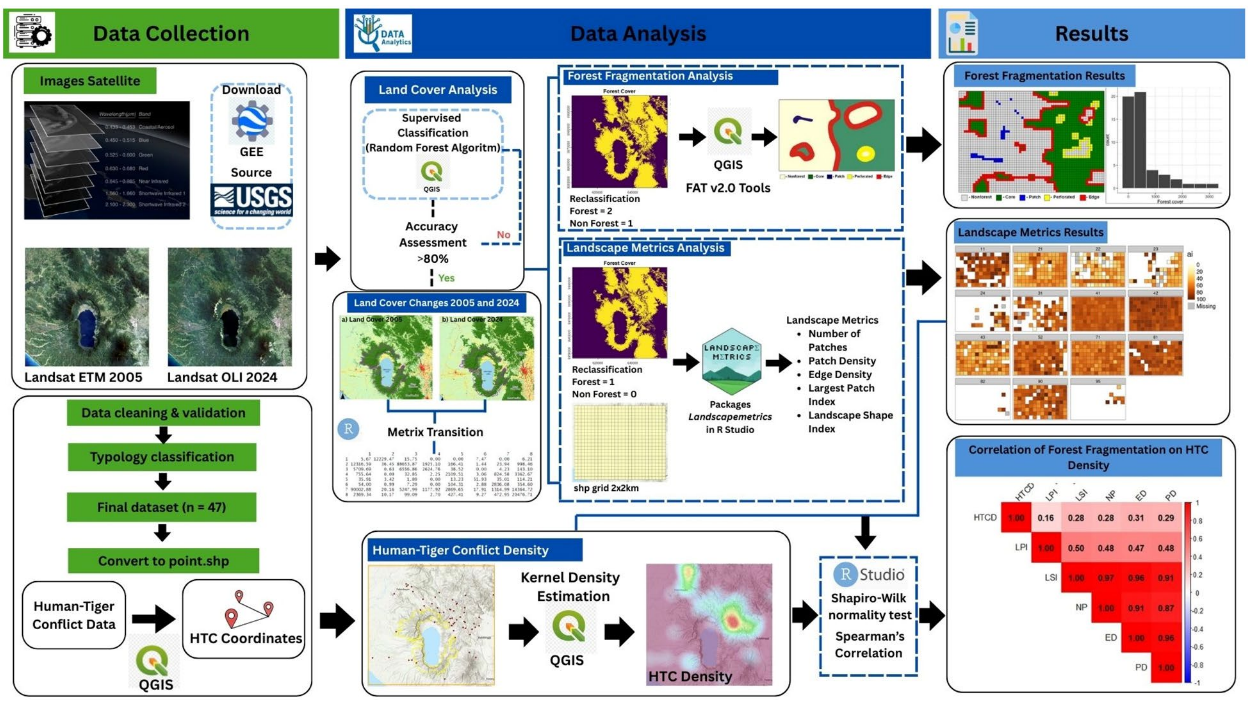

Figure 2. Methodological Flowchart.

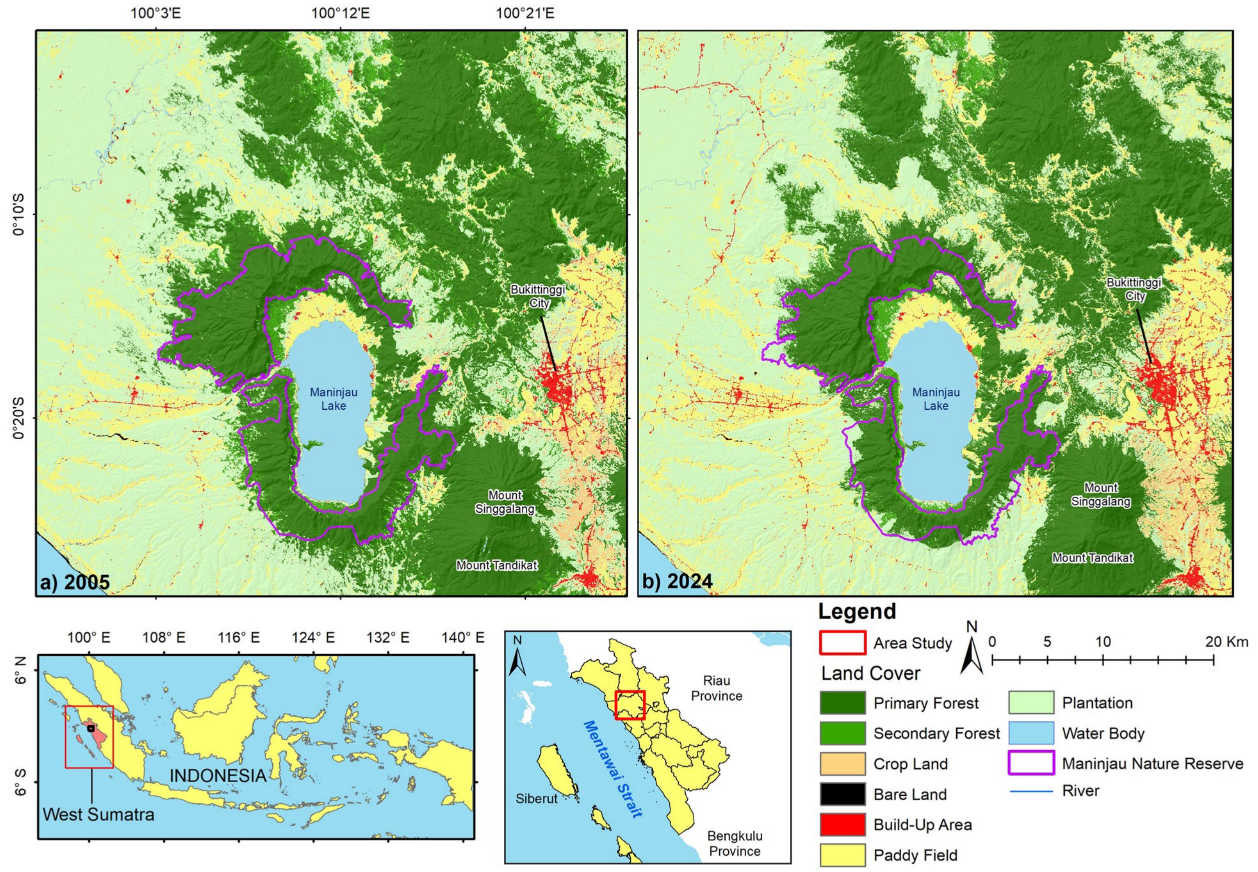

Figure 3. a) Land Cover 2005, b) Land Cover 2024.

methods were deemed appropriate for further analysis. Based on the results of the normality test, Spearman's rank correlation was employed as the statistical method to analyze the relationship between forest fragmentation and human-tiger conflict (HTC) density. Spearman's correlation is a non-parametric method used to assess the relationship between landscape metric variables and HTC density (Bocianowski et al., 2023). This method is particularly suitable for datasets that do not follow a normal distribution or contain outliers (Gibbons & Chakraborti, 2010). All statistical analyses were performed in RStudio using the *stats* package, and visualizations such as histograms of HTC typologies were generated using the *ggcorrplo*t package (R Core Team, 2023).

3. Results

3.1. Land Cover Changes and Accuracy Assessment

The land cover of the study area in 2005 comprised plantations, covering an area of 115,021 ha (40.9%). Next came the primary forest at 104,124 ha (37.0%), followed by secondary forest (15,079 ha/5.4%), dryland agriculture (7,091 ha/2.5%), open land (256 ha/0.1%), built-up areas (3,360 ha/1.2%), paddy fields (23,868 ha/8.5%), and water bodies (12,265 ha/4.4%). In 2024, plantations covered 111,250 ha (39.6%), depicting a marginal decline in the percentage of land use compared to 2005. The second largest land use type was again primary forest, covering 100,616 ha (35.8%), followed by secondary forest (5,733 ha/2.0%), dryland agriculture (5,729 ha/2.0%), open land (94 ha/0.01%), built-up areas (5,512 ha/2.0%), paddy fields (39,821 ha/14.2%), and water bodies (12,301 ha/4.4%) (Figure 3).

During the period from 2005 to 2024, the area under primary forests reduced by about 3,508 ha, along with a significant reduction in the area under secondary forests by about 9,346 ha. This shows that there was a conversion of forest lands to non-forest land use forms, especially to rice fields, plantations, and built-up areas. Likewise, agricultural land declined by 1,362 ha due to conversion to rice fields and settlements. Open land showed a reduction of about 162 ha, whereas built-up areas increased by 2,152 ha, and rice fields had the maximum growth rate of 15,953 ha.

(Table 3) shows the land cover change transition matrix between 2005 and 2024, illustrating both the direction and magnitude of transitions among land cover classes. Diagonal values represent areas that remained unchanged, whereas off-diagonal values indicate conversions between different land cover types. Overall, both primary and secondary forests experienced notable declines, as reflected by substantial transitions toward non-forest classes of the primary forest area recorded in 2005, only 89,321 ha remained as primary forest in 2024, while large portions transitioned into secondary forest (1,817 ha), plantation areas (12,115 ha), and paddy fields (988 ha).

The land class of secondary forests saw the same trend, where only 2,602 ha were unchanged, while the

Table 3. Transition of Land Cover Changes 2005 to 2024

	Land Cover 2024 (ha)							
Land Cover 2005	Primary Forest	Secondary Forest	Water Body	Crop Land	Bare Land	Built-up Area	Plantation	Paddy Field
Primary Forest	**89,283**	1,817	38	162	1	26	12,115	988
Secondary Forest	6,326	**2,600**	2	34	0	4	5,423	142
Water Body	18	0	**12,196**	1	8	1	16	30
Crop Land	31	2	2	**2,045**	3	777	710	3,263
Bare Land	2	0	6	12	**50**	31	35	31
Built-up Area	7	7	1	100	3	**2,770**	61	375
Plantation	5,339	1,142	41	2,770	18	1,394	**90,873**	14,230
Paddy Field	118	4	23	377	9	452	2,416	**20,220**

Table 4. Confusion Matrix of Land Cover 2005

Reference \ Predicted	Built-up Area	Water Body	Primary Forest	Secondary Forest	Plantation	Paddy Field	Bare Land	Crop Land
Built-up Area	**1,046**	0	0	0	11	0	83	5
Water Body	0	**78,790**	0	0	0	0	0	0
Primary Forest	1	1	**130,676**	2,684	1,009	0	7	41
Secondary Forest	0	0	637	**4,095**	446	0	0	13
Plantation	5	0	1,599	769	**56,085**	37	11	155
Paddy Field	1	0	3	0	109	**6,543**	22	22
Bare Land	40	0	0	0	0	0	**221**	0
Crop Land	13	0	4	0	83	22	2	**2,373**
User Accuracy (%)	94.58	100	98.31	54.25	97.13	99.11	63.87	90.95

Table 5. Confusion Matrix of Land Cover 2024

Reference \ Predicted	Built-up Area	Water Body	Primary Forest	Secondary Forest	Plantation	Paddy Field	Bare Land	Crop Land
Built-up Area	**6,171**	0	2	0	2	24	4	6
Water Body	0	**95,244**	0	0	0	0	0	0
Primary Forest	8	2	**290,539**	1,233	4,324	306	0	25
Secondary Forest	0	0	797	**3,891**	302	0	0	0
Plantation	1	0	2,720	191	**22,833**	137	0	33
Paddy Field	33	0	26	2	30	**21,718**	0	34
Bare Land	13	0	19	0	1	12	**102**	0
Crop Land	11	0	31	0	50	112	0	**1,658**
User Accuracy (%)	98.94	100	98.78	73.18	82.9	97.35	96.23	94.42

majority was converted to plantations (5,423 ha) and paddy fields (142 ha). The land class of plantation saw the most significant increase in area due to the presence of high persistence (90,914 ha) and large conversion inputs of primary forest (12,115 ha), secondary forests (5,423 ha), and paddy fields (14,230 ha). These trends signify that plantation and agricultural expansion are the major landscape changes observed in this study. Paddy fields had a mixed trend in that their area remained highly persistent (20,243 ha), and on the other hand, contributed significantly to the areas of plantations (14,230 ha) and dryland agriculture (3,263 ha). Lastly, there was an increase in both built-up and open land classes, albeit relatively minor compared to other land classes, due to conversions mainly from dryland agriculture (777 ha), plantations (1394 ha), and paddy fields (452 ha).

The classification accuracy for the land cover map 2005 produced a Kappa Coefficient (KC) of 0.95, an Overall Accuracy (OA) of 97.28%, with more details of User Accuracy (UA) presented in (Table 4). In the case of the 2024 data, the Kappa Coefficient (KC) was 0.95, an Overall Accuracy (OA) reached 97.68%, and User Accuracy (UA) details are provided in Table 5.

3.2. Typology of Human-Tiger Conflict

(Fig. 4) presents the typology of human-tiger conflict (HTC) incidents recorded between 2005 and 2024. A total of 47 conflict cases with complete information were documented across the Maninjau Nature Reserve landscape. Based on the data, the most common conflict typology was livestock predation, accounting for 34% of cases (n = 16), followed by specific incidents involving cattle predation (n = 6/13%), dog predation (n = 8/17%), buffalo predation (n = 7/15%), and goat predation (n = 3/6%). Other typologies included tiger attacks on humans (n = 1/2%), psychological disturbances to local communities (n = 1/2%), and one case of physical conflict (n = 1/2%). Additionally, four cases (n = 4) were classified as *no data* due to incomplete information.

The largest number of conflict incidents occurred between 2017 and 2018, with 13 cases reported in 2017 alone. A decrease in conflict events was noted between 2020 and 2023, followed by a rise in 2024. On the other hand, the most recurrent typology includes livestock predation, especially on buffaloes, cattle, and goats. The analysis shows a dynamic fluctuation of conflict typology in recent years. As shown in (Fig. 5) below, the HTC cases have been categorized based on land cover. Based on the chart, most HTC events take place in the plantation and agricultural lands. In the period between 2005 and 2024, plantation lands contributed 62% of incidents (n= 30), followed by 20% (n= 9) in edges of the primary forest, 16% (n= 7) in rice fields, and 2% (n= 1) in shrubs/small holders.

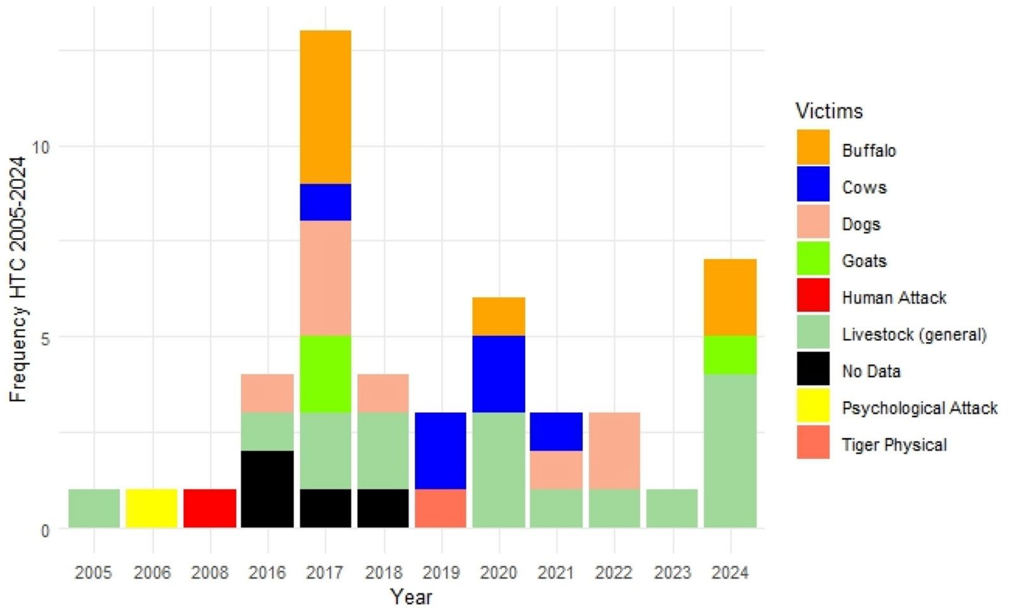

Figure 4. Typology of Human-Tiger Conflict in the Landscape of the Maninjau Nature Reserve.

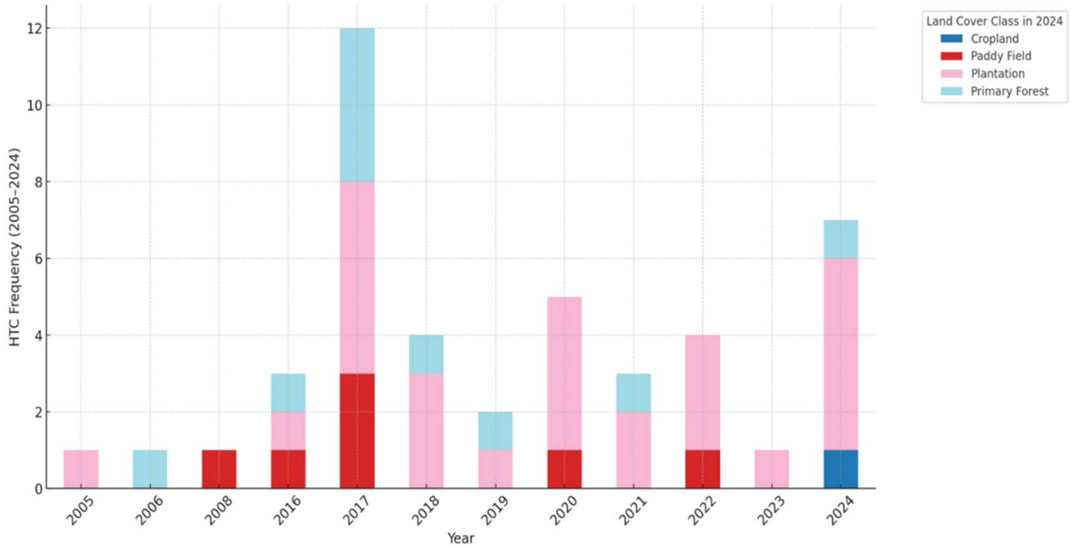

Figure 5. HTC Frequency 2005-2024 by Land Cover 2024.

3.3. Forest Fragmentation Patterns in Maninjau Nature Reserve Landscape

Based on the analysis using FAT v.2.0, forest fragmentation changes from 2005 to 2024 were quantified in hectares (ha). The most notable change occurred in edge areas, where approximately 6,760.63 ha transitioned to forest loss by 2024, indicating ongoing deforestation processes, particularly along forest boundaries. Additional transitions from edge areas were observed toward the perforated class (1,787.65 ha), large core areas (902.54 ha), medium core areas (6.10 ha), and small core areas (224 ha) (Fig. 6).

Large core areas experienced considerable fragmentation, with 2,601.35 ha converted into edge landscape, 3,502.44 ha into forest loss, 134.04 ha into medium core areas, 99.03 ha into patch, 10,497.08 ha into perforated, and 1,249.19 ha into small core areas. (Fig. 7) presents the changes in forest fragmentation classes, the patch class decreased by 1,451 ha (7%), and the edge class declined by 1,534 ha (7%). In contrast, the perforated class increased by 4,401 ha (20%), and the small core area class expanded by 318 ha (1%). Meanwhile, the medium core area and large core area classes decreased by 823 ha (4%) and 13,765 ha (62%).

The next set of results (Fig. 8) presents the spatial distribution and temporal changes of landscape metrics within the study area for the years 2005 and 2024, using the *landscapemetrics* package. The selected landscape metrics include Number of Patches (NP), Largest Patch Index (LPI), Edge Density (ED), Patch Density (PD), and Landscape Shape Index (LSI). Each metric was calculated for both years, and further analysis through change (Δ) maps was conducted to identify the spatiotemporal dynamics of forest fragmentation.

The Number of Patches (NP) shows a general decreasing trend in patch count (Fig. 8a, b, c). In 2005 (Fig. 8a), high NP values indicate a relatively high level of landscape fragmentation. The NP value in 2024

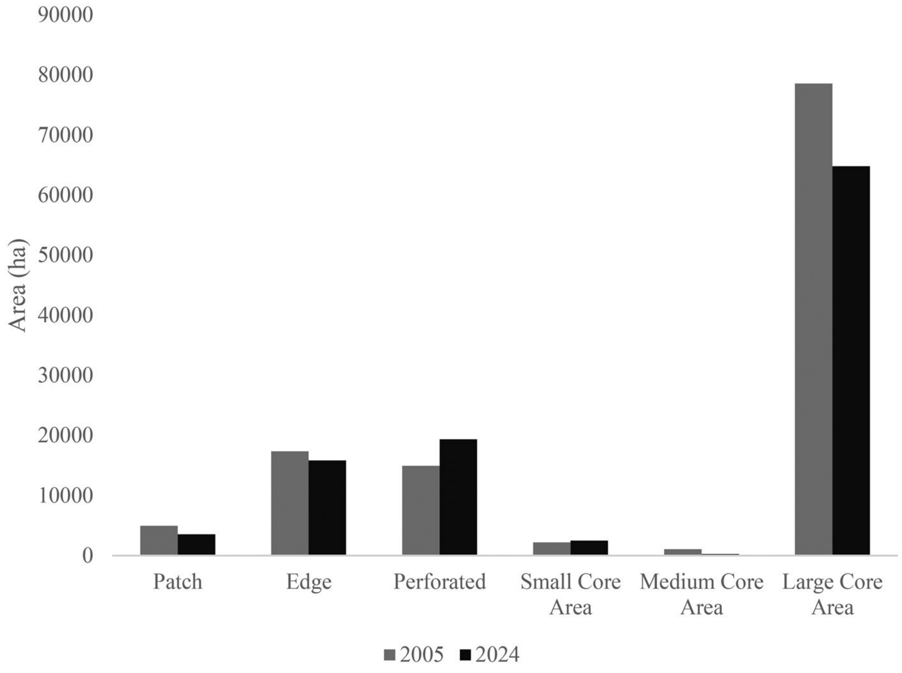

Figure 6. Forest Fragmentation Changes in the Maninjau Nature Reserve Landscape.

(Fig. 8b) shows a sharp decline in the number of patches, indicating the loss of small forest patches as a result of deforestation and forest degradation. The change map (Fig. 8c) shows that much of the landscape, particularly in the west and northern regions, experienced a reduction in the number of patches. This suggests the occurrence of patch merging or the loss of smaller patches. The Landscape Shape Index (LSI) also exhibited a general decline across the landscape (Fig. 8d and f). In 2005 (Fig. 8d), patch shapes were relatively complex, whereas in 2024 (Fig. 8e), they appeared more simplified. Negative LSI values across most of the landscape indicate ongoing deforestation processes or the loss of forest patches driven by anthropogenic activities, such as agricultural expansion and infrastructure development (Fig. 8f).

The Largest Patch Index (LPI) indicates a marked decline in large patch dominance over the period. In 2005, patch sizes showed a noticeable reduction, particularly in the western part of the study area, which appeared increasingly fragmented. By 2024, the LPI values did not exhibit substantial changes; however, the variation is more clearly illustrated in (Fig. 8i), which demonstrates that the reduction in size and the disappearance of patches occurred across a large portion of the conservation area landscape. Edge Density (ED) exhibited a consistent downward trend (Fig. 8j and l), reflecting a reduction in edge density and forest interface diversity. ED values in 2005 (Fig. 8j) were relatively high, but showed a clear decrease by 2024 (Fig. 8k). On the other hand, the 2024 ED values also showed an increase in the northern region, where the formation of new patches was observed in this region. The ΔED map (Fig. 8l) spatially confirms this landscape dynamics, particularly within core forest areas and edge forest areas. Patch Density (PD) followed a pattern similar to Edge Density (ED) and Number of Patches (NP), with a general reduction in the number of patches per unit area (Fig. 8m and o). (Fig. 8m), while PD values were high in 2005, they declined by 2024 (Fig. 8n). (Fig. 8o) reinforcing the interpretation that smaller, fragmented patches were either lost or absorbed into a simplified land cover unit.

Overall, the analysis reveals a reduction in the extent of several fragmentation classes. The above-mentioned pattern can be associated with the deforestation process as well as patch destruction that goes hand in hand with the formation of new fragmented zones, especially in the northern and eastern parts of the study site. The presence of only several small patches, simplifications in patch arrangement, as well as a reduction in edge and patch density, can be explained by the continuous degradation of the study site landscape under the influence of anthropogenic factors, such as agriculture and land cover transformation. This may lead to an increasing probability of human-tiger conflicts because of a reduction in functional core forests available for tigers, higher forest isolation, and more intense interaction between tiger territories and humans in peripheral zones.

Ecologically, the destruction of core forests can be perceived as functional fragmentation because of the disappearance of important interior forest landscapes needed to maintain biodiversity. The observed declines in patch and edge-based metrics, therefore, highlight an important limitation of relying solely on conventional fragmentation indices to infer landscape condition. When interpreted alongside core-area dynamics, the results clearly indicate a decline in habitat quality and connectivity, despite apparent reductions in fragmentation metric values. The findings emphasise that declining fragmentation metrics must be interpreted in conjunction with core-area loss, as metric reductions may also reflect landscape degradation and homogenisation rather than genuine ecological recovery.

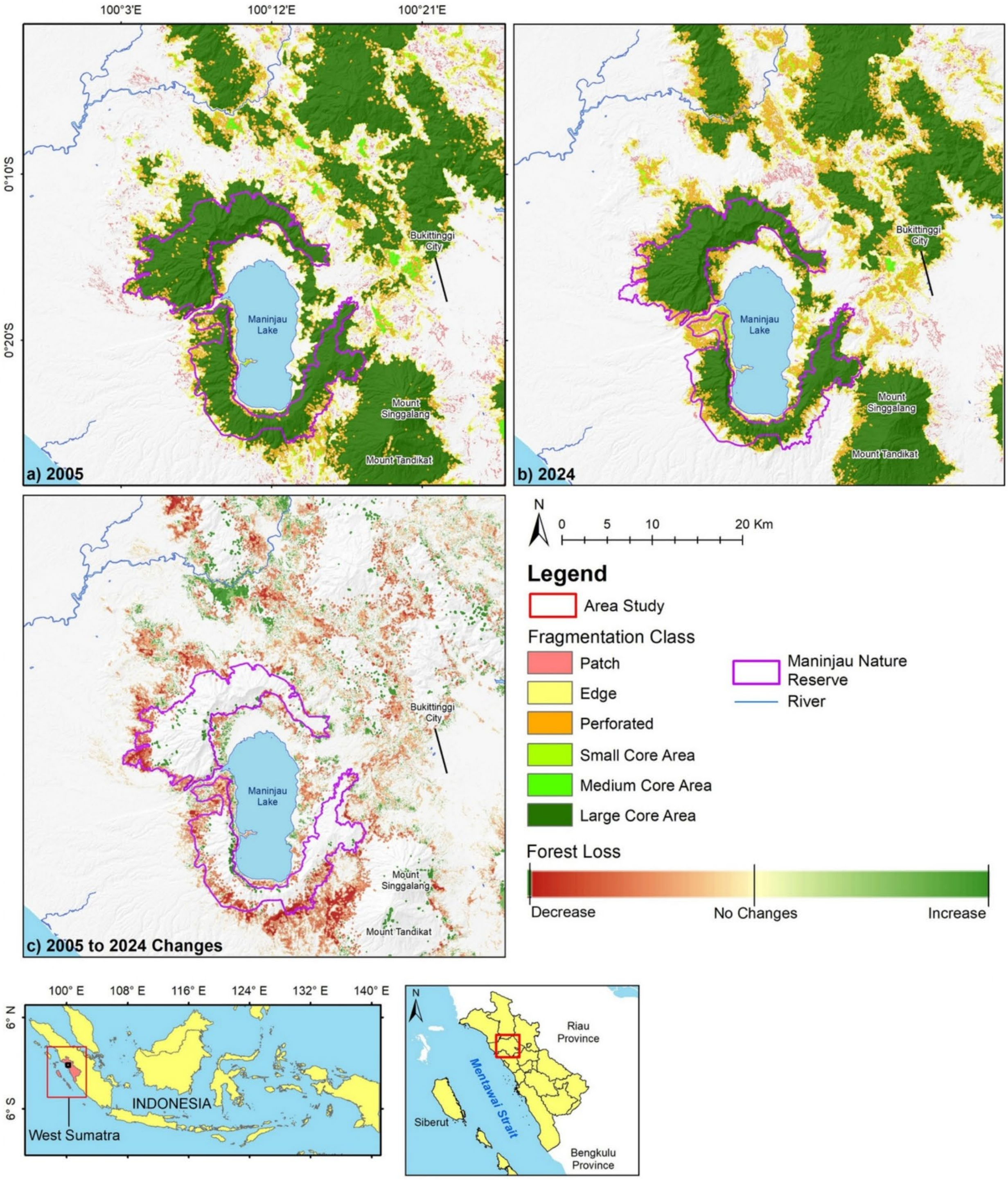

Figure 7. a) Forest Fragmentation 2005, b) Forest Fragmentation 2024, and c) Forest Fragmentation Changes 2005 to 2024. Red indicates a decrease in forest area, green indicates an increase in forest area, and yellow indicates no change.

3.4. Correlation between Forest Fragmentation and Human-Tiger Conflict Density

(Fig. 9) presents the results of the correlation analysis between landscape metrics and Human-Tiger Conflict (HTC) density using Spearman's rank correlation. The results indicate that all landscape indices are positively correlated with HTC density, although the strength of these relationships is generally weak. The highest correlation was observed between HTC density and Edge Density (ED) (ρ = 0.31), while weaker correlations were found with other metrics such as LPI (ρ = 0.16), Patch Density (PD) (ρ= 0.29), Landscape Shape Index (LSI) (ρ= 0.28), and Number of Patches (NP) (ρ= 0.28).

A particularly strong correlation was observed between PD and ED (ρ = 0.96), suggesting that a rise in edge density generally accompanies an increase in the patch density. Similarly, LSI and NP also exhibited a strong correlation (ρ= 0.97), indicating that as the number of patches increases, the landscape shape becomes more complex. In contrast, LPI and NP showed a weaker correlation (ρ = 0.48), implying that a high LPI value does not necessarily correspond to a large number of patches. This may suggest that when

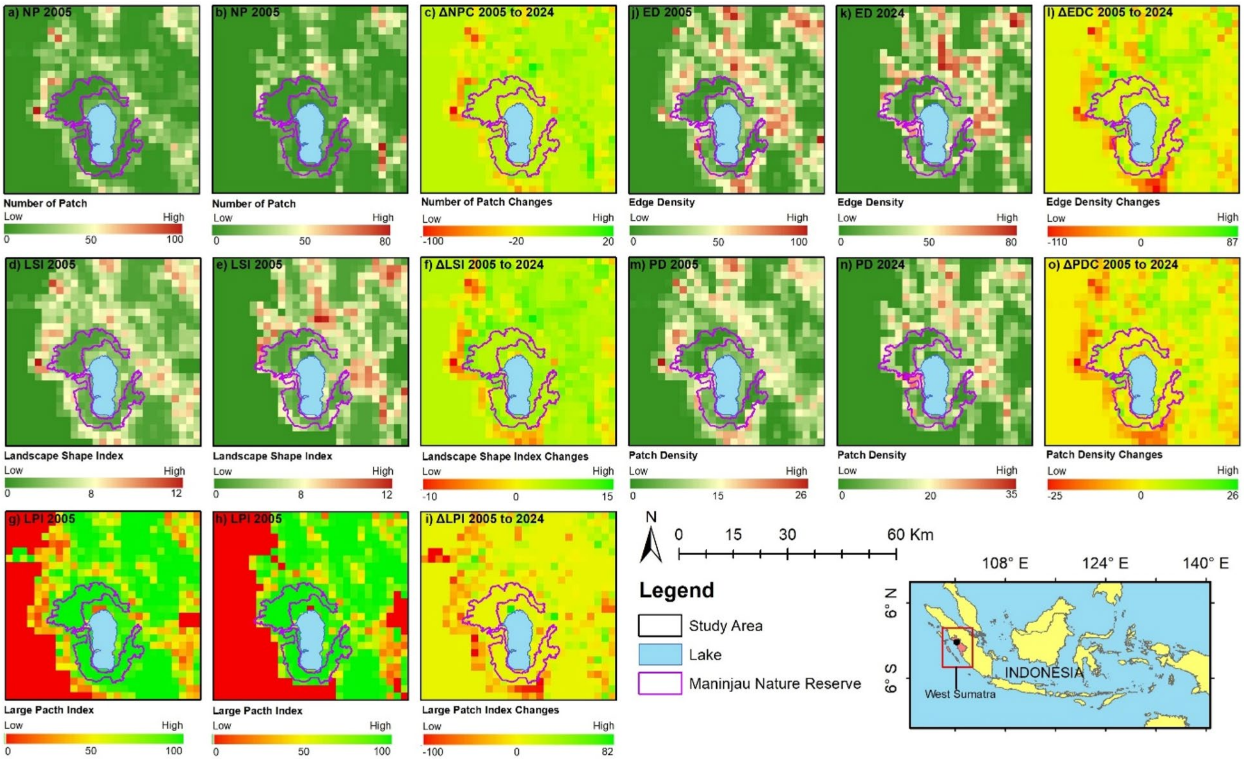

Figure 8. Landscape Metrics for 2005 and 2024, and their corresponding changes Δ, showing temporal shifts in fragmentation patterns. Number of Patches (NP (number) a, b), Landscape Shape Index (LSI (index) d, e), Largest Patch Index (LPI (percent %) g, h), Edge Density (ED (m/ha) j, k), Patch Density (PD (#/ha) m, n). Number of Patch Changes (Δ NPC, c), Landscape Shape Index Changes (Δ LSIC, f), Largest Patch Index Changes (Δ LPIC, i), Edge Density Changes (Δ EDC, l), Patch Density Changes (Δ PDC, o). A value of 0 indicates no change in the landscape, bright orange indicates an increase, and magenta indicates a decrease.

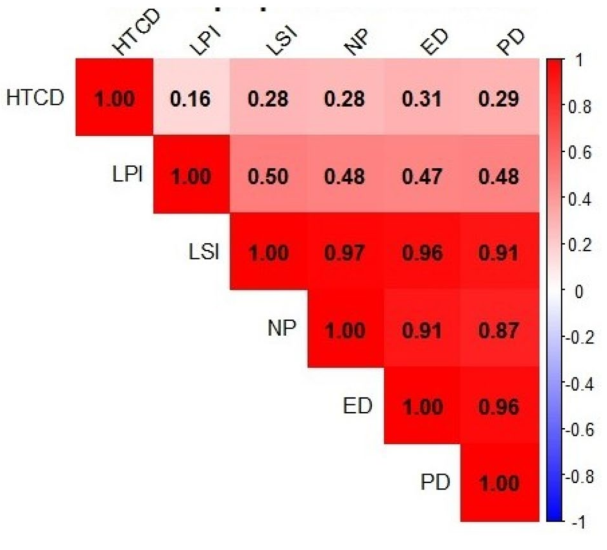

Figure 9. The relationship of Landscape Metrics with the Density of Human-Tiger Conflict in the Maninjau Nature Reserve Landscape. Red indicates the relationship between strong variables, while bright red shades indicate the relationship between weak variables.

a single large patch dominates the landscape, the total number of patches tends to decrease.

In addition, PD was strongly correlated with both LSI (ρ = 0.91) and NP (ρ = 0.87), indicating that higher patch density is associated with both a greater number of patches and increased shape complexity. LSI showed a weak correlation with LPI (ρ = 0.50) but was highly correlated with ED (ρ = 0.96). The correlation between LPI and ED was moderate (ρ = 0.47), suggesting that edge complexity is not strongly linked to the size of the largest patch. Finally, ED and NP showed a relatively strong correlation (ρ = 0.91), indicating that landscapes with more patches tend to exhibit higher edge densities.

4. Discussion

4.1. Key Findings: Forest Fragmentation and Human-Tiger Conflict Relationships

This study provides empirical evidence of the relationship between forest fragmentation dynamics and the density of human-tiger conflict (HTC) incidents within the Maninjau Nature Reserve Landscape. Our key findings reveal a positive correlation between all tested landscape metrics and conflict density (HTCD), with Edge Density (ED) exhibiting the strongest correlation (ρ=0.31), followed by Patch Density (PD) (ρ=0.29).

The implications of these results from the perspective of landscape composition versus configuration provide some interesting mechanistic insight into the processes involved. The significant correlation between edge density (ED) and HTC density (ρ = 0.31) lends credence to the assumption that configurational fragmentation, in particular the formation of longer and more complicated forest-human edges, is one factor influencing encounter likelihood, independent of the overall amount of forest loss. This result corroborates similar studies conducted on Persian leopards (*Panthera pardus saxicolor*) in Iran, where edge density turned out to be a more powerful predictor of depredations than the size of forest patches (Khosravi et al., 2024), as well as work done on brown bears (*Ursus arctos*) in Europe (Bautista et al., 2023). On the other hand, the lower correlation value found for largest patch index (LPI ρ = 0.16) implies that compositional fragmentation (decrease in size of largest forest patch) is less directly related to the occurrence of conflict. Nonetheless, this does not mean that compositional fragmentation is not an important variable. On the contrary, the considerable loss of large core forest habitats (62% reduction reported in Section 3.3) acts as a driving factor that forces tigers to use edge habitats, and thereby configurational variables gain significance. Such a hierarchical pattern of configurational variables being relevant only when certain compositional thresholds are surpassed has been established in human-elephant conflicts in India (Nad et al., 2022), and human-bear conflict models in Iran (Movasaghi et al., 2025). These results indicate that areas with high edge density serve as critical spatial predictors of conflict risk. In terms of HTC typology, approximately 85% of conflict incidents involved livestock depredation affecting local communities, primarily buffalo, cattle, and goats, with the highest concentration of incidents occurring in plantation areas (62%) and agricultural lands. This pattern underscores the role of landscape transformation characterized by increasing forest edge complexity driven by anthropogenic activities, in directly elevating the likelihood of negative interactions between humans and tigers.

4.2. Ecological Interpretation: Core Forest Loss, Edge Zones, and Prey Dynamics

This study carried out forest fragmentation analysis and 19 years of monitoring, and found that within the study area, the area of forest land classified as Large Core Area shrank by ±18,083.13 hectares. The disappearance of contiguous core forests gave rise to shorter, more spatially dispersed edge zones. The three drivers of change proposed by Gunawan et al. (2024), agricultural expansion, oil palm plantation expansion, and infrastructure expansion, can corroborate this observed shift. The ongoing shrinkage of large core forest areas is causing the continuous loss of the interior habitats essential for Sumatran tigers. Tigers and other large carnivores require large and continuous blocks of forest of sufficient size in order not to exhaust themselves making kills and moving about. As their primary habitats shrink and become more broken up, they become confined to the space along the edge of their habitat. Here, the corridors for their movement become combined with land altered by human activities. Most human-tiger conflicts occur in the forest edge environments, suggesting that if tigers occupy the forest edge, human-tiger conflicts, to some extent, will be inevitable. However, it is a new and important finding of this study that high conflict density was found in the areas with moderate rather than the highest edge density. These results imply that tigers have a tendency to be sensitive to human activities and thus avoid landscapes with highly fragmented ecosystems (Luskin et al., 2017; Sunarto et al., 2012). At the same time, the incremental pressure of human activities drives tigers to occupy fragmented ecosystems. A similar trend has been observed for the Bengal subspecies of tigers, tigers that inhabit mostly fragmented forests with a high percentage of human-modified areas (Harihar & Pandav, 2012).

The current findings also support the evidence that tigers prefer the edges of the forests in highly fragmented ecosystems for movement and migration (Pahlevi et al., 2025; Rahman et al., 2023; Saputra et al., 2025; Suyadi et al., 2012). This is aggravated by the presence of some wild boar (*Sus scrofa*), as they take advantage of agricultural landscapes with easy access to food (Allen et al., 2021; Yang et al., 2024). High prey availability near forest edges, particularly in agricultural areas, enhances functional connectivity and attracts tigers to these locations in pursuit of prey (Linkie & Ridout, 2011). This is also true for tigers and humans, creating an ecological trap that increases the risk of adverse interactions (Allen et al., 2020).

4.3. Human Dimensions and Land-use Context

Land use policies directly impact designed changes to cope with forest fragmentation. Most of the Forest loss happens in Other Land Use Areas (APL), but some plantation developments have taken place near the edge of the Maninjau Nature Reserve Landscape. This agrees with Umar (2021), reporting the slow shrinkage of the forests in the last 20 years, showing that the land use laws need to be enforced.

Multiple actors affect forest fragmentation; for example, landscape changes, such as land use permits issued by the government, do change forest fragmentation (Juniyanti et al., 2021). Conversely, community participation in socio-economic activities affects individual behavior, local initiatives, and collective engagement in forest conservation and rehabilitation efforts (Tito et al., 2016). The high incidence of livestock depredation further indicates inadequate livestock management practices, whereby animals are frequently left without secure enclosures, thereby increasing the likelihood of prolonged and recurrent human-tiger conflict.

4.4. Management and Mitigation Implications: Why Edge Density is A Practical Spatial Indicator

Additional comparative data from other carnivore-rich ecosystems further underscores the need to consider configurational versus compositional fragmentation in mitigating conflicts. For instance, in southern Iran, Khosravi et al. (2024) showed that attacks on livestock by the Persian leopard were best predicted by edge density and distance to the forest-agricultural boundary, similar to how we found that Edge Density (ρ = 0.31) is the most significant predictor of HTC density. On the other hand, Movasaghi et al. (2025) used configuration variables to predict future human-bear conflict hotspots in Iran and concluded that edge creation, and not only habitat loss, is responsible for maintaining such conflicts. In the Buxa Tiger Reserve of India, Nad et al. (2022) reported that the occurrence of human-elephant conflict increased nonlinearly with the increase in forest perforation and edge density, despite no change in total forest cover. Such interspecific similarities in findings suggest that configurational fragmentation, more specifically edge density, may be a generalizable spatial indicator of carnivore conflict risk.

The integration of forest fragmentation patterns and human-tiger conflict (HTC) incidence provides a valuable foundation for identifying priority areas for conflict mitigation. Landscape metrics suggest that edge density and human-tiger conflict density (HTCD) could be helpful spatio-temporal indicators of the placement of mitigation options, such as the implementation of warning systems (Ronoh et al., 2022). Further, these results support the case for conservation measures aimed at the reduction of habitat fragmentation in edge zones, where the overlapping of the areas of movement of wildlife and humans, where the greatest concentration of human-wildlife conflict occurs, is likely to happen (Bellotto-Trigo et al., 2023). Improving community education on livestock management, conflict reporting, and community-based conflict resolution is critical to improve human-tiger coexistence (Ekarini et al., 2022). Combining ED-based spatial analysis with culturally sensitive conservation and community engagement methods is likely to improve acceptance of mitigation measures. In West Sumatra, the perception of the tiger as *inyiak balang* is a starting point to build trust and obtain community participation, which is necessary for long-term coexistence (Mangunjaya, 2025; McKay et al., 2018). Beyond these spatial metrics, integrating spatial approaches with local socio-economic data and predictive conflict risk modeling is essential for developing adaptive and context-specific mitigation strategies that reflect the unique dynamics of human-tiger interactions across fragmented landscapes (Cheng et al., 2024).

4.5. Limitations and Future Research

There are some limitations associated with this research, among which are the limited sample sizes of conflict cases. This limitation arises because it is common in wildlife research to encounter such situations due to the elusive nature of animals involved in conflict situations. The data on the spatial position of the conflict was collected using a variety of sources of variable spatial accuracy. In this particular research, the data on prey density, tiger movements, and variations in land use intensity have not been considered.

Other environmental and human-related factors that were not considered in the present study, apart from habitat fragmentation measures, many other factors might affect the incidence of human-tiger conflicts but are not addressed in this study. They include (1) prey abundance availability of prey (wild boar, deer, among others) is an important aspect that impacts the movements of tigers and their probability of entering human settlements to look for prey (Linkie & Ridout, 2011), (2) livestock management unprotected livestock, poor livestock protection measures, and poor herding practices have been shown to greatly increase the chances of attacks on livestock (Khosravi et al., 2024), (3) human population density and behavior intensity of human use of forest edges, such as extraction of non-timber forest products, grazing, and night-time use of forest edges, among others, can change encounter probabilities (Struebig et al., 2018), (4) tiger behavioral ecology the individual characteristics of a tiger in terms of its ranging pattern, level of familiarity with humans, and stage in life history (dispersing sub-adults versus territorial adults) determines whether or not there will be a human-tiger conflict (Pahlevi et al., 2025), (5) land use policies and enforcement the effectiveness of land use zoning, enforcement against illegal encroachment, and the availability of a team to respond to conflicts differs across the landscape and through time (Juniyanti et al., 2021), and (6) socio-economic and cultural factors attitudes of local communities toward tigers, their tolerance toward the species, and cultural beliefs about the tiger (regarding it as '*inyiak balang*' in West Sumatra) affect reporting frequency and conflict escalation (Mangunjaya, 2025; McKay et al., 2018). The omission of these factors from our study implies that the correlations between the fragmentation indices and conflict density must be taken as associative, rather than causal, in nature.

Additionally, although the correlation analysis gives valuable insights, future researchers are advised to apply a more comprehensive approach that considers ecological, spatial, and socio-economic factors using state-of-the-art techniques like machine learning and multi-model inference in order to better understand conflict mitigation planning. In particular, future research needs to focus on collecting data simultaneously about the distribution of prey, the management practices of livestock rearing, and tiger movements (for example, using GPS collars) to separate the independent effect of fragmentation from other sources of conflict.

5. Conclusions

This study demonstrates that forest fragmentation plays a measurable role in shaping the spatial distribution of HTC in the Maninjau Nature Reserve landscape. The analysis revealed a substantial decline in large core forest areas between 2005 and 2024, accompanied by an expansion of edge-dominated and perforated forest classes. The investigation of HTC incident density, together with other variables used to represent landscape patterns, identified a clear tendency for HTC cases to occur in fragmented landscapes, mainly adjacent to forest edge zones and agricultural lands. Among the landscape metrics evaluated, Edge Density (ED) exhibited the strongest and most consistent positive association with human-tiger conflict (HTC) density. This suggests that increased forest-human interfaces are associated with elevated encounter risk between tigers and human activities. Although the observed correlations remain relatively weak, their consistent directionality is ecologically significant, pointing to landscape configuration more than forest loss alone does. Also, the high occurrence of livestock depredation strongly underscores how important fragmented edge environments are, because the relationship between ecological processes and human livelihoods becomes highly pronounced there. Overall, the findings suggest that Edge Density can function as a usable spatial marker for spotting areas prone to conflict and for focusing targeted mitigation efforts more effectively. Integrating fragmentation metrics into landscape planning and conservation management has the potential to contribute to more proactive and spatially informed strategies for reducing human-tiger conflict while supporting long-term tiger conservation in fragmented tropical landscapes. This conservation model not only supports the viability of tiger populations in fragmented landscapes but also promotes coexistence through the long-term strengthening of socio-ecological resilience. Furthermore, it is essential to develop a spatial risk model of HTC using advanced methods such as machine learning to support evidence-based mitigation planning.

Acknowledgments

We extend our sincere gratitude to the Ministry of Forestry of the Republic of Indonesia, Direktorat Konservasi Spesies dan Genetik (no. S.271/KSG/PSG.2/KSA.3.2/B/7/2025) and the Natural Resources Conservation Agency (BKSDA) of West Sumatra Province (no. S.637/K.9/TU/KSA.03.02/B/09/2025) for providing access to historical human-tiger conflict (HTC) data. We want to express our gratitude to the previous researchers who have provided this data. We also thank IPB University for the facilities and institutional support provided throughout the completion of this research. Our deepest appreciation goes to all village heads and local communities in the survey areas for their invaluable support, assistance, and participation in sharing information.

Author Contributions

HR: Conceptualization, Methodology, Writing-Original draft, Writing-review & editing, Data Curation, Visualization, LBP: Writing, Review & editing, Analysis Data, Visualization, and Supervision, HG: Conceptualization, Writing, Methodology, Review & editing, and Supervision.

Declarations

All authors declare no competing interests.

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