This paper was presented at the 21st International Conference on Sustainable Development, held at the Faculty of Social Science and Humanities, University of Ottawa, Ottawa, Canada, on July 15-16, 2025

Challenges in achieving Sustainable Development Goals for rural communities due to habitat fragmentation and human-elephant conflicts in South-Asian countries: A geospatial and socio-economic assessment based on the dry zone of Sri Lanka

H.M.B.S. Herath [1*], Nayanajith, J. [2], Jayasinghe K.D.P.P. [3]
[1,2,3] Department of Geography, Faculty of Humanities and Social Sciences,
University of Sri Jayewardenepura, Sri Lanka.
* Corresponding author: badrahearath@sjp.ac.lk

OIDA International Journal of Sustainable Development, Ontario International Development Agency, Canada.
ISSN 1923-6654 (print) ISSN 1923-6662 (online) www.oidaijsd.com
Also available at https://www.ssrn.com/index.cfm/en/oida-intl-journal-sustainable-dev/

Abstract: The rapid expansion of human settlements and agriculture in the Dry Zone of Sri Lanka has led to extensive forest fragmentation, severely threatening the habitat of the endangered Asian elephant and intensifying Human-Elephant Conflict (HEC). This ongoing conflict has escalated beyond a biodiversity conservation issue to a major socio-economic challenge, undermining food security, poverty reduction, and sustainable agricultural development in rural communities, causing challenges in achieving sustainable development goals. The main aim of this study was to assess the Land Use and Land Cover (LULC) changes of dry zone forests in Thirappane, Anuradhapura District, Sri Lanka, from 1995, 2010 and 2024. Sentinel-2 satellite images were used, and a Convolutional Neural Network (CNN)-based AI model was used to improve classification accuracy and to estimate temporal changes. The fragmentation parameters, such as patch density, edge density, and core area, were estimated using QGIS. Then, drivers for the habitat fragmentation and socio-economic influence on rural communities were evaluated using a field survey and a household survey carried out for selected Grama Niladhari Divisions The CNN-enhanced model demonstrated improved classification performance with overall accuracies of 89.1%, 90.3%, and 91.6% and Kappa Coefficients of 85%, 87%, and 89% for 1995, 2010, and 2024 respectively. Significant land cover changes were revealed over the study period, and fragmentation parameters indicated a marked increase in forest fragmentation over the study period, with edge density rising from 1.53 m/ha in 1995 to 1.84 m/ha in 2024, core area reducing from 14 ha to 6 ha, and patch density increasing from 0.029 to 0.054 patches/ha, reflecting reduced habitat quality and connectivity, resulting in more encroachment of elephants into cultivated areas. Major drivers for the forest fragmentation were agriculture and settlement expansion. As a result of the conflicts, the frequency of both elephant deaths and human deaths is escalating over time. There is a strong positive correlation ($R = 0.76$) between agricultural expansion and conflict frequency. Notably, 82% of respondents reported frequent crop damage, while 68% expressed dissatisfaction with existing mitigation strategies such as electric fencing. Loss of agriculture-based rural livelihoods, collapse of education of school children, and depression due to these conflicts are severe socio-economic problems encountered by rural communities. The findings highlight the urgent need for integrated land-use planning that aligns wildlife conservation with rural livelihood sustainability in conflict-prone areas in South Asian regions.

Keywords: Geospatial and Socio-economic Assessment, Forest Fragmentation, Human-Elephant Conflict, Land-Use Changes, Sustainable Development Goals, Dry Zone

Introduction

Sri Lanka's commitment to achieving the Sustainable Development Goals (SDGs), including SDG 1 (No Poverty), SDG 2 (Zero Hunger), SDG 13 (Climate Action), and SDG 15 (Life on Land), underscores the urgent need to enhance rural livelihoods, ensure food security, and maintain ecological integrity within the Dry Zone. This region, which covers nearly 70% of Sri Lanka's land area, plays a critical role in the nation's agrarian economy while providing essential ecosystem services and biodiversity support for rural communities (United Nations, 2015; Food and Agriculture Organization FAO, 2020). Historically, agriculture in Sri Lanka's Dry Zone was sustained through an indigenous tank-based irrigation system that efficiently managed seasonal rainfall to support rainfed paddy cultivation while preserving forest cover, soil fertility, and biodiversity (Panabokke, 2002; Madduma Bandara, 1985). Dating back to the 4th/3rd century BCE, these ancient systems enabled a harmonious coexistence between human livelihoods and ecological conservation across centuries (Abeywardana et al., 2019). However, the Mahaweli Development Project (MDP) launched in the 1970s, which diverted Mahaweli River water to Dry Zone districts including Anuradhapura, shifted rainfed agriculture toward irrigated agriculture while accelerating human settlements and infrastructure development in these regions (Kikuchi et al., 2003; Somaratne & Dissanayake, 2016). While this transition improved agricultural productivity and supported rural development, it also led to extensive land use changes, forest encroachment, and habitat fragmentation, contributing to environmental degradation (Dharmasena, 2010; Herath, 2020).

The Anuradhapura District, traditionally covered with extensive forest, has undergone substantial forest loss over the past three decades, largely owing to agricultural expansion, human settlement, and development—a trend well documented between 2010 and 2024 using GIS and remote sensing techniques (Bandara et al., 2025). The most rapid decline occurred between 2010 and 2024, reflecting intensified pressures on forest landscapes due to human activities, including irrigation-based agriculture, settlements, and road development. Over the past three to four decades, Sri Lanka has also experienced a rapid increase in human population, which has directly contributed to land use changes, forest fragmentation, and increased demand for agricultural expansion. Figure 1 illustrates the population and average growth rates in each year from 1871 to 2024 based on the data of the Department of Census and Statistics. According to national census data, Sri Lanka's population grew from approximately 14.8 million in 1981 to 18.8 million in 2001, 20.3 million in 2012, and is projected to reach around 22.2 million by 2024, representing an approximate 50% increase over 43 years (Department of Census and Statistics, Sri Lanka, 2022). Although the annual growth rate has gradually declined from 1.7% in 1981 to 0.5% by 2024, the increasing population has escalated demand for settlements and agriculture, driving encroachment into forested landscapes and contributing to habitat fragmentation. In Anuradhapura, the population density increased from 82 persons per square kilometer in 1981 to 128 persons per square kilometer by 2012 (Abeywardana et al., 2019). This demographic expansion has further increased human pressures on limited forest resources within the Dry Zone. The historical and recent population trends of elephants in Sri Lanka are summarized in Table 1.

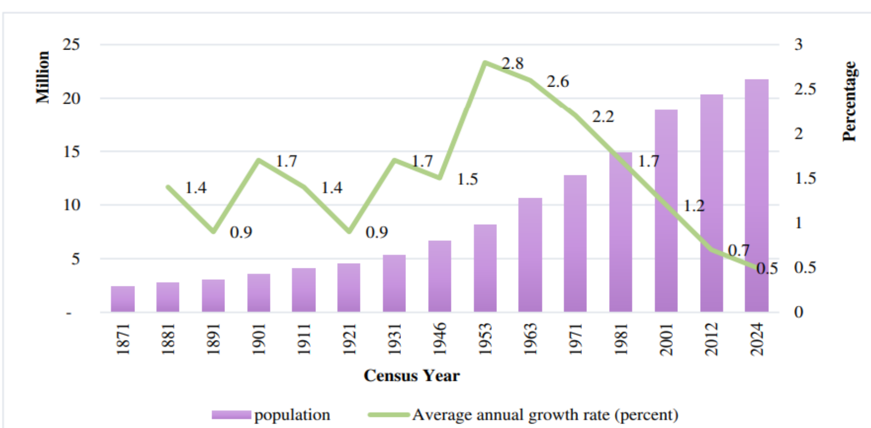

Figure 1: Population and average growth rates from 1871 to 2024
Source: Department of Census and Statistics, Sri Lanka (2024)

In parallel, the Asian elephant *(Elephas maximus)* population in Sri Lanka has also increased significantly over the last several decades, intensifying competition for space and resources between humans and elephants within the Dry Zone. The historical and recent population trends of elephants in Sri Lanka are summarized in Table 1.

Table 1: Elephant population trend in Sri Lanka (1951 to 2011)

Year/Period	Population Estimate	Source
1951	~1,500	Norris (1959)
1969	1,600–2,200	McKay (1973)
1978	2,000–5,000	Olivier (1978); Hoffmann (1978)
1990	2,700–3,200	Santiapillai & Jackson (1990)
1993	1,967 (dry season count, excluding north)	Hendavitharana et al. (1994)
2004	1,076 (Northwest and North)	Department of Wildlife Conservation (DWC)
2008	2,149 (North-central and East)	DWC
2011	5,879 (entire island)	DWC

The increase in elephant populations is attributed to legal protection, reduced poaching, and conservation initiatives (Fernando et al., 2021). However, this increase has not been matched by an expansion of suitable habitats, leading to increased contact between elephants and humans in agricultural landscapes.

The simultaneous growth of human and elephant populations, combined with the decline and fragmentation of forest cover, has led to a significant escalation of HEC in Sri Lanka. Currently, it is estimated that approximately 70 human and 250 elephant deaths occur annually due to HEC, with the Dry Zone, including Anuradhapura, being among the most severely affected regions (Fernando et al., 2021; Wickramanayake et al., 2020). Elephants frequently raid crops such as paddy, banana, and maize, which are essential for the livelihoods of rural communities, resulting in substantial economic losses, food insecurity, and psychological stress among farming households (Hoffmeier-Karimi & Schulte, 2015; Perera, 2009).

Forest fragmentation, characterized by the breaking up of contiguous forest landscapes into smaller, isolated patches, has been identified as a primary driver of HEC in Sri Lanka. Fragmentation reduces habitat quality and connectivity, increases edge effects, and disrupts traditional elephant migratory routes, forcing elephants to traverse agricultural lands and human settlements in search of food and water (Cushman et al., 2010; Laurance et al., 2018; Gunawardana et al., 2023). These changes not only increase the frequency and severity of HEC but also exacerbate socio-economic vulnerabilities in rural communities within the Dry Zone, further threatening the resilience and sustainability of local livelihoods (Wickramanayake et al., 2020).

Despite the critical role of forest fragmentation in driving HEC, systematic and quantitative analysis of fragmentation patterns using advanced geospatial and analytical methods remains limited within Sri Lanka's Dry Zone, representing a significant research gap (Herold et al., 2003; Liu et al., 2020). While geospatial technologies such as remote sensing and Geographic Information Systems (GIS) have been employed to monitor LULC changes, the integration of Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), to enhance LULC classification and temporal change detection in fragmented and heterogeneous landscapes remains underutilized in Sri Lanka (Zhang et al., 2019; Liu et al., 2020). This methodological limitation hinders the generation of accurate and granular datasets necessary for evidence-based conservation planning, land management, and the design of effective HEC mitigation strategies.

Furthermore, there is a critical need to understand the socio-economic impacts of HEC on rural farming communities, including crop and property damage, livelihood disruptions, psychological impacts, and community-level coping strategies, to design effective and locally appropriate mitigation measures (Bandara & Tisdell, 2003; Sitati et al., 2003). Incorporating local community perspectives into conservation planning is essential for building resilience while promoting coexistence and ecological sustainability in Sri Lanka's Dry Zone. Within this context, the DSD in the Anuradhapura District was selected as the study area due to its location in the dry zone's forest-agriculture interface, where forest fragmentation is intensifying alongside agricultural expansion. Thirappane has been identified as an HEC hotspot, with frequent crop raids and property damage reported along fragmented forest edges, water sources, and paddy field boundaries, highlighting it as a critical landscape to investigate the intersection of habitat fragmentation and human-elephant interactions. This area also represents typical dry zone socio-ecological conditions, making it an ideal case for examining spatial patterns of fragmentation and conflict dynamics while providing insights applicable to broader dry zone management.

Against this backdrop, the general objective of this study is to assess the LULC changes of dry zone forests in Thirappane, Anuradhapura District, Sri Lanka for the years 1995, 2010, and 2024. Specifically, the research aims to detect and analyze LULC changes and quantify forest fragmentation using remote sensing, geospatial techniques, and AI, particularly CNNs, to enhance classification accuracy and evaluate habitat quality and connectivity. The study further seeks to assess the relationship between forest fragmentation and HEC by examining how land use transformations influence elephant movement patterns and the frequency of conflict incidents. Finally, it investigates the socio-economic impacts of HEC on rural farming communities, with a focus on crop damage, livelihood disruption, food insecurity, and the effectiveness of existing mitigation strategies such as electric fencing. This research contributes to addressing critical gaps in knowledge and methodology, providing insights essential for sustainable land management, biodiversity conservation, and conflict-sensitive agricultural development in support of Sri Lanka's commitments to the Sustainable Development Goals.

Literature Review

Global Perspectives on Land Use and Land Cover (LULC) Change

Land Use and Land Cover (LULC) change has emerged as a significant global concern due to its far-reaching impacts on ecosystems, climate regulation, and biodiversity conservation (Foley et al., 2005; Turner et al., 2007). Anthropogenic drivers such as urban sprawl, agricultural expansion, deforestation, and infrastructure development are transforming natural landscapes at unprecedented rates, leading to habitat degradation and disruption of ecological processes (Lambin & Geist, 2006; Ellis et al., 2010; Seto et al., 2012). According to the Food and Agriculture Organization (FAO, 2020), approximately 4.7 million hectares of forests were lost annually between 2015 and 2020, primarily due to agricultural expansion and urban growth. Hansen et al. (2013) reported a global forest cover loss of over 2.3 million km² between 2000 and 2012, with the highest rates occurring in tropical regions, which are critical for carbon storage and biodiversity (Gibbs et al., 2010; Barlow et al., 2016).

These transformations are particularly significant in tropical areas, where deforestation accelerates climate change and reduces biodiversity by fragmenting habitats and disrupting ecological connectivity (Laurance et al., 2014; Newbold et al., 2015). Monitoring and analyzing LULC changes provide essential insights into spatial and temporal dynamics, informing sustainable land management and conservation planning (Song et al., 2018; Cai et al., 2019). Advances in remote sensing and geospatial analysis have enabled accurate, near-real-time assessments of land cover changes, supporting global and regional conservation efforts (Wulder et al., 2018; Li et al., 2020; Gong et al., 2020). Understanding global LULC dynamics provides essential context for addressing local conservation challenges in biodiversity hotspots, including Sri Lanka's ecologically sensitive Dry Zone (Gunawardana et al., 2023; Wickramanayake et al., 2020).

Regional Trends in Land Use and Land Cover Change in South and Southeast Asia

South and Southeast Asia are experiencing some of the most rapid LULC changes globally due to agricultural intensification, urban expansion, and large-scale infrastructure projects (Meyfroidt et al., 2013; Curtis et al., 2018). Countries including India, Indonesia, Myanmar, and Thailand have witnessed extensive deforestation and land conversion for agriculture, mining, and urban growth (Achard et al., 2002; DeFries et al., 2010). Infrastructure projects, such as roads, irrigation schemes, and hydropower developments, have further fragmented forest landscapes, resulting in biodiversity loss and increased human-wildlife conflicts (Wilcove et al., 2013; Zhou et al., 2014).

Sri Lanka shares similar regional characteristics, with the Dry Zone undergoing extensive land use change due to state-led agricultural development and resettlement initiatives (Madduma Bandara, 1985; Panabokke, 2002). The Mahaweli Development Program, one of the country's largest irrigation and resettlement projects, has transformed landscapes in districts like Anuradhapura, resulting in forest clearance and altered hydrology (Kikuchi et al., 2003; Dharmasena, 2010). Examining these regional LULC patterns provides a comparative lens to understand the ecological and socio-economic implications of such changes, supporting the formulation of transboundary conservation frameworks and resilient land management practices (Sloan & Sayer, 2015; Gaveau et al., 2014).

Forest Fragmentation and Its Ecological Consequences

Forest fragmentation, a key outcome of LULC change, involves the subdivision of large, continuous forest areas into smaller, isolated patches, causing significant ecological disruptions (Fahrig, 2003; Haddad et al., 2015). Fragmentation introduces edge effects, alters microclimates, and reduces habitat availability for interior-dependent species, negatively impacting biodiversity and ecosystem functions (Murcia, 1995; Laurance et al., 2002; Fischer & Lindenmayer, 2007). Reduced connectivity across landscapes poses particular challenges for wide-ranging species such as the Asian elephant (Elephas maximus), while increasing vulnerability to invasive species, fire, and illegal resource extraction (Cushman et al., 2010; Pfeifer et al., 2017).

In Sri Lanka, fragmentation is a growing conservation challenge, especially in the Dry Zone where agricultural expansion and settlement drive habitat loss (Wickramanayake et al., 2020; Fernando et al., 2005). Elephants require large, connected landscapes for seasonal migration and foraging, and fragmentation forces them into agricultural areas, escalating human-elephant conflict (Fernando et al., 2012; Leimgruber et al., 2003). The erosion of forest connectivity threatens conservation investments, emphasizing the need for integrated landscape management approaches and corridor restoration to enhance biodiversity conservation and reduce human-wildlife conflict (Laurance & Bierregaard, 1997; Corlett, 2016).

Land Use Change in Sri Lanka's Dry Zone

Sri Lanka's Dry Zone has undergone substantial land use transitions over the past several decades, largely driven by development programs and resettlement policies (Madduma Bandara, 1985; Panabokke, 2002). The Mahaweli Development Scheme converted extensive forest areas into irrigated agricultural lands, resulting in widespread deforestation and degradation of dry monsoon forests (Kikuchi et al., 2003; Dharmasena, 2010). These transformations have fragmented critical habitats and increased pressures on remaining ecosystems (Gunawardana et al., 2023).

Remote sensing studies have confirmed ongoing land cover changes in Anuradhapura District, indicating a decline in forest cover and increases in mixed-crop cultivation and built-up areas (Herath et al., 2022). The expansion of agriculture into forested areas leads to irreversible ecological damage, disrupts wildlife corridors, and intensifies human-wildlife conflicts (Wickramanayake et al., 2020; Fernando et al., 2005). Understanding these land use trajectories is essential for anticipating future conflicts and implementing adaptive, sustainable land management in the Dry Zone.

Human-Elephant Conflict: Causes, Consequences, and Management

HEC has emerged as a critical socio-ecological issue in Sri Lanka, particularly in regions undergoing rapid land use transitions (Fernando et al., 2012; de Silva & Ranjeewa, 2011). As habitats shrink and fragment, elephants are forced into agricultural landscapes to access food and water, leading to crop damage, property destruction, and fatalities for both humans and elephants (Fernando et al., 2005; Hoare, 2015). The conversion of forests to farmland and settlements underpins HEC escalation, as elephants lose access to traditional migration routes and habitats (Leimgruber et al., 2003; Chiyo et al., 2005).

Although mitigation strategies such as electric fencing, elephant drives, and translocation have been implemented, these often lack scientific planning and local community involvement, limiting their long-term effectiveness (Fernando et al., 2011; Osborn & Parker, 2003). The socio-economic impacts of HEC on rural households are severe, resulting in income loss, food insecurity, psychological distress, and educational disruptions for children (Bandara & Tisdell, 2003; Sitati et al., 2003). Addressing HEC requires integrated, landscape-level planning, community-led initiatives, and evidence-based management strategies that promote coexistence between humans and elephants (Graham et al., 2010; Fernando et al., 2012).

Role of AI and CNN-Based Models in LULC Change Detection

AI, particularly CNNs, has transformed LULC mapping and change detection, enabling improved classification accuracy in complex, heterogeneous landscapes (Zhu et al., 2017; Ma et al., 2019). CNNs extract hierarchical spatial and contextual features, surpassing traditional pixel-based approaches in identifying nuanced differences in land cover (Zhang et al., 2019; Li et al., 2020). Utilizing satellite datasets such as Sentinel-2 and Landsat, CNNs facilitate high-resolution monitoring of temporal and spatial land cover changes essential for landscape analysis and planning (Fu et al., 2017; Zhong et al., 2019).

In Sri Lanka's Dry Zone, where land cover patterns are complex and fragmented, CNNs enhance the detection of forest patches and agricultural encroachment, supporting the quantification of landscape metrics including patch density, edge density, and core area (Gunawardana et al., 2023). These AI models are adaptable using transfer learning and require relatively limited training data, making them practical for conservation and land use applications in resource-constrained contexts (Zhu et al., 2017; Gong et al., 2020).

Integrating LULC Detection with Socio-Economic Assessments

Assessing LULC changes without socio-economic context offers an incomplete understanding of conservation and development challenges (Ostrom, 2009; Turner et al., 2007). Integrating geospatial LULC analysis with socio-economic assessments provides insights into how landscape changes impact livelihoods, resource access, and community resilience (Ellis, 2013; Mertz et al., 2010). In Sri Lanka's rural communities, forest fragmentation exacerbates vulnerabilities in agriculture-dependent households, increasing exposure to crop damage and resource scarcity (Bandara & Tisdell, 2003; Fernando et al., 2005).

Combining satellite-based LULC data with household surveys, participatory mapping, and spatial analysis enables the identification of hotspots of ecological degradation and social vulnerability (Reid et al., 2009; Munroe et al., 2014). This integrated approach is critical for designing policies that are ecologically effective and socially equitable, supporting biodiversity conservation while aligning with the Sustainable Development Goals (UN, 2015; Sayer et al., 2013). Such holistic frameworks prioritize interventions addressing environmental degradation while enhancing community resilience, supporting sustainable conservation in Sri Lanka's Dry Zone.

Methodology

Study Area

This study was conducted in the Thirappane DSD, located in the southern region of the Anuradhapura District in Sri Lanka's North Central Province. Figure 2 illustrates the map of the study area. The selection of Thirappane DSD was grounded in secondary data analysis using incident records obtained from the Department of Wildlife Conservation (DWC), Sri Lanka. According to compiled incident data between 2015 and 2021, Thirappane reported 14 human deaths due to HEC, the highest among all DSDs in the district, while 19 elephant deaths were also recorded during the same period, again the highest in Anuradhapura District (Department of Wildlife Conservation, 2022). This dual prevalence of HEC incidents positions Thirappane as the most conflict-prone DSD in the district, justifying its selection as the focal point for this research.

To further narrow the investigation, three GNDs were selected based on the density of HEC reports, spatial proximity to forest fragments, and alignment with known elephant movement corridors. These included Sembukulama, Ethungama North, and Manakkulama, identified through incident mapping from DWC records, initial community consultations, and reconnaissance surveys conducted in the study area (Fernando et al., 2021).

Thirappane lies within Sri Lanka's Dry Zone, characterized by an average annual temperature range of 25°C to 30°C and annual rainfall between 1,000 millimeters and 1,500 millimeters, primarily received during the North-East monsoon (Panabokke, 2002; Department of Meteorology, Sri Lanka, 2023). The region supports predominantly agriculture-based livelihoods, with paddy cultivation being the primary economic activity. The expansion of irrigated agriculture and settlements under initiatives such as the Mahaweli Development Project (MDP) has contributed to land use changes and forest fragmentation, intensifying HEC as elephants encounter human-dominated landscapes in search of food and water (Kikuchi et al., 2003; Dharmasena, 2010).

Thirappane's position as an interface zone between forest habitats and agricultural lands makes it especially vulnerable to forest fragmentation, biodiversity loss, and direct wildlife-human interactions, leading to heightened HEC incidences (Wickramanayake et al., 2020). The selection of this site allows for a comprehensive analysis of spatial patterns of land cover change, ecological degradation, and its socio-economic consequences, providing critical insights for sustainable land use planning, HEC mitigation, and biodiversity conservation in Sri Lanka's Dry Zone.

Next page

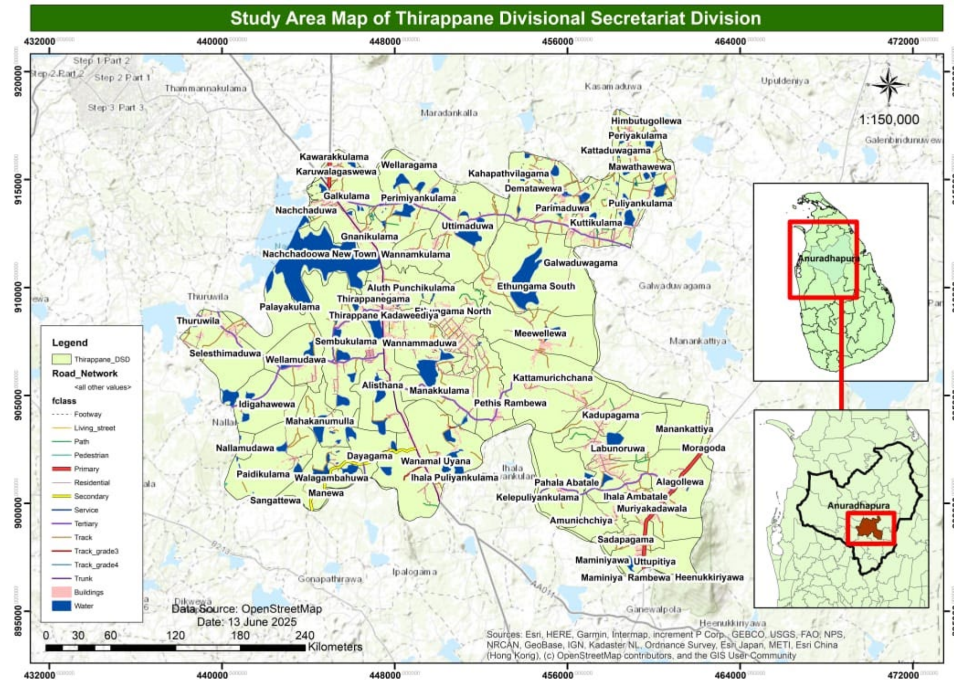

Figure 2: Study Area Map

Data Collection

This study utilized a mixed-methods approach, integrating spatial data and non-spatial quantitative and qualitative data collection strategies to assess the impact of LULC changes and forest fragmentation on HEC and rural livelihoods in the Anuradhapura District, with a focus on the Thirappane DSD using spatial data acquired from satellite images. The approach included both primary data collection from villages in Thirappane DSD and the integration of secondary data from institutional sources to ensure robust analysis.

Geospatial Approach

Spatial data were gathered from multi-temporal satellite imagery (1995, 2010, and 2024), sourced from Landsat and Sentinel platforms, and processed for LULC classification. These datasets were selected not only for their temporal coverage and spatial resolution but also for their compatibility with advanced classification techniques. In particular, a pre-trained Convolutional Neural Network (CNN) model was later applied during the data processing phase to enhance the classification accuracy of LULC outputs. Supplementary land use maps from the Survey Department and GPS data from field surveys were used to validate imagery. Table 2 summarizes the spatial data type, sources and purposes of the spatial data for the spatial analysis.

Table 2: Spatial data types, sources, and their purposes

Spatial Data Type	Source	Purpose
Satellite Imagery	Landsat 4-5TM (1995), Landsat 8 OLI (2010), Sentinel-2A MSI (2024)	LULC classification and detection of forest fragmentation
GPS Mapping Data	Field-based GPS tracking	Validate land use classes and map elephant paths
Land Use Maps	Survey Department of Sri Lanka	Support accuracy enhancement in LULC classification
Elephant Corridor Data	Department of Wildlife Conservation	Identify Elephant movements
Remote Sensing Earth Data	BigEarthNet v1.0	For remote sensing image understanding

The non-spatial data collection involved both primary and secondary data sources. Sixty households (20 from each GND) were selected through convenience sampling, a method chosen for its feasibility in rural and sometimes inaccessible settings. Structured household surveys were used to collect data on land use practices, crop types, frequency and severity of elephant encounters, damage valuation, and adaptive behaviors.

The Socio-Ecological Costs of Habitat Fragmentation and Human-Elephant Conflict

To gain deeper insights into the drivers and consequences of LULC change and habitat fragmentation, a field survey and household-level qualitative data collection were conducted in the study area. Semi-structured interviews were held with key officials from the Forest Department, Department of Wildlife Conservation, and local Grama Niladhari (GN) officers. These interviews explored institutional challenges, perceptions of land management, observed elephant movement trends, and the effectiveness of mitigation strategies such as electric fencing, elephant deterrents, and compensation processes for crop and property damages.

In addition, Focus Group Discussions (FGDs) were conducted in each GND with groups of farmers, elders, and youth to capture community-level experiences of HEC, LULC transitions, and adaptation practices. Discussions were structured around themes including crop and property damages due to elephant raids, income instability, displacement risks, disruptions to children's education, and psychological stress experienced by farming households. Special emphasis was placed on understanding the economic burden borne by households due to crop losses, including paddy, banana, and maize, and the coping mechanisms employed by communities in response to repeated damages.

Field observations were made across all three GNDs (Sembukulama, Ethungama North, and Manakkulama) and surrounding buffer zones, including visits to croplands, forest edges, and water sources frequently visited by elephants. These observations were used to ground-truth classified satellite imagery, validate community reports on elephant raids and conflict hotspots, and study spatial patterns of habitat degradation and elephant pathways within the fragmented landscape. Table 3 summarizes the qualitative data collection components and explicitly includes the assessment of damages experienced by farmers.

Table 3: Qualitative Data sources and their purposes

Qualitative Data Type	Source	Purpose
Semi-Structured Interviews	Forest and Wildlife Officials, GN Officers	Explore institutional understanding, policy constraints, and management of HEC and compensation processes for farmer damages
Focus Group Discussions (FGDs)	Farmers, women, and youth in three GNDs	Document community perceptions of LULC changes, crop and property damages due to HEC, livelihood impacts, and coping mechanisms
Field Observations	Cropland, forest edges, elephant trails, Water sources	Verify LULC classifications, spatially map conflict zones, and observe evidence of elephant incursions and crop damage

This comprehensive qualitative assessment ensured that the socio-economic impacts of habitat fragmentation and HEC on rural farming communities were systematically captured alongside ecological observations, providing a holistic understanding necessary for informed conservation planning and the development of conflict-sensitive land management strategies in Sri Lanka's Dry Zone.

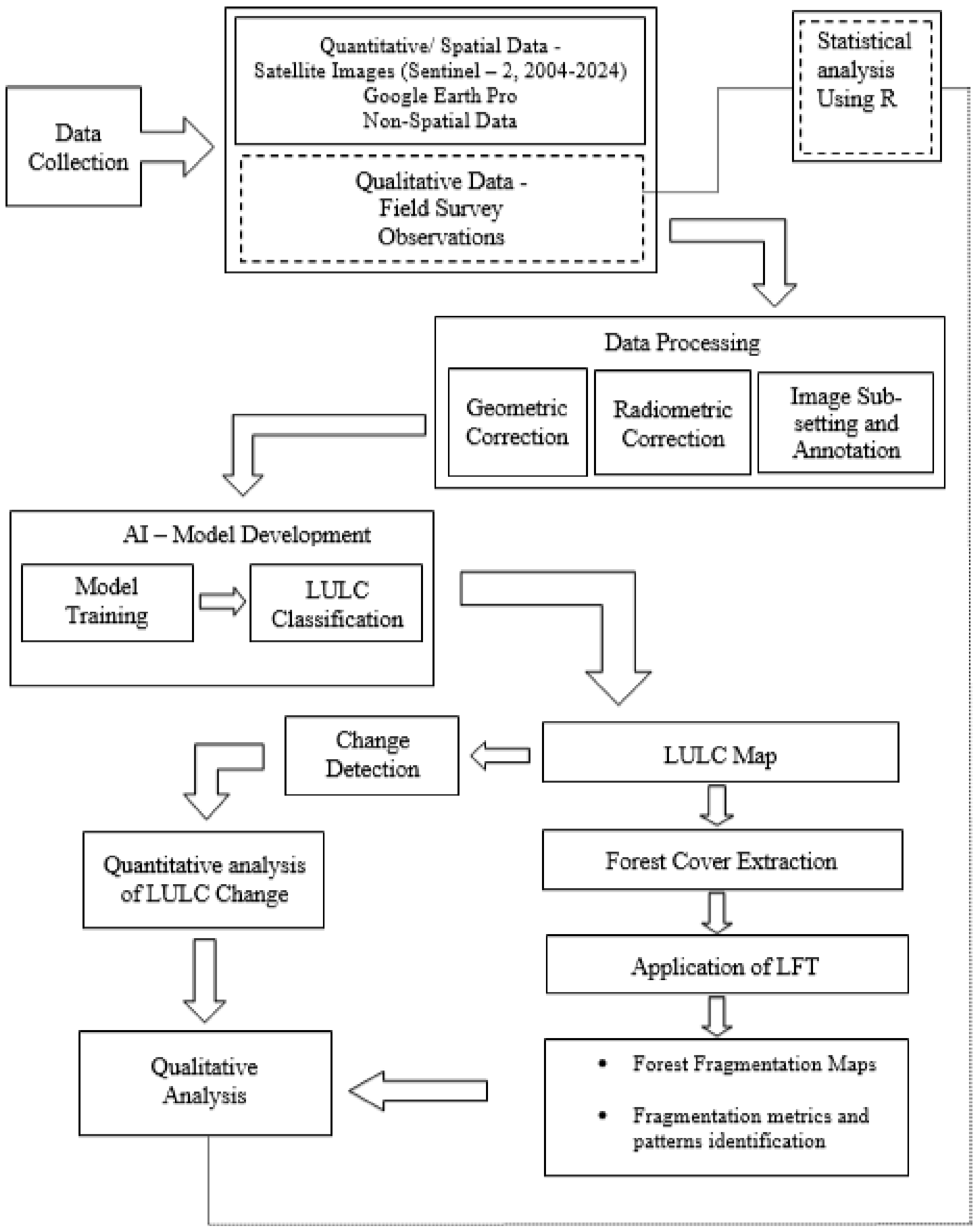

Figure 3: Methodological flow diagram for the geo-spatial assessment

Figure 3 illustrates the overall methodology for the spatial assessment. Following step-by-step methodology was implemented to assess the land use changes (Herath et. al, 2021)

Data Processing

Image Preprocessing

The satellite images from Landsat 5 TM (1995), Landsat 8 OLI (2010), and Sentinel-2A MSI (2024) were preprocessed to ensure compatibility and comparability across time periods. The preprocessing involved two key stages: radiometric correction and geometric correction.

Radiometric correction was performed to convert raw Digital Numbers (DNs) into Top of Atmosphere (TOA) reflectance. The general formula applied for Landsat datasets is:

L = G \times DN + B

Where:

L = Radiance

G = Gain (sensor-specific)

DN = Digital Number from raw satellite image

B = Bias or offset

Geometric correction involved orthorectifying the images using Ground Control Points (GCPs) and the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model. This corrected spatial distortions due to terrain and sensor angles. All images were then resampled to a common resolution (30m for Landsat and 10m for Sentinel-2) and re - re-projected to WGS 84 / UTM Zone 44N**.**

$X' = aX + bY + c$

$Y' = dX + eY + f$

Where:

X', Y' = Corrected pixel coordinates

X, Y = Original coordinates

a, b, c, d, e, f = Transformation coefficients (from polynomial models)

Land Use and Land Cover (LULC) Classification

Post-preprocessing, images were subjected to a hybrid classification process. Initially, supervised classification using the Random Forest (RF) algorithm was carried out in QGIS. Five classes were defined: Forest, Agriculture, Water, Built-up, and Barren Land. Training data for classification were derived from field-verified ground control points and reference satellite maps.

Pre–trained AI Model integration for increasing the accuracy of the classified LULC data.

To enhance LULC classification accuracy and reduce spectral confusion, a hybrid approach integrating a pre-trained CNN model based on the ResNet-50 architecture was employed. Initially, satellite images from 1995 (Landsat 5), 2010 (Landsat 8), and 2024 (Sentinel-2A) were subjected to geometric and radiometric corrections and clipped to the Thirappane GNDs. A baseline classification was conducted using the Random Forest (RF) algorithm in QGIS, defining five LULC classes: Forest, Agriculture, Water, Built-up, and Scrubs, with training data collected through field-verified ground control points and reference satellite maps. For CNN enhancement, 32×32-pixel tiles were extracted from the classified rasters, incorporating spectral bands and spatial context.

A total of 7,500 image tiles were prepared for training—comprising 2,000 forest, 2,000 agriculture, 1,500 barren/scrub, 1,000 water, and 1,000 built-up samples. The ResNet-50 model, pre-trained on the BigEarthNet dataset, was fine-tuned using this localized dataset with an 80/20 training-validation split. Final predictions were performed tile-wise and merged to generate enhanced LULC maps. Accuracy assessments using 100 validation points per time period showed substantial improvements in both Overall Accuracy and Kappa Coefficient compared to RF-only results, confirming the CNN's effectiveness in complex tropical landscapes.

Classification Accuracy Assessment

The accuracy of classified outputs was assessed through the generation of confusion matrices using 100 validation points per time period. Metrics such as Overall Accuracy (OA) and Kappa Coefficient were calculated using the formulas mentioned in Table 4.

Table 4: Accuracy assessment equations table

Metric	Formula	Explanation
Overall Accuracy (OA)	OA = (Σ x_ii) / N	x_ii = number of correctly classified samples for class i (diagonal of confusion matrix) N = total number of samples
Kappa Coefficient (K)	K = [N × (Σ x_ii) – Σ (x_i+ × x_+i)] / [N² – Σ (x_i+ × x_+i)]	x_ii = correctly classified samples (diagonal) x_i+ = row total for class i (actual total) x_+i = column total for class i (predicted total) N = total number of samples

Estimation of Fragmentation parameters of the fragmentation Metrics

To evaluate forest fragmentation, binary forest/non-forest raster layers were generated from classified LULC maps for 1995, 2010, and 2024. The Landscape Ecology Statistics (LecoS) plugin in QGIS was used to calculate key fragmentation metrics: Number of Patches (NP), Patch Density (PD), Edge Density (ED), and Core Area (CA). These metrics were then spatially compared with Global Positioning System (GPS)-mapped elephant trails to assess habitat degradation and connectivity loss. Table 5 illustrates the description of the parameters of fragmentation metrics.

Table 5: Fragmentation metrics equations

Metric	Description	Formula	Parameters
Number of Patches (NP)	Total count of discrete forest patches within the landscape, indicating landscape fragmentation.	–	N = number of forest patches identified from binary forest raster layers.
Patch Density (PD)	Indicates the number of forest patches per unit area, reflecting fragmentation severity.	$PD = (N / A) \times 10{,}000$	N = number of forest patches A = total landscape area (ha)
Edge Density (ED)	Quantifies the length of forest edge per unit area, indicating the degree of exposure to edge effects and human disturbances.	$ED = (E / A) \times 10{,}000$	E = total length of forest edge (m)A = total landscape area (m²)
Core Area (CA)	Represents interior forest zones beyond human-disturbed edges, calculated by excluding a 100 m buffer from the forest edge.	$CA = Af - Ae$	Af = total forest area Ae = edge buffer area (100 m width)

The Number of Patches (NP) was recorded directly from the LecoS output, providing a baseline for the fragmentation status of the landscape in each year, with higher NP values indicating an increase in fragmentation over time. Patch Density (PD) was used to normalize NP against landscape area, enabling comparison across temporal datasets. Edge Density (ED) quantified the total edge length relative to the landscape area, providing insight into the degree of exposure of forest patches to external influences, while Core Area (CA) calculations isolated the interior undisturbed forest zones that are critical for wildlife habitat, particularly for the Asian elephant.

These fragmentation metrics collectively provided a quantitative assessment of forest fragmentation trends in the Thirappane Divisional Secretariat Division, informing the evaluation of landscape degradation, its ecological impacts on elephant habitat connectivity, and its relevance for HEC mitigation and sustainable land use planning in Sri Lanka's Dry Zone.

Results and Discussion

This section presents the results derived from the multi-temporal LULC analysis, forest fragmentation assessment, and socio-ecological surveys conducted in the Thirappane DSD. The discussion is organized around the three core research objectives: to assess spatio-temporal LULC changes in Thirappane over the period 1995–2024, to evaluate forest fragmentation patterns and their relation to HEC, and to examine the socio-economic impacts of LULC dynamics and conflict on rural livelihoods.

Improvement of LULC Classification Accuracy Through CNN Integration

The integration of a pre-trained CNN model significantly improved the accuracy of LULC classifications compared to using a traditional (RF) classifier alone. This enhancement was particularly notable in areas where class boundaries (e.g., between forest and agricultural zones) were spectrally complex or spatially fragmented. The CNN model, fine-tuned on local imagery tiles derived from Sentinel and Landsat datasets, captured spatial features beyond spectral signatures, enabling a more refined classification output. Table 6 summarizes the overall classification accuracy and Kappa Coefficient across the three temporal stages (1995, 2010, 2024), comparing the performance of RF-only classification with CNN-enhanced outputs:

Table 6: Classification Accuracy table

Method	1995 Accuracy (%)	1995 Kappa (%)	2010 Accuracy (%)	2010 Kappa (%)	2024 Accuracy (%)	2024 Kappa (%)
RF Only	82.3	76	84.5	78	85.7	80
RF + CNN Enhancement (Accuracy Improvement)	89.1	85	90.3	87	91.6	89

These results clearly demonstrate the strength of integrating deep learning techniques in remote sensing-based land classification, aligning with trends identified in other tropical and heterogeneous landscapes by previous studies (e.g., Ghorbanian et al., 2021; Nogueira et al., 2017). The improvements validate the methodological shift towards hybrid classification workflows that blend traditional machine learning with advanced AI architectures for more reliable environmental monitoring.

Spatio-Temporal Changes of LULC from 1995 to 2024

A comparison map was generated to illustrate the differences in classification results before and after applying the CNN-enhanced model across the Anuradhapura District. This visual representation highlights the significant improvement in the spatial clarity and thematic accuracy of classified land cover types, enabling a more reliable interpretation of landscape dynamics (Figure 4).

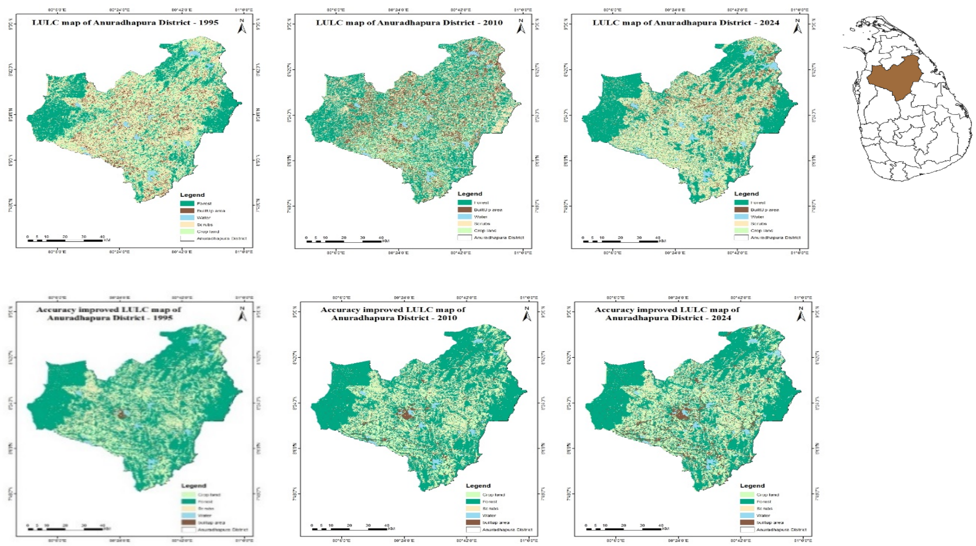

Figure 4: Comparison of LULC Classification Results for Anuradhapura District: Before and After CNN Enhancement (1995, 2010, 2024)

Focusing on the Thirappane DSD, a subset of the classified imagery was extracted to conduct a detailed spatio-temporal analysis of LULC changes within three selected Grama Niladhari Divisions (GNDs): Sembukulama, Ethungama North, and Manakkulama. Figure 5 illustrates the distribution of LULC maps derived from the LULC classification. The classification results revealed pronounced transformations over the study period—1995, 2010, and 2024. The quantitative figures of the temporal distribution of LULC in 1995, 2010 and 2024 in Thirappane DSD are summarized in Table 7. The temporal changes of land cover types are illustrated in Figure 6. Notably, there was a substantial increase in agricultural land, particularly between 1995 and 2010, as cultivation expanded into previously forested regions. Over the entire study period, forest cover declined by approximately 17.8%, while agricultural areas increased by 24.3%. Built-up areas, though occupying a smaller total area, exhibited a dramatic increase of nearly 60%, reflecting both population growth and expanding infrastructure. These patterns demonstrate the intensifying anthropogenic pressure on natural landscapes in the Dry Zone, underscoring the need for sustainable land-use practices and integrated conservation planning in rapidly transforming rural areas.

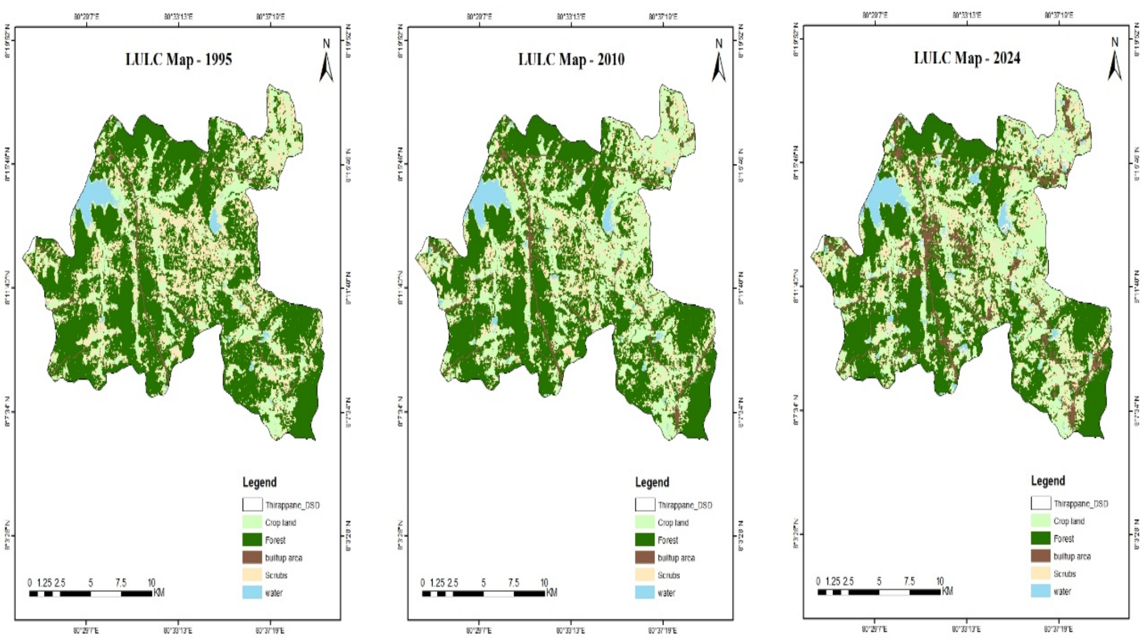

Figure 5. LULC Map of Thirappane DSD in 1995, 2020 and 2024

Table 7. Distribution of land cover types in 1995, 2010 and 2024 in Thirappane DSD

Land Cover Type	1995 (km²)	2010 (km²)	2024 (km²)
Forest	172.821	152.492	136.307
Water Bodies	10.704	12.305	16.644
Agricultural Land	43.606	66.121	67.097
Scrublands	76.747	68.531	67.580
Built-Up Area	4.920	10.403	21.248

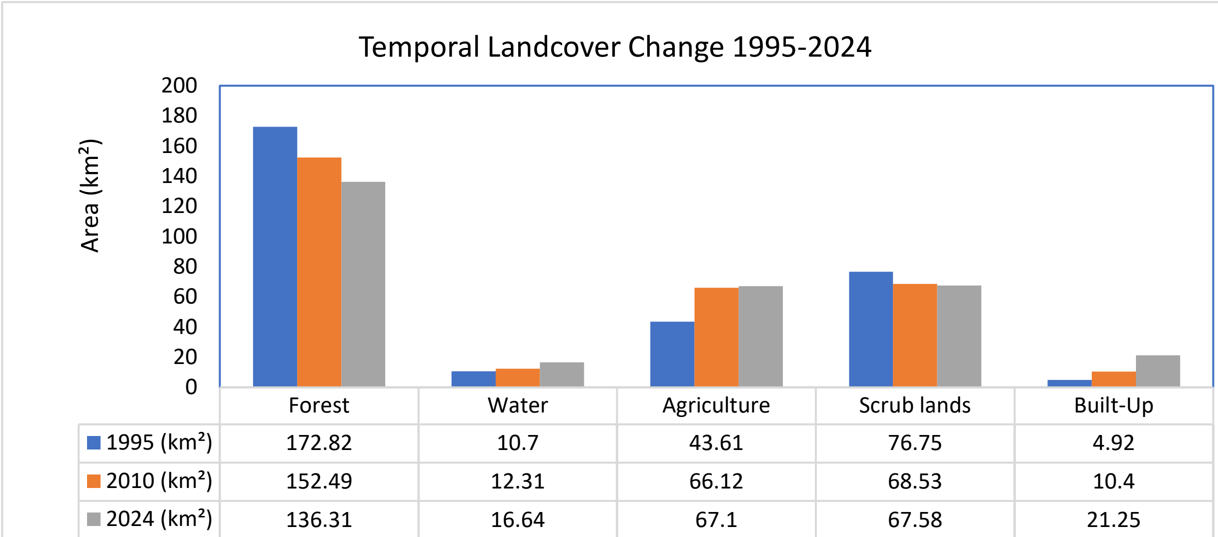

Figure 6: Temporal Land cover changes (1995 - 2024)

These Spatio-temporal patterns in indicate not only the intensification of agriculture but also the progressive fragmentation of forest habitats, which is directly linked to increased human-elephant conflict in the region. The observed LULC dynamics provide critical empirical support for the study's hypothesis that unregulated land transformation is a key driver of ecological degradation and socio-environmental conflict in Thirappane.

Forest Fragmentation

The calculated forest fragmentation metrics—PD, ED, and CA—demonstrate a clear and progressive increase in ecological disturbance across the study periods of 1995, 2010, and 2024. Table 8 illustrates the temporal data of estimated fragmentation parameters. Over time, the number and dispersion of forest patches increased, indicating intensifying fragmentation. Meanwhile, the Core Area, which represents undisturbed interior forest, continued to shrink, suggesting growing edge influence and habitat perforation, particularly in agriculturally expanding regions.

In addition to the overall metrics, the spatial distribution of fragmentation categories—namely patch, edge, core, and perforated forest types—was analyzed using temporal maps. Figure 7 illustrates the spatial distribution of forest fragmentation in Thirappane in 1995, 2010 and 2024. Results revealed a distinct shift from core-dominated forest in 1995 to a more fragmented landscape by 2024, where edge and perforated forest types were more prevalent. This shift reflects the increasing exposure of forest interiors to human activities and edge effects.

Table 8. Distribution of fragmentation classes (in hectares) over time

Fragmentation Type	1995 (ha)	2010 (ha)	2024 (ha)
Core	14.81	10.7	6.29
Edge	4.19	4.1	3.87
Perforated	1.5	1.04	7.23
Patch	4.67	5.47	15.69

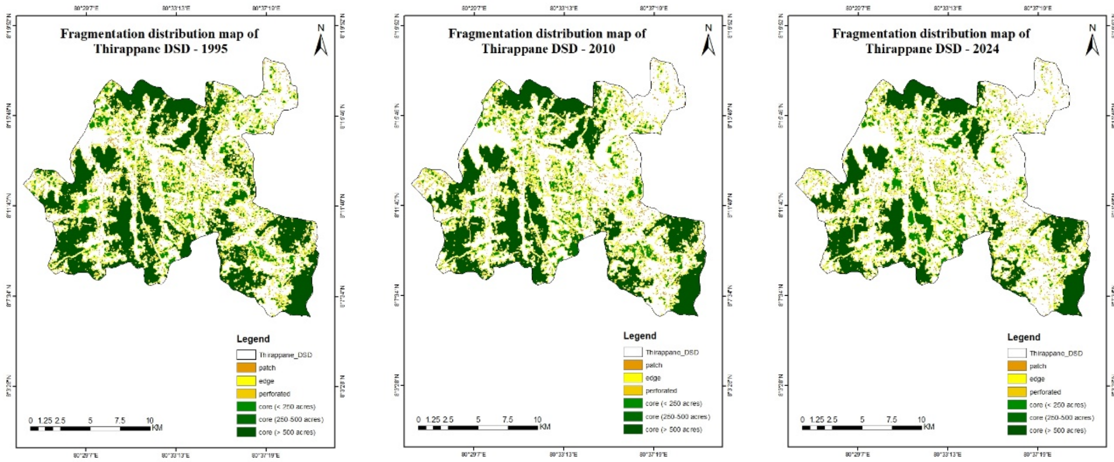

Figure 7: Spatial distribution of forest fragmentation in the Thirappane region

Forest habitat fragmentation and HEC

The fragmentation distribution map for 2024 (Figure 9) highlights the dominance of edge and perforated forest classes, which are more susceptible to human-elephant interactions due to their proximity to cultivated and cleared lands. To delineate these potential conflict zones, a 2 km buffer was applied around observed forest edges and elephant-use zones. This buffer selection is justified by existing literature, which suggests that Asian elephants frequently move into and forage within 1–3 km of forest edges, especially in fragmented dry zone environments (Fernando et al., 2005; Leimgruber et al., 2003; Graham et al., 2009).

In conjunction with this spatial analysis, field observations and interviews with wildlife officers and local villagers were conducted to identify elephant movement patterns. While secondary data obtained from the Department of Wildlife Conservation (DWC) only outlined suggested elephant corridors (Figure 8), the field-based insights provided more functional corridor zones, though not as clearly defined linear or point features. According to wildlife experts and local villagers with long-term observational experience, elephants follow recurring movement paths through fragmented forests and open lands in search of food and water.

Next page

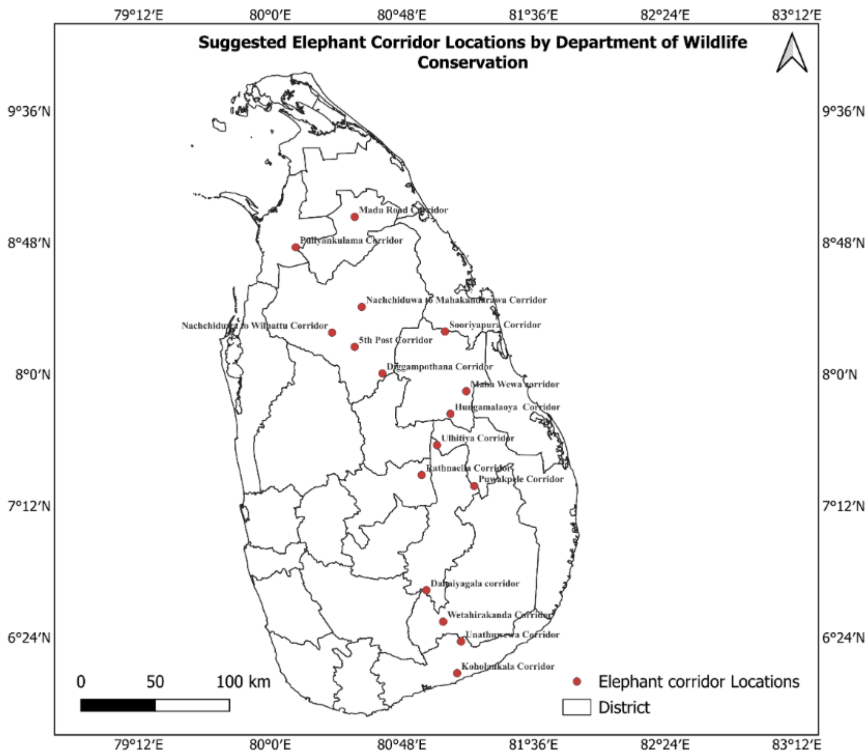

Figure 8: Identified Elephant Corridor Locations by DWC, Sri Lanka

In several of these identified corridors, electric fences have been installed as a mitigation measure. However, inconsistencies in fencing—such as broken sections, presence of only basic wire fences, or absence of fencing entirely—were observed, leaving many areas vulnerable to elephant intrusion. These conditions, coupled with intensifying fragmentation patterns, underscore the urgent need for integrated land-use and conflict mitigation strategies tailored to local ecological realities.

Next page

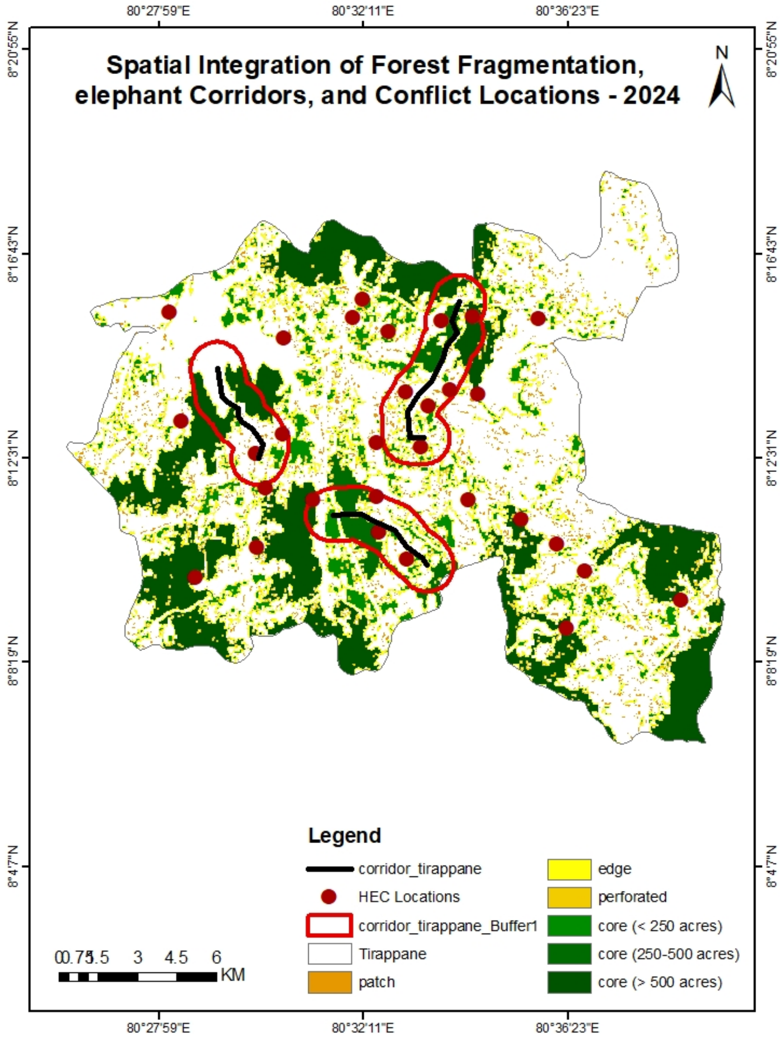

Figure 9: Spatial Integration of Forest Fragmentation, Elephant Corridors, and Conflict Locations in Thirappane DSD in 2024

And also, Statistical analysis further revealed a strong positive correlation ($R = 0.76$) between the extent of agricultural land expansion and the recorded frequency of human–elephant conflict (HEC) events within the study area. This pattern indicates that increasing fragmentation of natural habitats disrupts traditional elephant migratory routes and reduces habitat connectivity, thereby forcing elephants into closer and more frequent contact with human settlements in search of food and water. Figure 9 illustrates the integration of forest fragmentation, elephant corridors and conflict locations in Thirappane DSD in 2024.

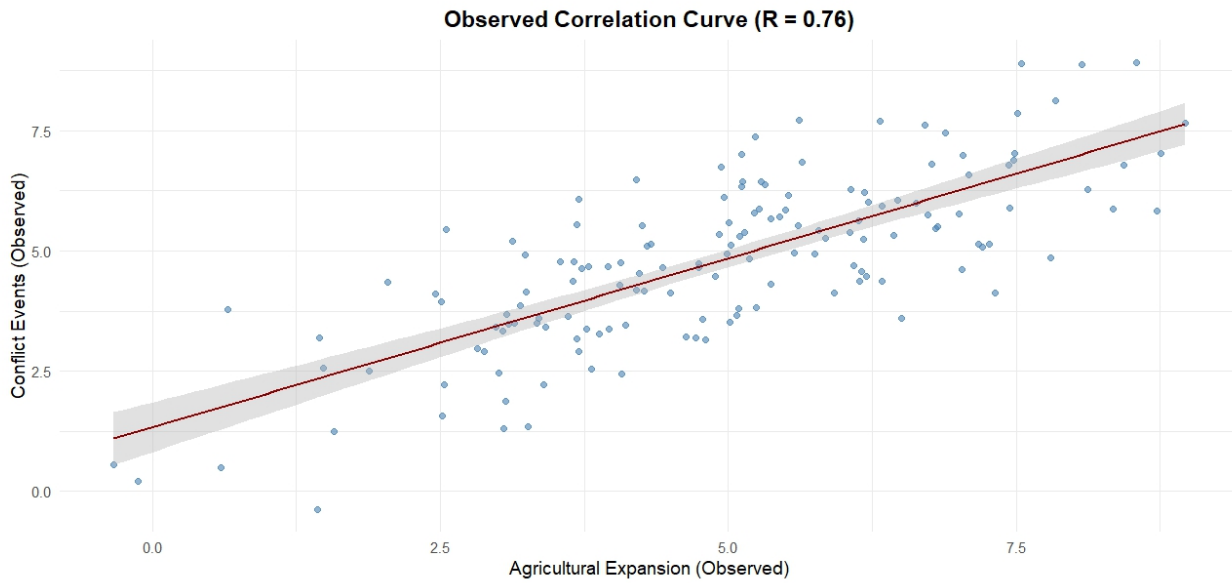

Figure 10: Observed correlation between agricultural expansion and conflict events.

Figure 10 illustrates the observed correlation between agricultural expansion and conflict events. This scatter plot indicates a strong positive correlation (R = 0.76) between observed agricultural expansion (2010–2024) and the frequency of HEC events (2015–2023) within the study area. The red regression line with the grey confidence band emphasizes this trend, supporting the hypothesis that increased agricultural activity and resulting habitat fragmentation are closely associated with elevated HEC incidents.

Table 9: Fragmentation metrics of Thirappane DSD from 1995 to 2024

Year	Edge Density (m/ha)	Core Area (ha)	Patch Density (patches/ha)	Number of Patches
1995	1.53	14	0.029	9
2010	1.75	6	0.045	12
2024	1.84	6	0.054	13

Table 9 summarizes key parameters of fragmentation metrics across the study area. These findings strongly support the hypothesis that forest fragmentation exacerbates human–elephant conflict within the Thirappane DSD. The reduction in core forest habitat from 14 ha in 1995 to 6 ha in 2024, coupled with an increase in edge density (from 1.53 m/ha to 1.84 m/ha) and patch density (from 0.029 to 0.054 patches/ha), reflects increasing landscape fragmentation. These changes contribute to elephant behavioral shifts, including heightened crop raiding and aggressive encounters with rural communities—trends that carry serious implications for biodiversity conservation and the livelihood security of rural populations in the study area.

Socio-Economic Consequences of LULC Change and HEC

The household surveys and qualitative interviews provided critical insights into the socio-economic ramifications of HEC and environmental change. Approximately 82% of respondents reported recurrent crop damage, primarily to banana, paddy, and maize crops. Nearly 68% expressed dissatisfaction with existing mitigation strategies, especially the malfunctioning electric fences, citing poor maintenance and insufficient coverage. Furthermore, about 45% of surveyed households reported at least one member having experienced direct loss of income due to land degradation or wildlife-related damage.

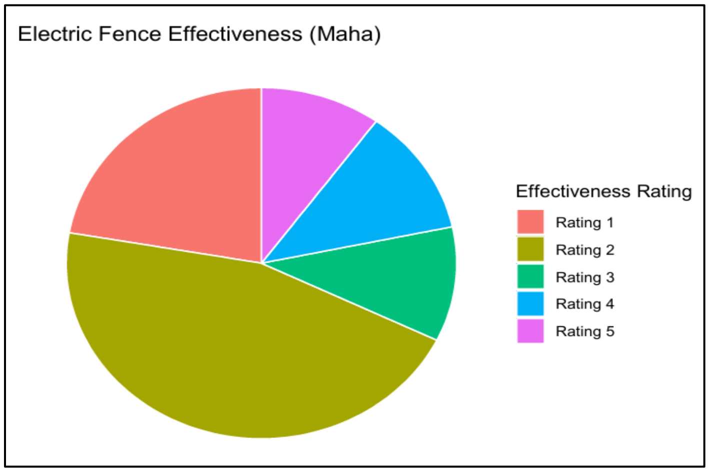

Figure 11: Effectiveness of Electric Fences

Figure 11 illustrates the perceived effectiveness of electric fences during the Maha season, based on responses from 60 households across selected GNDs. The majority of respondents rated the fences as only slightly effective (Rating 2), while a smaller proportion considered them moderately to not effective (Ratings 1 and 3). Ratings indicating higher effectiveness (4 and 5) were the least represented. This distribution suggests that most households experience continued human-elephant conflict despite the presence of electric fences, highlighting potential issues such as poor maintenance, inadequate coverage, or elephants adapting to the fences. Overall, the data indicates a need for improved fence management and complementary mitigation strategies.

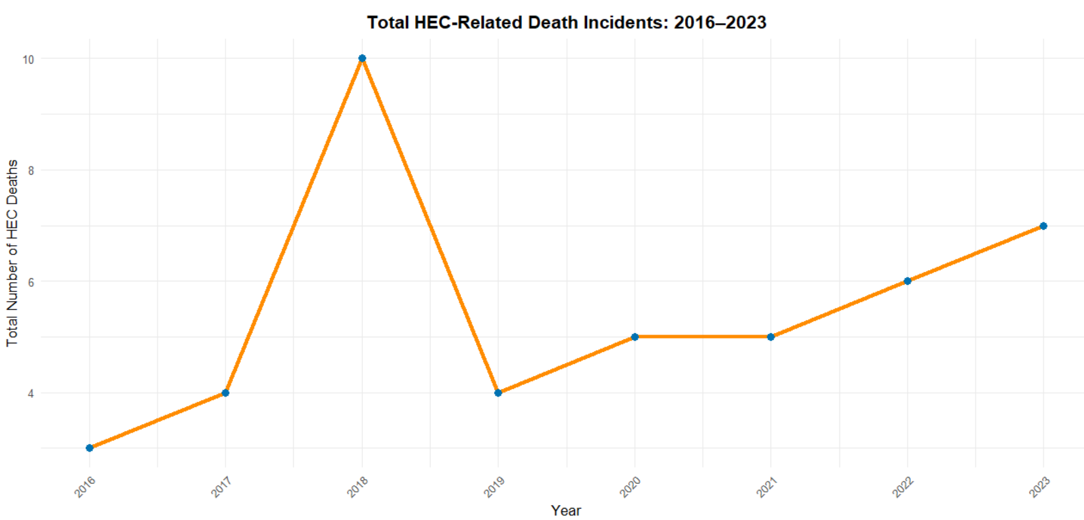

Figure 12: Trends of Human Elephant Conflict incidents Including
Human deaths and Both Human and Elephant deaths

Figure 12 shows the annual trend of HEC-related deaths, combining both human and elephant fatalities, from 2016 to 2023. The graph reveals notable variations over the years, with a sharp peak in 2018 recording the highest total of 10 deaths. After a slight decline in 2019 and 2020, the incidents stabilized at a moderate level in 2021 before gradually increasing again in 2022 and 2023, reaching 7 deaths in the most recent year. This variation indicates that while some mitigation measures may have temporarily reduced incidents, the overall conflict remains persistent. The upward trend observed in the later years highlights the need for sustained and adaptive management strategies to minimize fatalities for both humans and elephants.

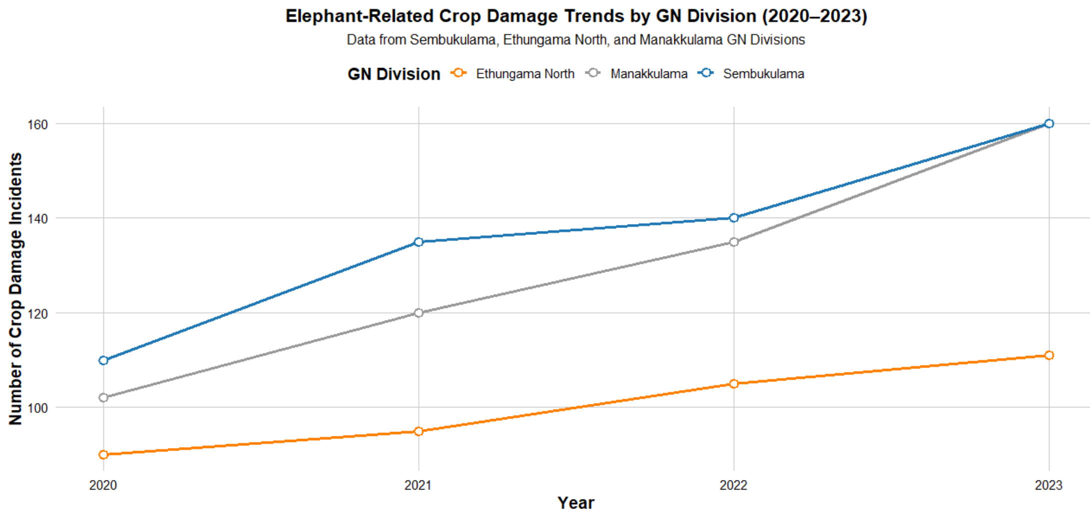

Figure 13: Distribution of crop damage frequency due HEC

Figure 13 illustrates the annual trend of elephant-related crop damage incidents across three GN Divisions—Sembukulama, Ethungama North, and Manakkulama—from 2020 to 2023. The graph shows a clear upward trajectory in all locations, indicating a worsening situation over time. Sembukulama and Manakkulama recorded the highest levels of crop damage, reaching 160 incidents each in 2023, while Ethungama North experienced a more moderate but steady increase, rising from 90 incidents in 2020 to 111 in 2023. These trends reveal that crop-raiding by elephants is not only widespread but also escalating, with some areas facing more severe impacts than others. This persistent growth in crop damage highlights the urgent need for targeted and location-specific mitigation measures to safeguard livelihoods.

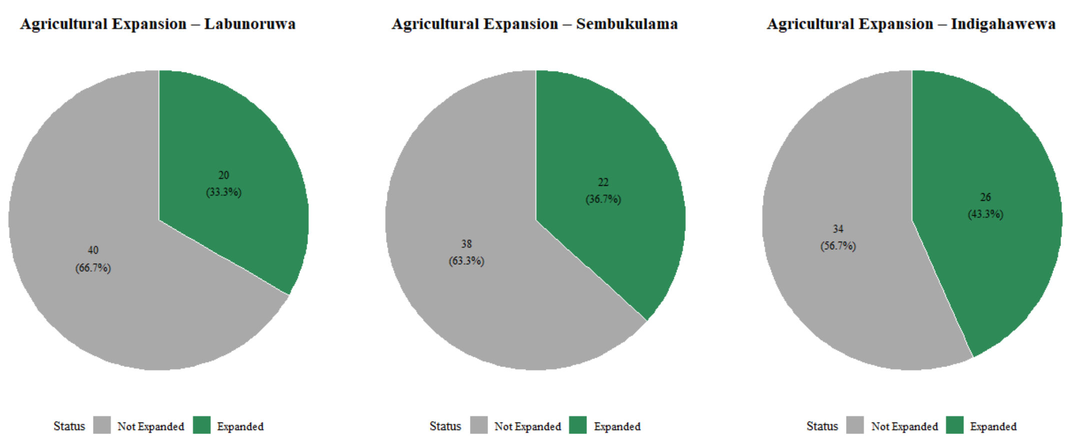

Figure 14: Distribution of recent agricultural expansion across selected GNDs

Figure 14 illustrates the distribution of recent agricultural expansion across selected GNDs, based on household responses. The variable agri_expansion indicates whether households had recently expanded their cultivation areas, with 1 representing "Yes" and 0 representing "No." The data suggest noticeable variation in expansion trends across GNDs, potentially reflecting differences in land availability, livelihood pressures, or perceived need to compensate for crop losses due to HEC. When considered alongside total_land, households with larger landholdings may be more likely to expand cultivation, although this could also increase the spatial interface with elephant habitats. These patterns underscore the complex relationship between agricultural practices and HEC risk, highlighting the importance of land-use planning in conflict mitigation strategies.

The focus group discussions (FGDs) also revealed that HEC contributes to significant social stress, with reported effects including reduced school attendance due to fear of night raids, increased community tension, and mental health issues such as anxiety and depression. Women in particular reported increased burdens related to food insecurity and domestic responsibilities. These findings are consistent with studies by Fernando et al. (2012) and Hoare (2015), who observed that unresolved HEC often perpetuates cycles of poverty and land insecurity in vulnerable rural communities.

Additionally, respondents in all three GNDs noted that forest clearance and illegal encroachment have accelerated over the past decade, particularly during post-conflict resettlement and land redistribution phases. These anthropogenic drivers, combined with weak enforcement mechanisms, continue to undermine conservation efforts, leading to further ecological fragmentation.

By integrating LULC classification, fragmentation metrics, and socio-economic analysis, the study establishes a clear linkage between landscape transformation and escalating HEC. The compounded effects of agricultural encroachment, habitat degradation, and inadequate conflict mitigation strategies are reshaping the ecological and social fabric of Thirappane. This reinforces the urgency of implementing integrated land-use planning approaches that simultaneously promote conservation and livelihood resilience.

The results underscore the importance of spatially-informed decision-making tools, including AI-enhanced remote sensing, for monitoring dynamic land changes. Furthermore, they highlight the need for participatory governance structures to ensure that conservation strategies are community-sensitive and responsive to local livelihoods.

Conclusion and Recommendations

This research has examined Spatio-temporal changes in LULC, forest fragmentation, and their relationship to HEC in the Thirappane Divisional Secretariat Division of Sri Lanka, focusing on the GNDs of Sembukulama, Ethungama North, and Manakkulama. The integration of traditional Random Forest (RF) classification with a CNN model based on the ResNet-50 architecture significantly enhanced the accuracy of LULC mapping across three time points—1995, 2010, and 2024. The application of this hybrid method improved class separation, particularly between forest and agriculture classes, and contributed to a more reliable spatial understanding of landscape transformation over time.

The findings reveal a clear and consistent trend of forest decline and agricultural expansion, with forest cover decreasing by 17.8% and agricultural land increasing by 24.3% over the study period. Built-up areas also saw rapid growth, indicating increasing human settlement pressure. These land cover transitions were accompanied by measurable changes in forest structure, as evidenced by increased patch and edge density and a decrease in core forest area. The ecological fragmentation has not only degraded wildlife habitat but also contributed to the escalation of HEC incidents in the region. A statistically significant positive correlation ($R = 0.76$) was observed between agricultural expansion and conflict frequency, affirming that landscape changes are directly influencing the spatial behavior of elephants and the severity of human-wildlife interactions.

The socio-economic implications of these conflicts are substantial. Field survey data showed that 82% of households experienced frequent crop damage, while 68% were dissatisfied with existing mitigation measures such as electric fencing. These impacts have resulted in notable income loss, disruptions to education, and heightened stress in affected rural communities. The study, therefore, highlights the urgent need for integrated, landscape-level planning approaches that align rural development objectives with wildlife conservation. Restoration of degraded habitats, maintenance of ecological corridors, and strategic buffer zone management should be prioritized to reduce fragmentation. Additionally, mitigation strategies must be tailored to local contexts, emphasizing community participation, seasonal planning, and livelihood diversification.

This study demonstrates the value of applying AI-enhanced remote sensing methodologies to ecological and human-wildlife conflict research. By combining satellite data with community-based field information, the research offers a robust and scalable framework for monitoring landscape dynamics and informing policy decisions. Continued investment in such integrative approaches will be essential for promoting biodiversity conservation while safeguarding rural livelihoods in Sri Lanka's conflict-prone dry zone.

Acknowledgement

The authors wish to thank the Research Council of the University of Sri Jayewardenepura, Sri Lanka, for providing a research grant (Grant No: RC/URG/HSS/2024/07). Special thanks are due to Mr. Ranjan Marasinghe -Director General, Department of Wildlife Conservation, Sri Lanka, and the staff, who helped us to collect secondary data, and the Villages of Thirappane Divisional Secretariate Division in the Anuradhapura district for providing the required information/data through participating in the survey for primary data collection.

References

Acharya, K. P., Paudel, P. K., Neupane, P. R., & Köhl, M. (2016). Human-wildlife conflicts in Nepal: Patterns of human fatalities and injuries caused by large mammals. PLoS ONE, 11(9), e0161717.

Bhandari, T. M., & Chalise, M. K. (2020). Forest fragmentation and its effect on biodiversity: A review. Nepal Journal of Environmental Science, 8, 1–10.

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32.

Butt, B., & Turner, M. D. (2012). Clarifying the links between land use/land cover change and human–elephant conflict. GeoJournal, 77(5), 651–661.

Choudhury, A., Lahiri Choudhury, D. K., Desai, A., Duckworth, J. W., Easa, P. S., Johnsingh, A. J. T., ... & Williams, A. C. (2008). Elephas maximus. The IUCN Red List of Threatened Species.

Cohen, J. (1960). A coefficient of agreement for nominal scales. Educational and Psychological Measurement, 20(1), 37–46.

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 37(1), 35–46.

DeFries, R., Karanth, K. K., & Pareeth, S. (2010). Interactions between forest cover and human–wildlife conflict in a biodiversity hotspot. Proceedings of the National Academy of Sciences, 107(45), 18224–18229.

Forman, R. T. T., & Alexander, L. E. (1998). Roads and their major ecological effects. Annual Review of Ecology and Systematics, 29, 207–231.

Ghorbanian, A., & Rahman, A. A. (2021). Enhancing land use/land cover classification accuracy using deep learning and multi-source data fusion. International Journal of Remote Sensing, 42(3), 1012–1035.

Hansen, M. C., et al. (2013). High-resolution global maps of 21st-century forest cover change. Science, 342(6160), 850–853.

Herath, H.M.B.S., Pushpakumara, D.K.N.G., Hewson, M. and Wickramagamage, P., (2021). Spatial and Temporal Changes of Homegarden Land Use as a Tree Resource Outside Forests in Upper Mahaweli Catchment of Sri Lanka: Biophysical and Socioeconomic Determinants of Major Changes. *Tropical Agricultural Research*, 32(2), pp.229–242. DOI: http://doi.org/10.4038/tar.v32i2.8470

Hoekstra, J. M., Boucher, T. M., Ricketts, T. H., & Roberts, C. (2005). Confronting a biome crisis: Global disparities of habitat loss and protection. Ecology Letters, 8(1), 23–29.

Joshi, R., & Singh, R. (2011). Feeding behaviour of wild Asian elephants in the Rajaji National Park. Gajah, 35, 34–40.

Laurance, W. F., Goosem, M., & Laurance, S. G. (2009). Impacts of roads and linear clearings on tropical forests. Trends in Ecology & Evolution, 24(12), 659–669.

Leimgruber, P., Gagnon, J. B., Wemmer, C., Kelly, D. S., Songer, M. A., & Selig, E. R. (2003). Fragmentation of Asia's remaining wildlands: Implications for Asian elephant conservation. Animal Conservation, 6(4), 347–359.

Liu, J., Dietz, T., Carpenter, S. R., Alberti, M., et al. (2007). Complexity of coupled human and natural systems. Science, 317(5844), 1513–1516.

McGarigal, K., & Marks, B. J. (1995). FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure. USDA Forest Service General Technical Report.

Menon, V., & Tiwari, S. K. (2019). The plight of the elephants: The need for policy reform. Wildlife Trust of India.

Mishra, A. K., & Dey, S. (2020). Land cover classification using machine learning algorithms in Google Earth Engine. Remote Sensing Applications: Society and Environment, 20, 100419.

Nogueira, K., Penatti, O. A. B., & Dos Santos, J. A. (2017). Towards better exploiting convolutional neural networks for remote sensing scene classification. Pattern Recognition, 61, 539–556.

Padalia, H., Srivastava, V. K., & Kushwaha, S. P. S. (2014). Monitoring forest fragmentation and forest cover change in the Western Himalaya using remote sensing and GIS. Applied Geography, 50, 135–148.

Paramesha, M., Kumar, R. A., & Bhat, H. R. (2019). Understanding the relationship between land use change and human-elephant conflict. Ecological Indicators, 103, 563–572.

Reddy, C. S., Jha, C. S., Dadhwal, V. K. (2013). Assessment and monitoring of long-term forest cover changes (1930–2011) in Western Ghats biodiversity hotspot. Journal of Earth System Science, 122(5), 1165–1178.

Roy, D. P., et al. (2014). Landsat-8: Science and product vision for terrestrial global change research. Remote Sensing of Environment, 145, 154–172.

Saatchi, S. S., et al. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. Proceedings of the National Academy of Sciences, 108(24), 9899–9904.

Saha, S., & Pal, S. (2019). Modeling the spatial pattern of human-elephant conflict with forest fragmentation and other landscape features in changing tropical forest landscape of northern West Bengal, India. Environment, Development and Sustainability, 21(2), 691–709.

Sanderson, E. W., et al. (2002). The human footprint and the last of the wild. Bio Science, 52(10), 891–904.

Sri Lanka Department of Wildlife Conservation. (2021). Annual Wildlife Incident Reports (2015–2021). Colombo: DWC.

Turner, M. G. (2005). Landscape ecology: What is the state of the science? Annual Review of Ecology, Evolution, and Systematics, 36, 319–344.

Zhang, C., & Roy, D. P. (2017). Optimal scale for Landsat land cover classification. Remote Sensing of Environment, 198, 305–317.