Geospatial and AI-Based Modelling to Assess Temporal and Spatial Dynamics of Forest Fragmentation.

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ABSTRACT: *The accuracy necessary for conducting precise temporal analyses and effectively extracting forest cover is often insufficient in traditional geospatial techniques used for assessing forest fragmentation. With an emphasis on examining the geographical and temporal dynamics of forest fragmentation in Sri Lanka's Anuradhapura District, the study addresses this issue by presenting a geospatial and artificial intelligence (AI) model intended to improve land use and land cover (LULC) classification accuracy. The major goal is to create a model that can be used to identify patterns of forest fragmentation and the main factors causing the loss of forests, all while offering practical conservation advice. With an overall accuracy of 92% in forest cover extraction, the AI-based model surpassed conventional techniques by integrating Convolutional Neural Networks (CNNs) with non-spatial data, aerial pictures, and medium-resolution satellite imagery data from sentinel – 2. Significant fragmentation was revealed through a temporal analysis conducted from 2004 – 2024 using classified satellite images processed by the developed AI model, in conjunction with the Landscape Fragmentation Tool, available in QGIS 3.38.2, which showed a 29.37% loss in core forest areas, an 82.61% increase in patch density, a 37.84% increase in edge density and a 25.93% increase in forest patches. The main factors contributing to the loss of forests were the spread of agriculture, population increase, and infrastructure. The study emphasizes the need for sustainable land management practices to prevent further degradation and shows how integrating AI and geospatial techniques can provide a robust framework for monitoring forest fragmentation. These findings provide important insights for focused conservation strategies.*

Keywords: Geospatial techniques, AI-based modeling, forest fragmentation, spatial and temporal dynamics

Introduction

Habitat fragmentation, the process of breaking up large, continuous habitats into smaller, isolated patches, is a pressing environmental issue with significant negative impacts on biodiversity, ecosystem services, and efforts to mitigate climate change. This phenomenon is primarily driven by human activities such as agricultural expansion, urban development, and infrastructure projects, which collectively disrupt natural landscapes and lead to a decrease in habitat connectivity (Wilcove et al., 1998). The impacts of habitat fragmentation are particularly acute in regions of high ecological value in Sri Lanka (Wijesinghe & Brooke, 2005).

The Anuradhapura District, covering approximately 7,179 square kilometers, is a region of considerable ecological and historical significance. However, recent analyses have documented a significant decline in forest cover, which decreased by about 29.37% from 2004 to 2024, with core forest areas shrinking to only 25% of their former extent (Authors, 2024). This period also saw an 82.61% increase in patch density, reflecting increased forest fragmentation, and a 37.84% rise in edge density, indicating a greater proportion of forest edge habitat compared to core forest areas. This loss of forest cover is largely attributed to increased land demand driven by population growth and socio-economic development. The population of Sri Lanka rose from approximately 745, 693 in 2001 to 860,575 and in 2012, and reached around 954,000 by 2021 (Department of Census and Statistics, 2012, 2022). This population growth has intensified pressures on land resources, leading to the conversion of forests into agricultural and urban areas.

The ecological consequences of habitat fragmentation are significant, as it often leads to smaller, isolated forest patches, which can pose threats to species that rely on large, continuous habitats. For example, species such as the Sri Lankan leopard (*Panthera pardus kotiya*) and the Asian elephant (*Elephas maximus*), both of which depend on extensive forested areas, can face increased threats due to fragmentation. This geographic isolation can contribute to challenges such as reduced genetic diversity, increased mortality, and difficulties in finding adequate resources, thereby placing these species at greater risk (Kumar et al., 2016). Additionally, fragmentation disrupts critical ecosystem services, including water regulation and soil protection, which are essential for maintaining regional environmental health (Newmark, 2008).

Traditional methods for analyzing LULC changes, such as satellite imagery interpretation combined with basic supervised classification techniques, have been used to study forest fragmentation. However, these conventional approaches often fall short in capturing the complex dynamics of fragmentation, particularly in areas with intricate land use patterns like Anuradhapura (Olofsson et al., 2014). These methods may struggle to accurately differentiate between forest edges and core areas, leading to less precise assessments of fragmentation and its ecological impacts (Wulder et al., 2018).

Recent advancements in AI and machine learning provide promising solutions to address these limitations. CNNs have shown significant improvements in LULC classification by leveraging large datasets and sophisticated algorithms to detect complex patterns that simpler models might miss (Zhao et al., 2019). CNNs are particularly suited for analyzing the intricate land use patterns in Anuradhapura, where various types of land use are closely interconnected (Liu et al., 2020). By incorporating AI techniques into the analysis, it is possible to achieve higher accuracy in classifying LULC and assessing forest fragmentation.

The primary objective of this study is to overcome the limitations of conventional geospatial methods by developing and applying an advanced geospatial and AI-based model for more accurate LULC classification and forest fragmentation analysis in Anuradhapura District. This research aims to enhance the precision of forest cover classification and evaluate fragmentation patterns over a 20-year period, from 2004 to 2024. Specific objectives include identifying forest fragmentation patterns using the LFT, determining attributes of the landscape such as core forest and patch forest, and uncovering the primary land use changes driving fragmentation. The study will utilize medium-resolution optical satellite imagery, aerial photographs, and non-spatial data to achieve these objectives.

By employing advanced geospatial and AI techniques, this research seeks to provide a comprehensive understanding of the factors driving forest fragmentation in Anuradhapura. The insights gained from this study are expected to inform effective conservation strategies and policy formulation, helping to better manage natural resources and protect the district’s rich biological diversity (Turner et al., 2013). Through a detailed analysis of spatial and temporal fragmentation patterns, this work aims to contribute to the development of targeted conservation measures that address the specific needs of the district's fragmented landscapes.

Literature Review

LULC Dynamics and Forest Fragmentation

Forest fragmentation means that big, several connected forest areas are separated and become smaller by human actions like farming, deforestation, constructing towns or cities and other essential facilities. Whenever this phenomenon occurs, it has further implications in our quest to understand the variety as well as distribution of species, the functions of ecological services, and in managing impacts of climate change. Landscape fragmentation leading to habitat fragmentation, this making edge effects higher and core forest areas lower is difficult for wildlife especially those that require large unbroken areas of habitats. For example, the Sri Lankan leopard (*Panthera pardus kotiya*) and Asian elephant (*Elephas maximus*) species have large habitat requirements that provide essential resources to support their biological needs and are thus most sensitive to fragmentation (Haddad et al., 2015). Based on the findings of Kumar et al. (2016) isolation resulting from fragmentation negatively affects genetic factor pool, higher mortality addition to the limitation of resources. In general, fragmentation reduces the functions of the landscape's integrity by interrupting ecosystem services such as water regulation and soil conservation in addition to compromising litter and carbon storage, which exacerbates environmental degradation (Newmark, 2008).

Other studies that have been undertaken in regard to forest fragmentation have very strongly emphasized on the impact on the general demographic trends or rather the suffrage of the overall species. Habitat fragmentation, according to Fahrig's assertion in 2003, has impacts on species richness and produces both direct and indirect negative effects on the population sizes of species, making them more susceptible to vulnerability in extinction. Consequences as diverse as these require a more comprehensive view of fragmentation and its effects and the formulation of proper countermeasures.

Conventional Methods for Land Use Land Cover Classification.

Conventional methods for LULC classification, including Maximum Likelihood Classification (MLC), Decision Tree classifiers, and k-Nearest Neighbors (k-NN), have long been important to remote sensing due to their simplicity and reliance on spectral information and basic statistical models. The accuracy of these methods generally ranges from 65% to 75%, heavily influenced by the complexity of the landscape. For example, MLC, which assumes a normal probability distribution among different classes, has been noted to achieve around 70% classification accuracy in relatively homogeneous land cover areas (Lu & Weng, 2007). However, in more heterogeneous environments, such as urban areas where land types often exhibit similar spectral characteristics, MLC can encounter issues with spectral confusion, thus compromising accuracy. Decision Tree classifiers tend to perform slightly better, with reported accuracy around 75%, especially when enhanced with additional data such as topographical or texture information (Pal & Mather, 2003). Nevertheless, these conventional techniques remain limited in their ability to detect subtle variations in land cover types, particularly in complex landscapes (Rodriguez-Galiano et al., 2012).

The advent of machine learning and AI has significantly transformed the landscape of LULC classification, leading to remarkable improvements in accuracy. Algorithms such as Random Forest (RF) and Support Vector Machines (SVM) have surpassed the performance of traditional methods, achieving accuracy levels above 90% in various studies (Rodriguez-Galiano et al., 2012). For instance, RF has shown exceptional capability in managing large, complex datasets and capturing intricate spatial relationships, especially in Mediterranean landscapes, where it has been reported to exceed 90% accuracy. SVM also excels in addressing non-linear relationships among land cover types, achieving accuracies beyond 85% (Pal & Mather, 2003). The emergence of deep learning techniques, particularly CNNs, has further elevated classification accuracy, often surpassing 95%, particularly in urban or forested environments characterized by high-resolution imagery (Nogueira et al., 2017). These advanced AI methodologies are increasingly favored by researchers for their efficacy in overcoming the limitations of traditional methods, making them invaluable for regions with mixed or overlapping land cover types. This shift towards integrating machine learning and AI into LULC classification signifies a pivotal change in the field, with an emphasis on enhancing the accuracy and reliability of land cover mapping, thus positioning these modern algorithms as crucial tools for future remote sensing studies.

Developed Strategies of AI and Machine Learning for LULC Classification

With the development of new and emerging algorithms in machine learning within the recent years especially the CNNs, the classification of LULC has been areas. Recurrent CNNs have been shown to excel in constructing high-level features and have been employed for interpretation of various large datasets, identification of intricate relation patterns that would be disregarded by other approaches. According to Zhao et al. (2019) CNN has the capacity to enhance the performance of LULC classifications through the object detection. Due to the availability of satellite data, CNNs are capable of performing feature extraction and arrive at better classification results due to better discrimination of land covers.

The utilization of CNNs, as was the Ultralytics YOLOv8 model applied in this paper, is one of the major developments in geospatial science. CNNs have the ability to classify several land-use categories with high precision through training on labelled data which offer a better perspective of fragmentation processes Zhao et al. (2020). It is crucial to use such models especially when dealing with satellite and aerial imagery since the generation of the forest and the non-forest area map can be easily done such that even the small patches which otherwise would be overlooked by other traditional method such as the line transect method can be easily identified (Cutler et al., 2007).

Integrated AI and Machine Learning Approaches for Analyzing LULC Dynamics and Forest Fragmentation

The incorporation of artificial intelligences-based models with more conventional geographical information system approaches is as a result a strong tool for analyzing forest fragmentation. Hansen et al. (2013) have proved that the advancement of the geographical remote sensing technology in conjunction with sophisticated techniques in machine learning model can increase the measurement of errors in the assessment of forest cover. In this study, accuracy of the AI-based LULC classification model was established at 92% while F1-Score calculated at 0. 89, Thereby stressing on the effectiveness of integrating artificial intelligence with geographical information systems.

Due to the capacity of AI models to handle large data sets with efficiency and accuracy it has become a crucial tool in the analysis of forest fragmentation. They noticed that through applying the tools like CNNs and the LFT the researchers can develop more precise and intricate maps of the cover of forest that will help with the choice of a correct strategy of the protection (Pouliot et al., 2014). The use of the above-mentioned methods enhances a complete approach towards characterizing both the spatial and temporal distribution of forest fragmentation, which enhances understanding of the factors catalyzing forest decay and depletion.

Socio-Economic Forces Leading to Fragmentation of the Forest

Some of the causes of forest fragmentation include social and economic factors such as population pressure, land development for agriculture and infrastructural developments. Also, in Sri Lanka, the human population rose from 18 approximately 8 million in 2001 up to almost 26 million in 2022 put pressures to land resources (Department of Census and Statistics 2012, 2022). This population expansion has therefore increased the number of farmers hence an increase in the area under cultivation and expansion of urban centers hence transformation of forests into arable land and other developments. Newmark (2008) concluded that population increase and economic development lead to deforestation especially in the third world countries where there are weak land use laws that do not take consideration of conservation.

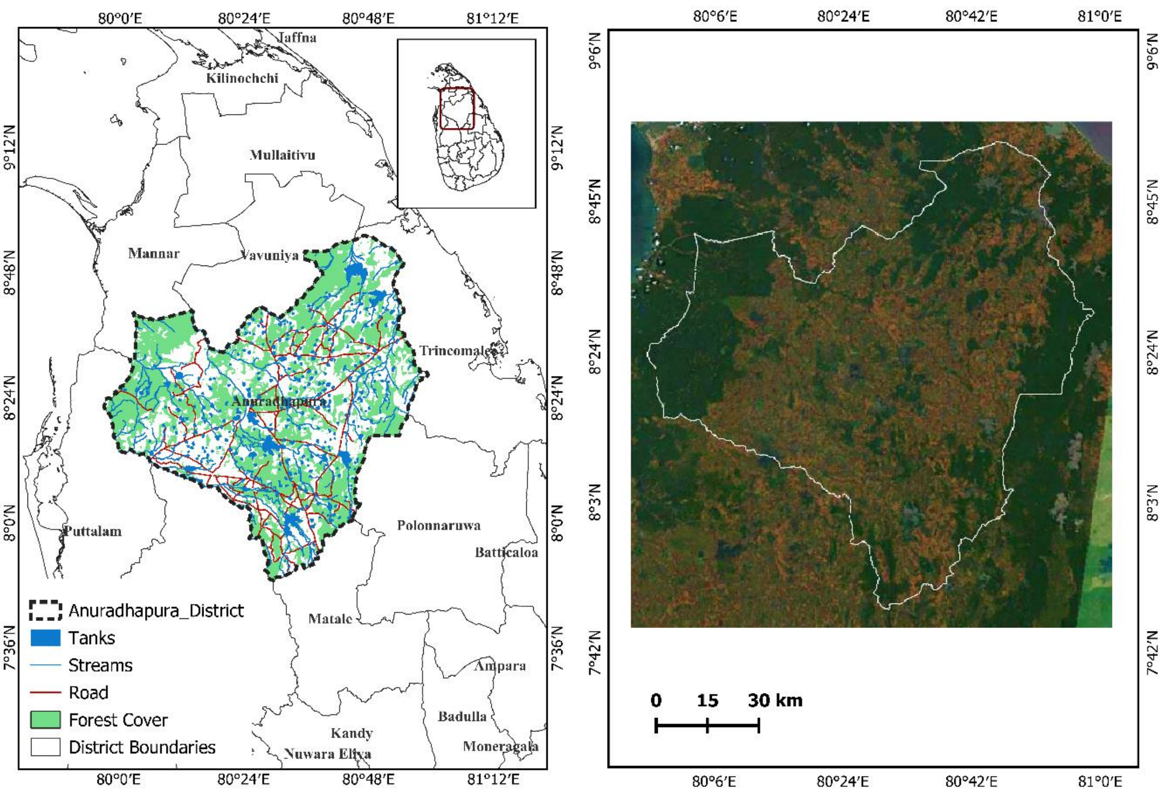
In order to fully capture the complexities of forest fragmentation, particularly in tropical regions like Sri Lanka, there are still insufficient comprehensive models that integrate quantitative geospatial data, despite the advances in AI and machine learning for LULC classification. Moreover, whereas previous research has focused on either temporal or spatial dynamics, very little has been done to examine how these variables interact over lengthy time periods, creating gaps in our knowledge of the long-term causes and ecological effects of fragmentation. By fusing cutting-edge AI methods with long-term temporal research, this work seeks to close this knowledge gap and offer a more comprehensive understanding of forest fragmentation and its socioeconomic causes.

Methodology

Study Area

Anuradhapura District lies in the North Central Province of Sri Lanka covering an area of approximately 7,179 square kilometers and the major climate prevailing in the region is the dry zone which has an average temperature between 25 ^{O}C – 30 ^{O}C and the average rainfall is between 1,000 - 1,500 mm where a major part of the rainfall is during the North- East monsoon period of October to In fact surprisingly significant for history and administration the same district as per the census of 2001 has about 745,693 populations in the district in 22 DSD Divisional Secretariats Divisions and 694 GND Gram Niladhari Divisions. The Malwathu Oya River which crosses the district possess an irrigation importance since it helps the vast plains having extensive paddy fields and some of the oldest tanks in Sri Lanka. The physical resources of the district encompass a mix of a forest and agricultural land masses, water source and the areas that are characterized by structures which include the Sacred City that is found in the eastern side of the river and New Town on the western side of the river. Direct conversion of habitat, which has been defined as a proximate change factor more directly associated with the direct effects of human use of land now shows that further human activities such as agricultural conversion and urbanization are even threatening the environmentally fragile sites, the protected forests and the wildlife reserves. Such aspects render Anuradhapura as one of the important sites when assessing the fragmentation of the forest and its impacts on the species' distribution and the land.

(a) (b)



Source: Sentinel-2 imagery obtained using Sentinel Hub EO Browser, provided by the European Space Agency (ESA), 2023.

Figure 1: Location of the study area **a** study area boundary **b** true color composite Sentinel – 2 in 2023

Methodological Flow Diagram

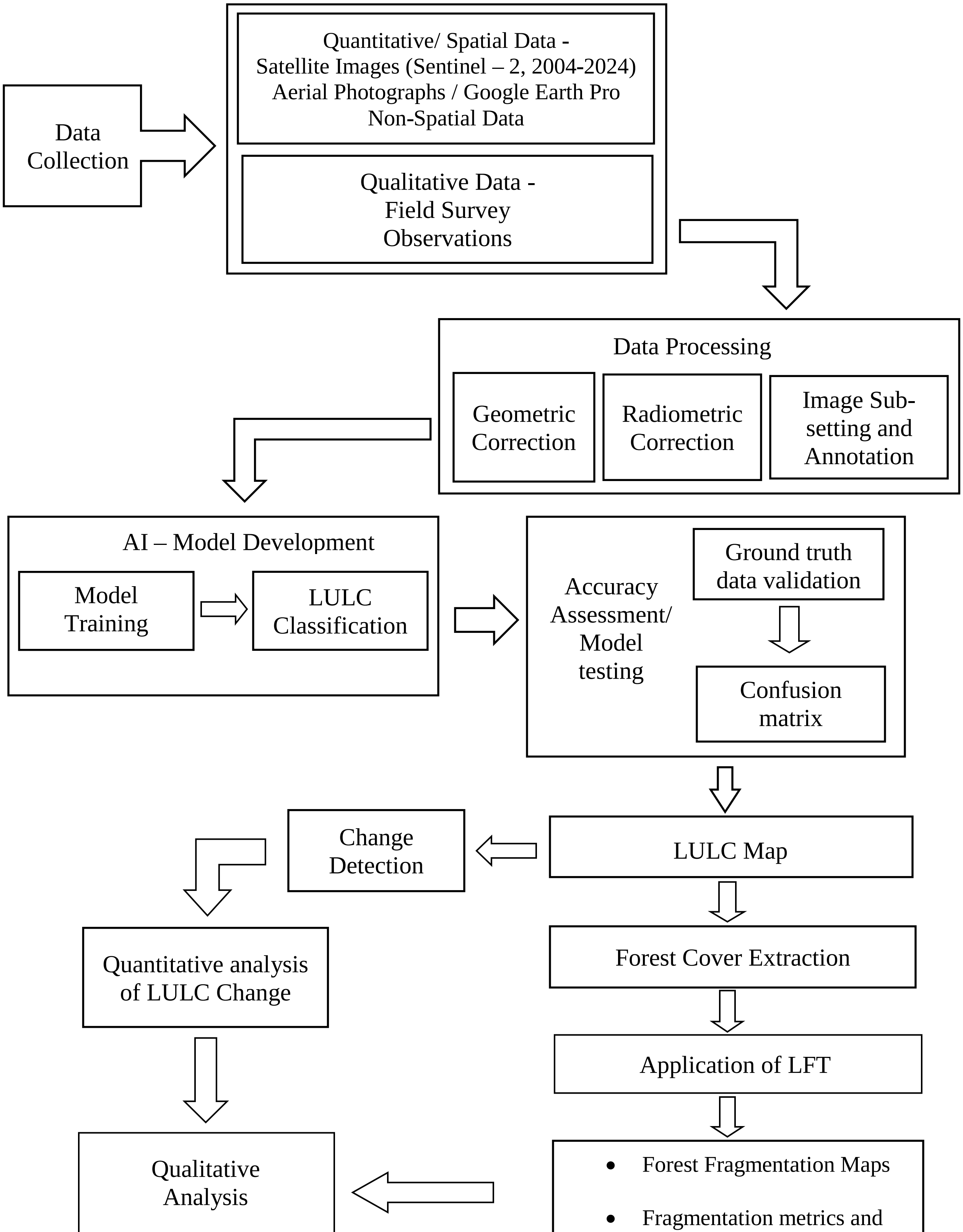


Figure 2: Methodological Flow Chart

Data Collection

Both quantitative/ Spatial and qualitative data were used in the work so as to provide detailed insight into the fragmentation of forest in the District of Anuradhapura.

Quantitative/ Spatial Data:

A combination of spatial and non-spatial data was utilized to analyze forest fragmentation in Anuradhapura District over a 20-year period. Medium-resolution optical satellite imagery from Sentinel Hub and Google Earth Pro was collected for the years 2004, 2014, and 2024, allowing for the identification of temporal changes in forest cover and serving as training data for the AI model. all the relevant details relating to both qualitative and spatial data, including satellite imagery, aerial photographs, and socio-economic factors, are summarized in the table below for clarity and comprehensive reference.

Table 1: Data Sources and Objectives for LULC Classification and Change Detection (2004-2024)

Data Type	Source	Objective	Acquisition Date
Sentinel – 2 Satellite Images	Sentinel Hub	LULC classification and change detection	2004 - 2024
Google Earth Pro Images	Google Earth Pro		2002 - 2024
Aerial Photographs	Survey Department, Sri Lanka, University of Sri Jayewardenepura		Various
secondary data- Population and Land use	Department of Census	Understand socio-economic drivers behind LULC change and forest fragmentation	2004-2024

Source: Compiled by the author based on research data sources

Qualitative Data:

Interviews and Focus Groups: Explanation of data collection techniques and instruments Semi structured interviews and focus group discussions were conducted with local people including forest department, farmers and other community members. These interactions gave an understanding of the existing cultural perception on fragmentation of the forest, human influence and its effects on the community.

Field Observations: Samples for the direct observation were collected during the field visits to the important forested sites within the district. These observations were useful in confirming the satellite and aerial imagery that were collected and also in contextualizing the findings of the qualitative data.

Table 2: Qualitative Data Sources and Purposes for Forest Fragmentation Study

Qualitative Data Type	**Source**	**Purpose**
Semi-Structured Interviews	Forest Department Officials	To gather local perceptions of forest fragmentation, its causes, and impacts on livelihoods
Focus Group Discussions	Locals such as farmers and other members of the community	In order to determine perceived group attitudes to changes in land-use and the management of forests
Field Observations	Direct observations during field visits to key forested areas in Anuradhapura	To validate satellite and aerial imagery and provide context for interpreting qualitative data

Source: Compiled by the author based on field research and data collection methods

Data Preprocessing

Before analysis and use, the satellite and aerial imagery underwent several preprocessing steps:

Geometric Correction: Ensured that all images were aligned to a common coordinate system (WGS 84 UTM Zone 44N), reducing spatial distortions.

Equation for Coordinate Transformation:

$$xgeo = xproj \cdot cos(\phi) - yproj \cdot sin(\phi)$$

$$ygeo = xproj \cdot \sin(\phi) + yproj \cdot \cos(\phi)$$

Radiometric Correction: Applied to normalize the differences in sensor calibration and atmospheric conditions between images from different years.

$$Radiance = M_L \times DN + A_L$$

M_L: Radiance multiplicative scaling factor

A_L: Radiance additive scaling factor

$$Reflectance = \frac{Radiance \times d^2}{ESUN \times \cos\theta s}$$

ESUN: The mean solar exoatmospheric irradiance

Image Sub setting and annotating: The study area was extracted from the larger datasets to focus analysis on the Anuradhapura District. And also, using sentisight.ai annotated 15000 satellite images into several land use classes for AI model training.

Table 3: Land Use Classification Scheme for Forest Fragmentation Study

Class ID	Land Use Class	Description
1	Forest area	Dense tree-covered areas, including natural forests and plantations.
2	Built-Up area	Areas with buildings, roads, and other man-made structures.
3	Water	Rivers, lakes, ponds, and other water-covered areas.
4	Vegetation	Areas used for farming, including fields, orchards, clear cut, plowed land and plantations.
5	Shrublands	Open areas dominated by grasses.
6	Coastal area	Bare soil

Source: Developed by the author for land use classification in the study area

Geospatial and AI-based Model Development

The geospatial and AI-based model was developed to enhance the accuracy of LULC classification. The model integrated the following algorithms:

Convolutional Neural Networks (CNNs): The Ultralytics YOLOv8 model, for object detection and classification purpose, the best-in-class CNN, was used. This model is trained with the help of Sent-Sight for the selected collection of satellite images which is marked and annotated. Created cohesive AI tool used in this research work have classified the dataset with a high accuracy of 92%.

Source Code for the Model: https://github.com/nayanajith99/AI-Habitat-Mapping-

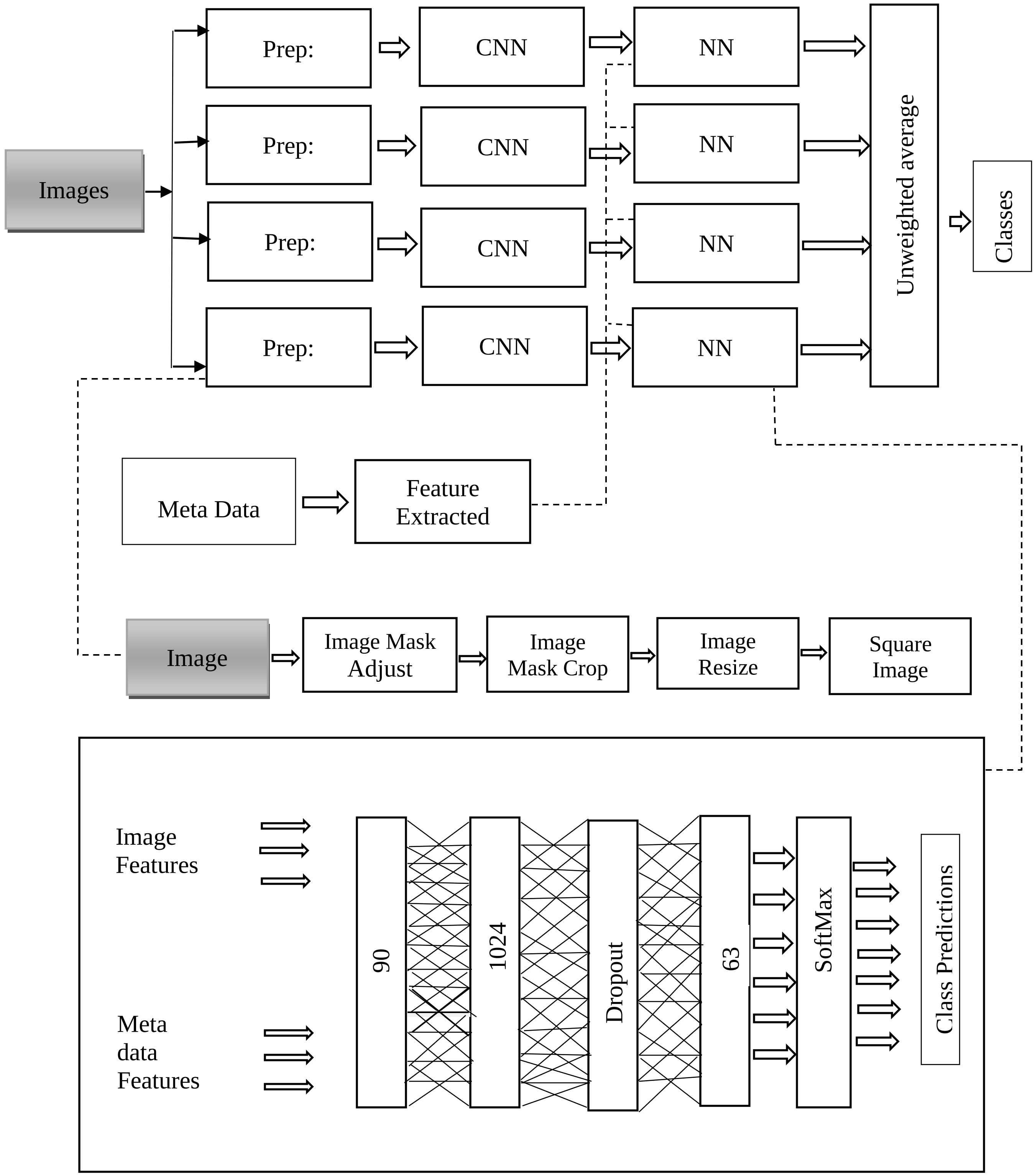


Figure 3: CNN Model Architecture

Application of the Landscape Fragmentation Tool

Temporal changes of forest fragmentation from the years 2004 and 2024 were determined with the help of the LFT. It was used to categorize the landscape into types including the core forest, edge density, Patch density and the patch forest. These classifications were made with a view of expressing the degree of fragmentation after which the results were compared over the 20-year period.

Core Forest Area (2004 - 2024):

$$Core\ Forest\ Area\ _{2024} = Core\ Forest\ Area\ _{2024} \times (1 - Rate\ of\ Decrease)$$

Number of Patches (2004 - 2024):

$$Number\ of\ Patches_{2024} = Number\ of\ Patches_{2024} \times (1 + Rate\ of\ Increase)$$

$$Edge\ Density = \frac{Total\ Edge\ Length}{Total\ Area} \times 10{,}000$$

$$Patch\ Density = \frac{Number\ of\ Patches}{Total\ Area} \times 100$$

Validation and Accuracy Assessment

Field observations and Kappa Coefficient were used to test the reliability of the LULC classification along with the independent validation datasets. The extraction of the forest cover achieved an accuracy of 95%, and an F1-Score of 0. 89. These metrics were used to be able to evaluate the performance of the model and gain confidence over the results obtained.

$$Overall\ Accuracy: Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

TP: True Positives, representing the number of correctly classified positive cases

TN: True Negatives, representing the number of correctly classified negative cases

FP: False Positives, representing the number of negative cases that were incorrectly classified as positive

FN: False Negatives, representing the number of positive cases that were incorrectly classified as negative

And also, the performance of the YOLOv8 model was evaluated using standard metrics, including precision, recall, F1-Score, and mean Average Precision (mAP). The equations for these metrics are:

$$Recall: R = \frac{TP}{TP + FP}$$

$$Precision: P = \frac{TP}{TP + FN}$$

$$F1 - Score: F1 = 2 \times \frac{P \times R}{P + R}$$

Qualitative Analysis

The interview, focus group, and field observations data collected were coded and analyzed thematically. Several themes regarding the causes of increasing forest fragmentation including agricultural expansion, change of land ownership right and enforcement of policies were established. These themes were then merged with the quantitative data to draw out an obligation of the causes for forest fragmentation in the study region.

Results and Discussion

Geospatial and AI-based Model Development

In Figure 4, the habitat segmentation using the Ultralytics YOLOv8 model is depicted. The model processed medium-resolution satellite imagery and classified different land use and land cover (LULC) types, including built-up areas, forest areas, and vegetation. The left panel shows the input image, while the right panel displays the predicted image with detected regions. The model output highlights the detected areas with associated confidence levels, such as built-up areas (98.022%), forest areas (93.233%), and vegetation (88.194%), providing valuable insights into habitat mapping for LULC analysis.

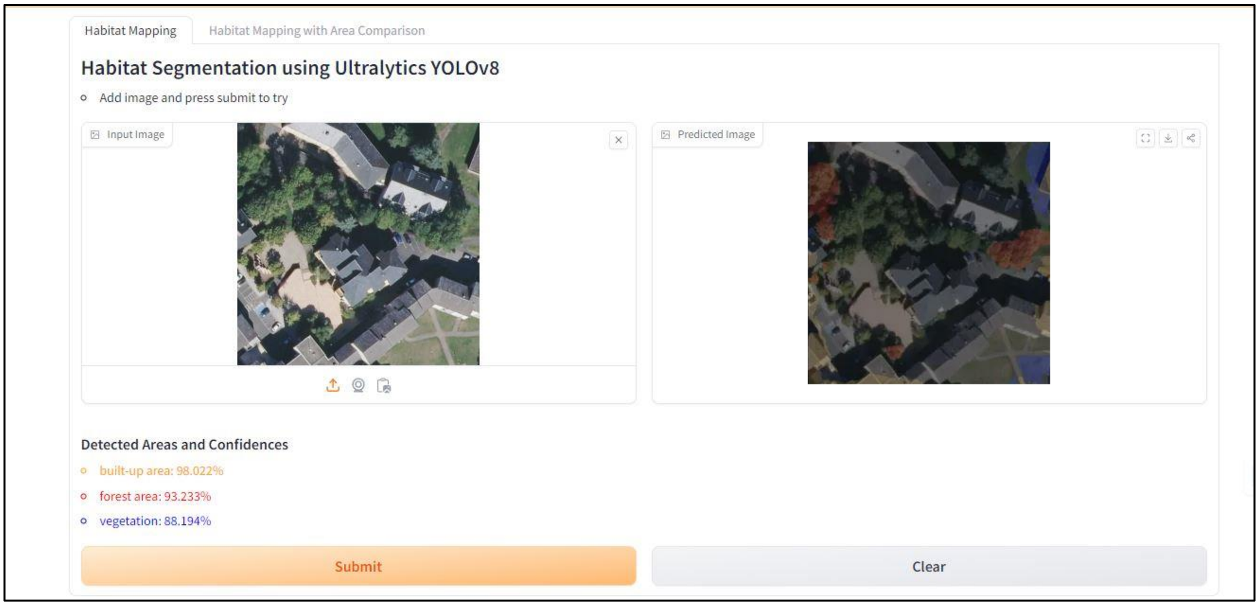


Figure 4: Output Generated from the AI Based Model

This model can compare satellite images of the same area from 2004 and 2024. It calculates the percentage of change in land cover over these two time periods. By analyzing the differences between the images, the model quantifies how much the area has changed, providing insights into the extent of land use changes.

(2004) (2024)

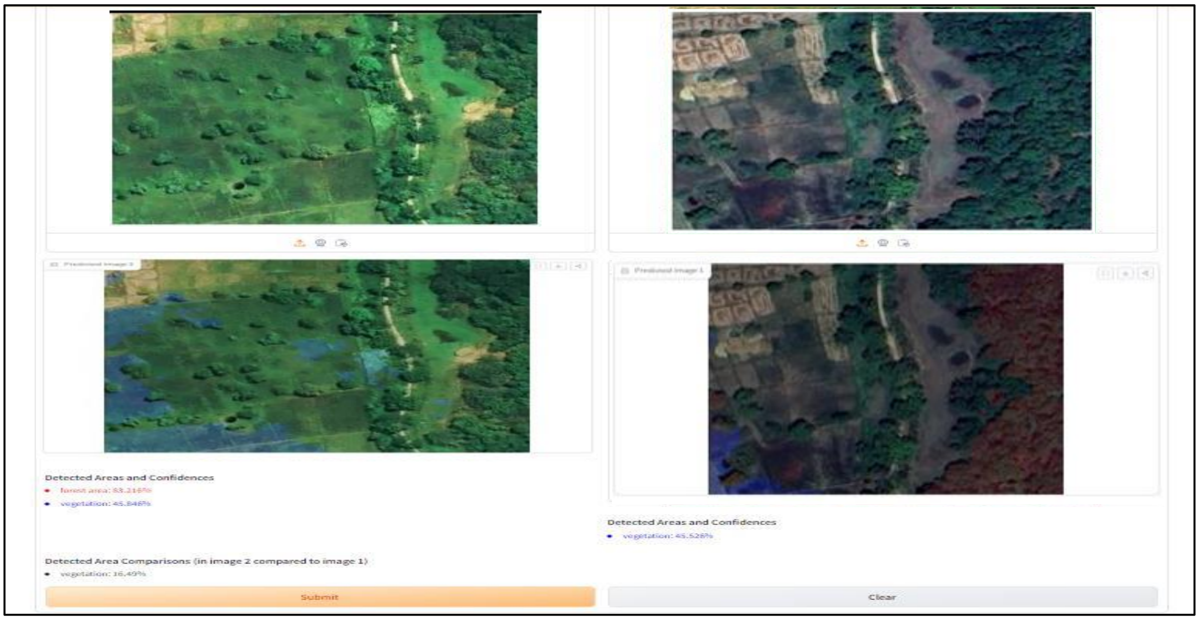


Figure 5: Temporal Changes from 2004 to 2024

Land Use Classification Maps

Consequently, the LULC maps in this study were derived from images expected from an AI based model. These images were then post processed in QGIS to work out the interactive map models that summarize the changes in the temporal aspects of land use as predicted by the AI. These classified raster layers were also saved in KML format for more usability in various software including Google Earth Pro. These maps offer an understanding of the spatial usage of land, with emphasis on five general usage types at various time periods.

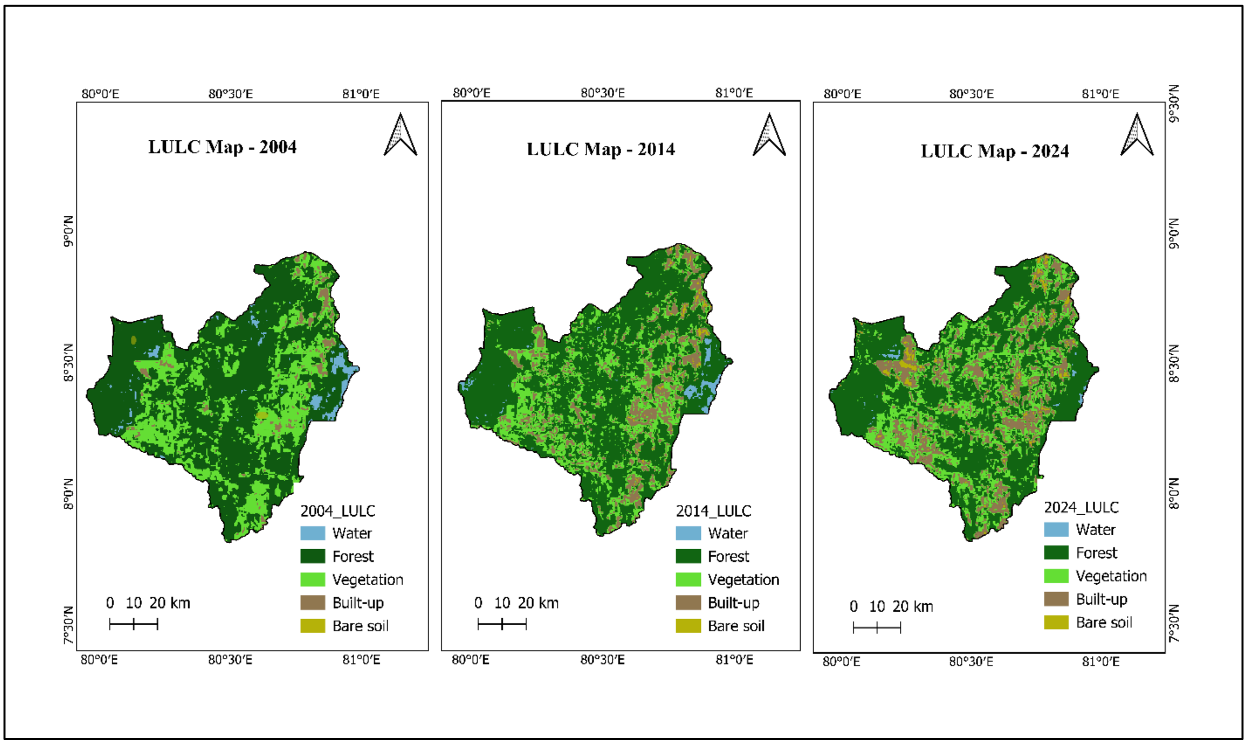


Figure 6: LULC Map of Anuradhapura District - 2004, 2014, 2024

Forest Cover Classification Accuracy

The developed geospatial and AI-based model with an integration of CNNs demonstrated substantial enhancement in the assessment of precise LULC classification in the Anuradhapura District. Field ground truth points were collected in the field in order to monitor and assess the usefulness of the model through a validation dataset containing twenty-six points. Finally, the results showed an overall classification accuracy of 92% for the extraction of forest cover. kappa coefficient of 0.97, indicating strong agreement between the classified output and the reference data. This means that the expected agreement is very close to 1. (The Kappa coefficient was calculated for a smaller area due to time constraints in collecting ground truth data.)

$$Kappa\ Coefficient(\kappa) = \frac{Po - Pe}{1 - Pe}$$

$P_{O:}$ *Observed Agreement (the proportion of times the model's prediction matches the true classification)*

$P_{e:}$ *Expected Agreement (the proportion of agreement expected by chance)*

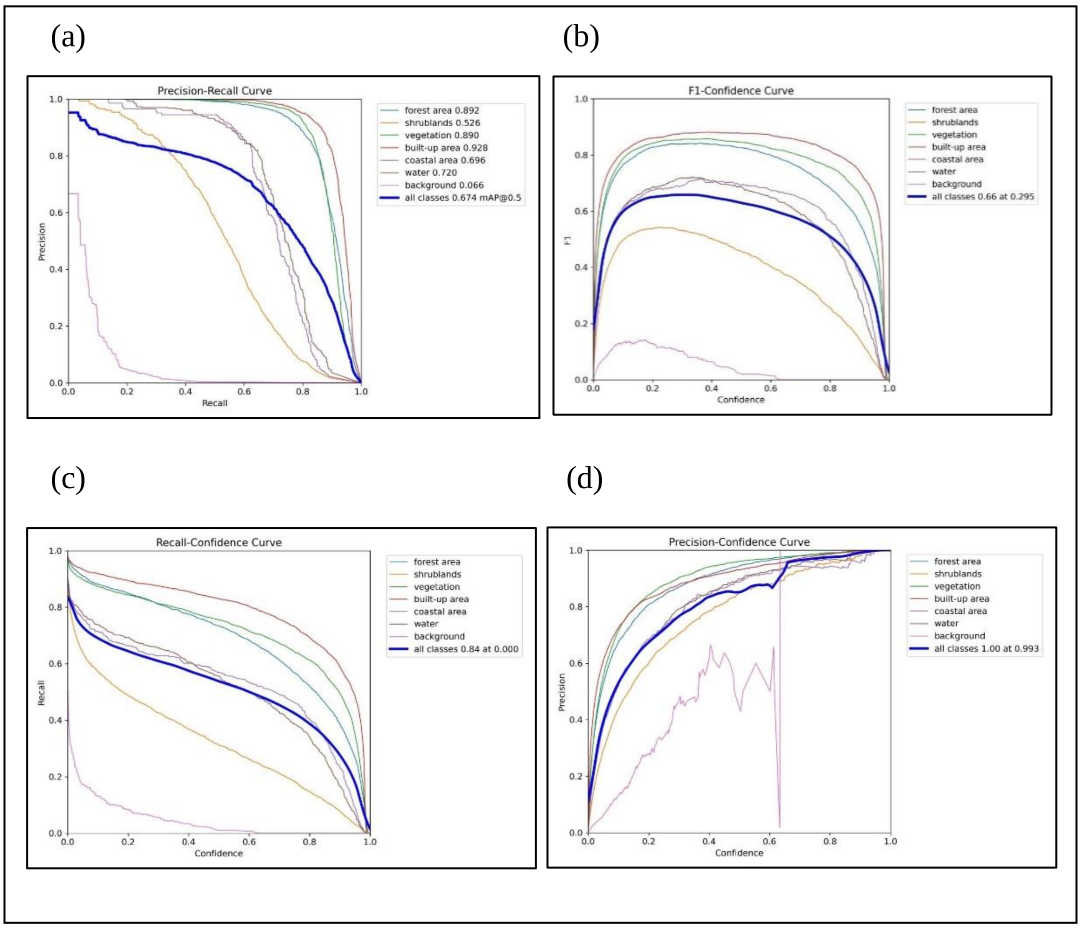


Figure 7: **a** Precision - Recall Curve **b** F1 - Confidence Curve

c Recall - Confidence Curve **d** Precision - Confidence Curve

Different sides of the performance of AI-based categorization models are shown in Figures (a), (b), (c), and (d). Figure 8 (a) presents the Precision – Recall Curve, highlighting the balance between precision and recall at different thresholds. Figure 8 (b) shows the F1 – Score Vs. Confidence Curve, illustrating the how F1 – score varies with confidence levels, reflecting overall model accuracy. Figure 8 (c) shows the Precision Vs. Confidence Curve, demonstrating how precision changes with different confidence thresholds, highlighting trade – offs between precision and confidence. the relationship between recall and confidence is finally shown in Figure 8 (d), which shows how recall varies as one's confidence in the model's predictions changes.

And also, Table 4 presents the Precision, Recall, and F1-Score values for the Land Use and Land Cover (LULC) classification model used in this study. These metrics evaluate the performance of the AI-based classification model across different land cover types, including Forest, Shrubland, Vegetation, Built-up areas, Coastal Areas, and Water Bodies. The table highlights the model's ability to accurately classify each category.

Table 4: Precision, Recall, and F1-Score for Land Cover Classification

Land Cover Type	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Forest	95	89.8	92.2
Shrubland	52.6	38.5	44.5
Vegetation	89	79.3	83.9
Built-up	92.8	87.8	90.2
Coastal Areas	88.3	78.1	82.88
Water Bodies	92	79.4	85.23

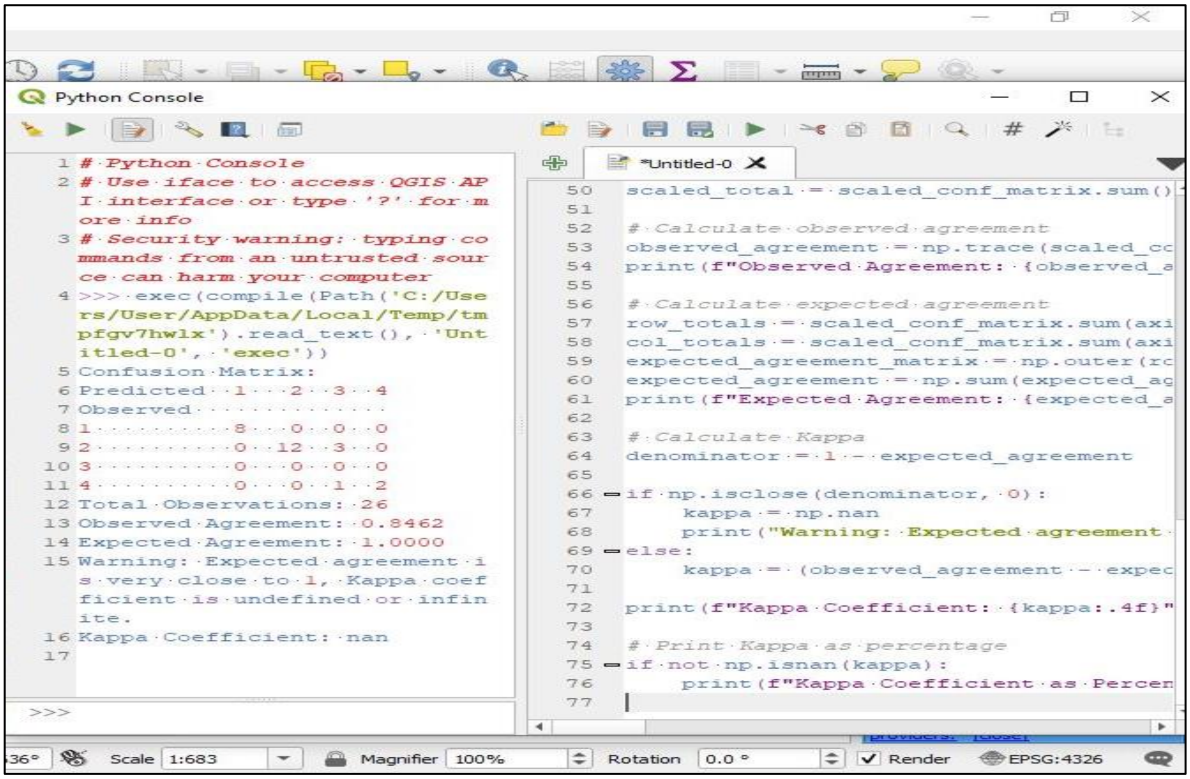


Figure 8: Calculation of Kappa Coefficient

Results of the Forest Fragmentation Analysis.

The changes are depicted in Figure 10, which shows the distribution of core forest area, patch density, edge density and patch across the 2004 to 2024. The LFT based spatial distribution maps generated to recognize fragmentation, show prone areas mostly along the edges of Anuradhapura District due to agricultural land conversion and infrastructural developments.

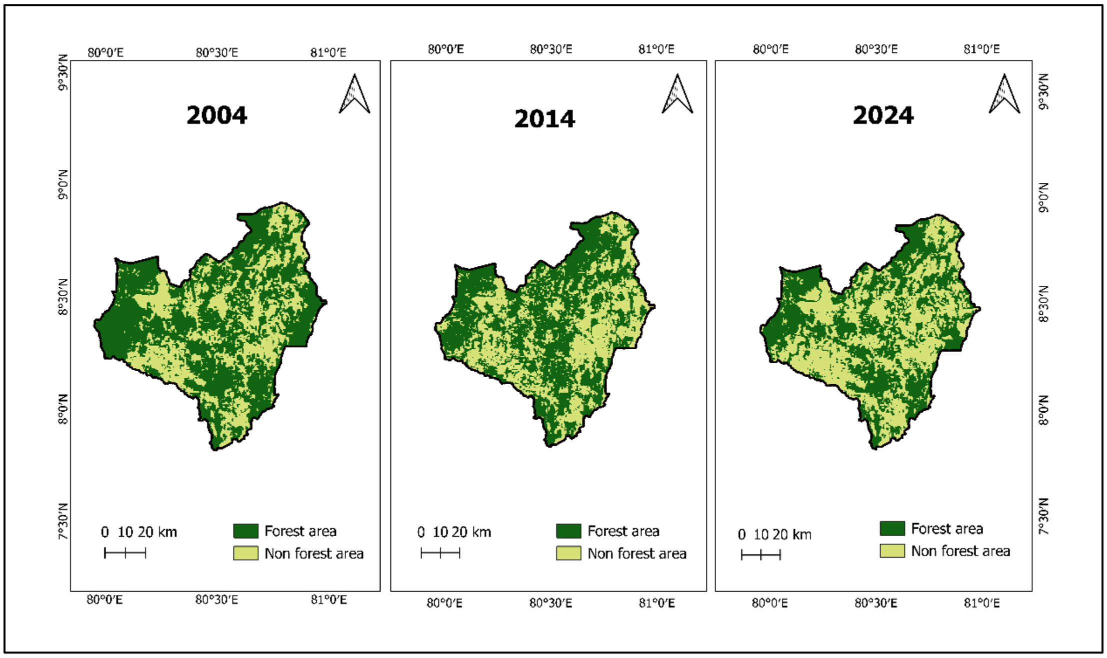


Figure 9: Distribution of the forest cover in 2004, 2014 and, 2024

The analysis of forest fragmentation in the Anuradhapura District from 2004 to 2024 reveals significant trends in forest loss and habitat fragmentation. The core forest area has decreased by 29.37% over this 20-year period, reflecting a substantial reduction in forest cover. This decline is consistent with the growing anthropogenic pressures, such as agricultural expansion, urbanization, and infrastructural developments, which are known to drive deforestation in many tropical regions, including Sri Lanka. According to Laurance et al. (2014), forest fragmentation often results in the rapid decline of core forest habitats, which play a crucial role in biodiversity conservation, carbon sequestration, and maintaining ecosystem resilience. The implications of this core forest loss are severe, as it disrupts species habitats, leading to local extinctions, especially for species that depend on large, continuous forest patches for survival. In the Anuradhapura District, this fragmentation not only threatens biodiversity but also reduces essential ecosystem services such as water regulation and carbon storage, which are vital for both environmental sustainability and the well-being of local communities.

The 25.93% increase in the number of patches further supports the notion that the landscape is becoming increasingly fragmented. This rise indicates that the forest is breaking up into smaller, isolated patches, a pattern that makes it harder for species to migrate and maintain healthy populations. Fahrig (2003) highlighted that isolated patches are less likely to support viable populations, particularly for species that require large territories. This fragmentation aligns with findings by Haddad et al. (2015), who noted that forest fragmentation accelerates biodiversity loss by confining species to smaller patches, which increases inbreeding, reduces genetic diversity, and weakens ecosystem resilience. In Anuradhapura, the growing number of patches signals that forest habitats are becoming more disconnected, creating additional challenges for wildlife conservation.

Patch density, which reflects the number of patches per square kilometer, has increased by 82.61%. This considerable rise suggests that the landscape is undergoing more severe fragmentation. As Ewers and Didham (2007) noted, high patch density is a sign of increased habitat fragmentation and reduced habitat connectivity. This pattern can severely impact species movement and migration, resulting in isolated populations and degraded ecological functions. The increasing patch density in Anuradhapura highlights the forest's growing fragmentation, where wildlife faces greater obstacles in moving between patches and maintaining genetic diversity. This fragmentation, if left unchecked, could have long-term negative effects on the district’s forest ecosystems.

Edge density has also increased by 37.84%, further indicating that the forest landscape is being heavily fragmented. The higher edge density means there is more forest edge exposed to non-forest environments, which creates "edge effects." These edge effects, as noted by Murcia (1995) and Laurance et al. (2011), alter microclimates, expose forest patches to invasive species, and reduce habitat quality for many forest-dependent species. The rising edge density in Anuradhapura suggests that more of the forest is subject to edge effects, which weaken the ecosystem by causing higher mortality rates in trees and reducing the overall resilience of the forest. This trend implies that the interior forest areas, which are critical for maintaining biodiversity, are shrinking as more forest is exposed to external disturbances.

The findings of this analysis point to the urgent need for conservation strategies to address forest fragmentation in Anuradhapura. The rapid decline in core forest area, coupled with increases in the number of patches, patch density, and edge density, demonstrates the degradation of forest habitats at a concerning rate. To combat these negative trends, it is crucial to implement strategies such as promoting reforestation to reconnect isolated patches and restore core forest areas, reducing edge effects, and enhancing habitat connectivity. Additionally, establishing wildlife corridors can help species move between fragmented patches, improving biodiversity conservation efforts. Strengthening the protection of forest areas in Anuradhapura is also essential to prevent further fragmentation caused by land-use changes. In conclusion, this analysis highlights the alarming level of forest fragmentation in the district, and immediate actions are needed to mitigate its impacts on biodiversity, ecosystem services, and overall forest health.

Table 5: Changes in Core Forest Area, Number of Patches, Patch Density and Edge Density in Anuradhapura District (2004-2024)

LULC Category	**Area in 2004 (sq km)**	**Area in 2014 (sq km)**	**Area in 2024 (sq km)**	**Percentage Change (2004-2024)**
Core Forest	3153.83	2631.71	2227.34	- 29.37%
Number of patches	189	235	238	+ 25.93%
Patch density	2.30	3.90	4.20	+82.61%
Edge density	7.4 m/ha	9.5 m/ha	10.2 m/ha	+ 37. 84%

Drivers of Fragmentation

Combining the quantitative data on LULC with the qualitative data derived from interviews with the stakeholders helped to explain the trends that have been observed in terms of fragmentation. Agricultural expansion was established as the major process, especially in the pragmatic zones that spread across the North and eastern part of the district, where extensive forest has been converted to agricultural lands. Similar validation is provided by the policy documents, land use data evidencing the trend of the increment in the area of agricultural land use in the past twenty years (Land Use Policy Planning Department, 2011; Department of Census and statistics, Various Years; Forest Department of Sri Lanka, Various Year).

The quantitative analysis also identified a significant correlation between population growth and the rate of forest fragmentation, with higher fragmentation rates observed in areas with greater population pressures. This was further driven by qualitative findings and where the people interviewed raised alarm over the depletion of the forest cover due to increased land use for human settlement and infrastructure development. And also, we can improve this study further to identify those factors using AI/ML.

Policy Implications and Recommendations

Therefore, it would be pertinent to propose specific conservation and policy remedies for combating the problem of forest fragmentation, especially in the Anuradhapura District. This is evidenced by decrease in the size of the core forest area and increase in the number of patches of forests suggesting high levels of forest fragmentation in the last two decades. Any such changes do not only have an impact on the diversity of species, but also negatively affect the state of forest bio- regional reserves. Wildlife corridors are important in holding a connected habitat with the ability to facilitating movement of wildlife from one patch of forest to another.

As pointed out in many papers, Including Beier and Noss, 1998 and Chetkiewicz, 2006, forest fragmentation hampers movement of wildlife leading to species fragmentation and Isolated species with limited genetic variation which exposes them to hazards of inbreeding. In the Anuradhapura District, layout plans aimed at connecting different patch of forest to form wildlife corridor will improve the dispersal of individuals and facilitate gene flow among the species. Hence, it will benefit in increasing genetic variation and therefore preventing genetic threats to extinction in species. should focus on those regions where small fragmented forests are limited and establish connections with the large continuous forest tracts. The corridor design has been identified by Bennett (2003) as the riparian corridors and the ecological networks that enhance species movement and minimizes the impacts of fragmentation of habitats on the biodiversity.

Causes of forest fragmentation can be attributed to anthropogenic factors particularly the alterations in land use, whereby the forest land is converted to agricultural land. For instance, the idea of agro forestry can be viewed as a suitable approach that would enable the continuation of the farming practices while at the same time preserving the forests. While practicing agroforestry trees are grown along with crops to yield economic returns in addition to extending the cover of the forests and the services they offer (Jose, 2009). It has been established that application of this approach reduces deforestation and forest degeneration in many areas (Schroth et al., 2004; Zomer et al., 2016). Thus, the project proposal When implemented in the Anuradhapura District might alleviate the pressure on the forest land by encouraging agroforestry while supporting the livelihood of the people. Further, any practice that reduce the pressure on forest resources such as land-use zoning that limits agricultural encroachment into areas that contain important forest areas can also help in reducing the extent of forest fragmentation.

There are policies to protect forests but their implementation is a problem and especially in countries where cases of illegal cutting down of trees and deforestation are common. To prevent the situation from deteriorating any further it is therefore paramount to strengthen law enforcement particularly in areas of fragmentation which are considered high risk. Research has it that when there is increased implementation of forest protection laws, there will be a decreased case of unlawful acts (Nunes et al., 2013). There are legal frameworks for protection of forests such as the Forest Ordinance of Sri Lanka but the enforcement measures are weak. Measures that can be taken in this case include recruitment of personnel especially the forest rangers, application of remote sensing that can help monitor from time to time and increased penalties to those people who conduct the act of deforestation.

It is concluded that an incorporation of geospatial and artificial intelligence techniques together with field data offer an effective approach for evaluating and mitigating forest fragmentation. The methods based on the use of remote sensing and machine learning models, which was used in this study, provide a more accurate and timely estimates of the changes in LU and its impact on forest ecosystems (Pal, M., & Mather, P.M., 2005). These tools allow tracking fragmentation dynamics and, thus, evaluation of the efficacy of conservation efforts in successive time intervals. According to Turner et al. (2001) such Metrics based on remote sensing may help to identify the patterns of fragmentation and plan the conservation measures.

Hence the important childcare that conservation efforts should be directed in order to address the problem of forest fragmentation in the Anuradhapura District. It is only possible to stop the ongoing loss of the forest cover and bring overall ecological balance if wildlife corridors are created, the calls for sustainable use of the land are observed, and the policies are reinforced. The formulated recommendations based on both analyzed data and extant literature form a multi-faceted and holistic strategy toward the problem of forest fragmentation and toward the long-term conservation of Sri Lanka's Forest ecosystems.

Conclusion and Recommendation

Conclusion

It was possible to build and implement the geospatial and AI-based model as part of this study and increase the effectiveness of LULC classification for assessing forest fragmentation in the Anuradhapura District in Sri Lanka. The combination of specific advanced proposed machine learning algorithms known as CNNs classifier also enhanced the precision of forest cover extraction adequacy at a 92% accuracy. The method known as the LFT was used successfully to map out spatial and temporal changes in forest fragmentation over a period of twenty years during which the extent of core forest was significantly reduced and that of edge forest significantly increased.

These show that forest fragmentation has occurred mainly in the agricultural lands and infrastructural developments in the Anuradhapura District especially on the northern and eastern sectors. Information that was obtained from the interviews and focus group discussion highlighted socio-economic factors that enhanced changing population pressure and land use policies. As a consequence of habitat loss due to fragmentation can pose a major threat to species diversity, potentially affecting species such as the Sri Lankan leopard (*Panthera pardus kotiya*) and the Asian elephant (*Elephas maximus*), which rely on expansive habitats. The isolation caused by fragmented landscapes may challenge the survival of these species, potentially leading to reduced genetic diversity and limited access to resources.

This study underscores the significance of testing a mixed methods research design when studying forest fragmentation process. It serves a strong foundation to accurately map and analyze land cover changes in real geospatial environment that in turn are useful in making conservation and policy decisions.

Recommendations

According to the findings made in the study, the following recommendations have been made with an aim of reducing the effects of forest fragmentation during land use processes in the Anuradhapura District. Another is formulation of wildlife corridors to tackle the effects of fragmentation advised by. In the areas where the forest patches are far distant, these corridors would link the otherwise separated forested area and make accessible much larger area which can be partitioned into several small fragments. Such corridors are crucial for allowing animals to cross cites and species barriers hence minimizing on genetic mortality. These behavioral pathways promote the genetic exchange between species, which in turn preserve the biological diversity and balance losses resulting from fragmentation of the habitats.

Furthermore, since forest fragmentation is greatly caused by the expansion of agricultural activities, it is equally important to promote sustainable agriculture. Trends have further revealed that agriculture is one of the most significant causes of forest fragmentation especially as farming activities grow. The use of agricultural activities is vital in supporting human lives, but it should be done by using techniques that can support ecological systems too. There are other methods including agro forestry and conservation agriculture that can provide solutions about how to increase productivity while maintaining little or no impact on these environments. These practices include planting trees within agricultural fields and adopting practices that spare the soil and the natural environment, this way; farmers will be protecting forested areas while enhancing productivity of the farms at the same time.

Other approaches to realize landscape fragmentation include enhancing policy implementation and enhancing land-use planning. To this end, it requires backing legal instruments with the use of polity measures for instance the policy that bars mining and logging on native lands must enforce the illegal actions that lead to onward loss of forests. The enhancement of stricter regulation in land use planning especially the core forest can help to impede the rate of development that poses threat to the forest ecosystems. There is also need to update the land use policies to encompass the aspects of Biodiversity and Ecosystem services with a view of giving direction in the use of land with an overall goal of conserving bio-diversity.

To enhance the success of these attempts of conservation, people, within the communities that the animals inhabit need to be sensitized. Thus, local communities are very important in forest conservation and are effectively used in minimizing forest fragmentation. Technological awareness programs should be launched with the aim of creating consciousness in the inhabitants of the community about forest ecosystems and the usefulness of sustainable utilization of land resources. Through engagement to the community or the local people involved in coming up with these conservation strategies, people will feel part of protecting the forests that are exploited today.

Last but not the least, constant surveillance and studying of the effects of various measures undertaken in the line of conservation are important so as to review the need for corrections or modifications. The future evaluation of forest fragmentation and the pattern of land use changes will help to determine the effectiveness of the current strategies that have been implemented in conservation of forests. Further researches are required to analyze the potential consequences of land use and land cover fragmentation in terms of bio-diversity and ecosystems at a longer period of time. Furthermore, the study of new methods of categorizing and, therefore, solving the issue of land-use fragmentation will facilitate the enhancement of conservation's procedures progressively. All these attempts are essential, if the forest ecosystems of the Anuradhapura District, and the natural capital in general, is to be conserved and commonly utilized sustainably.

Limitation

Despite the fact that this study had access to high-resolution satellite imagery but medium-resolution optical satellite images were utilized instead since the local PC could not handle and interpret the massive amounts of high-resolution data with ease. It would have taken a lot more memory, storage, and computing power to handle high-resolution datasets, yet these resources were not easily accessible. Although the medium-resolution data might have made it more difficult to detect finer landscape characteristics, it offered a more controllable alternative that allowed for efficient analysis while keeping acceptable processing speeds.

Furthermore, it took a lot of effort to prepare and handle the massive datasets, especially for the model training and validation stages. Extensive computational resources were needed for the AI-based classification model, and the lack of high-capacity hardware further hindered the training process. The time needed for data preprocessing, model optimization, and accuracy evaluations was increased by these hardware constraints. Notwithstanding these limitations, the model operated with excellent accuracy, and the findings offer insightful information on the dynamics of forest fragmentation. Better hardware resources could handle data with better resolutions and speed up processing times for future studies.

And also, the model occasionally misclassifies shrubland areas as forest or vegetation, contributing to an 8% margin of error. This misclassification is particularly pronounced due to the relatively low confidence and accuracy associated with shrubland classification. The limited number of training samples for shrublands restricts the model's ability to accurately differentiate these areas from other land cover types. As such, this limitation highlights the need for a more robust dataset to enhance the model's performance in accurately identifying shrubland classifications.

References:

Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, R. E. (1976). *A land use and land cover classification system for use with remote sensor data* (Vol. 964). US Government Printing Office.

Cutler, D. R., Edwards Jr, T. C., Beard, K. H., Cutler, A., Hess, K. T., Gibson, J., & Lawler, J. J. (2007). *Random forests for classification in ecology*. *Ecology*, 88(11), 2783-2792. https://doi.org/10.1890/07-0539.1

Department of Census and Statistics. (2012). *Census of Population and Housing*. Government of Sri Lanka.

Fahrig, L. (2003). *Effects of habitat fragmentation on biodiversity. Annual Review of Ecology, Evolution, and Systematics*, 34(1), 487-515. https://doi.org/10.1146/annurev.ecolsys.34.011802.132419

Haddad, N. M., Brudvig, L. A., Clobert, J., Davies, K. F., Gonzalez, A., Holt, R. D., ... Townsend, P. A. (2015). *Habitat fragmentation and its lasting impact on Earth's ecosystems. Science Advances*, 1(2), e1500052. https://doi.org/10.1126/sciadv.1500052

Kodric-Brown, A., & Brown, J. H. (2008). Isolation of African protected areas and the impact on biodiversity. Frontiers in Ecology and the Environment, 6(6), 321-328. https://doi.org/10.1890/070002

Kumar, P., Koshy, R., Bhat, M., & Sinha, S. (2016). *Habitat fragmentation and its impact on biodiversity: An Indian perspective. Journal of Environmental Management*, 183, 108-121. https://doi.org/10.1016/j.jenvman.2016.08.031

Liu, X., Zhang, X., & Zhao, Y. (2020). *Land use and land cover classification using deep learning-based models: A case study in China. Remote Sensing*, 12(8), 1209.

Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing, 28(5), 823–870. https://doi.org/10.1080/01431160600746456

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. https://doi.org/10.1016/j.patcog.2016.07.001

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). *Good practices for estimating area and assessing accuracy of land change. Remote Sensing of Environment*, 148, 42-57. https://doi.org/10.1016/j.rse.2014.02.015

Pal, M., & Mather, P. M. (2003). An assessment of the effectiveness of decision tree methods for land cover classification. Remote Sensing of Environment, 86(4), 554-565. https://doi.org/10.1016/S0034-4257(03)00132-9

Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a Random Forest classifier for land-cover classification. ISPRS Journal of Photogrammetry and Remote Sensing, 67, 93–104. https://doi.org/10.1016/j.isprsjprs.2011.11.002

Turner, M. G., Gardner, R. H., & O'Neill, R. V. (2013). *Landscape ecology in theory and practice: Pattern and process. Springer Science & Business Media*.

Turner, M. G., Gardner, R. H., & O'Neill, R. V. (2013). *Landscape ecology in theory and practice: Pattern and process. Springer Science & Business Media*.

Ultralytics. (2023). *YOLOv8: Real-Time Object Detection. Ultralytics Documentation*. https://docs.ultralytics.com/yolov8