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Identifying human elephant conflict hotspots through satellite remote sensing and GIS to support conflict mitigation

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ABSTRACT

Human-elephant conflict (HEC) is a significant issue in Sri Lanka and many parts of the world where elephants and humans coexist. To address HEC, this study integrates remote sensing and GIS analysis, focusing on monitoring changes in greenery. The study prepared the latest land cover and land use (LCLU) maps with Sentinel-2 satellite data, correlating them with reported HEC incidents reported in 2021 and 2022 to identify HEC hotspots in two forest-dominated regions of Southeast Sri Lanka. High-resolution sentinel-2 satellite imagery were used to detect areas of human activities and elephant habitats in proximity to each other. Random Forest (RF) and Support Vector Machine (SVM) classification methods were used for LCLU classification. The overall accuracy of the classification was 97.31 and 94.62, and kappa was 0.95 and 0.90 for RF and SVM, respectively. Multi-temporal normalised difference vegetation index (NDVI) analysis provided insights into vegetation health and coverage, offering a clear picture of greenery changes. Monthly changes in vegetation cover readings were quantified using NDVI values derived from MODIS data, identifying suitable regions for elephants to forage frequently. Furthermore, Kernel density estimation identified high-density areas for reported incidents of human and elephant deaths. This process involved assigning weight to conflict incidents within a 5 km radius, considering the proximity to the forest, and evaluating greenery changes using NDVI values, revealing varying levels of HEC risk, ranging from very high to low. The LCLU map, created using the RF classifier, indicates that all potential HEC hotspots for very high and high HEC risks are closely aligned with forest boundaries. The findings support HEC mitigation strategies through community awareness, HEC hotspots mapping and restoration practices to ensure a sustainable human-elephant coexistence. This method will help policymakers in wildlife conservation to identify high risk HEC zones to support HEC mitigation. In conclusion, this study highlights the potential of integrating remote sensing and GIS techniques in demarcating HEC hotspots in Sri Lanka to support conflict mitigation efforts.

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1. Introduction

1.1. HEC and its impact on both humans and elephants

The human-elephant conflict (HEC) presents a significant challenge to wildlife conservation and human livelihoods in many parts of the world, including Sri Lanka (Köpke et al., 2023). HEC observed in elephant range countries (Gross et al., 2022; Prakash et al., 2020) arises primarily due to the competition for space and resources between humans and elephants, exacerbated by habitat fragmentation, agricultural expansion, and population growth. Various management strategies have been developed and practised at different scales to prevent and mitigate HEC (Thakshila D. Gunawansa et al., 2023a,b; Jarungrattanapong and Olewiler, 2024; Nguyen et al., 2021). However, HEC remains pervasive as most existing prevention strategies are driven by site-specific factors that only offer short-term solutions, while mitigation strategies frequently transfer conflict risk from one place to another (Somu and Palanisamy, 2022; Urio, 2020).

This conflict negatively impacts local communities and the elephant population. It has contributed to the critical endangerment of the African forest elephant and the listing of the African savannah elephant and Asian elephant as endangered species (IFAW, 2023; Riddle et al., 2010). All three remaining elephant species are included in the International Union for Conservation of Nature's Red List of Threatened Species (Bonnald et al., 2024). Wild elephants are distributed in 50 countries worldwide, 13 in Asia and 37 in Africa (Perera and Tsuchiya, 2009). The current population of wild Asian elephants (*Elephas maximus*) is estimated to range from 35,000 to 50,000, with approximately 16,000 in captivity (de Nazareth and Nagarathinam, 2012). Across all Asian range states, there is a concerning trend of significant declines in wild elephant populations, largely attributed to human-related factors (Bai et al., 2022; Morley and Van Aarde, 2007; Sitati et al., 2003).

The rapid increase in human populations in Asia and Africa has led to expansion of urban area and extending agricultural fields (Meyer and Turner, 1992; Yang et al., 2022), encroaching on wildlife areas and impacting traditional elephant habitats (Breuer et al., 2016; Köpke et al., 2021). In Asia, approx. Wild elephants can damage 10 to 15 percent of total agricultural output, threatening human security and well-being (Kitratporn and Takeuchi, 2020). Managing competition between people and elephants for space and resources is a critical conservation issue. This has reduced elephant habitat, degraded forage, and decreased landscape connectivity (Shaffer et al., 2019).

Change in land cover and land use (LCLU) in rural Sri Lanka are a major driving force behind habitat change, which significantly impacts the distribution of wildlife (Billah et al., 2021; Mishra et al., 2020). In 1992, the forest cover in Sri Lanka was 1,624,757.5 ha in 2019, it was 1,377,799.1 ha, a decrease from 24.8 percent to 21 percent over a mere 27 years (Ranagalage et al., 2020). African and Asian elephants are prone to such conflict due to the increasing proximity between elephants and human settlements and the encroachment of human activities into elephant habitat areas. Their presence can lead to significant burdens for local communities due to crop damage, property destruction, infrastructure harm, and even threats to human safety. Retaliation by killing elephants can occur, emphasising the urgent need to address the issue with effective mitigation programmes.

When widespread damage occurs, the economic impact on affected communities is significant. HEC encompasses various negative physical interactions between humans and elephants (Mumby and Plotnik, 2018), resulting in injuries, deaths, and economic loss with crops, properties, and livestock damages (Di Minin et al., 2021; Enukwa, 2017; Jiang et al., 2021; Naha et al., 2020). Such negative interactions pose significant conservation and social challenges, food insecurity, emotional distress, and restricted mobility in affected human communities (Fernando et al., 2023). Individuals residing in areas with frequent HEC may suffer from psychological trauma and safety concerns (Sampson et al., 2021). The associated perceptions and fear exacerbate the conflict, posing direct interactions and making mitigation a challenge (Dickman, 2010; Mumby and Plotnik, 2018).

HEC has become a major concern in conservation biology worldwide (Bai et al., 2022; Billah et al., 2021; Bonnald et al., 2024; Anwar, 2023) and requires immediate attention (Zafir and Magintan, 2016). Within the 13 elephant range countries, almost two-thirds of the habitat suitable for elephants has declined within 300–500 years (de Silva et al., 2023). Humans may have to abandon their homes and land due to the danger elephants pose (Evans and Adams, 2018). At the same time, elephants can be forced to leave their natural habitat due to habitat destruction or fragmentation (Nyaligu and Weeks, 2013). Despite its small land area, Sri Lanka has a considerable wild elephant population, approximately 0.1 elephants/km^2 compared to 0.01 elephants/km^2 in India (Fernando et al., 2011; Perera et al., 2012).

The application of remote sensing and geographic information system (GIS) technology in ecological studies of elephants has rapidly increased in recent decades (Thakshila D Gunawansa et al., 2023a,b; Kitratporn and Takeuchi, 2020; Perera et al., 2012; Rathnayake et al., 2022; Withanage et al., 2023). However, studies based on spatial analysis focusing on identifying potential HEC risk zones remain relatively limited, particularly in the context of Sri Lanka. Compared to other Asian and African countries, where research in this area has seen more extensive development. This research gap underscores the pressing need to employ advanced satellite remote sensing techniques and GIS methodologies to identify potential critical conflict hotspots and inform targeted mitigation efforts. Therefore, this study was conducted to predict potential HEC hotspots, ultimately contributing to more effective conflict mitigation strategies in Sri Lanka.

1.2. Research objectives

The primary objective of this study is to identify HEC hotspots through a comprehensive analysis utilising satellite remote sensing and GIS techniques. The study focused on four key objectives to achieve this goal: (1) produce accurate LCLU maps using Sentinel-2 satellite imagery; (2) investigate the spatial distribution of human and elephant death incidents; (3) use moderate-resolution imaging spectroradiometer (MODIS) satellite data to evaluate greenery changes through the normalised difference vegetation index (NDVI); (4) identify HEC hotspots by analysing greenery changes and LCLU patterns and correlating these changes with conflict incidents.

2. Materials and methods

2.1. The study area

The study was conducted in two forest-dominated areas of Southeast Sri Lanka, shown in Fig. 1, covering parts of the Southern, Uva, and Sabaragamuwa provinces. This area occupies approximately 5836 km^2 and includes a variety of types of LCLU, such as forests, open forests, paddy fields, and cultivated tropical crops. The environment is hot and humid, with a mean annual temperature of around 29 °C. Temperatures can reach 37 °C during the dry season (Anwar, 2023). The region includes the national parks of Udawalawe, Yala, Lunugamvehera, Bundala, and Weheragala, and Bundala-Wilmanna and Katagamuwa wildlife sanctuaries, home to many elephants. Based on individual identification, the Udawalawe National Park holds a population of between 804 and 1160 elephants (Fernando et al., 2011; Silva et al., 2011), resulting in a high density of wild elephants, approximately 1.02–1.16 elephants/km^2 (Fernando et al., 2011).

Furthermore, agriculture dominates land cover in the central region, with primary crops being rice, banana, and maise (Kumarage and Arunakumara, 2017). The consistently low height of this region allows elephants to spread quickly onto the agricultural land. The northeast monsoon season, which occurs from December to February, brings an average rainfall of 898 mm, with the highest precipitation in November, December, and January, experiencing up to 336 mm of rain (Department of Meteorology, 2023).

The selected study area included forest-dominated regions characterised by diverse LCLU patterns. This selection was based on many historical HEC incidents and noticeable variations in LCLU patterns within these areas. By focusing on regions with a significant history of HEC incidents, the study could explore these conflicts' causes, patterns, and trends.

2.2. Overview of HEC incident data

Based on the previous HEC incident data, Fig. 2 illustrates a detailed comparison of the deaths of humans and elephants due to the HEC in Sri Lanka from 2010 to 2022. The graph highlights the variations and trends in deaths for each species, clearly visualising potential conflict points. In particular, these data are compared to the densities of the elephant and human populations over the same period, allowing for a deeper understanding of the correlation between population densities and death rates.

Understanding the patterns and trends of HEC incidents over time is essential for organising effective mitigation strategies and conservation efforts. This study uses regression analysis to investigate the relationship between time and HEC incidents, as shown in Fig. 3. Coefficients of determination (R^2) of 0.7065 and 0.7605, respectively, were used to predict the relationship between the year and HEC incidences. These equations express the proportion of variance in HEC incidents that the year variable can explain. Equation $R^2 = 0.7065$ indicates that approximately 70.65 percent of the variability in HEC incidents can be explained by time. This shows a moderate degree of association between time and HEC incidents.

On the other hand, equation $R^2 = 0.7605$ indicates that temporal changes account for around 76.05 percent of the variability in HEC incidents. This higher R-squared value suggests a stronger linear relationship between time and HEC incidents.

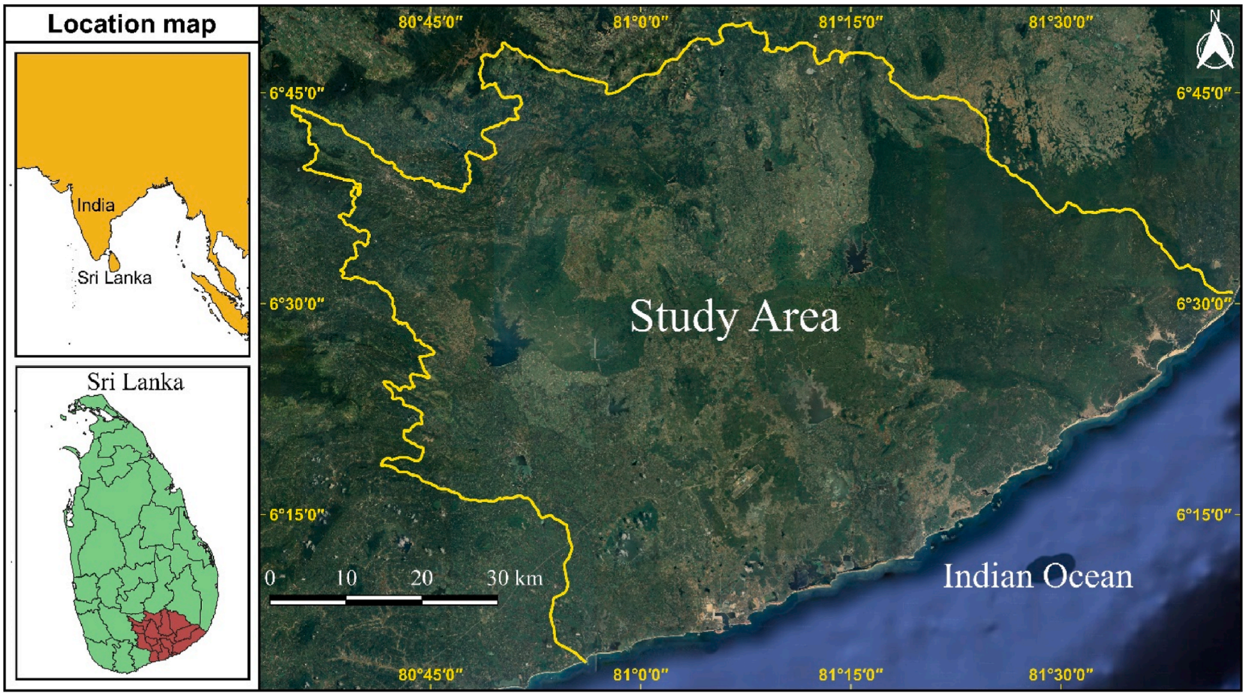

Fig. 1. Map of the study area.

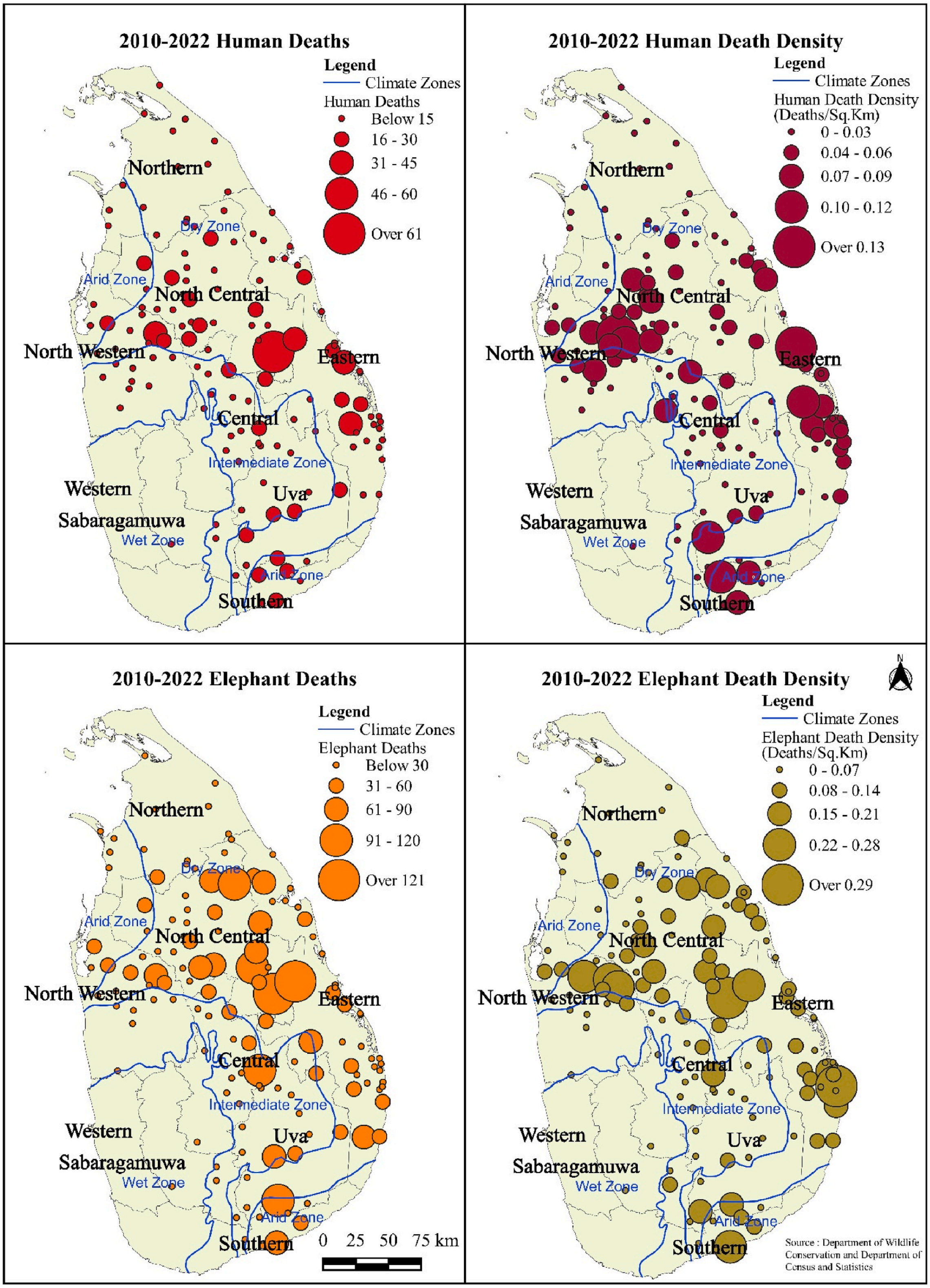

Fig. 2. Comparative analysis of elephant and human deaths and densities in Sri Lanka from 2010 to 2022.

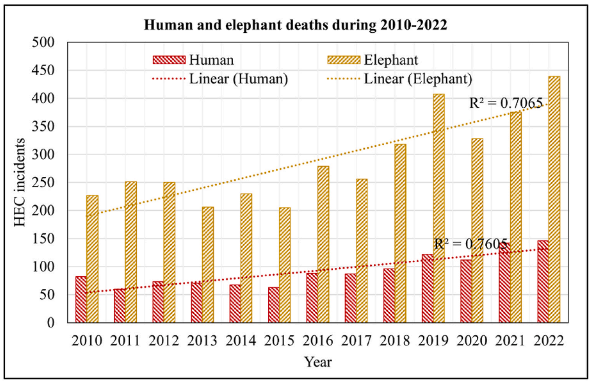

Fig. 3. Temporal trend of human and elephant deaths reported from 2010 to 2022.

2.3. Data

Three key datasets were used to identify the HEC hotspots: reported HEC incidents from the Sri Lankan Department of Wildlife Conservation (DWC), Sentinel-2 and MODIS satellite data, and rainfall data from the Department of Meteorology.

2.4. HEC data

HEC incident records were obtained from the DWC of Sri Lanka for 12 years, from 2010 to 2022 (Department of Wildlife Conservation, 2023). HEC data are organised into four categories: human deaths, elephant deaths, human injuries, and property damages. These incidents have been documented with location information, wildlife region, district secretary's division (DSD), district, and incident date (or year). The initial phase of the study focused on identifying HEC hotspots and analysing incident reports from 2018 to 2020. Quantum Geographic Information System (QGIS) 3.28 software was used to map the data and identify hotspots. DWC and field data were collected between January 2021 and January 2022 to validate identified hotspots. The study was intended to correctly identify high-risk locations using a combination of statistics and spatial analysis.

2.5. Satellite data

This study involved Sentinel-2 and MODIS data collected from June 2021 to January 2022. Sentinel-2 imagery was classified and analysed separately for two temporal periods: dry and rainy seasons. The latest QGIS 3.28 software was used to analyse the MODIS data.

2.6. Sentinel-2 satellite data

The development of the Copernicus programme has facilitated effective monitoring of the Earth's surface by producing the Sentinel-2 multispectral products (Zhang et al., 2021). The Sentinel-2 mission's primary objective is to provide free access to high-resolution satellite data for monitoring LCLU, climate change, and disasters (Phiri et al., 2020). In addition, Sentinel-2 is intended to deliver high-resolution satellite data for land monitoring, emergency management, security, climate change, and marine studies. LCLU types on the mainland are artificial surfaces such as roads and paved areas, forest areas, agricultural areas, and small water bodies (ESA, 2015). Sentinel-2 satellite data can potentially improve forest classification on medium to large scales due to high spatial resolution. Sentinel-2 has 13 spectral bands, three spatial resolution levels of 10 m, 20 m, and 60 m (ESA, 2014), a 290 km swath, and a radiometric resolution of 12 bits. The Sentinel-2 constellation consists of twin satellites: Sentinel-2A (launched on June 23, 2015) and Sentinel-2B (launched on March 7, 2017) (Phiri et al., 2020). These Sentinel-2 satellites revisit each ten days, thus, the combined constellation revisit frequency is five days.

2.7. MODIS satellite data

MODIS was launched into Earth's orbit by the National Aeronautics and Space Administration (NASA) on Terra (EOS AM satellite) in 1999 and Aqua (EOS PM satellite) in 2002. The instruments capture data in 36 spectral bands ranging in wavelength from 0.4 to 14.4 μm. Spatial resolutions ranging from 250 m to 1 km (two bands at 250 m, five bands at 500 m, and 29 bands at 1 km) are applied to map vegetation dynamics and processes at a large scale. Due to the coarse spatial resolution, MODIS data sets are suitable for mapping LCLU types over large areas. The swath is 2330 km (cross-track) by 10 km (along-track at the nadir). Together, the instruments image the entire Earth every one to two days (Elshora, 2023). Combining multiple types of imagery can lead to better monitoring results through image fusion.

MODIS data provide a precious set of real-time details of relatively large green patches on the ground (Perera and Tateishi, 2012). Rapid satellite data streams in operational applications benefit vegetation monitoring when information can be delivered as fast as changing surface conditions (Brown et al., 2015). MODIS data, including NDVI and true colour images, are freely available via the NASA website (NASA, 2023; Perera et al., 2012). The NDVI was used to assess vegetation health and density in the region of interest for this study.

2.8. Rainfall data

Daily total rainfall data were collected from the Department of Meteorology (Ranagalage et al.) for nine months, from May 01, 2021 to January 31, 2022. This information was collected from the seven distinct rainfall stations illustrated in Fig. 4. This data collection aimed to clarify the precipitation patterns and variations observed across these stations within the specified time frame.

2.9. Sentinel data analysis

For this study, 12 Sentinel-2 level-2A (L2A) imagery from 2021 to 2022 from 104 available imagery was selected. These selected images cover the entire study area, with four separate Sentinel-2 imagery captures covering the entire area and a minimal cloud cover of less than 14 percent. Details of the selected Sentinel-2 imagery are given in Table 1.

2.10. Image classification categories and algorithms

Six LCLU classification categories were identified within the study area, highlighting the region's vast diversity of landscape and variegated land use. The selected classification schemes represent human-induced transformations and natural variations. Table 2 lists the definitions of these categories.

2.11. Image classification methods

In this study, the Sentinel-2 satellite imagery was classified using supervised classification, random forest (RF), and support vector machine (SVM) algorithms. Training sites were selected using a combination of resources, including Google Earth, on-site field data, prior knowledge, and publicly available information. These training areas provide essential references for the algorithms to recognise the spectral signatures associated with each LCLU type.

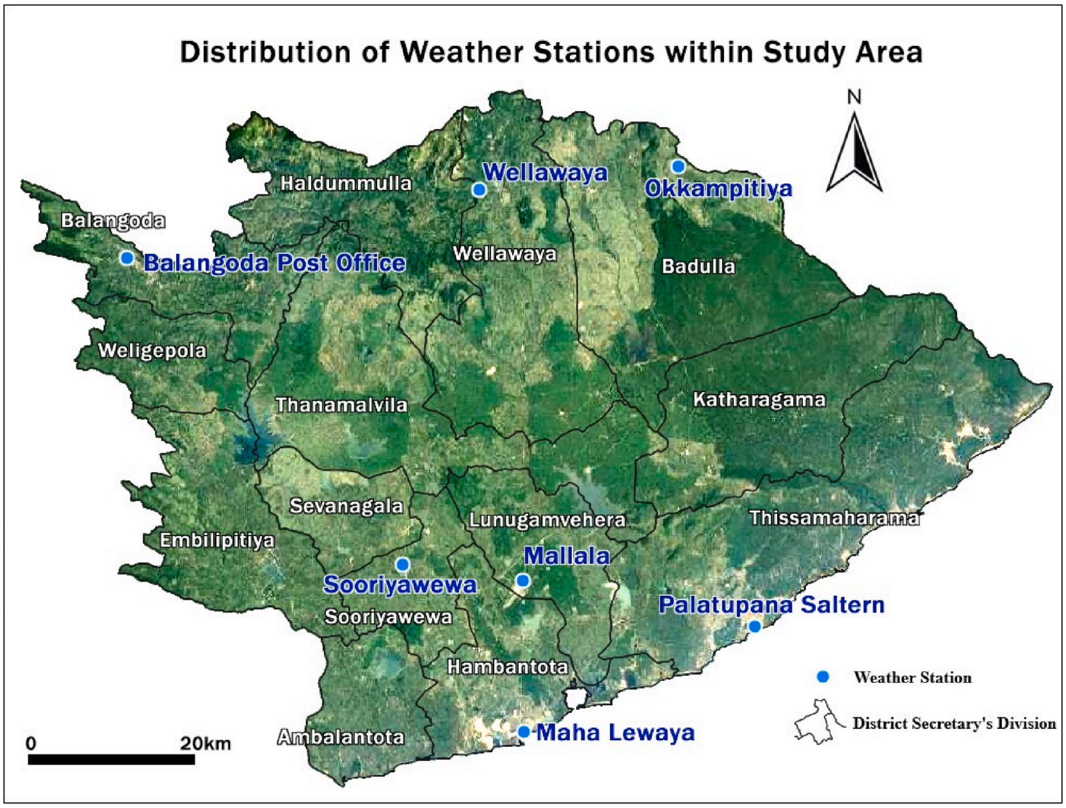

Fig. 4. Distribution map of weather stations within the study area.

Table 1
The characteristics of the Sentinel-2 data used in this study.

Satellite	Processing level	Cloud cover percentage	Date of acquisition
Sentinel-2A	Level-2A	0.38–13.78	June 21, 2021
Sentinel-2A	Level-2A	0.41–11.90	January 22, 2022

Table 2
LCLU categories and definitions.

LCLU category	Definition
Forest	Trees and bushes, covered by natural, newly forested, or planted forests
Open forest	Moderately tall trees and an open canopy that lets in some light
Homestead/Other crops	A house, the adjoining area of land, and the land planted for crops, including cultivated land on a commercially large scale
Sand/Residential land/Open land	Sand on the sea floor or seashore, land specifically for living or dwelling for individuals or households, land used for townships and rural settlements, unbuilt land with insignificant or no vegetation cover
Paddy field	A flooded field of arable land used for growing rice
Inland water	Any of the water, such as reservoirs, ponds, and tanks, within the territory

2.12. RF classification

The RF classifier is an ensemble tree-based classifier that chooses features randomly from the training dataset to minimise tree correlations (Gislason et al., 2006). It builds models using bootstrap aggregation using two parameters, mtry and ntree. These parameters function independently to create a final prediction by randomly selecting samples from the training dataset (Genuer et al., 2010). Specifically, mtry denotes the number of predictors tested at each decision tree node split, while ntree indicates the number of decision tree runs performed during each iteration (Chabalala et al., 2022). All trees are combined to achieve a final prediction. Thus, applying various decision trees grown using different random subsets decreases bias and prevents overfitting in the model. The bootstrap aggregating (bagging) method is robust against model fitting and helps develop a stable model.

In this study, the SNAP 9.0.0 image processing software was used for RF classification, and data preprocessing for Sentinel-2 imagery was performed using the Level-2A algorithm in Sen2Cor within the Sentinel Application Platform (SNAP) provided by the European Space Agency (ESA). SNAP seamlessly integrates with Sentinel satellite data, which is advantageous when working with imagery heavily reliant on Sentinel data. SNAP offers comprehensive support for the preprocessing, visualisation, and analysis of Sentinel data. Moreover, SNAP is optimised for efficiently processing large volumes of satellite data, leveraging parallel processing and optimisation techniques. Furthermore, SNAP benefits from a large user and development community, providing ample support, documentation, and tutorials for RF classification. Fig. 5 shows the methodology followed for the RF classification of Sentinel-2 data. In this study, the RF model was optimised, and the model accuracy was maximised by setting mtry and ntree parameters to 3200 and 50, respectively.

2.13. SVM classification

The principle behind the SVM classifier is a hyperplane that separates the data for different classes (Szuster et al., 2011). The focus is on constructing the hyperplane by maximising the distance from the hyperplane to the nearest data point of either class (Nguyen et al., 2020). These nearest data points are known as support vectors. By mapping the input data into a high-dimensional space, the kernel function converts nonlinear boundaries in the original data space into linear boundaries in the high-dimensional area, which can then be located using an optimisation algorithm (Huang et al., 2002). Therefore, the selection of the kernel function and the appropriate values for the corresponding kernel parameters, referred to as the kernel configuration, can affect the performance of the SVM (Shafizadeh-Moghadam et al., 2017).

The Orfeo Toolbox (OTB) software is an open-source remote sensing project (Michel and Grizonnet, 2015). This OTB 8.1.0 plugin was used for SVM classification integrated with QGIS 3.28. The OTB plugin was optimised using a cost parameter with an optimal parameter setting of one. The training and validation sample ratio was selected as 0.5 percent of the study. This SVM classification was executed in QGIS 3.28 using a linear kernel-type algorithm (De Luca et al., 2019). Fig. 6 shows the methodology followed for the SVM classification of Sentinel-2 data.

2.14. Accuracy assessment

Confusion matrices were created to compare the actual and assigned classes. This included the overall accuracy (OA), user accuracy (UA), producer accuracy (PA) and the kappa coefficient (Kc). A total of 188 randomly selected points were used for this accuracy assessment. Validation data were obtained from various resources, including Google Earth, on-site field data, prior knowledge, and publicly available information. The performances of the SVM and RF classifiers were measured.

A high accuracy in LCLU has to be maintained in this study for several reasons. First, maps help to determine the pattern of LULC change and its correlation with HEC. Accurate LULC data is essential for identifying and characterising potential HEC hotspots, as it provides detailed information about the types and distribution of LULC features that may attract or deter elephants, such as agricultural fields, forest patches, or human settlements. High-accuracy maps essential for pinpointing potential conflict hotspots accurately. Additionally, precise maps provide valuable spatial information on the distribution and intensity of HEC occurrences, enabling targeted mitigation efforts and resource allocation.

2.15. MODIS data analysis

Analysis of MODIS data has been an instrumental tool in monitoring and understanding various ecological dynamics worldwide. Previously, researchers (Perera and Tateishi, 2012) demonstrated the successful applicability of MODIS NDVI products in detecting changes in forest cover in Sri Lanka (Perera et al., 2012). Based on those research findings, a detailed analysis was conducted on the seasonal NDVI values in the study area. These locations also included HEC hotspots identified during the study. Out of the 123 MODIS

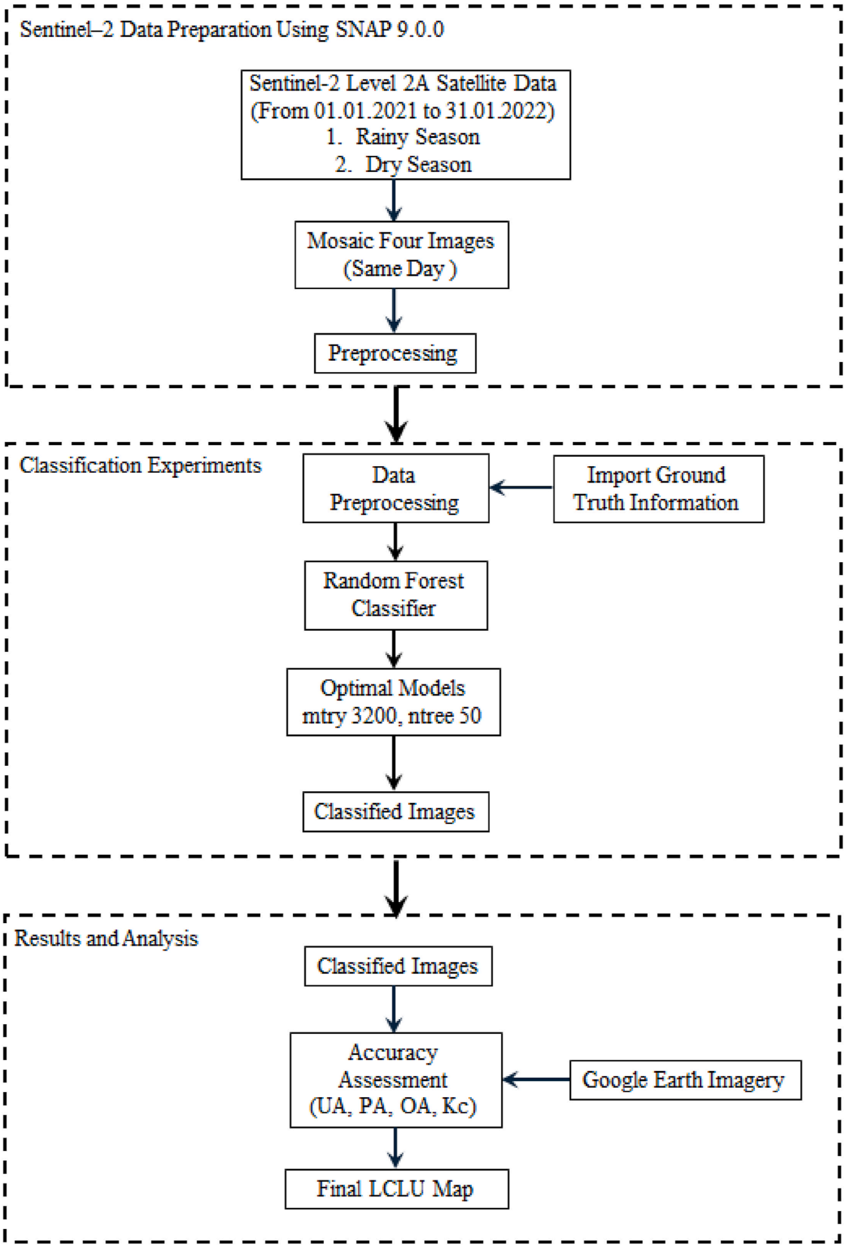

Fig. 5. Workflow diagram of the RF classification process.

images examined, 54 were selected for this study's NDVI analysis due to their minimal cloud coverage. The NDVI image was derived using Equation 01, and the red and near-infrared (Köpke et al.) bands were used to compute the NDVI in this study.

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} = \frac{B2 - B1}{B2 + B1} \qquad 1$$

The methodology used in this study will be directly applied to other regions with differing environmental and socio-economic characteristics. By utilising satellite imagery, it can effectively cover large areas typically affected by HEC. Through GIS, various environmental and anthropogenic factors contributing to HEC can be analysed spatially, allowing for the identification of hotspots where conflicts are most prevalent.

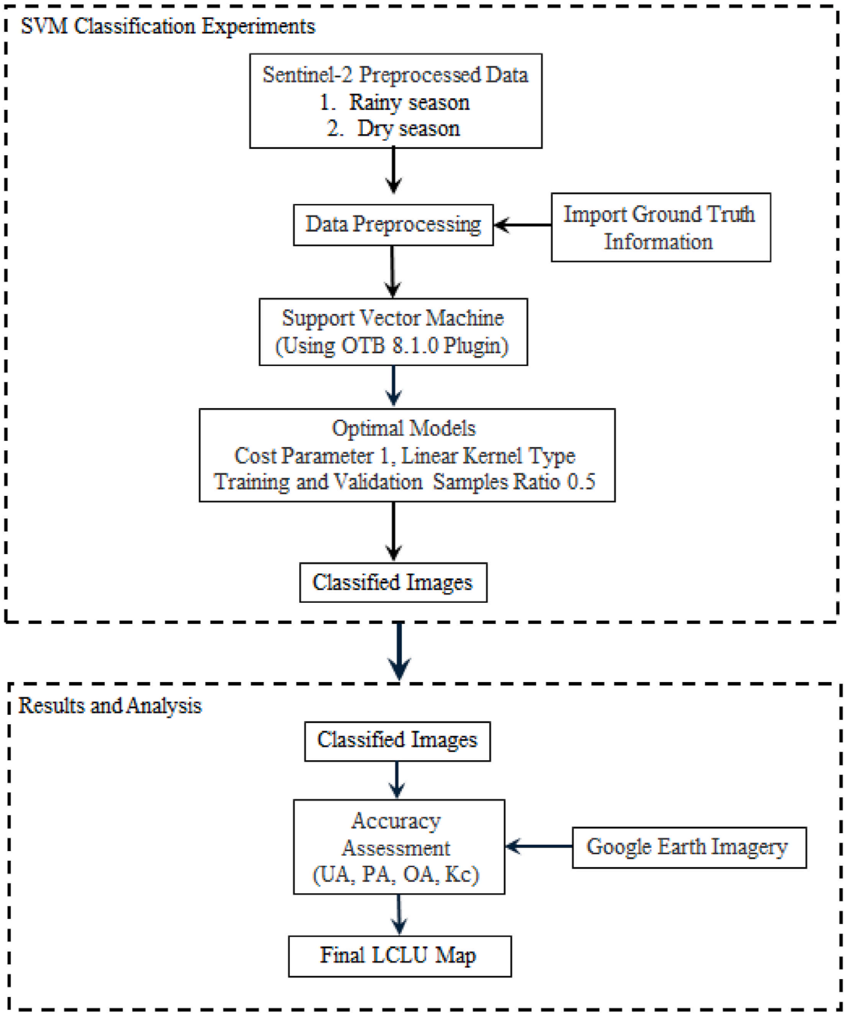

Fig. 6. Workflow diagram of the SVM classification process.

3. Results

3.1. LCLU classification

The RF and SVM methods were used to produce LCLU classification maps which are illustrated in Figs. 7 and 8, respectively. Tables 3 and 4 comprehensively present the classification accuracies.

Tables 3 and 4 present the classification accuracy of different LULCs over six months. The six-month interval between June and January encompasses different seasons, which can significantly impact the appearance of the LCLU. Seasonal planting and harvesting cycles could influence changes in agricultural land cover, such as paddy fields. This can lead to variations in classification accuracy over the different months. Any environmental changes occurring within these six months, such as deforestation, urbanisation, or water body dynamics, can also impact the LULC classification results.

The spatial analysis of the LCLU map shows distinct patterns for various classifications. The outputs derived from SVM and RF classifiers exhibit more precise and pronounced boundaries of the areas designated as forest, open forest, and homestead and other crops. Conversely, regions characterised by sand/residential land/open land, paddy fields, and inland water are reasonably classified in all utilised classifiers. Further quantitative insights into the accuracy and reliability of these classifications can be found in Table 5, which details the OA and Kc of each classification. The RF classifier has been detected as a highly accurate LCLU model with a Kc.

3.2. Analysis of NDVI

The NDVI is a widely used index for image classification, continuous monitoring, and the rapid assessment of forest quality. The highest NDVI values correspond to dense vegetation, forests, or crops at their peak growth stage. Based on growth characteristics, forest areas can be extracted by the difference in NDVI values between the dry and rainy seasons, reflecting vegetation growth dynamics. NDVI analysis was performed to evaluate vegetation health and cover, and the NDVI threshold value varied between −1 and +1.

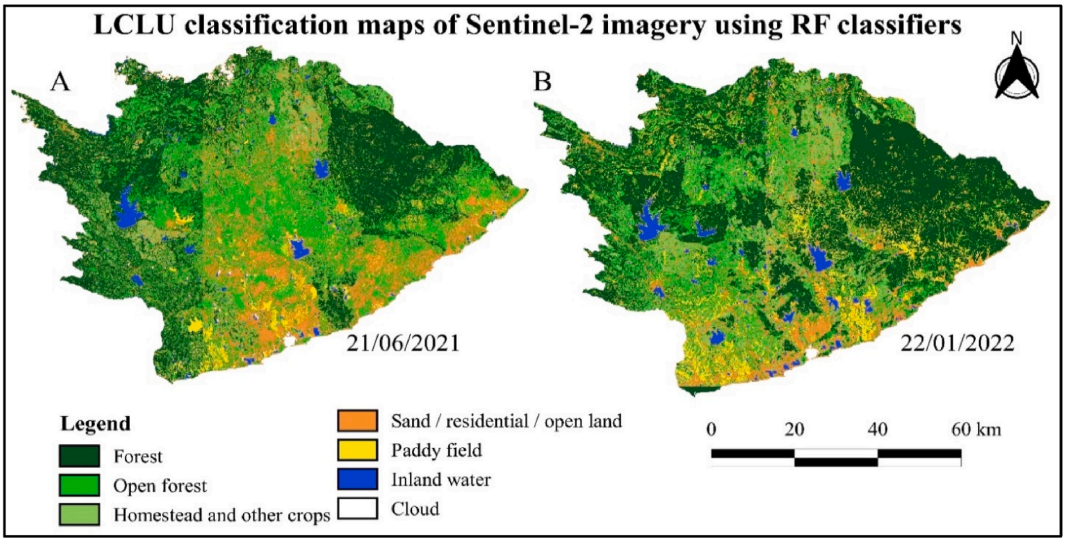

Fig. 7. LCLU classification maps of Sentinel-2 imagery using RF classifiers for 2021 to 2022.

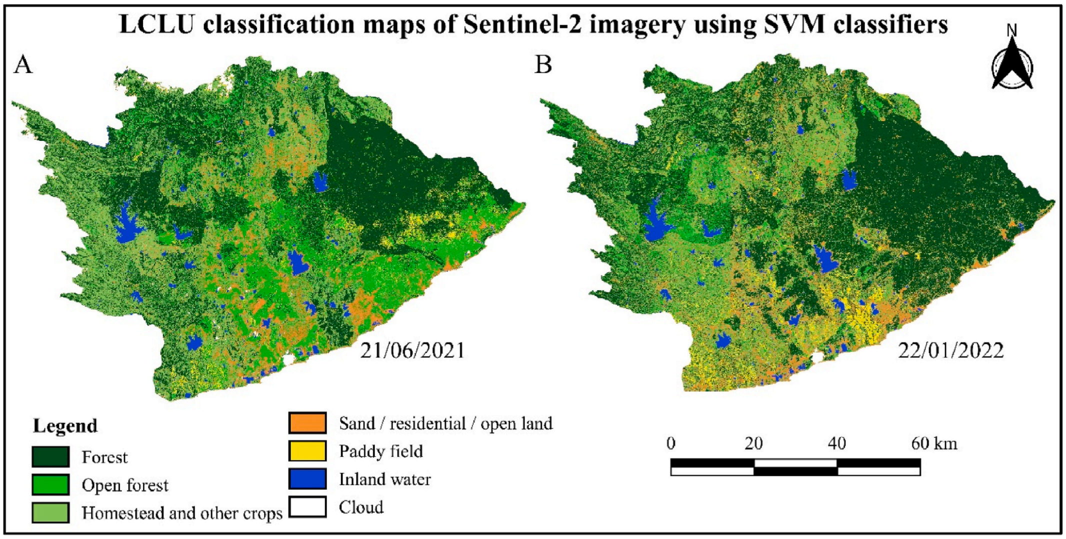

Fig. 8. LCLU classification maps of Sentinel-2 imagery using SVM classifiers for 2021 to 2022.

Table 3
PA and UA for RF classification results of classification images taken on June 21, 2021 and January 22, 2022.

Classification Scheme	June 21, 2021		January 22, 2022	
	PA %	UA %	PA %	UA %
Forest	100.00	98.59	98.88	98.88
Open forest	87.93	96.23	100.00	92.31
Homestead and other crops	89.47	94.44	88.46	95.83
Sand/Residential land/Open land	66.67	66.67	95.00	95.00
Paddy field	100.00	83.87	100.00	100.00
Inland water	100.00	100.00	100.00	100.00

Fig. 9 shows NDVI values significantly vary between these two phenological periods. In the study area, the dry season is from May to September 2021, while the transition to the rainy season occurs in October 2021. The recorded rainfall data from May 2021 to August 2021 indicate a rainfall level of less than 150 mm per month, except for Balangoda Post Office Weather Station (Fig. 10). NDVI values notably increased from September 2021, aligning with rainfall (Fig. 11). The NDVI image can discriminate between forests in the dry and rainy seasons because the NDVI values of forests are much higher than those of other vegetation

Table 4
PA and UA for SVM classification results of classification images taken on June 21, 2021 and January 22, 2022.

Classification Scheme	June 21, 2021		January 22, 2022	
	PA %	UA %	PA %	UA %
Forest	91.43	88.89	97.75	95.60
Open forest	79.31	93.88	79.17	86.36
Homestead and other crops	89.47	62.96	92.31	88.89
Sand/Residential land/Open land	33.33	33.33	95.00	100.00
Paddy field	96.15	100.00	100.00	100.00
Inland water	100.00	100.00	100.00	100.00

Table 5
Comparison of classification performance of RF and SVM classification.

Date	Classification Methods	OA	Kc
June 21, 2021	RF	94.68	0.93
	SVM	87.77	0.83
January 22, 2022	RF	97.31	0.95
	SVM	94.62	0.90

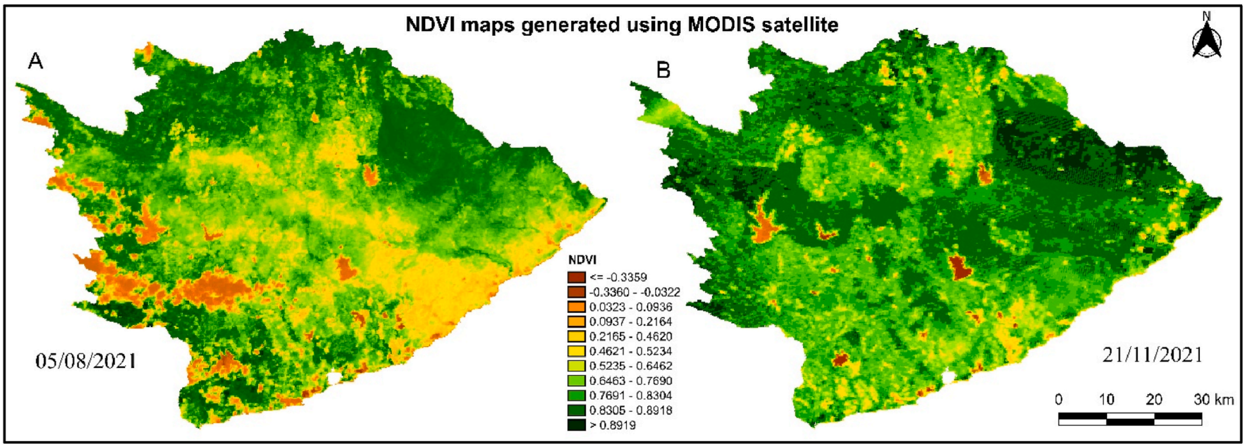

Fig. 9. NDVI results of the study area: (a) NDVI map in the dry season; (b) NDVI map in the rainy season.

types. NDVI values of vegetation in the rainy season increase significantly and can be easily distinguished from other LCLU types, such as water and bare land.

Fig. 12 visually represents the monthly seasonal vegetation changes over nine months from May 01, 2021 to January 31, 2022 using NDVI. During a dry period from June to August, the Hambantota region, which includes Maha Lewaya, Mattala, Suriyawewa, and Okkampitiya, recorded monthly rainfall levels of less than 150 mm. In the subsequent months, a considerable increase in NDVI values occurred. To be precise, from September 2021 to January 2022, such values increased and even exceeded 0.6, indicating a landscape with healthy vegetation.

3.3. Detection of HEC hotspots

Detecting high-density conflict points with QGIS involved systematically analysing recorded human and elephant death incidents from 2018 to 2021 (see Fig. 13). The kernel density estimation (KDE) method quantified the spatial distribution of human and elephant deaths using historical incident data from the selected period and was used to identify areas with a high density of such incidents. This analysis revealed eight specific geographic points. Fig. 13 shows the spatial distribution of these focal points for HEC hotspots.

Human and elephant death incidents within a 5 km radius were analysed using a spatial weight matrix (Rathnayake et al., 2022). The calculation involved determining the incident count within a 5 km radius and assigning weights ranging from 0 to 0.3 based on the distance from the designated reference point. An accurate LCLU map was utilised to evaluate the proximity to forested areas from the eight identified high-density conflict points. Weights were assigned between 0 and 0.5 based on the distance from the nearest forested area. Additionally, the impact of changes in greenery on incident occurrences was considered, with weights assigned between 0 and 0.2.

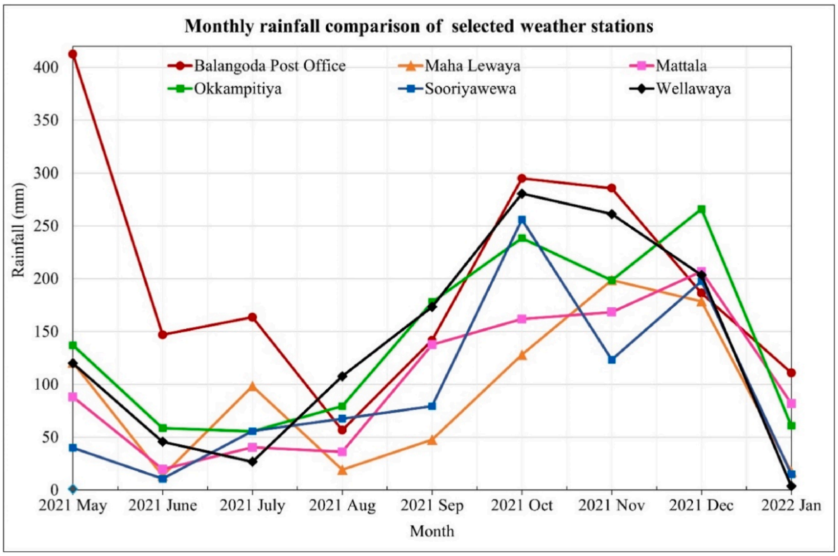

Fig. 10. Monthly variation of rainfall from May 2021 to January 2022.

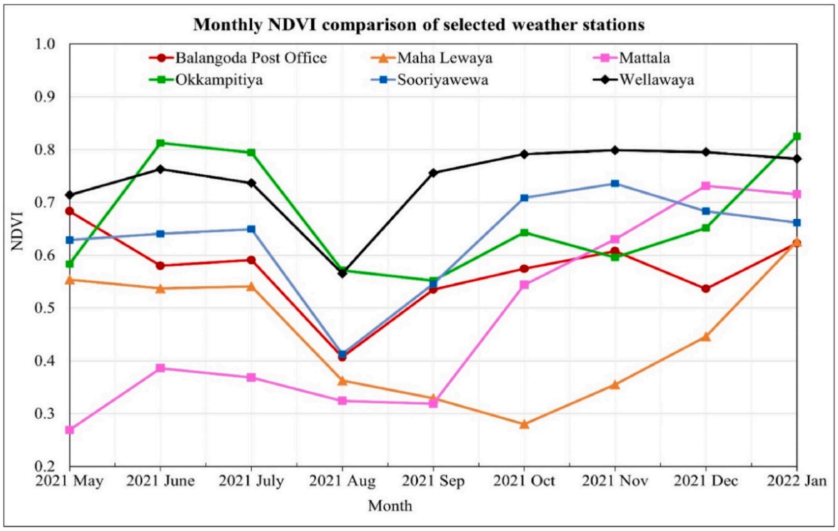

Fig. 11. Monthly variation of NDVI from May 2021 to January 2022.

The integration of estimated weights determined the total weight for each identified high-density point, as outlined in Table 6. This comprehensive approach enabled a detailed understanding of the factors contributing to the concentration of HEC incidents in specific areas.

3.4. HEC hotspots

Identifying HEC hotspots revealed a range of risk values, from a 0.8741 (very high) to 0.1593 (relatively lower). Consequently, based on conflict probability, the model was used to classify these HEC hotspots into four distinct risk categories, as detailed in Table 7.

According to Fig. 14, notably, all hotspots categorised as very high and high risk were located close to forest boundaries. This spatial relationship highlights the significant influence of forested regions on the occurrence of HEC incidents, further emphasising the critical need for conservation and mitigation efforts in these areas.

4. Discussion

HEC poses a significant challenge in many parts of the world, including Sri Lanka, where it threatens wildlife conservation and human livelihoods. Understanding HEC incident patterns and trends is crucial for developing effective mitigation and conservation strategies. In this study, regression analysis was used to investigate the relationship between years and HEC incidents, with a moder-

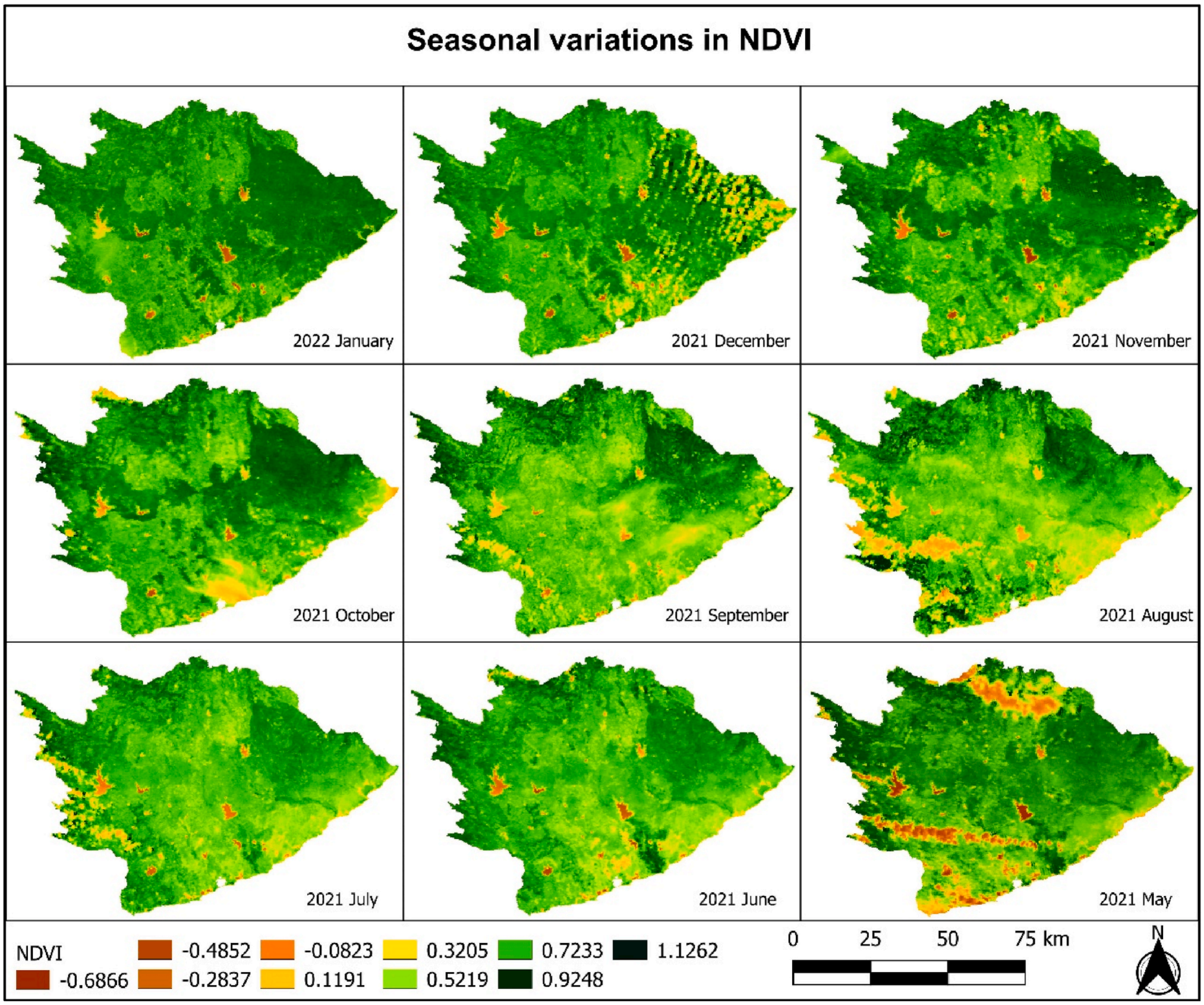

Fig. 12. Monthly seasonal variations in NDVI from May 2021 to January 2022.

ate association identified. Sri Lanka has a significant population of wild elephants, approximately 0.1 elephants/km^2 compared to 0.01 elephants/km^2 in India.

Sentinel-2 L2A imagery with less than 14 percent cloud coverage and MODIS satellite data with minimal cloud coverage were utilised to produce six LCLU classification schemes within the study area, illustrating the region's vast diversity of landscapes and varied LCLU. Sentinel-2 satellite imagery was classified using supervised classification methods, RF, and SVM algorithms. SNAP 9.0.0 and QGIS 3.28 software with OTB 8.1.0 plugin tools were used in this classification.

Training sites were chosen using a combination of resources, including Google Earth, on-site field data, prior knowledge, and public datasets. The RF model was optimised, and the model accuracy was maximised by setting two main parameters, mtry at 3200 and ntree at 50. This SVM classification was executed using a linear kernel-type algorithm with a setting of 1 for cost parameters and training and validation sample ratio of 0.5 percent.

Confusion matrices were created to compare the actual and assigned classes. For this accuracy assessment, 188 randomly selected points were used. The RF classifier achieved a higher accuracy overall of 97.31 percent, while the SVM classifier reached 94.62 percent. Kc values that peak at 0.95 for RF and 0.90 for SVM indicate a strong consistency between the ground truth and the processed classifications. The results confirm that RF and SVM are reliable and accurate methods for classifying Sentinel-2 satellite imagery into LCLU maps.

Moreover, NDVI analysis provides insights into vegetation health and its correlation with rainfall patterns. During the dry season from May 2021 to August 2021, the recorded rainfall level was less than 150 mm per month. In this period, NDVI values were lower, indicating reduced vegetation cover. However, following increased rainfall, NDVI values rose notably in September 2021, indicating healthy vegetation cover with such values exceeding 0.6.

The KDE technique was used to identify areas with a high density of humans and elephants. Subsequently, eight specific geographic points were pinpointed as exhibiting a heightened density of human and elephant death incidents. A spatial weight matrix

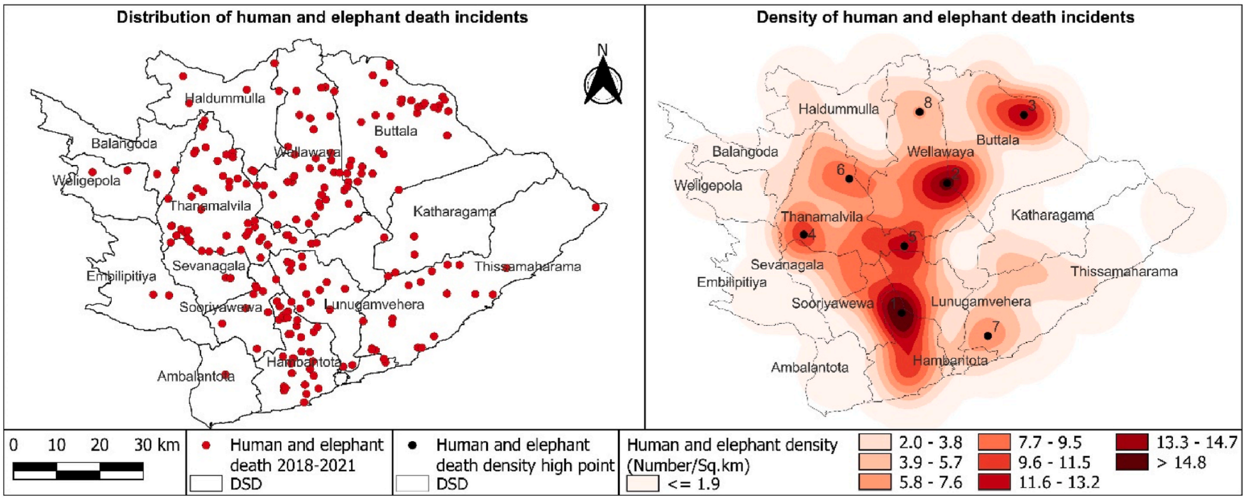

Fig. 13. (a) Distribution of reported human and elephant death incidents from 2018 to 2021; (b) The density of human and elephant death incidents per km^2 within the study area.

Table 6
High-density points of human and elephant deaths and conflict probability.

Point ID	Conflict probability
1	0.8714
2	0.7093
3	0.8074
4	0.8278
5	0.2283
6	0.2378
7	0.1593
8	0.5742

Table 7
Conflict probability and risk level of HEC hotspots.

Conflict probability	Risk level
0–0.25	Very high
0.26–0.50	High
0.51–0.75	Moderate
0.76–1.00	Low

was used for further analysis. For human and elephant death incidents within a 5 km radius of each point, weights ranging from 0 to 0.3 were assigned based on the distance from the designated reference point. Also, the proximity to forest areas from these points was measured using an LCLU map with weights from 0 to 0.5 assigned. Additionally, the impact of changes in greenery on incident occurrences was considered based on NDVI and weights were assigned from 0 to 0.2 accordingly.

Identifying HEC hotspots revealed a range of risk values, from a very high 0.8741 to a relatively lower 0.1593. Therefore, the model classified these HEC hotspots into four distinct risk categories: very high, high, moderate, and low. Specifically, three hotspots were classified as very high risk and two as high risk, all strategically situated close to forest boundaries.

The main strength of this study is its proposed and validated HEC high-risk zone identification method by integrating GIS and satellite data fusion techniques. Remote sensing and GIS analysis have been successfully combined to monitor changes in greenery correlated with HEC incidents. The purpose of identifying high-risk HEC zones using remote sensing and GIS is to alert communities of high-risk HEC hotspots and provide some guidance for implementing HEC mitigation plans.

The proposed method in this study has several limitations in real-world applications. The availability and quality of input data heavily influence the accuracy of satellite data classification. Although satisfactory results for LCLU classification can be obtained, securing enough cloud-free images is difficult. The accuracy of the classification model depends on the appropriate representativeness and quality of the training data. Classification accuracy can be compromised if training data do not adequately capture the variability and characteristics of target LCLU classes. This may have an adverse effect on classification accuracy.

The adopted study methodology will be applied to other regions dealing with similar human-wildlife conflict, considering several factors such as scalability, similar characteristics, and adaptability. The ability to scale up or down is essential for its applicability to different regions, ensuring that the methodology remains effective and feasible.

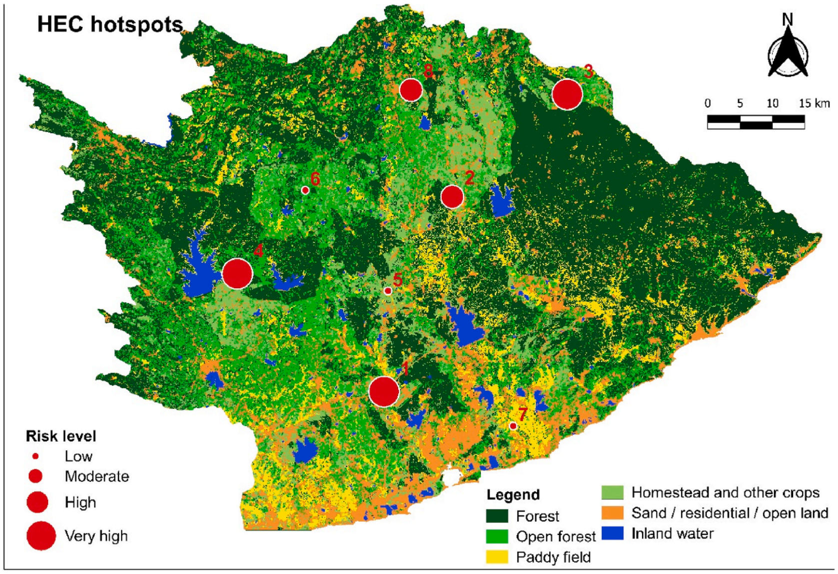

Fig. 14. HEC hotspots and their risk level.

5. Conclusions

With significant economic, social, and ecological implications, HEC in Sri Lanka poses a significant threat to local communities and the elephant population. This study comprised an investigation into utilising Sentinel-2 satellite imagery for LCLU classification in Sri Lanka and MODIS satellite data for monitoring changes in greenery. Remote sensing and GIS techniques were applied to examine the relationship between HEC incidents and LCLU changes in two forest-dominated regions of Southeast Sri Lanka from 2021 to 2022.

The efficiency of RF and SVM classification methods in producing LCLU maps using Sentinel-2 satellite data was evaluated. The RF classifier achieved a higher overall accuracy of 97.31 percent compared to the SVM classifier, which reached 94.62 percent, still a robust result. The strong consistency between ground truth and processed classifications, indicated by Kc values peaking at 0.95 for RF and 0.90 for SVM, underscores the effectiveness of RF and SVM in classifying Sentinel-2 satellite imagery into LCLU maps.

NDVI analysis was carried out to evaluate vegetation health and cover, revealing fluctuations and changes in greenery. Following a dry period from May 2021 to August 2021, significant increases in NDVI readings were observed in the Hambanthota and Moneragala districts. NDVI values exceeded 0.6 with rainfall. Moreover, a correlation between rainfall and NDVI was established, with increased rainfall corresponding to higher NDVI values and healthier vegetation cover.

For HEC hotspot detection, the KDE technique was used to identify high incident density. Spatial weight matrices were employed to assess factors such as the count of human and elephant death incidents within a 5 km radius, proximity to forested areas, and changes in greenery, with hotspots classified into four risk categories: very high, high, moderate, and low. Notably, three very high risk and two high-risk HEC hotspots were situated close to forest boundaries.

The findings of this study offer valuable insights for mitigating HEC and fostering coexistence between humans and elephants. Sentinel-2 imagery and MODIS satellite data can facilitate the timely identification of greenery changes, aiding in detecting HEC hotspots. Collaborations with local governments are essential for implementing inclusive strategies incorporating wildlife conservation and HEC mitigation into LCLU policies. Augmenting strategy with machine learning models trained on historical HEC incidents and greenery changes can enhance predictive capabilities, while interactive community feedback platforms can further refine mitigation efforts. Importantly, these strategies and methodologies are transferable to other regions facing similar HEC challenges.

In conclusion, the precision mapping of HEC high-risk zones in Sri Lanka and other affected regions through GIS and satellite data fusion is crucial for evidence-based conservation strategies. This study underscores the potential of HEC hotspot identification for precision in mapping HEC zones in Sri Lanka and any other country with HEC, to promote effective resource allocation, community engagement and awareness, data-driven decision-making, international collaboration, and research. In conclusion, demarcating high-risk zones of HEC in Sri Lanka through GIS and satellite data fusion is crucial for evidence-based, effective conservation strategies.

CRediT authorship contribution statement

Thakshila D. Gunawansa: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Conceptualization. **Kithsiri Perera:** Writing – review & editing, Visualization, Methodology, Conceptualization. **Armando Apan:** Supervision. **Nandita K. Hettiarachchi:** Supervision.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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Abbreviations

DWC	Department of Wildlife Conservation
ESA	European Space Agency
GIS	Geographic Information System
HEC	Humane Elephant Conflict
KDE	Kernel Density Estimation
LCLU	Land Cover and Land Use
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalised Difference Vegetation Index
Kc	Kappa Coefficient
OA	Overall Accuracy
OTB	Orfeo Toolbox
PA	Producer Accuracy
QGIS	Quantum Geographic Information System
RF	Random Forest
SVM	Support Vector Machine
UA	User Accuracy

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