University of Southern Queensland

DEMARCATING HIGH-RISK ZONES OF HUMAN-ELEPHANT CONFLICT IN SRI LANKA UTILIZING GIS AND A SATELLITE DATA FUSION APPROACH

A Thesis submitted by

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ABSTRACT

The escalating human-elephant conflict (HEC) in countries like Sri Lanka demands urgent attention due to several factors: rapid population growth, agricultural expansion, infrastructure development, and climate change impacts. From 2010 to 2022, human and elephant deaths have doubled, resulting in 1,208 human and 3,771 elephant fatalities. Globally, Sri Lanka ranked second in annual human deaths and had the highest per capita death rate from HEC between 2006 and 2021. This study aims to identify high-risk HEC zones through a comprehensive analysis to monitor changes in greenery utilising satellite remote sensing and GIS techniques. The study analysed multi-seasonal land cover and land use (LCLU) changes utilising Sentinel-2 satellite data. These were correlated with recorded HEC incidents to identify potential high-risk zones. The study relied on random forest (RF), support vector machine (SVM), and object-based image analysis methods for LCLU classification, conducted in two forest-dominated regions of southeast Sri Lanka from 2021 to 2022. According to the findings, the RF and SVM methods have higher accuracy. 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. Therefore, these two methods were selected for analysis in this study. Monthly greenery changes were further quantified using normalised difference vegetation index (NDVI) analysis and NDVI values derived from moderate-resolution imaging spectrometer data, identifying suitable regions where elephants forage frequently. Furthermore, using kernel density estimation, the study 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. This revealed varying levels of HEC risk, ranging from very high to low. The LCLU map, created using the RF classifier, indicates that all identified 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 and 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.

CERTIFICATION OF THESIS

I Thakshila Dilupama Gunawansa declare that the PhD Thesis entitled *Demarcating High-risk Zones of Human-Elephant Conflict in Sri Lanka Utilizing GIS and a Satellite Data Fusion Approach* is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes.

This Thesis is the work of Thakshila Dilupama Gunawansa except where otherwise acknowledged, with the majority of the contribution to the papers presented as a Thesis by Publication undertaken by the student. The work is original and has not previously been submitted for any other award, except where acknowledged.

Date: 22.02.2024

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Student and supervisors' signatures of endorsement are held at the University.

STATEMENT OF CONTRIBUTION

The articles produced from this doctoral research thesis were a joint contribution of the candidate and supervisors. Details of the scientific contribution of each author in the respective journal publications and a conference publication are provided as follows.

Paper 1: Chapter 3

Gunawansa, T. D., Perera, K., Apan, A., & Hettiarachchi, N. K. (2023). The human-elephant conflict in Sri Lanka: history and present status, *Biodiversity and Conservation, 32(10),* 3025–3052. https://doi.org/10.1007/s10531-023-02650-7. ***(Scopus Ranked Q1, Impact Factor: 3.7)***

Author	Task Performed	Contribution %
Thakshila D. Gunawansa (PhD Candidate)	Literature review, method development, programming, data analysis, preparation of figures and tables, compilation, writing, and manuscript revision.	70
Kithsiri Perera (Principal Supervisor)	Supervision and assistance in model concepts, detailed comments on the manuscript, editing, and guidance to preparation for submission.	20
Armando Apan (Associate Supervisor)	Comments on the draft manuscript and the language used.	5
Nandita K. Hettiarachchi (Associate Supervisor)	Comments on the draft manuscript and the language used.	5

Paper 2: Chapter 4

Thakshila, G., Perera, K., Armando, A., & Nandita, H. (2022). Application of Sentinel-2 satellite data to map forest cover in Southeast Sri Lanka through the random forest classifier. *Journal of Advances in Engineering and Technology*, 1(1), 1-10. https://doi.org/10.54389/KYTI8887.

Author	Task Performed	Contribution %
Thakshila D. Gunawansa (PhD Candidate)	Literature review, method development, programming, data analysis, preparation of figures and tables, compilation, writing, and manuscript revision.	70
Kithsiri Perera (Principal Supervisor)	Supervision and assistance in model concepts, detailed comments on the	20

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Armando Apan (Associate Supervisor)	Comments on the draft manuscript and the language used.	5
Nandita K. Hettiarachchi (Associate Supervisor)	Comments on the draft manuscript and the language used.	5

Paper 3: Chapter 5

Gunawansa, T. D., Perera, K., Apan, A., Hettiarachchi, N. K., & Bandara, D. Y. (2023). Greenery change and its impact on human-elephant conflict in Sri Lanka: a model-based assessment using Sentinel-2 imagery, *International Journal of Remote Sensing, 44(16),* 5121-5146. https://doi.org/10.1080/01431161.2023.2244644. ***(Scopus Ranked Q1, Impact Factor: 3.6)***

Author	Task Performed	Contribution %
Thakshila D. Gunawansa (PhD Candidate)	Literature review, method development, programming, data analysis, preparation of figures and tables, compilation, writing, and manuscript revision.	65
Kithsiri Perera (Principal Supervisor)	Supervision and assistance in model concepts, detailed comments on the manuscript, editing, and guidance to prepare for submission.	20
Armando Apan (Associate Supervisor)	Comments on the draft manuscript and the language used.	5
Nandita K. Hettiarachchi (Associate Supervisor)	Comments on the draft manuscript and the language used.	5
Dhananjaya Y. Bandara	Field data collection.	5

Paper 4: Chapter 6

Gunawansa, T. D., Perera, K., Apan, A., & Hettiarachchi, N. K. (2024). Identifying human elephant conflict hotspots through satellite remote sensing and GIS to support conflict mitigation. *Remote Sensing Applications: Society and Environment*, *35*, 101261. https://doi.org/https://doi.org/10.1016/j.rsase.2024.101261.

(Scopus Ranked Q1, Impact Factor: 4.7)

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Kithsiri Perera (Principal Supervisor)	Supervision and assistance in model concepts, detailed comments on the manuscript, editing, and guidance to prepare for submission.	20
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I enjoyed every moment of my doctorate studies, and it has been an enormous honour and privilege. Finally, I thank everyone who has contributed to this accomplishment.

Thakshila Dilupama Gunawansa
22nd February 2024

DEDICATION

This dissertation is dedicated to my mother, father, and husband for their love, sacrifice, and inspiration.

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(Excluding publications included in Chapters 3–6)

ABBREVIATIONS

DS	Divisional Secretariat
DT	Decision trees
DWC	Department of Wildlife Conservation
ESA	European Space Agency
GFW	Global forest watch
GIS	Geographic Information Systems
HEC	Human-elephant conflict
IUCN	International Union for Conservation of Nature
KDE	Kernel density estimation
LCLU	Land cover and land use
MODIS	Moderate-resolution imaging spectrometer
NASA	National Aerospace Science Administration
NDVI	Normalised difference vegetation index
OBIA	Object-based image analysis
OTB	Orfeo Toolbox
RF	Random forest
SVM	Support vector machine
USGS	United States Geological Survey

CHAPTER 1: INTRODUCTION

1.1 Background of the study

Human-elephant conflict (HEC) poses a significant challenge to conservation and socio-economic stability (Billah et al., 2021; Thakur et al., 2016). Despite several efforts to address this problem, it remains unresolved, particularly in Africa and Asia (Shaffer et al., 2019), home to most of the world's elephant population (Gubbi et al., 2014). HEC encompasses a complicated socio-ecological challenge (Sanare et al., 2022) and ethical considerations (Velempini, 2021).

The longstanding interaction between elephants and humans is complicated due to several factors: the rapid growth of the human population (Ogutu et al., 2014), land conversion for agricultural expansion, infrastructure development (Billah et al., 2021), and climate changes (Shaffer et al., 2019). This situation particularly affects areas where human settlements and elephant habitats overlap (Kamau & Sluyter, 2018; Locke, 2013; Thekaekara, 2019) in rural and semi-urban areas (Anuradha et al., 2019; Fernando et al., 2005). The consequences of HEC include human injuries, deaths (Kuswanda et al., 2022), retaliatory killings of elephants (Munyao et al., 2020), crop raiding, property damage (Nyirenda et al., 2018) and poaching elephants for ivory (Gunawansa et al., 2023; Shaffer et al., 2019).

In Sri Lanka, specific potential causes and contexts contribute to HEC: changes in land cover and land use (LCLU) patterns, habitat loss (Tennakoon et al., 2015), and competition for resources (Köpke et al., 2021; Perera, 2009; Perera et al., 2012). Due to the high mortality rates of the Sri Lankan elephant, the International Union for Conservation of Nature (IUCN) has listed the Sri Lankan elephant (*Elephas maximus maximus*) on the Red List of Threatened Species (Rathnayake et al., 2022).

The country's forest cover was 1,624,757.5 ha in 1992, and in 2019, it was 1,377,799.1 ha. During these 27 years, the forest cover of Sri Lanka's land area decreased from 24.8 percent to 21 percent (Ranagalage et al., 2020). This forest cover loss is due to urbanisation (Fernando & Pastorini, 2011), agricultural expansion (Fernando & Edussuriya, 2016), fire, fuelwood gathering, invasive species, and climate changes (Samarasinghe et al., 2022), all of which exacerbate the HEC issue. With limited space on the island for feeding and migration, elephants and humans increasingly compete for natural resources, intensifying the conflict (Perera & Tateishi, 2012). An elephant's home range varies from 50 to 150 km^2 according to food availability and habitat type (Gunawansa et al., 2023).

Population growth and agricultural expansion have caused tremendous pressure on land use (Fernando et al., 2021; Köpke et al., 2021; Perera & Tateishi, 2012). Figure 1-1 illustrates the rural and total population trends in Sri Lanka from 1960 to 2022 (The World Bank Group, 2023b). This figure shows the rural population has expanded dramatically from 8.25 million in 1960 to 17.8 million in 2020 due to the growth of the human population and the improvement of the country's free healthcare system (The World Bank Group, 2021).

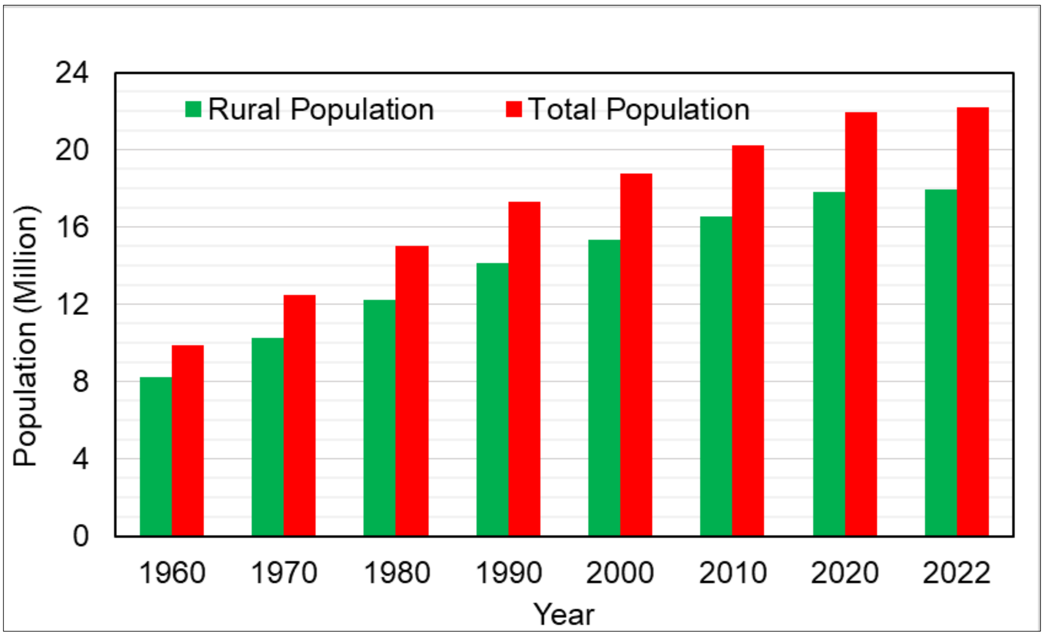

Figure 1-1: Rural and total populations of Sri Lanka from 1960 to 2022 (The World Bank Group, 2023a).

Elephants and humans rely on natural resources such as water and vegetation (Santiapillai et al., 2010). Consequently, the depletion of these resources leads elephants to encroach into human settlements (Gunawansa et al., 2023; Russ, 2019), increasing the competition for water and food (Fernando, 2015). As a result, elephants destroy vast fields of crops, leading to enormous financial losses for farmers in a short period (De Silva & Srinivasan, 2019). This pressure on resources contributes to the economic impact of HEC (Köpke et al., 2023), especially in agriculture-dependent rural communities. During the crop-raiding season, farmers and their families are compelled to protect their crops and property, resulting in sleep deprivation, fatigue, limited work opportunities, increased exposure to infectious diseases, and psychological stress (Anuradha et al., 2019; Parker et al., 2007). Such indirect costs are traditionally challenging to assess and do not easily transfer into economic value (Gunawansa et al., 2023).

Traditional management approaches such as general fencing, trenches, acoustic measures, lights, agricultural deterrents, elephant watch towers, and beehive fences (Fernando et al., 2008) have proven reactive and localised. The Sri Lankan government also initiated electric fences, translocation, and the establishment of elephant corridors (Madhushanka & Ranawana, 2021). However, the durability and effectiveness of these approaches vary, emphasising the need for more intelligent and dynamic management techniques.

Understanding the changing dynamics of elephant habitats, identifying HEC hotspots using accurate forest cover maps, and implementing effective mitigation strategies are essential to addressing the HEC issue in Sri Lanka. The urgent need for intelligent and dynamic management techniques is evident in the variability of the effectiveness of existing approaches.

1.2 Statement of the problem

Sri Lanka is a tropical island in the Indian Ocean with a total land area of 65,525 km^2 located between latitudes 5º 55' and 9º 51' and longitudes 79º 52' and 81º 51' (Wijesundara et al., 2023). With the third highest human population density among the 13 Asian elephant range countries (Cabral de Mel et al., 2023), after Bangladesh (Montez, 2021) and India (Fernando & Pastorini, 2011), Sri Lanka has witnessed a significant rise in HEC incidents over the past 15 years. The severity of the conflict is underscored by the country's global position of second-highest in annual human deaths and highest in per capita human deaths from HEC (Prakash et al., 2020; Rathnayake et al., 2022).

The Department of Wildlife Conservation (DWC) reported alarming statistics, indicating only 142 tuskers in Sri Lanka's forests in 2011 (Köpke et al., 2021; The Department of Wildlife, 2023). Sri Lanka has 10-20 percent of Asian elephants in their natural habitat while accounting for only around two percent of their global range (Fernando et al., 2011; Perera, 2009). Figure 1-2 presents the numbers of deaths of humans and elephants from 2010 to 2019 due to HEC and indicates how the severity of the conflict has continued.

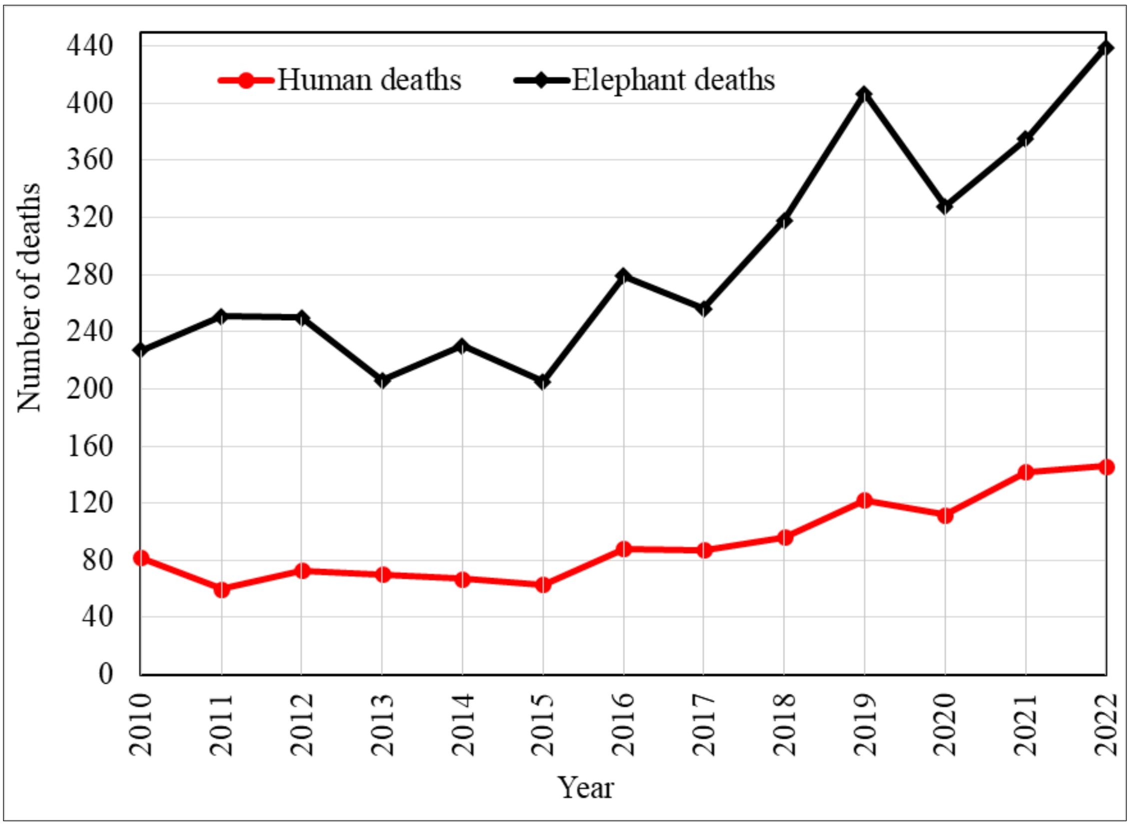

Figure 1-2: Human and elephant deaths in Sri Lanka from 2010 to 2022 (DWC).

Furthermore, HEC data revealed 18,409 incidents from 2015 to 2022. Property damage has increased by over 238 percent since 2015, accounting for a significant portion of the 14,145 listed property damage events due to HEC. Human injuries are also frequent, with 801 documented incidents (DWC).

The distribution of HEC incidents across Divisional Secretariats (DS) divisions highlights the conflict's prevalence in the dry zone, with human deaths reported in 112 DS divisions and elephant deaths in 131 DS divisions (Figure 1-3). Most damage to property occurred in Polonnaruwa (797 events) and Anuradhapura (689 events), while for human injuries, 60 cases were reported in Anuradhapura and 28 in Batticaloa, emphasising the urgent need to identify high-risk zones accurately.

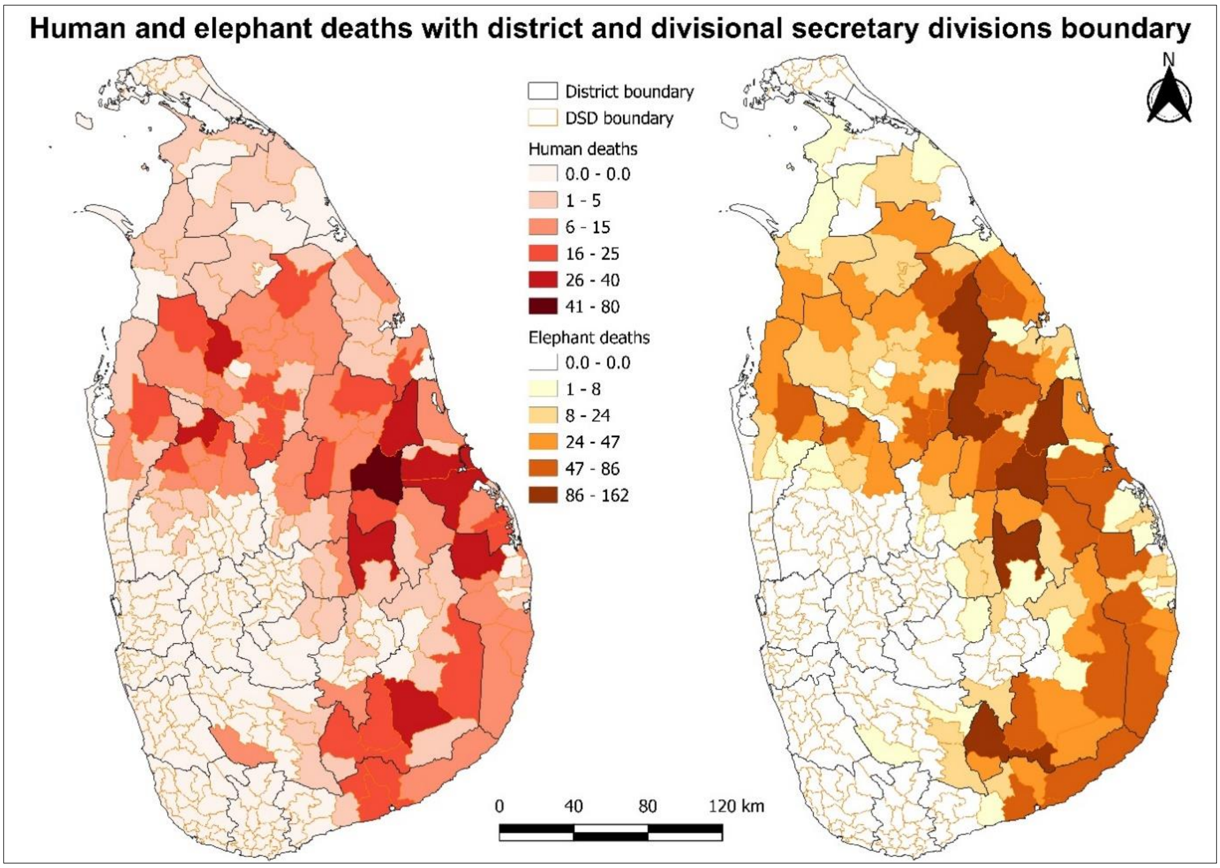

Figure 1-3: Distribution of human and elephant deaths across districts with DS divisions from 2010 to 2022 (DWC).

Hundreds of elephants are killed annually as a result of intentional or unintentional human actions that are caused directly or indirectly by HEC (Cabral de Mel et al., 2023). In 2022, elephant deaths occurred for various reasons, including ten falling into agricultural wells, abandoned quarries, or gem pits, 14 due to train accidents, and 51 from electrocutions through contact with low-lying electric power lines or lethal electric fences, according to the DWC. Furthermore, 60 elephants were intentionally killed, and another 59 were shot using explosives such as *hakka patas* (DWC, 2022b).

Efforts to mitigate HEC include using elephant thunder crackers, constructing electric fences, and translocating problematic elephants. Between 2010 and 2018, the DWC built 2,402 km of new electric fences. Figure 1-4 shows wild elephants next to the electric fence in Bulugolla village, Central Province, Sri Lanka. In 2018, DWC spent US$ 1.068 million on selected HEC mitigation activities such as elephant thunder crackers, compensation, capture and translocation, and elephant drives (Prakash et al., 2020). In addition, in 2022, the government was required to pay US$ 342,159.86

for 160 human deaths, US$ 39,042.83 for 192 cases of human injuries and US$ 684,013.87 for 2,741 incidents of property damage. The financial burden on the government for compensation and mitigation activities further underscores the urgency of effective HEC management (DWC, 2022a).

In this study, remote sensing and geographic information system (GIS) technologies were used to address this complex issue by identifying HEC hotspots. A multidisciplinary approach incorporates machine learning algorithms to analyse spatial and temporal data, considering three key factors: HEC incidents, LCLU patterns, and rainfall data. This study aims to develop a method to identify high-risk zones accurately for mitigating HEC in Sri Lanka and globally by addressing this critical issue.

High-resolution satellite imagery is required to capture detailed LCLU patterns. Sentinel-2 higher spatial resolution is necessary for detailed analysis of specific areas, such as Southeast Sri Lanka. This allows for accurate mapping of LCLU of large-scale features. MODIS data provides comprehensive coverage, making it suitable for regional analysis. RF classification method is selected due to its high accuracy, especially when dealing with complex and heterogeneous data.

Figure 1-4: Wild elephants beside the electric fence in Bulugolla village, Central Province, Sri Lanka. (Source:Bhammar, 2017)

The following research questions are addressed:

a) Is there critical land pressure in Sri Lanka to accommodate its human and elephant populations?
b) Is the HEC a significant environmental issue in Sri Lanka?
c) What is the suitable forest area size for elephant habitat in Sri Lanka?
d) How can an accurate forest map of the study area be produced by excluding thick vegetation in villages?
e) Using satellite data, is it possible to identify dynamics in vegetation greenery with high temporal resolution (weekly)?
f) Can GIS and satellite remote sensing technologies be applied to identify local movement patterns of wild elephants and HEC hotspots?

1.3 Significance of the study

The need for effective measures to mitigate the impact of HEC on human communities and elephant populations has reached a critical juncture. Despite implementing specific mitigation measures, there is an absence of standardised frameworks in the field. This study addresses this critical gap by developing a standardised framework for monitoring and predicting high-risk HEC hotspots using remote sensing and GIS techniques. Applying these methods will enhance precision in identifying areas prone to HEC, enabling more effective mitigation strategies and fostering a safer coexistence between humans and elephants in the region.

The system for forest map development significantly contributes to HEC management by identifying and predicting HEC hotspots. By identifying high-risk zones through GIS and satellite data fusion, the study provides a pathway to more effective, informed, and comprehensive conservation strategies. Moreover, this system is proved to be accurate and cost-effective. The same methodology can thus be extended to monitor various forest covers. The technology's capacity to monitor different forest types means it is adaptable and has the potential for effective application across different HEC zones, with adjustments tailored to local conditions and needs. The proposed method can be used in all HEC zones throughout Sri Lanka and various global regions experiencing similar challenges.

1.4 Research aim and objectives

The research presented in this thesis, based on the research questions, uses a satellite data fusion approach with GIS modelling to identify HEC risk zones in Sri Lanka. More specifically, the research objectives are to:

a) Assess the impact of ever-increasing human and elephant populations on HEC. This objective was fulfilled by writing a review paper titled *"The human-elephant conflict in Sri Lanka: history and present status"*. ***The article has been published in the Journal of Biodiversity and Conservation (Vol. 32, pages 3025-3052).***

b) Develop an accurate forest map through the fusion of high-resolution Sentinel + MODIS (Moderate-resolution imaging spectrometer) + Google Earth and GIS data. This objective was achieved with journal papers *"Application of Sentinel-2 satellite data to map forest cover in Southeast Sri Lanka through the random forest classifier"* and *"Greenery change and its impact on human-elephant conflict in Sri Lanka: a model-based assessment using Sentinel-2 imagery".* ***The articles have been published in the Journal of Advances in Engineering (Vol. 1, pages 049-1 to 049-10) and the Technology and International Journal of Remote Sensing (Vol. 44, pages 5121-5146).***

c) Map elephant habitat-friendly forest areas using GIS and satellite RS. This objective was achieved with the journal paper *"Identifying human-elephant conflict hotspots through satellite remote sensing and GIS to support conflict mitigation." The articles were* ***published in the Journal of Remote Sensing Applications: Society and Environment (Vol 35).***

d) Map the HEC hotspots and patterns of elephant movements using GIS and satellite RS. This objective was similarly achieved with the same journal paper, *"Identifying human-elephant conflict hotspots through satellite remote sensing and GIS to support conflict mitigation"* ***The articles have been published in the Journal of Remote Sensing Applications: Society and Environment (Vol 35).***

1.5 Scope and limitations of the study

a) The scope of the study is to establish HEC risk spots and link research findings to issue possible warnings of upcoming HEC hotspots.

b) To achieve this scope, the researcher produced a highly accurate forest cover map and monitored dynamic changes in forest greenery, linking it with local weather data.

c) As part of this scope, the researcher identified elephant movements according to changing conditions in feeding grounds.

Limitations: At this stage, there is a lack of sufficient ground-level information on elephant movements, and difficulties exist in observing elephant behavioural changes, although green cover is available, and the movement of the elephants is affected by electric fences. Implementing data analysis steps may identify further limitations related to the study's scope.

1.6 Organisation of the thesis

The following chapters in this thesis are papers demarcating HEC high-risk zones in Sri Lanka using a satellite data fusion approach and GIS. The thesis is presented as a series of chapters in research papers. Three have been published in peer-reviewed journals. A final paper is currently under submission. The thesis comprises four research papers that collectively address the four research objectives. These four research papers constitute the core of the thesis and are included in Chapters 3–6. More specifically, the thesis has been organised into seven chapters.

Chapter 1 presents the introduction, background, statement of the research problem, the study's aim and objectives, the significance of the research, and the thesis structure.

Chapter 2 is a review of the literature relevant to the research topic. The first section is a systematic review of the published literature on HEC and mitigation measures used worldwide. The second section deals with existing spectral sensing technologies and data analysis algorithms. It includes the LCLU of highlights of the study area and methods for the classification of Sentinel-2 satellite data. An emphasis is placed on detecting greenery change, specifically using satellite data and machine learning -based analysis.

Chapter 3 presents an article published in the *Journal of Biodiversity and Conservation*. It is devoted to the history and present status of HEC in Sri Lanka. It outlines the range and ecology of elephant species, the causes and consequences of HEC, the status of HEC in Sri Lanka, economic losses due to HEC, and conflict prevention and mitigation strategies, especially highlighting the traditional methods people use to mitigate HEC.

Chapter 4 comprises an article published in the *Journal of Advances in Engineering and Technology*. It outlines Sentinel-2 data collection, processing, and classification using RF and vegetation monitoring with an NDVI.

Chapter 5 consists of an article published in the *International Journal of Remote Sensing*. It briefly describes the study area and the general methods used for this research: evaluation of the Sentinel-2 satellite data, HEC data acquisition, satellite data classification schemes and classification systems and an evaluation of the method's accuracy.

Chapter 6 presents a manuscript published in the *Journal of Remote Sensing Applications: Society and Environment*. It outlines the evaluation of greenery changes and LCLU patterns, identifying HEC hotspots and correlating greenery changes with conflict incidents.

Chapter 7 constitutes a discussion of the conclusions drawn from each previous chapter. It includes remarks, limitations, and recommendations for future research in this domain. It also offers further discussion on the conclusions made in Chapters 3-6.

CHAPTER 2: LITERATURE REVIEW

2.1 Human-elephant conflict and its severity

Wild elephants are distributed in 50 countries worldwide, including 13 in Asia and 37 in Africa (Perera, 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 & Nagarathinam, 2012). A concerning trend has been observed across all Asian range states: a significant decrease in wild elephants, mainly due to human-related factors (Bai et al., 2022; Morley, 2007; Sitati et al., 2003).

The rapid increase in human populations in Asia and Africa has led to expanding cities and extending agricultural fields (Meyer & Turner, 1992; Yang et al., 2022), encroaching on wildlife areas and impacting traditional elephant habitats (Breuer et al., 2016; Köpke et al., 2021). This has reduced elephant habitat, degraded forage, and decreased landscape connectivity (Shaffer et al., 2019).

HEC encompasses various negative physical interactions between humans and elephants (Mumby & Plotnik, 2018), resulting in crop damage, injuries and deaths (Enukwa, 2017; Naha et al., 2020). The associated perceptions and fear exacerbate the conflict, posing direct interactions and making mitigation a challenge (Dickman, 2010; Mumby & Plotnik, 2018).

HEC has become a major concern in conservation biology worldwide and requires immediate attention (Zafir & Magintan, 2016). Within the 13 elephant range countries, almost two-thirds of the habitat suitable for elephants has declined within 300 to 500 years (de Silva et al., 2023). Such negative interactions pose significant conservation and social challenges, food insecurity, emotional distress, and restricted mobility in affected human communities (Fernando et al., 2023).

Elephants, being long-living animals, depend on food, water, and social and reproductive partners for survival (Fritz, 2017; Poole & Granli, 2009). Reduced access to food during the dry season leads elephants to venture into villages for food, particularly crops such as rice and other upland crops (Fernando et al., 2021; Jackson et al., 2008). The affected village people react by harming or killing the elephants (Billah et al., 2021), particularly in communities and villages adjacent to the natural habitats of the elephants (Mekonen, 2020).

HEC is unavoidable in areas with a significant elephant population and limited land resources for habitats and villagers (Griffin, 2015). Addressing this complex challenge is required for the well-being of both wildlife and humans (Behera et al., 2020; Goswami et al., 2014; LaDue et al., 2021). Sri Lanka has a history of severe HEC, emphasising the urgency of addressing this complicated and nuanced issue.

2.2 Existing methods used to mitigate human-elephant conflict in Sri Lanka

In many countries, lethal control is no longer an acceptable method for dealing with HEC (Cabral de Mel et al., 2023). Sri Lanka has implemented strict laws protecting elephants, imposing fines and jail terms for violators (Gunawansa et al., 2023;

Jayewardene, 2002). Various management strategies have been developed and implemented on multiple scales to prevent and mitigate HEC.

Rather than resorting to lethal measures, standard practices to mitigate HEC involve relocating problematic elephants from conflict areas. This can be through translocation (Fernando et al., 2012), domestication (Athauda, 2006), or directing them into protected areas (Köpke et al., 2021), focusing primarily on problematic individuals (Köpke et al., 2023). However, studies reveal that captured and translocated elephants often return to their original territory (Fernando et al., 2012), making this approach ineffective as a long-term solution (De Silva & Srinivasan, 2019).

Commonly available HEC mitigation approaches, such as physical and biological barriers (Hoare, 2012) or repellent techniques (Gunaryadi et al., 2017), often have drawbacks or prove ineffective in the long run due to elephants habituating to them quickly (Fernando et al., 2008). Electric fences emerge as the most effective method if adequately constructed and maintained (VerCauteren et al., 2006). Despite some inherent problems, such as lack of flexibility and movement restrictions (Boone & Hobbs, 2004; Jachowski et al., 2014), for both elephants and non-targeted species (Cabral de Mel et al., 2022), electric fences are effective, long-term solutions in mitigating HEC.

Several measures have been implemented to prevent elephants from entering crop fields: establishing protected areas (Nyhus & Tilson, 2000), ecological corridors (Nyaligu & Weeks, 2013), and electric fences (Osipova et al., 2018), scaring elephants away (Sitati et al., 2005), acoustic measures, and agricultural and light-based deterrents (Mahalakshmi et al., 2018).

Establishing protected areas for elephants to ensure elephant access to habitats for feeding, breeding, and residing could play a vital role in addressing HEC in Sri Lanka (Fernando et al., 2008). The corridors connecting paths for seasonal migration support elephants in accessing food sources during the dry season (Osipova et al., 2019) as they require 150 kg of food and 100 l of water per day (Athauda, 2006; Bandara, 2020).

Farmers have traditionally used acoustic deterrents such as shouting, drums, tins, and firecrackers (Babbar et al., 2022). The DWC provides elephant firecrackers to farmers in high HEC areas (Fernando et al., 2008). Lighting, including fires, torches, flashlights, and hanging lamps with lights along perimeters, helps drive away elephants (Nelson et al., 2003). Lighting fires has been a universal method of protecting crops against elephants and other wild animals since ancient times (Gunawansa et al., 2023; Mahalakshmi et al., 2018).

To further reduce the impacts of elephants on agriculture, farmers can grow less attractive crops alongside those elephants eat. Examples of repellent crops are ginger, onion (Karunananda, 2020), cinnamon, and citrus (Nyirenda et al., 2023), all of which offer both protection and financial benefits (Dagar, 2016). Crop-guarding practices range from individual farmers guarding isolated fields to collective efforts by farmers or village societies (Findlay, 2016; Makindi, 2010). Elevating huts on trees provides a vantage point for observing fields and offers a degree of safety (Fernando et al., 2008; Köpke et al., 2023; Szott et al., 2019).

2.3 The current state of human-elephant conflict in Sri Lanka

Historically, Sri Lanka's wet zone was home to numerous elephants (Fernando et al., 2011). The most significant change in elephant distribution and numbers on the island occurred during the colonial era from 1505 to 1948 (Katy, 2010). During this period, the wet zone underwent extensive settlement and was transformed into commercial agricultural land (Abeyratne & Takeshima, 2020; Bebermeier et al., 2023). Elephants, considered pests, were frequently shot dead, which eliminated them from this zone (Jayewardene, 1994). Consequently, they migrated to the dry zone, where their population and density increased due to numerous abandoned reservoirs providing water sources (Fernando et al., 2011; Fernando et al., 2005).

Currently, elephants are more concentrated in the dry zone (Gunawansa et al., 2023) which includes Wilpattu (North Western and North Central Provinces), Yala (Southern and Uva Provinces), Udawalawe (Sabaragamuwa and Uva Provinces), and Minneriya National Park (North Central Province). However, the elephant population is declining, with only 5,879 individuals recorded in the 2011 elephant census (Nijamir, 2023; Withanage et al., 2023). In 2008, Sri Lanka was estimated to have the highest elephant population in Asia, with a density of 0.088 elephants/km^2 (Karunananda, 2023; Perera & Tateishi, 2012).

Sri Lanka’s forest cover decreased to 21 percent in 2019 (Ranagalage et al., 2020), and forest loss and degradation have forced wildlife, including elephants, into closer contact with humans, leading to competition for shared resources such as space and water (Zoysa, 2022). Over the past four decades, large-scale agricultural development projects in the dry zone under the Mahaweli Development Scheme have significantly increased habitat fragmentation and HEC incidents (Köpke et al., 2021).

HEC incidence is widespread in 16 of the 24 districts of Sri Lanka (A district is a type of administrative division that, in some countries, is managed by the local government) (Fernando et al., 2021).

Elephants in various lowland provinces gravitate towards areas with abundant agricultural lands, especially in the Eastern, Northern, Northwestern, Southern, Central, and Uva provinces (Gunawansa et al., 2023; Nijamir, 2023). Their seasonal movements are influenced by food availability, with a preference for grass, especially during the dry season when they travel to water sources in search of fresh grass (Campos-Arceiz et al., 2008; Karunatilaka et al., 2021). Many elephants live outside protected areas, where agricultural land conversion restricts access to water and traditional movement corridors (Nijamir, 2023). Furthermore, during the dry season, elephants often enter human settlements looking for water resources (Perera, 2009; Zoysa, 2022).

Deforestation, habitat fragmentation, and agricultural expansion in Sri Lanka have led to significant losses in forest habitats for wild elephants (Fathima Sajla & Famees, 2021) who prefer habitats affording them lower visibility to avoid human interaction (Pastorini et al., 2015; Prakash et al., 2020). However, HEC has escalated over the past decade, resulting in deaths for both humans and elephants. According to the DWC, approximately 304 elephants and 100 humans die annually in Sri Lanka due to HEC, with the highest recorded number of elephant deaths, 439, in 2022. In the same year, the highest number of human deaths was recorded, 146, the highest number for 50 years (Rathnayake et al., 2022). Alongside these mortalities, an increase in HEC in the last decade has also led to more frequent property damage, crop raids, and injuries involving humans and elephants (Choudhury et al., 2008; Fernando et al., 2011; Köpke et al., 2021; Prakash et al., 2020; Santiapillai et al., 2010).

2.4 Forest mapping in Sri Lanka

Forest mapping in Sri Lanka holds importance due to the unique biodiversity of this island nation (Gunatilleke et al., 2008; Gunawardene et al., 2007), which falls within one of the world's 34 biodiversity hotspots (Sudhakar Reddy et al., 2017). The diverse flora and fauna, many of which are endemic, necessitate detailed and accurate mapping to ensure their preservation (Green et al., 2009). Forests in Sri Lanka are important for carbon sequestration, which is vital in combating climate change

(Stanturf et al., 2015). Additionally, these forests are central to the hydrological cycle, influencing water resource management (Vose et al., 2011).

To comprehend the patterns and drivers of forest cover changes, Sri Lanka requires comprehensive studies that use robust analytical techniques (Ranagalage et al., 2020). The demand for reliable forest cover information has increased, but many existing studies are localised and outdated (Mayaux et al., 2005). Accurate and current mapping is essential for effective environmental management and conservation (Lecours, 2017).

Forests are key natural resources that contribute directly and indirectly to the socio-economic fabric of Sri Lanka (Çömert et al., 2019). Assessing forest cover in Sri Lanka is essential to lower pressure on forest lands and HEC (Perera et al., 2012). Since the early 15th century, Sri Lanka's land cover has rapidly changed due to human settlements, agricultural expansion, fire, fuelwood gathering, invasive species, and climate changes such as floods and drought, underscoring the need for up-to-date forest mapping (Ranagalage et al., 2020). This mapping is invaluable for various applications, including agriculture monitoring, land policy development, land cover assessment, forest monitoring and management, scientific research, urban planning, and conservation (Grabska et al., 2019; Thanh Noi & Kappas, 2018). To protect biodiversity, mapping and monitoring habitats are fundamental (Iglseder et al., 2023).

Regionally, increasing forest loss rates have been observed in Sri Lanka over the last 100 years, particularly in the dry zone, which covers 59 percent of the country and receives 1750 to 900 mm of annual rainfall (Nisansala et al., 2020; Rathnayake et al., 2020). Historical records show a drastic reduction in forest cover from the inception of British control in 1843 (Perera et al., 2012). About 90 percent of Sri Lanka was originally covered by forests (Lindstrom et al., 2011), this reduced to 44 percent by 1956 (Illangasinghe et al., 1999). From 1976 to 1985, forests were lost at an annual rate of 0.49 percent (Sudhakar Reddy et al., 2017). From 1976 to 2014, the forest decreased by 5.5 percent (Sudhakar Reddy et al., 2017). Figures 2-1 and 2-2 illustrate the changes in forest cover in Sri Lanka and the study area from 2001 to 2022 (GFW, 2024).

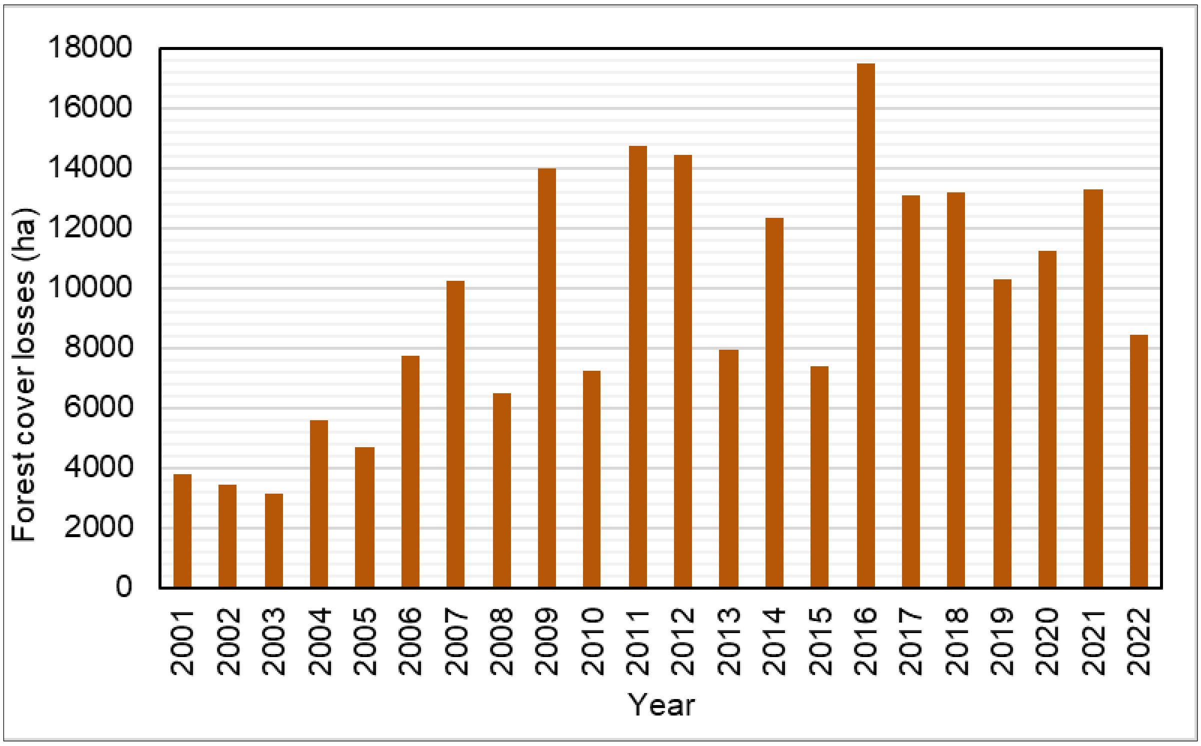

Figure 2-1: Forest cover losses in Sri Lanka from 2001 to 2022 (GFW)

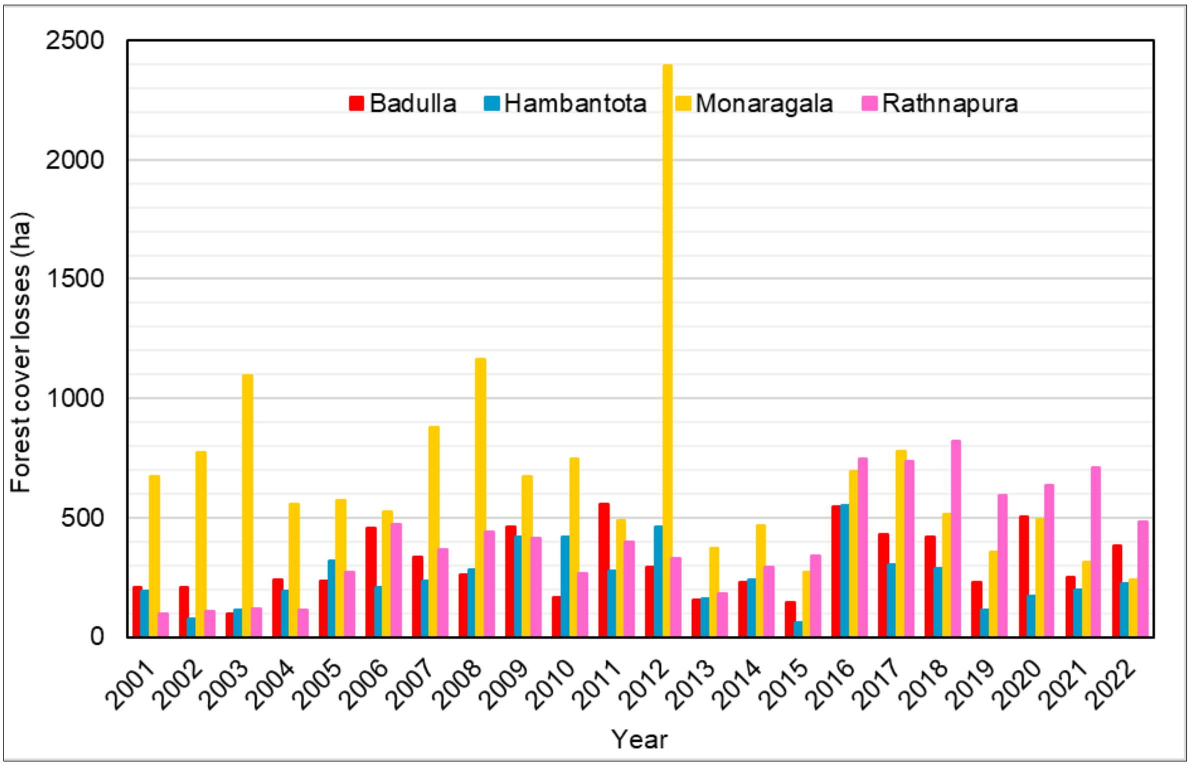

Figure 2-2: Forest cover losses in Badulla, Hambantota, Monaragala, and Rathnapura from 2001 to 2022 (GFW)

Challenges in forest mapping in Sri Lanka include illegal deforestation, limited resources, and topographical variations (Lindström et al., 2012). These challenges complicate keeping the maps updated and accurate (Premakantha et al., 2021). Financial and technological constraints are recognised as limiting the scope and frequency of forest mapping (White et al., 2016). Integrating advanced technologies such as machine learning can significantly enhance the precision and efficiency of forest mapping (Pu, 2021) (see Section 2.1.8 for an elaboration of machine learning techniques). Satellite imagery, GIS, and drones are used to map forests (Nitoslawski et al., 2021; Ruwaimana et al., 2018). Satellite imagery covers large areas and can detect changes over time (Nitoslawski et al., 2021), while remote sensing provides high-resolution imagery for detailed analysis, even in difficult-to-access regions (Willis, 2015). Although satellite imagery alone cannot detect changes, image-processing algorithms tools can analyse and identify these changes.

2.5 Satellite remote sensing in forest mapping

Remote sensing is the science of acquiring, processing and interpreting images and related data from aircraft-associated images, aircraft, and spacecraft. These technologies record the interaction between matter and electromagnetic energy (Pachori et al.; Sabins, 1999). Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (Iverson et al., 1989; Kidder & Haar, 1995; Lechner et al., 2020; Roy et al., 2017; U.S. Geological Survey, 2023). A forest cover map provides information on the size, shape and spatial distribution of forests and thus assists in classifying the landscape into patterns (Ganz et al., 2020). Earth surface data, captured by sensors in different wavelengths, undergoes radiometric and geometric corrections before extracting spectral information (Manikiam, 2014; Roy et al., 2017).

Remote sensing satellite data is valuable for producing up-to-date LCLU classifications (Steinhausen et al., 2018). Moreover, earth observation data sets are constantly applied to gather information about LCLU changes (Chaves et al., 2020; Kpienbaareh et al., 2021). LCLU changes reflect the dynamics of this interaction. These can be caused by humans, as seen in deforestation, urbanisation, and agriculture intensification, or by natural actions like droughts, floods, and wildfires (Chaves et al., 2020). Satellite images provide extensive geographical coverage at a low cost and ensure consistent, repeatable measurements on a spatial scale (Aasen et al., 2018; Blount et al., 2022; Cihlar, 2000; Rogan & Chen, 2004; Rwanga &

Ndambuki, 2017). Using open-source software with satellite remote sensing data enables cost-effective and standardised mapping of ecosystem extents and dynamics over large areas with high temporal resolution (Crowson et al., 2019; Murray et al., 2018; Shojanoori & Shafri, 2016).

The free and open availability of Earth observation data with global coverage is provided by systematic collection and archival by space agencies, such as the European Space Agency (ESA) Sentinel series and the United States (U.S. Geological Survey) National Ocean and Atmospheric Administration advanced very high-resolution radiometer, the National Aerospace Science Administration (NASA) MODIS, and NASA and the United States Geological Survey Landsat series have enabled the rapid development of private and public data commons (Turner et al., 2015; Wulder et al., 2018).

2.5.1 Application of MODIS satellite data in forest mapping

NASA launched MODIS into Earth orbit as a key instrument for the Earth Observing System (Xiong et al., 2009). MODIS has provided comprehensive data on Earth's systems on board the satellite Terra in 1999 and the satellite Aqua in 2002 (NASA, 2023a). MODIS acquires data in 36 spectral bands ranging in wavelengths from 0.4 to 14.4 μm and offers a diverse range of valuable information data to understand the planet (NASA, 2023a).

The spatial resolutions of MODIS vary across its spectral bands, with two bands at 250 m, five at 500 m, and 29 at 1 km (NASA, 2023b). This variation allows for detailed observations of specific phenomena while maintaining a broad coverage area (Lobser & Cohen, 2007). Such detailed resolution is pivotal for studying various features of Earth, from large-scale environmental changes to more localised events (Bronstert et al., 2002).

The data types that MODIS captures are vast and include spectral albedo, land cover, spectral vegetation indices, snow and ice cover, surface temperature, fire, and several biophysical variables (Reed et al., 2009). These data are essential for the computation of global carbon cycles, hydrological balances, and the biogeochemistry of critical greenhouse gases (Running et al., 1994). Monitoring these variables is essential for understanding the Earth's climate system and the impacts of climate change (Ojima et al., 1991).

The MODIS swath is 2,330 km cross-track by 10 km along-track at nadir (NASA, 2023a), allowing it to image the entire Earth every one to two days (Elshora, 2023). This frequency is vital for timely monitoring dynamic environmental processes and changes (Nagendra et al., 2013). Regular and comprehensive data coverage is essential to track and manage forest fires, droughts, and floods (Brown et al., 2015).

Regarding practical applications, MODIS data have proven invaluable for monitoring forests and updating field conditions regularly (Perera et al., 2012). Their relevance extends to scenarios that require prompt information about vegetation conditions, such as during droughts, floods, or fire hazards (Brown et al., 2015). Rapid data flow from MODIS is essential in operational applications, especially where speedy information dissemination is needed to keep pace with changing surface conditions (Zhao et al., 2022).

MODIS data are freely available through the NASA website (Perera & Tsuchiya, 2009; Strabala et al., 2003). Many scientists have successfully made land cover maps or clarified land cover status based on these data (Friedl et al., 2002; Hall et al., 2002; Perera & Tsuchiya, 2009; Price, 2003). The availability of these data has significantly advanced global environmental research and monitoring, providing a detailed and accessible dataset for numerous studies (Tamiminia et al., 2020).

2.5.2 Application of Sentinel satellite data in forest mapping

The Sentinel-2 mission, an integral part of the ESA and the European Union's Copernicus programme, is essential to improve our capabilities in forest mapping and LCLU monitoring (Balsamo et al., 2018; Gascon et al., 2017; Malenovský et al., 2012; Phiri et al., 2020; Sarvia et al., 2021; Transon et al., 2018). The Sentinel-2 constellation comprises twin satellites, Sentinel-2A and Sentinel-2B (Ienco et al., 2019; Segarra et al., 2020). The individual Sentinel-2 satellite has a revisit frequency of ten days, and the combined constellation revisit frequency is five days (Ienco et al., 2019; Main-Knorn et al., 2017; Suhet, 2015). This combination improves data acquisition frequency, offering comprehensive coverage of the Earth's surface.

Sentinel-2 satellite data can potentially improve forest classification on medium to large scales due to high spatial resolution, including 13 spectral bands. These bands are divided into three spatial resolution levels: four bands with a 10 m resolution, six bands with a 20 m resolution, and three bands with a 60 m resolution (Gargiulo et al., 2019; Lanaras et al., 2018; Sentinel, 2014). The 10 and 20 m bands are particularly adept at detailed land cover or water mapping, agriculture and forest applications, and managing various natural risks, including floods and fires. In contrast, the 60 m bands are more suitable for broader environmental monitoring activities such as pollution monitoring and cloud estimation (Drusch et al., 2012; Wang et al., 2016).

A notable aspect of the Sentinel-2 mission is its free access policy, making this high-value data available to a broader audience, including researchers and policymakers in developing countries (Phiri et al., 2020; Segarra et al., 2020). This improves global access to high-quality satellite data, fostering a more inclusive environmental monitoring and research approach (Main-Knorn et al., 2017). This cooperation has resulted in the excellent availability of data (via free access), instruments (software), and techniques (algorithms) for processing such data (Burton, 2016; Gomes et al., 2020; Jha & Chowdary, 2007), providing the RS community new applications and tools to conduct research (Macarringue et al., 2022).

Since its inception, the primary objective of the Sentinel-2 mission has been to provide high-resolution satellite data for LCLU monitoring, climate change and disaster monitoring (Agency, 2015; Jonnalagadda, 2023; Malenovský et al., 2012; Sentinel, 2014). This has significantly contributed to the advancement of RS applications, particularly in environmental conservation and sustainable management of natural resources (Askar et al., 2018).

2.6 Classification strategy

LCLU classification using RS imagery is a critical process in various fields such as agricultural practice, forest management, biological resource management, and land use inventories and planning (Arowolo et al., 2018; Belay & Mengistu, 2019; Rajendran et al., 2020; Talukdar, Singha, Mahato, Praveen, et al., 2020). The LCLU classification strategy involves assigning land cover classes to pixels in satellite images and categorising them into different types (Alshari & Gawali, 2021; Anderson, 1976), such as water bodies, urban areas, forests, agricultural lands, grasslands, and mountains (Hamdy et al., 2023).

The selection of an appropriate classification system is essential in LCLU assessment and requires the consideration of many factors (Macarringue et al., 2022; Rwanga & Ndambuki, 2017). Specific LCLU classes, such as urban areas, forests, agricultural land, and mountains, are defined and tailored to the region's characteristics (Ngondo et al., 2021). The adaptability of the classification system to the project's requirements and the area's specifics is critical for accurate representation (Iglseder et al., 2023). Selecting an appropriate classification system, post-classification processing, and accuracy assessment are essential steps in image classification (Lu & Weng, 2007). Data from satellite-based sensors such as Sentinel-2 and MODIS showed potential for classifying and monitoring habitat groups (Iglseder et al., 2023).

Machine learning techniques such as artificial neural networks, SVM, RF and object-based image analysis (OBIA) are increasingly used in LCLU classification (Carranza-García et al., 2019). SVM and RF were noted for their effectiveness (Ma et al., 2017; Mountrakis et al., 2011; Talukdar, Singha, Mahato, Pal, et al., 2020). Two elements determine LCLU classification accuracy: sensor characteristics and image data-related factors such as spatial and temporal resolution, processing software and hardware (Deng et al., 2008).

Accuracy assessment is integral to the LCLU classification process (Foody, 2002; Rwanga & Ndambuki, 2017). This involves comparing the classified data with ground truth data or other reliable sources to evaluate the classification's accuracy (Abbas & Jaber, 2020; Foody, 2002). This step is important for validating the results and making the necessary adjustments to the classification process (Dihkan et al., 2013).

2.6.1 Random forest classification

The RF classifier is a powerful machine learning tool initially relatively unknown in land remote sensing (Ghamisi et al., 2017; Rodriguez-Galiano et al., 2012). RF classification has been increasingly considered for classifying multisource RS and geographic data (Gislason et al., 2006). As a sophisticated machine learning algorithm, the RF operates by constructing a multitude of decision trees (Wijesekera et al.) during training and outputting the classified classes (Fernández-Delgado et al., 2014; Hayes et al., 2014).

Robust RF classification generates multiple DTs using a randomly selected subset of training samples and variables. The ensemble approach involves many DTs, each given a random subset of the training data and predictor variables (Breiman, 2001; Ramezan et al., 2021). The versatility of RF lies in its capacity to estimate missing values and its flexibility in handling various data analyses, including regression, classification, survival analysis, and even unsupervised learning (Rodriguez-Galiano et al., 2012).

Key advantages of RF classification include its non-parametric nature, high classification accuracy (Ham et al., 2005), and the ability to determine variable importance in LCLU mapping (Maxwell et al., 2018; Rodriguez-Galiano et al., 2012).

RF requires training and test data for supervised classification, with the classification output of individual trees depending on the number of training samples and the number of trees generated, which are important input parameters (Akbari et al., 2020; Pal, 2005).

RF's popularity in RS analyses has been growing (Chen & Cheng, 2016; Fernández-Delgado et al., 2014; Ghamisi et al., 2017; Gislason et al., 2004; Ham et al., 2005; Khatami et al., 2016; Maxwell et al., 2019; Maxwell et al., 2018; Pal, 2005; Ramo & Chuvieco, 2017). Two parameters, ntree and mtry, are essential in this setup, with mtry often set to the square root of the number of input variables (Belgiu & Drăguţ, 2016; Pal, 2005). Using a bagging operation, the RF generates multiple DTs (ntree) based on a randomly selected subset of training data. Each tree is independently grown to its maximum size without pruning, based on a bootstrapped sample from the training dataset, and each node is split using the best among a subset of input variables (mtry) (Breiman, 2001). The classification is then predicted based on each tree predictor's most popular voted class.

2.6.2 Support vector machine classification

The SVM is one of the most widely used machine learning classifiers, providing highly accurate LCLU classification results using remotely sensed images (Adam et al., 2014; Cortes & Vapnik, 1995; Mountrakis et al., 2011; Shetty, 2019). SVMs are a non-parametric statistical learning method that has recently been used in numerous applications in image processing (Górriz et al., 2017). For advanced machine learning tasks, the SVM provides a suite of highly effective algorithms for handling high-dimensional data (Tariq, Jiango, et al., 2023). Another significant advantage of SVM in this field is its robustness against overfitting, especially in cases with fewer training samples (Baumes et al., 2006).

The SVM may achieve high classification accuracy using a small training sample set (Foody & Mathur, 2004; Zhang & Wang, 2003). Such mapping is essential for sustainable management and conservation of natural resources (Sannigrahi et al., 2020; Zekeng et al., 2019). SVMs require user-defined parameters, and each parameter affects the kernels differently. Therefore, the classification accuracy of SVMs is based on the choice of these parameters and kernels (Ustuner et al., 2015). Kernel functions commonly used in SVMs can be generally aggregated into four groups: linear, polynomial, radial basis function, and sigmoid kernels (Kavzoglu & Colkesen, 2009).

SVMs are designed to produce an ideal hyperplane, also known as a decision boundary, which exploits the distance between the nearest samples (support vectors) to the plane and neatly divides classes (Cervantes et al., 2020). The model prioritises training instances on the periphery of the class distribution's support vectors while effectively discarding the rest (Chen et al., 2014). This classification method assumes that only the training samples located on the class boundaries are necessary to make accurate distinctions (Rajendran et al., 2020). As the SVM can achieve high accuracy even with tiny training datasets, this helps to reduce the overall cost of training data gathering (Fonseca et al., 2021).

The SVM algorithm can efficiently process and classify these images into different types of land cover, such as water bodies, vegetation, and urban areas, even when the data have a large number of spectral bands (Karakacan Kuzucu & Bektas Balcik, 2017; Keshtkar et al., 2017; Momeni et al., 2016).

2.6.3 Object-based image analysis classification

OBIA (Feizizadeh et al.) is a method primarily used for precisely classifying multi-temporal images, followed by GIS-based change detection (Samal & Gedam, 2015). OBIA has been applied more frequently for RS image classification than pixel-based analysis (Blaschke, 2010; Kindu et al., 2013; Luo & Mountrakis, 2011; Whiteside et al., 2011). A key advantage of OBIA is its ability to integrate various characteristics of objects, including spectral values, shape, and texture. One of its strengths is combining spectral and spatial information to extract target objects (He et al., 2016).

The methodology of OBIA encompasses several critical steps, beginning with the segmentation of satellite imagery into homogeneous and meaningful segments (Amanzadeh et al.). Subsequent steps include extracting relevant features from these segmented objects and training classifiers using known data samples to accurately recognise patterns and features within the imagery. Finally, classified segments are used for various analytical purposes (Singh et al., 2021).

The OBIA classification process is enhanced by its support for multiple bands for multiresolution segmentation and classification (Feizizadeh et al.). Over the past few years, OBIA has been frequently applied in diverse fields such as vegetation analysis (Yu et al., 2006), forest cover (Heyman et al., 2003) and water body extraction (He et al., 2016).

However, the accuracy of OBIA can vary depending on the specific nature of the landscape and the types of images used in the analysis (Dronova et al., 2011). The OBIA of satellite imagery has been successfully implemented using the Orfeo Toolbox (OTB) in the QGIS environment (Singh et al., 2021).

2.7 Normalised difference vegetation index

NDVI is the simplest and most commonly utilised objective measure of vegetation density (Pu et al., 2008). It is critical in environmental health studies, particularly in urban settings where measuring greenness is important (Martinez & Labib, 2023). Significantly, NDVI can provide a quantifiable assessment of urban vegetation, a key factor in numerous environmental studies (Li et al., 2015).

The surrounding greenness in urban areas is typically characterised in one of two ways: as the percentage of green spaces in the designated area based on LCLU maps or through the measurement of photosynthetically active greenness (Gascon et al., 2016). The latter is often quantified using satellite-derived NDVI, a technique that reflects the amount of dynamic green vegetation in a given area (Hmimina et al., 2013).

The product of NDVI is a common data source for LCLU mapping that can provide valuable phenological information about vegetation, especially on agricultural lands (Baeza & Paruelo, 2020; Usman et al., 2015). This makes NDVI an indispensable tool in agricultural management and environmental monitoring, offering insight into various stages of crop development (Atzberger, 2013; Singh et al., 2020).

Compared to other vegetation types, such as grasslands and forests, croplands have distinct characteristics at different stages of development, sowing, growth, and harvest (Estel et al., 2015; Wang et al., 2018). NDVI uses multi-spectral remote sensing data to effectively discern these stages, providing vital information for LCLU classification on a range of LCLU, including vegetation, water bodies, open areas, scrub areas, hilly areas, agricultural areas, and different types of forestation (Gandhi et al., 2015; Gao et al., 2017).

NDVI utilises a normalised index that measures the difference ratio between the near-infrared and red bands of the electromagnetic spectrum (Li et al., 2014). This spectrum ranges from -1 (representing surfaces utterly devoid of vegetation) to +1 (surfaces fully covered by vegetation) (Patón, 2020), with intermediate values representing areas with weak or no plant cover, namely water bodies, sand, snow (Pettorelli, 2013). However, interpreting these values can be challenging due to their dimensionless nature, which can sometimes result in vague interpretations at a scale of analysis (Reis & Lopes, 2019).

The threshold method is commonly used to extract vegetation information from data (Bhandari et al., 2012), especially for cropland in the sowing, development, and harvest stages. Due to its cyclical variability, cropland differs from other vegetation types, such as grasslands and forests (Yang et al., 2017). Thus, distinguishing agriculture from woodland and grasslands is difficult using a single image (Strong et al., 2017). However, incorporating vegetation phenology information and textural features of each category can significantly improve the accuracy of the LCLU classification (Huang et al., 2020).

The applications of NDVI have expanded considerably due to the availability of long-term satellite data covering extensive geographic areas (Baldi et al., 2008). These data sets offer increasingly higher spatial and temporal resolution, broadening the potential for advanced environmental analysis and agricultural management (Martinez & Labib, 2023).

The significance lies in their ability to distinguish between healthy and stressed vegetation. The chlorophyll in healthy plants strongly absorbs red light while reflecting infrared light (Zahir et al., 2022). Conversely, stressed or unhealthy vegetation reflects more red and less infrared light. This contrast helps to identify areas of dense, healthy vegetation versus sparse or distressed vegetation, aiding in forest health assessment, biomass estimation, and habitat monitoring (Haindongo, 2009).

The calculation of NDVI is achieved by Equation (2.1). It is essential to note that the red and near-infrared bands are integral to this. Specifically, the red corresponds to the B4 band, while the near-infrared corresponds to the B8 band, according to the requirements of the ESA SNAP algorithm (Köpke et al.; Krtalić et al., 2021).

$$NDVI = \frac{NIR - Red}{NIR + Red} = \frac{B8 - B4}{B8 + B4} \tag{2.1}$$

The NDVI is calculated from MODIS-derived indices by Equation (2.2). This index uses reflectance values from specific MODIS bands: ρ_{RED} for the red band (621–670 nm, MODIS band 1) and ρ_{NIR} for the near-infrared band (841–875 nm, MODIS band 2) (DeFries & Townshend, 1994; Gu et al., 2007; Han et al., 2010; Tariq, Yan, et al., 2023).

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} = \frac{B2 - B1}{B2 + B1} \quad (2.2)$$

CHAPTER 3: PAPER 1 – THE HUMAN-ELEPHANT CONFLICT IN SRI LANKA: HISTORY AND PRESENT STATUS

3.1 Introduction

This chapter is an exact copy of an article published in 2023 in *Biodiversity and Conservation*, *32*(10), pp. 3025–3052.

This article comprehensively explores HEC in Sri Lanka, emphasising its gravity and far-reaching implications. The introductory description provides an extensive overview of the historical context, detailing the numerous factors contributing to this conflict, including habitat loss, evolving agricultural practices, and changing LCLU patterns. A significant focus is directed towards solving the traditional methods local Sri Lankan communities use to mitigate the impacts of HEC. Furthermore, the article offers a critical assessment of the literature and research gaps related to HEC in Sri Lanka, suggesting areas for future research. The investigation extends to the conflict's potential social and economic impacts on local communities, emphasising the need for an all-inclusive understanding. The article concludes with a discussion of the implications of HEC in Sri Lanka for greater conservation efforts, human well-being, and sustainable development, highlighting the importance of the topic for national and global audiences.

3.2 Published paper

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REVIEW PAPER

The human-elephant conflict in Sri Lanka: history and present status

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Abstract
Human-elephant conflict (HEC) is a severe conservation, socio-economic and environmental issue of forests and ecosystems in elephant inhabiting countries, including Sri Lanka. Due to the rapid growth of human and elephant populations, both struggles to share limited land resources. The major causes and contexts of HEC in Sri Lanka include land use change, habitat loss due to human population growth, crop raiding behavior, problem elephants, and changes in agriculture practices. Since 2019, 125 people and 370 elephants have killed annually on average due to the conflict. Also, Sri Lanka has recorded the highest annual elephant deaths and second-highest human deaths due to HEC. The human death rate has increased by approximately 42% over previous three decades. The Sri Lankan government provides compensation for death and disability of the human caused by elephants and for elephant-damaged houses or properties. The Sri Lankan elephant (*Elephas maximus maximus*) is an endangered subspecies. It's home range is restricted to 50–150 km^2 and depends on the availability of food, water, and shelter of the habitat in which they live. Various management strategies have been developed by the government and villagers to prevent and mitigate HEC. Today, Sri Lankan elephants are protected under Sri Lankan law, with punishment by fines and jail terms. This article reviews the history, present status, and traditional conflict management of HEC in Sri Lanka. We suggest a satellite data fusion approach with GIS modeling to identify risk zones of HEC to develop further protective measures for humans and elephants.

Keywords Asian elephant · Human-elephant conflict · Crop and property damages · Traditional mitigation methods · Sri Lanka

Communicated by David Hawksworth.

Extended author information available on the last page of the article

Introduction

More than 50 countries worldwide are home to the world's wild elephant, mainly in Africa and with just 13 in Asia (Perera 2009; Wijesekera et al. 2021; World Wildlife Fund, 2022). There are estimates of 51,000 to 66,000 elephants in Asia, but only 35,000 to 50,000 live in their natural habitats (Nakandala et al. 2014). Sri Lanka is home to 10% of Asian elephants living in their natural habitat, accounting for around 2% of the global range of Asian elephants (Fernando et al. 2011; Perera 2009). Asian elephants are classified into three subspecies: the Indian (*Elephas maximus indicus*), the Sumatran (*Elephas maximus sumatranus*), and the Sri Lankan (*Elephas maximus maximus)* (Animalia 2022; Fleischer et al. 2001; Sukumar 2006).

Currently, elephants live in five South Asian countries, Bangladesh, Bhutan, India, Nepal, and Sri Lanka (Fernando and Pastorini 2011). In Bangladesh, Bhutan, and Nepal, there are less than 500 wild elephants in the whole country (Fernando and Pastorini 2011; Sukumar 2006). According to the most recent estimate in 2017, mainland India has the largest population of Asian elephants, with 29,964 (Koshy 2021; Montez 2021). Sri Lanka has about 5,787 elephants, including 1,107 calves and 122 tuskers (World Wildlife Fund, 2019), according to the elephant census conducted in 2011. This contrasts starkly with the estimates of the population size in the 19th century, between 12,000 and 14,000 (Fernando et al. 2011; Katupotha and Sumanarathna 2016; Santiapillai and Read 2010). According to an elephant estimation conducted in 2011 by the Department of Wildlife Conservation (DWC), less than 10% of the Sri Lankan subspecies are tuskers, most likely due to selective hunting and poaching for ivory (Fernando et al. 2011; Köpke et al. 2021; Wikramanayake 2022). Sri Lanka has the second-largest population of wild elephants in South Asia (Menon and Tiwari 2019). When the estimated elephant population is divided by the land area, India had an elephant density of 0.0008 per km^2, while Sri Lanka had a density of 0.088 per km^2 in 2008 (Perera and Tateishi 2012).

Although wild elephants were once widespread throughout Sri Lanka, they are now restricted to the dry zone lowlands, Northern, Eastern, North Western, North Central, Southern, and part of Uva Provinces, as shown in Fig. 1 (De Silva and Srinivasan 2019; Menon and Tiwari 2019).

Except for the Sinharaja Forest and a few areas of Central Province, such as Wilgamuwa, Dambulla, and Laggala Pallegama, elephants live in the country's wet zone (Bandara and Tisdell 2005). Elephants are also found in Sri Lanka's major national parks, including Udawalawe, Yala, Lunugamvehera, Wilpattu, and Minneriya (Fernando et al. 2011). Apart from these areas, orphaned elephants are kept in Sri Lanka's Pinnawela Elephant Orphanage, which was established in 1975 to care for orphaned or abandoned baby elephants because of HEC (Fernando et al. 2011). Elephants often invade human settlements and cause damage to property, crops, and lives called problem elephants. In Sri Lanka, these elephants are captured and translocated to the elephant-holding ground in Horowpothana, North Central Province. This holding ground provides a safe and secure environment for problem elephants to be relocated to and receive appropriate care.

HEC is a severe conservation, socio-economic and environmental issue in elephant range countries' forests and ecosystems (Shaffer et al. 2019). Humans and elephants are under significant threat from HEC in various parts of Asia, including Sri Lanka (Thant et al. 2021). When elephants and humans interact, when elephants move through human settle-

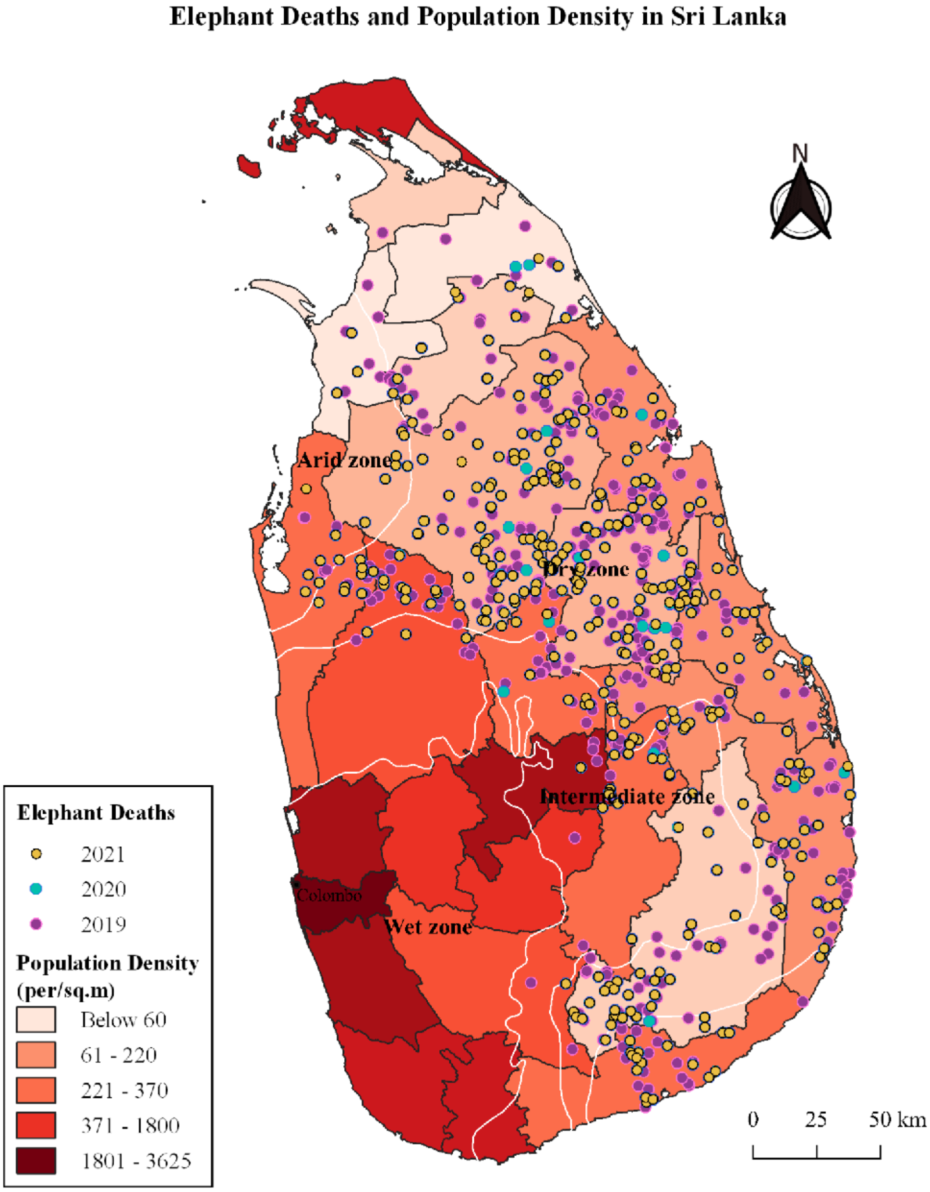

Fig. 1 Sri Lanka population density in 2019 and distribution of elephant deaths between 2019 and 2021. (Central Bank of Sri Lanka, 2019, DWC)

ments, there is a conflict due to crop raiding, household damage, injuries, humans killed by elephants, or vice versa (Billah et al. 2021; Das et al. 2014; Sitati et al. 2003). The intensity of HEC varies significantly due to ecological and socioeconomic factors such as food availability, size of protected areas, agricultural practices, human density, seasonal climate variations, and socio-cultural beliefs (Fernando et al. 2005). Furthermore, HECs are unavoidable in regions with a large elephant population due to the intense competition between elephants for resources such as food, water, and shelter (Tiller et al. 2021).

Crop raiding has a direct impact on the livelihoods of humans. It destroys crops and nearby properties, as well as poses a threat to human safety by causing injuries or killing people in some incidents (Pant et al. 2015; Vibha et al. 2021). This conflict primarily occurs where villages are located close to elephants' natural habitats (Enukwa 2017). People who contend with elephant depredation daily increasingly perceive them as agricultural pests, an unwelcome burden, and a threat to their own survival and well-being (Fernando et al. 2005). The local communities' negative perceptions of elephants in many cases strongly undermine conservation efforts for elephant populations (Vibha et al. 2021). African and Asian elephants are vulnerable to conflict because they spend a significant amount of time living near humans outside protected areas. Furthermore, their large size makes them more dangerous, increasing the risk of conflict (Tiller et al. 2021). Asian elephants are forest animals, and Sri Lankan elephants spend the day in low-visibility habitats such as scrub and secondary forests, only venturing out into the open at night (Fernando et al. 2021; Psaradelis 2021).

Asian elephants (*Elephas maximus)* are listed in the International Union for Conservation of Nature (IUCN) red data book as endangered species (IUCN 2020). Elephants may live for 60–70 years or more, depending on regular migration over large distances to search for food, water, and social and reproductive partners (Hart et al. 2008; Shaffer et al. 2019; Sukumar 2003). Also, elephants are intelligent animals with impressive memories (Katupotha and Sumanarathna 2016). Asian elephants have gained international attention due to an estimated 50% decline in their population over the past three generations, as well as the rapid shrinkage of their habitat range (Choudhury et al. 2008; Neupane et al. 2013; Williams et al. 2020). This study is a status investigation of the current level of HEC in Sri Lanka and the methods used to mitigate it. Several specific measures have been implemented and practiced at different scales for preventing and mitigating the problem. However, there is a lack of generic frameworks that provides a standardized approach to implementation. The relationship between the habitat of elephants and changes in land cover, particularly greenery, has not been established in Sri Lanka due to the lack of up-to-date and detailed information on forest cover changes. Therefore, identifying the HEC risk zone hotspot map is essential to reduce HEC in Sri Lanka. There is an extremely urgent need for a standard framework to monitor, identify and predict the hotspots of HEC risk zone. We suggest applying a satellite data fusion approach with GIS modeling to identify risk zones of HEC in Sri Lanka.

A previous study has been conducted assessing important to management of forest lands as well as to mitigate the risk of HEC in Sri Lanka. Satellite imagery used as an additional cost-effective approach to support ground-based studies, forest cover or green area monitoring (Perera and Tateishi 2012). Especially can use in remote or inaccessible regions. The successful applicability of Normalized Difference Vegetation Index (NDVI) products for forest cover change detection in Sri Lanka was presented in two previous studies (Perera and Tateishi 2012; Perera and Tsuchiya 2009). Based on those research findings, seasonal NDVI values of a selected location in south Sri Lanka (area including Udawalawe national park) was analyzed as a case study.

Satellite data fusion allows for long-term monitoring of HEC, facilitating the detection of trends and changes over time. By analyzing historical satellite images fused with recent data, researchers can assess the effectiveness of conservation measures. Satellite data fusion enhances the accuracy and precision of land cover classification and mapping.

The developed system will significantly contribute to managing HEC by identifying patterns of elephant movements using accurate changes in forest greenery and weather patterns. This system will encourage researchers to devise new methods for increasing the safety and well-being of people and elephants.

Study objectives

This review paper aims to explore the complex issue of HEC in Sri Lanka by providing a comprehensive overview of the historical context, examining the primary drivers of conflict such as habitat loss, changing agricultural practices, and land use patterns. Furthermore, identify the traditional methods people use to mitigate in Sri Lanka. The paper also seeks to identify gaps in the existing literature and research on HEC in Sri Lanka, suggesting areas for future investigation. In addition, the potential social and economic impacts of the conflict on local communities will be explored. Finally, the implications of HEC in Sri Lanka for broader conservation efforts, human well-being, and sustainable development will be discussed, highlighting the significance of this topic for both national and global audiences.

Literature review

Elephant species range and ecology

Elephants are the planet's largest terrestrial mammals, the African elephant (*Loxodonta*) being the largest (Bandara and Tisdell 2005; Naha et al. 2020; Sukumar 2006). Among Asian elephant species, the Sri Lankan is physically the largest of the subspecies and also the darkest in color (Bandara and Tisdell 2005). The host order and family of Sri Lankan elephants are Proboscidea, and Elephantidae (Cappellini et al. 2014).

Elephants are friendly social animals that live in groups known as a clan or a herd (Lakshmanaprabu et al. 2018). Elephants form deep family bonds and live in tight matriarchal groups of related females (Katupotha and Sumanarathna 2016). The herd is led by the oldest and often largest female, the matriarch (Rutherford and Murray 2021). The Sri Lankan elephant herd typically consists of 12 to 20 singles or more, and may include young juvenile, nursing, lactating, and other adult elephants (World Wildlife Fund, 2022).

Males leave the family unit between 12 and 15 years and may lead solitary lives or temporarily live with other males (Entertainment 2022). Elephants have a very structured social order, and male and female elephants have very different social lives (Katupotha and Sumanarathna 2016). Females spend their entire lives in tightly knit family groups of mothers, daughters, sisters, and aunts, and adult males live primarily solitary lives (Katupotha and Sumanarathna 2016). A typical Asian elephant family herd has a home range of 100-1,000 $km^{2,}$ but in Sri Lanka, it is more restricted to 50–150 km^2 (Shaffer et al. 2019; Sukumar 2006). Home range sizes depend on the availability of food, water for drinking and bathing, and shelter in the region (Sukumar 2006). Elephants mainly rely on water for cooling due to the evaporation of water from the skin (Dunkin et al. 2013; Williams 2019). More recently, elephants' home ranges have been disturbed by development activities such as roads, fences, and canals (Fernando et al. 2008).

Sri Lankan elephants can reach 6.4 m in length, and 2-3.5 m in height at the shoulder, and weigh 3,000–5,000 kg (World Wildlife Fund, 2022). Among other physical characteristics, their ears are small, not covering the shoulders, and they have two humps on their forehead (Bandara and Tisdell 2002; Grannan 2022). The trunk has one lobe at the tip, the front feet have five toes, and the back feet have four (Bandara and Tisdell 2005). Only male elephants have tusks, with the heaviest recorded tusk weighing 39 kg (Bandara and Tisdell 2005).

The elephant uses its trunk to release water and pick up and insert foods into their mouth when drinking and eating (Gruber et al. 2000; Racine 1980). While resting, the elephant stands up but does not make any specific movement (Bates et al. 2008; Pruett 2021). The elephant's trunk can draw water, spray it on its body, and throw mud or dirt on its back when grooming (Krishnan and Braude 2014). Because of these biological needs, elephants live in proximity to water sources such as lakes, irrigation tanks, and rivers (Pozo et al. 2018).

The elephant's digestive system is inefficient, and 40–50% of its food intake is passed through as undigested matter (Kingdom 2021; Sukumar 2006; Williams 2019). As a result, the elephant spends approximately 19 h daily eating and seeking a continuous and abundant food and water supply. Its diet is strictly herbivorous, with a daily food requirement of approximately 10% of its body weight (Krishnan and Braude 2014; Sitompul et al. 2013). Most elephants consume 100–150 kg of food daily, with mature adult males requiring more food than females (Fernando et al. 2022). Many types of grass, juicy leaves, fruits, small stems, and roots are included in the elephant diet, but grasses are only available seasonally in most Asian elephant habitats (Fernando 2015; Sukumar 2006; Zubair et al. 2005). In Sri Lanka, male elephants are mostly responsible for crop damage (Ekanayaka et al. 2011) since they search for more food compared to female elephants. Elephants can produce approximately 100 kg of dung per day while wandering around an area that can cover up to 324 km^2, and this helps to disperse germinating seeds (World Wildlife Fund, 2022). Therefore, elephants can be described as either eating machines or manure manufacturers, depending on their activity at the time (International Elephant Foundation, 2001). Elephants are always near a source of fresh water because they need to drink at least 80–160 L daily (Sajla and Famees 2022; World Wildlife Fund, 2022).

Elephants sleep about four hours per day, and about two hours of this are spent standing (Katupotha and Sumanarathna 2016). The Asian elephants can reach speeds of 40 km/hr while running and up to 6.4 km/hr when walking (Bandara and Tisdell 2005). They are excellent swimmers and have been known to swim for long distances. Reports reveal that one elephant swam about 2.5 km across the Trincomalee Harbor to Sober Island, and a 3.048 m high elephant swam across the Senanayaka Samudra Reservoir (Katupotha and Sumanarathna 2016). In 2017, the Sri Lankan navy rescued an elephant swimming in the ocean about 16 km off Sri Lanka's northeast coast (Guardian 2017).

Asian elephant species have one of the most extended gestation periods in the animal kingdom, lasting 18–20 months (Taylor and Poole 1998; Tuntasuvan et al. 2002). Sri Lankan elephants' gestation can extend up to 680 days, and they typically give birth to a single calf, which exits the womb weighing 90.7 to 136.1 kg (Animals 2021). Female elephants reach sexual maturity at ten years old and give birth once every four to six years (Animalia 2022). When a calf is born, it is raised and protected by the whole matriarchal herd. Elephants are an oddity among mammals because they grow until they die, usually around the age of 60 (Bandara and Tisdell 2005).

The loss of teeth is the leading cause of death among mature elephants. When an elephant's last set of teeth wears down, they lose the ability to chew and digest (CGTN 2020). Therefore, their natural cause of death is generally starvation or malnutrition (CGTN 2020). However, according to local reports, 70% of elephants died near water holes containing algal blooms, which can produce toxic microscopic organisms known as cyanobacteria (Weston 2020). All these biological, ecological, and behavioral facts about elephants have elevated the HEC in the island nation of Sri Lanka, where feeding grounds for them are extremely limited.

Causes and consequences of Human Elephant Conflict (HEC)

The HEC exists whenever and wherever humans and elephants coexist (Fernando et al. 2005). However, the conflict has recently intensified, due to the changing agricultural practices and land use patterns (Anuradha et al. 2019). Mattala airport has been established by clearing forest covers of approximately 2,000 ha (PEAD 2015), and the airport has fragmented wild elephant habitat and hindered the wild elephant corridors (Bandara 2020). The Department of Wildlife states that the wild elephant population in Sri Lanka has increased to 7,000 (Ministry of Agriculture 2023). In 2011, it had been reported that the number of those animals on the island had been around 5,787. Various human needs, including land utilization, have increased in response to the rapid growth of the human population (Fernando et al. 2021). According to World Bank projections based on the United Nations population division's world urbanization prospects, Sri Lanka's rural population has continuously increased throughout recent history (The World Bank Group 2022).

Due to the natural growth of the population and the advancement of the country's free healthcare system, the rural population of Sri Lanka has increased significantly from 8.25 million in 1960 to 17.8 million in 2020 (Perera and Tateishi 2012; The World Bank Group 2022). Figure 2 illustrates the national and rural population growth over the last six decades. Notably, this nearly doubled between 1960 and 2000.

However, agriculture is the primary source of income for rural communities in Sri Lanka. More land is being cleared for permanent agricultural activities for food production (Anni and Sangaiah 2015; Fernando 2015; Fernando et al. 2021). Due to the rapid growth of rural population, local communities are increasingly attracted to settle near areas of conservation or forests that are protected (De Silva 1998). While less productive compared to modern agro-methods, traditional farming practices allow for a more harmonious relationship between human and elephant through resource partitioning (Fernando et al. 2005). To increase the yield per hectare, new agricultural activities have emerged, with the potential for human and elephant coexistence decreasing rapidly, throughout Asia (Fernando et al. 2005).

Human activities have often expanded and encroached on elephant habitation areas (Fernando 2015; Fernando et al. 2021). The ongoing expansion of human settlements resulted in many infrastructure development activities, such as the Mahaweli Development Project (Dissanayake et al. 2018; Paranage 2019; Talukdar et al. 2022). This is a notable multipurpose development scheme with the primary objectives of human settlement, hydroelectricity generation, and farmland irrigation (Burchfield and Gilligan 2016). State interventions have led to both population increase and major land-cover transformations in the dry zone of northeast Sri Lanka (Paranage 2019).

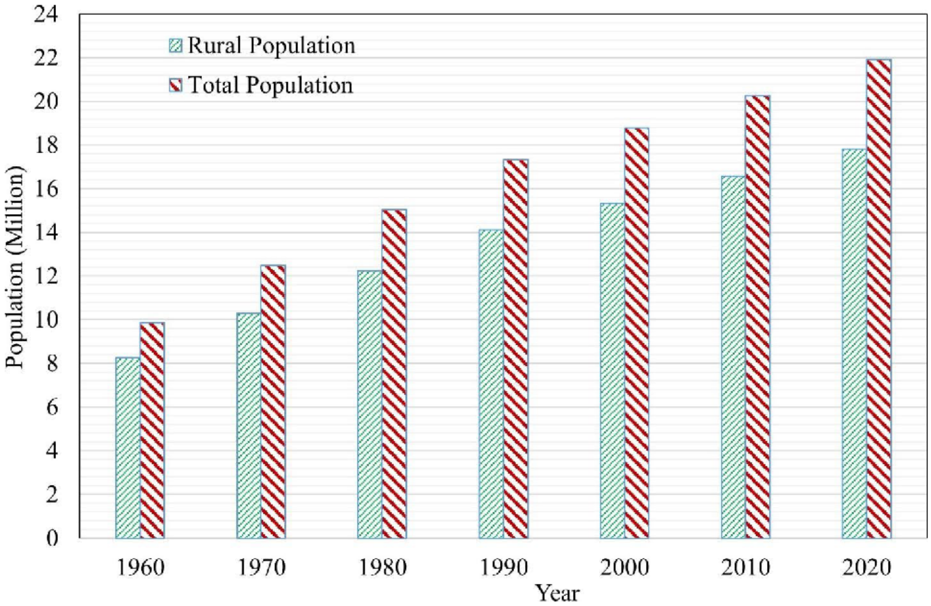

Fig. 2 Total population and rural population of Sri Lanka from 1960 to 2020 (https://data.worldbank.org/)

Human settlement areas are concentrated around permanent water sources because this facilitates agricultural expansion (Anni and Sangaiah 2015; Loarie et al. 2009). These expansions have led to a significant decrease in the size and range of elephant populations, as well as a reduction in the connectivity of elephant habitats in their historical ranges (Calabrese et al. 2017; Thouless et al. 2016). As their habitats have started shrinking, elephants are progressively forced into close contact with human, resulting to more frequent and severe conflict over space and resources, ranging from crop raiding to reciprocal loss of life (Liu et al. 2017). Consequently, farmers have become incompatible neighbors in many Sri Lankan elephant range areas, and these populations cannot coexist peacefully where agriculture is the predominant land use (Animals 2021; Bandara and Tisdell 2002).

The forest cover in Sri Lanka was reported to be 21.0% (1,377,799.1 ha) in 2019, down from 24.8% (1,624,757.5 ha) in 1992 (Ranagalage et al. 2020). Additionally, declining biodiversity and scarcity of resources, particularly food and water, have resulted in increased wildlife habitat fragmentation (Köpke et al. 2021; Shaffer et al. 2019). Forest loss and degradation bring wildlife closer to humans, competing for shared resources such as space and water (Mumby and Plotnik 2018). Consequently, wildlife such as elephants raid crops, damage property, and kill humans, leading to further escalation of the conflict, including retaliatory wildlife killings (Acharya et al. 2017; Haven 2019a).

The survival and continuation of elephants in their range countries are severely threatened by HEC. This is due to the development and well-being of human communities who coexist with these large herbivores (Shaffer et al. 2019). Habitat fragmentation increases the contact between elephants and agriculture, and conflict intensity is usually higher in more fragmented habitats (Sukumar 2003). During a drought, elephants require water to survive. However, when water becomes scarce, they may gather around village farm wells and other water tanks to access the limited supply of available water (Perera and Tateishi 2012). The degradation of elephant natural habitat resources such as water is also apparent in some regions, and severe droughts may force elephants to disperse into new habitats where conflict may escalate (Sukumar 2006).

The status of the HEC in Sri Lanka

HEC incidences are common in Sri Lanka, and over 59.9% of Sri Lanka's elephants are restricted to the lowland dry zone (Fernando et al. 2021; Rathnayake et al. 2022). Notably, approximately 69.4% of the elephant's range in Sri Lanka is in areas where people live, a problem expected to worsen in the future (Fernando et al. 2021). Therefore, HEC is a challenge to the Sri Lankan government for policymaking and planning (Prakash et al. 2020; Sukumar 2006).

In this country, HEC has commonly manifested as direct attacks on people, resulting in human injuries, deaths, crop depredation, property damage, elephant injuries, and deaths (Leimgruber et al. 2011; Santiapillai et al. 2010). Sri Lanka has the highest annual elephant deaths and the second-highest human deaths in the world, while India holds the first rank (Huaxia 2020; News 2020; Ranawana 2020). More than 600 humans and 450 elephants are killed annually during crop raiding in Asia, with India and Sri Lanka accounting for more than 80% (Sukumar 1990; Williams et al. 2020).

Elephants are being squeezed into smaller areas of their remaining natural habitat, surrounded by crops that elephants like to eat (Palita and Purohit 2008). Farmers experience risk losing their entire livelihood in one night due to crop raiding (Bandara and Tisdell 2002). Small-scale agriculture is the main economic activity in rural Sri Lanka. Banana, coconut, sugarcane, and seasonal crops are cultivated during the rainy season, including paddy, maize, pumpkin, green chili, bitter gourd, and watermelon (Campos-Arceiz et al. 2009; Ranaweerage 2012). Rice, banana, coconut, cassava, corn, papaya, and sugarcane are wild elephants' most preferred crops while they avoid lime, orange, sesame, and cashew (Santiapillai et al. 2010; Webber et al. 2011). It has also been observed that elephants tend to consume more nutritious crops like sugarcane, rice, and the tops of pineapples (Haven, 2019) Additionally, bananas are a preferred food for elephants due to their high nutritional value and ease of digestion (Haven 2019b). Interestingly, it appears that elephants are not fond of the smell of citrus trees (Rathnayake 2020).

It is known that elephants raid crops throughout the year, but their activities are intensified during certain months (Bandara and Tisdell 2002). Elephants raid paddy fields in January when the grain matures and continue until harvesting is completed (Ranaweerage 2012; Santiapillai et al. 2010). They damage bananas during every stage of the crop's life (Santiapillai et al. 2010). Mango trees are attacked during their fruiting seasons, from May to June and November to December (Bandara and Tisdell 2002). Elephants also attack perennial crops, such as jackfruit and coconut, when other crops are unavailable along their usual raiding routes (Bandara and Tisdell 2002; Campos-Arceiz et al. 2009).

Additionally, there is damage to the crops cultivated in home gardens, such as bananas and coconuts (Gross et al. 2020). Elephants enter home gardens more frequently because they can reach food with less effort than in the jungle, where food is scarce (Thennakoon et al. 2017). Once they become used to attacking villages for food, the behavior could continue even during the rainy season (Fernando and Pastorini 2011; Ranasinghe 2021).

The slash-and-burn farming system or “chena” is a local variety of shifting cultivation practiced in the villages in the vicinity of the forest (Lindström et al. 2012). The elephants influence chena cultivation because chena farmers occupy the forests around villages (Tsuji and Fujimura 2020). From October to the end of January, villagers guard their crops, prevent approaching elephants (Tsuji and Fujimura 2020). After harvesting, people limit their movement to the resulting forest patches and open areas, and elephants take advantage of this opportunity to move closer to the villages (Fernando et al. 2005). Since February, there tends to be a significant increase in raids on village dwellings, partially due to the end of chena activities (Campos-Arceiz et al. 2009).

Most HEC incidents are caused by small groups of elephants in Sri Lanka, usually one to three (Campos-Arceiz et al. 2009). Male elephants move alone or in small temporal groups, whereas female elephants move in larger family-based groups (Fernando and Lande 2000; McKay 1973). Damage to houses is determined by their proximity to elephant corridors, construction condition, dryness in elephant habitat regions, the amount of grain stored inside the house, and crops grown in the home garden (Bandara 2020; Perera and Tateishi 2012; Thennakoon et al. 2017). The extent of damage caused by elephants varies depending on whether the structure is a permanent or temporary dwelling (Galappaththi et al. 2020). Villagers believe a bump by an elephant can be enough to collapse a temporary house (Thennakoon et al. 2017).

Wild elephants damage houses regularly, especially when food, mainly paddy, is stored inside (Hedges et al. 2005). Elephants have a keen sense of smell, and they can detect paddy and other goods such as salt stored inside houses and knock down the walls to feed on them (Campos-Arceiz et al. 2009; Gunawardhana and Herath 2018). A few elephants may have become accustomed to raiding houses, doing so repeatedly in Sri Lanka (Campos-Arceiz et al. 2009). Therefore, keeping rice sacks in the same rooms where people sleep is common because it reduces the risk of elephant attacks (Ranaweerage 2012).

The year can be divided into four seasons based on elephant raiding frequency: the dry season with serious damage, the rainy season with low damage, the post-rainy season with serious damage, and the transitory season with low damage (Campos-Arceiz et al. 2009). During the dry season, typically from May and October, elephants tend to move in search of water. This movement often leads to an escalation in conflict, making it a period of increased anticipation for potential clashes (Gubbi 2012; Gubbi et al. 2014). In addition, paddy fields located far from the housing area are targeted by elephants because of their proximity to water sources such as lakes and tanks, as well as the surrounding forests (Ranaweerage 2012).

People attempt retaliatory attacks on elephants as a solution to elephants raiding and destroying crop fields regularly (Perera 2009). People have tried to kill elephants in various ways, including explosives such as “hakkapatas,” poisoned foods such as pumpkins laced with chemicals, and gunfire (Gunawardhana and Herath 2018). Hakkapattas kill most elephant calves, and a total of 69 elephants were killed by these explosives in 2021, while 64 were killed by electrocution, 45 by gunfire, and four by toxic chemicals. In addition, 69 elephants were killed by these explosives in 2020, while 66 were killed by electrocution, 46 by gunfire, and two by poisoning (DWC, 2020). An average of 200 animals are intentionally killed annually, with 70 to 80 human casualties (Köpke et al. 2021).

Figure. 3 shows the changes in the number of human and elephant deaths in Sri Lanka since 1991. Although these were equal in 1991, the number of elephant deaths has con-

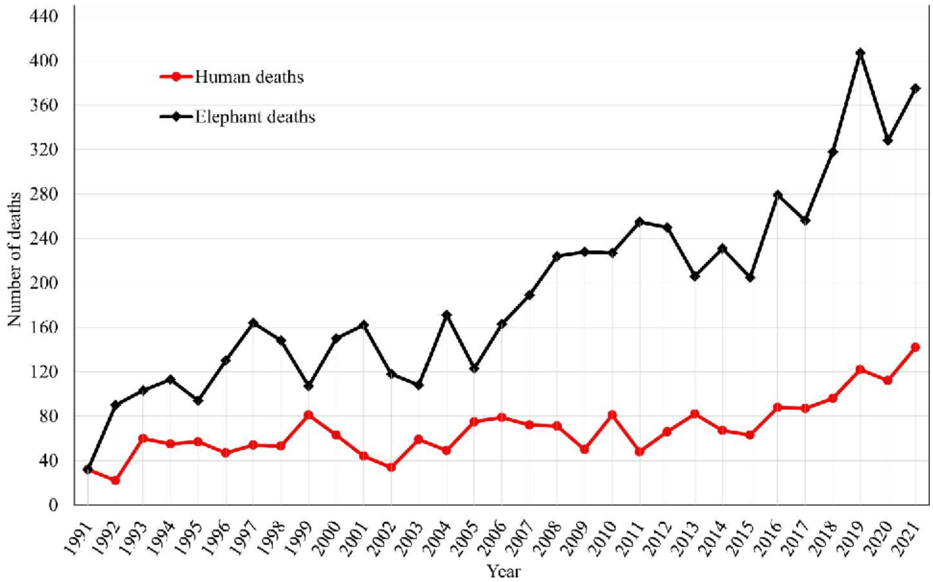

Fig. 3 Human and elephant deaths in Sri Lanka from 1991 to 2021 (DWC)

sistently been higher from that year onwards, with a sharp increase in recent years. The majority are due to HEC, indicating that violence against elephants has increased. This underscores the severity of the issue.

The average annual human death rate due to HEC from 2012 to 2021 was 93, from 2002 to 2011 it was 62, and from 1992 to 2001 it was 54. Therefore, the human killing rate by elephant has been increased by approximately 42% over the previous three decades, with the 2021 figure reaching 142, a marked increase. Despite fluctuations, the number of HEC caused human deaths has exceeded 100 per year over the last three years. Overall, within the last 30 years, 2,111 human and 5,954 elephant casualties were reported due to the HEC.

According to the DWC (Fig. 4), human deaths are more concentrated in the wildlife regions in Anuradhapura, Polonnaruwa, Ampara, Monaragala, Batticaloa, and Kurunegala, while elephant deaths are spread throughout the affected HEC region. The majority of human casualties are male since most HEC incidents occur at night when females in Sri Lankan villages generally do not go out (Galappaththi et al. 2020).

According to Fig. 5, the number of properties damaged has fluctuated but increased. From 2011 to 2021, this reached more than 1,000 per year, with a peak of 2,195 incidents recorded in 2020. Between 1991 and 2021, a total of 27,344 cases were reported, with the worst incidents occurring in Polonnaruwa, Ampara, Badulla, Monaragala, Anuradhapura, and Kurunegala (Fig. 4).

The Sri Lankan government has implemented some laws to protect elephants because killing elephants is illegal (Gardner 2008). These include a fine of between USD 756 (LKR 150,000) and USD 2,520 (LKR 500,000) or a jail term of two to five years, or both (Gardner 2008; Wikramanayake 2022) for killing an elephant.

The DWC of Sri Lanka manages the only scheme that compensates farmers for deaths, injuries, crop loss, property damage, and specific problems that vary from place to place

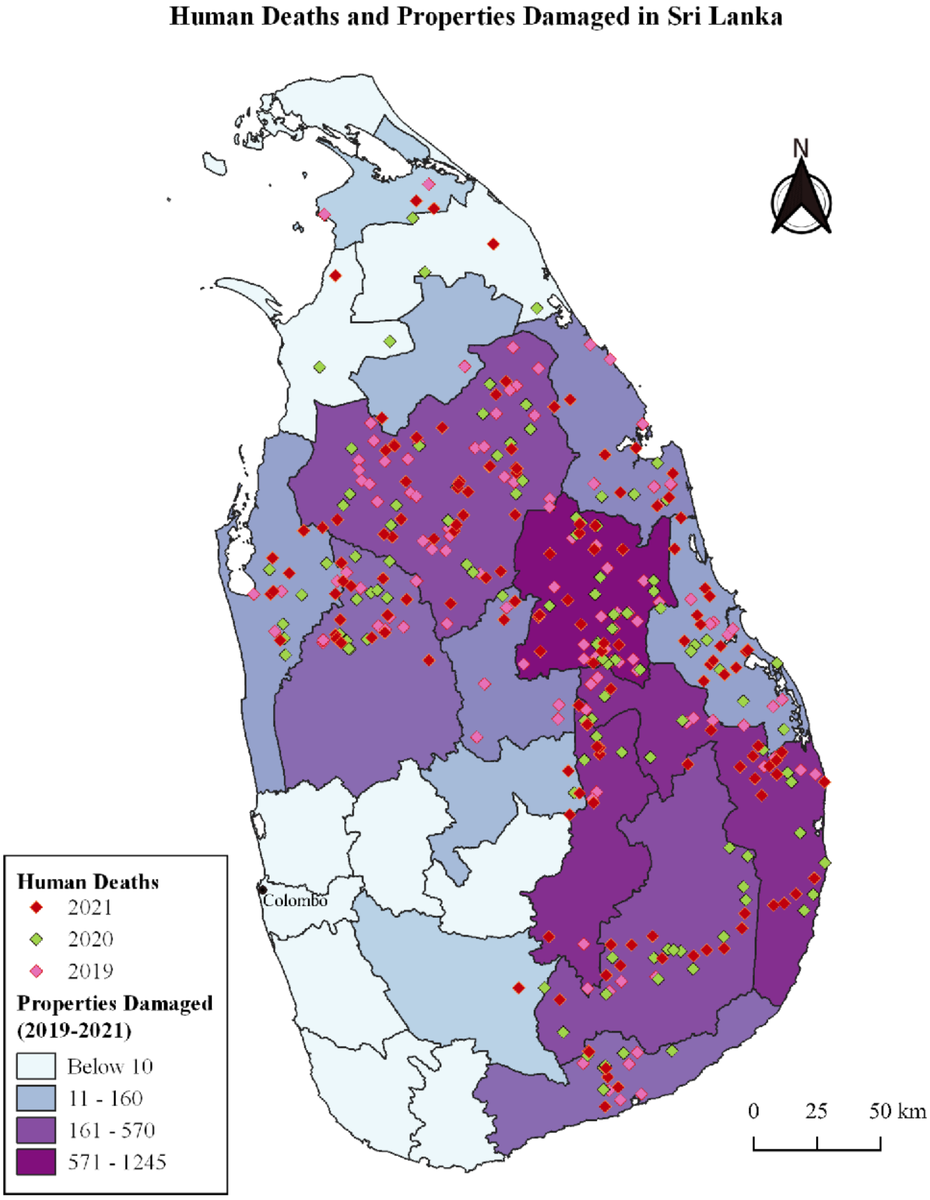

Fig. 4 Number of human deaths and properties damaged in Sri Lanka from 2019 to 2021 (DWC)

caused by elephants in the HEC area (Bandara and Tisdell 2003; Talukdar et al. 2022). Previously, there was also an additional scheme under the Department of Social Services to pay compensation for the damage caused by elephants. After 2nd August 2021, it was amended to make payment through district secretaries (Bandara and Tisdell 2002) to compensate for death, total or partial disability, and house and property damage caused by attacks by protected wildlife.

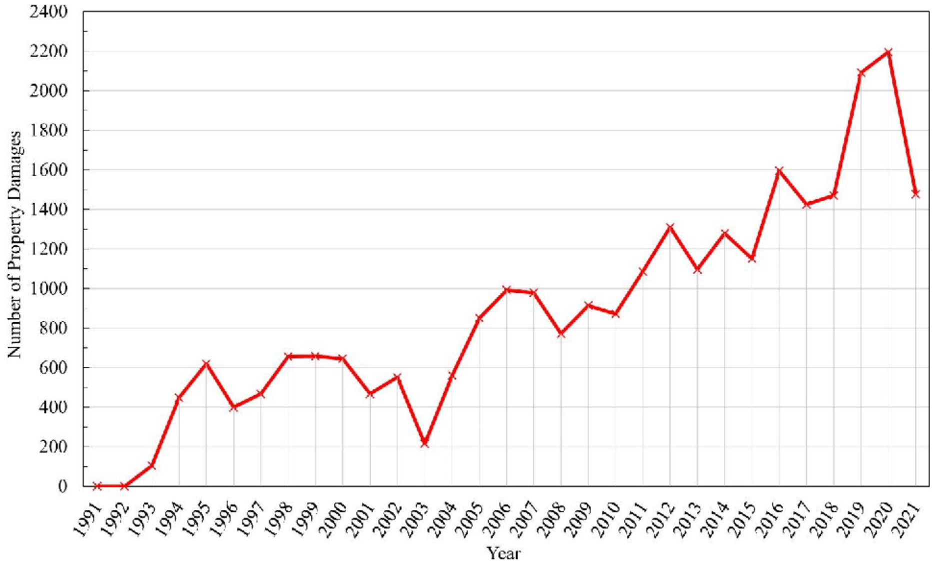

Fig. 5 Number of properties damaged in Sri Lanka from 1991 to 2021 (DWC)

According to the DWC, any victim of an elephant-related death will receive USD 5,040 (LKR 1,000,000) regardless of gender or age, with funeral expenses covered by USD 504 (LKR 100,000) and the remaining USD 4,536 (LKR 900,000) going to dependents or legal guardians. Also, the compensation for "complete disability" is USD 5,040 (LKR 1,000,000) regardless of gender or age. People who are partially disabled or have suffered physical injuries now receive up to USD 756 (LKR 150,000), including a daily hospital allowance of between USD 7.56 (LKR 1,500), and USD 252 (LKR 50,000). Partially disabled people who cannot work due to a medical condition will be compensated daily by between USD 4.03 (LKR 800) and USD 352.80 (LKR 70,000), after being released from hospital. In addition, all medical testing, equipment, and medication prescribed by the doctor must be obtained from a third party, with a maximum compensation of USD 151.20 (LKR 30,000). The compensation for systemic fracture management via traditional Ayurveda medicine is up to USD 50.40 (LKR 10,000). In addition, compensation for houses and properties damaged by wild elephants is up to USD 1,008 (LKR 200,000).

Economic losses due to HEC

HEC can be classified as direct or indirect according to its impact on people (Sampson et al. 2021). Direct HEC has a physical and economic impact on rural communities, whereas indirect HEC has a broad and indirect social impact on people and society (Nyumba et al. 2020; Shaffer et al. 2019). Such indirect costs may form a significant component of the conflict perceived by local people (Sampson et al. 2021).

Elephants cause direct economic damage in agricultural areas by destroying crops, loss of life, injury, livestock, and other property damage (Nyirenda et al. 2018). Although other wildlife species such as parrots, peacocks, wild boars, porcupines, monkeys, rabbits, and flying squirrels also damage crops, elephants are feared the most because of their ability to eat and trample a large number of crops in a single night (Gunawardhana and Herath 2018; Santiapillai et al. 2010). It has been estimated that a typical farmer in elephant-affected areas of Sri Lanka loses over USD 200 annually due to crop damage (Santiapillai et al. 2010).

The indirect impacts of HEC are less tangible than physical damage (Santiapillai et al. 2010). These include fear of attack, and disruption of livelihoods, community activities, and daily activities (Sampson et al. 2021; Tripathy et al. 2022). This may restrict people's movements between villages, mainly where attacks have recently occurred (Tripathy et al. 2022). Such fear among children may reduce school attendance or interfere with collecting fuel wood, wild fruits, or other resources such as wood apples and wild mango (Dharmaratne and Magedaragamage 2014).

Furthermore, resources are lost due to uncompensated activities such as guarding crops (Sampson et al. 2021). Farmers and their families are required to guard their crops and property during the crop raiding season, resulting in loss of sleep and energy, lost time, reduced opportunities for employment, increased exposure to infectious diseases, and psychological stress (Parker et al. 2007). Such indirect costs do not translate well to economic value and are difficult to calculate conventionally. Basically, people are living in fear.

The opportunity cost of different conflict management approaches can be calculated as the income forgone due to the farming households' commitment to dealing with the threat of elephants (Woodroffe et al. 2005). It can be identified as a percentage loss of annual income (Dharmaratne and Magedaragamage 2014).

The DWC spends funds annually for selected HEC mitigation activities for elephant thunder, compensation, capture and translocation, and elephant drives (Horgan and Kudavidanage 2020; Prakash et al. 2020). Sri Lanka spent USD 2.74 million constructing electric fences in 2019 and 2020, resulting in 4,756 km of electrified fencing (Köpke et al. 2021). According to statistics provided between 2011 and 2018, USD 0.76 million was paid as compensation for human deaths and USD 1.7 million for property damage (World Wildlife Fund, 2019). According to records, USD 0.05 million was paid for injuries in 2017 and 2018 (World Wildlife Fund, 2019).

Conflict prevention and mitigation strategies

Implementing HEC mitigation measures is imperative to enhance the sustainability of conservation efforts and improve the coexistence between people and elephants (Enukwa 2017). The advantages of implementing HEC mitigating measures may include improved attitudes and tolerance of farmers toward wildlife, a decline in crop losses, human death and injury, and a decline in elephant mortality (Jackson et al. 2008). A better understanding of the characteristics of HEC enhances the establishment of effective mitigation strategies and promotes the well-being of humans and wild elephants (Thant et al. 2021).

Multiple techniques have been implemented across the Asian and African elephant ranges to prevent them from entering crop fields and to scare them away when they are found feeding on farms (Shaffer et al. 2019). To protect crops from elephants, people shoot them away, use firecrackers and thunder flashes, acoustic deterrents, light-based devices, agriculture-based deterrents, electric fences, bee colonies at borders, protected areas and elephant corridors (Enukwa 2017; Gross et al. 2017; Köpke et al. 2021). Mathtala International Airport, Hambantota International Harbor, Magam Ruhunupura International Convention Centre, Hambantota Administrative Complex, and the International Cricket Stadium in Southern

Province, Sri Lanka, have fragmented the wildlife habitat, which has led to the formation of new corridors, such as the land belt connecting Mattala Airport and Malala Ara, Southern Province, Sri Lanka (Bandara 2020; PEAD 2015; Xinhuanet 2023). Sri Lanka's Road Development Authority design an elevated bridge, the underside of which would function as a corridor for travelling elephants (Xinhuanet 2023). Some artificial corridors, such as in the Andarawewa, Southern province of Sri Lanka, have also been constructed (Bandara 2020). Currently, wild elephants utilize this corridor to safely cross under the expressway. However, numerous incidents have been recorded where wild elephants, including calves have attacked the electric fence, broken the fence, and crossed to the other side from many places on the highway (Bandara 2020).

Traditional methods people use to mitigate HEC

Sri Lankan farmers use different traditional methods to mitigate HEC, frequently combining multiple techniques and changing strategies over time as elephants test the enacted measures to access desired resources (Hoare 1999; Perera 2009). Much of the effort to address the conflict has been focused on risk prevention by keeping humans and elephants separated (Shaffer et al. 2019).

The traditional conflict mitigation methods attempt to limit elephant movements into agricultural areas using barriers such as wooden fences, beehive fences, elephant watchtowers or guardhouses, and trenches (Enukwa 2017). Farmers' defenses in fields at night include chasing animals by banging on tins or drums, shouting, and throwing objects (Enukwa 2017; Sajla and Famees 2022). Chili peppers and fire are also used to scare elephants and keep them away from crop fields (Gross et al. 2017; Köpke et al. 2021).

Trench excavation

Physical exclusion methods such as trenches are commonly used to deter elephants from entering farmland and human settlements (Fernando et al. 2008). A trench must be broad and deep enough to prevent an elephant from stepping over it. Some communities have constructed elephant trenches along their boundaries, of approximately three meters deep and two to three meters wide (Mackenzie and Ahabyona 2012; Parker et al. 2007).

Trench excavation has been considered and proven as a potential and effective strategy for keeping elephants away from crops (Davies et al. 2011; Hedges and Gunaryadi 2010). These trenches serve as a physical barrier, preventing elephants from accessing human settlements (Nelson et al. 2003; Tchamba 1996). However, there are significant drawbacks associated with this method. One major challenge is the labor-intensive nature of trench construction and maintenance, which requires a significant amount of manpower and resources (Zhang and Wang 2003) in larger-scale applications (Enukwa 2017; Shaffer et al. 2019), and their presence creates defined boundaries that limit potential land use options (Nelson et al. 2003). Additionally, waterlogging in the trenches and the obstruction of rock boulders during excavation make the process more difficult (Zafir and Magintan 2016). Furthermore, elephants possess the ability to easily collapse trench walls using their immense body weight, especially in humid areas where they leverage their strength to render the trench ineffective (Enukwa 2017; Zafir and Magintan 2016). Moreover, trenches are susceptible to erosion and caving-in of side walls, which can fill up the trench and enable elephants to cross it (Fernando et al. 2008). Also, they limit potential land use options by creating defined boundaries (Nelson et al. 2003). These factors highlight the limitations and challenges associated with using trenches as a long-term solution for deterring elephants and protecting crops.

Acoustic deterrents

Acoustic deterrents are any noises used to discourage elephants, either through the shock value of an unexpected loud noise or specific noises that frighten elephants (Ball et al. 2022). Farmers scare away crop-raiding elephants by yelling, setting off firecrackers, hitting metal objects, and beating drums and tins. These are perhaps the most widely used methods throughout affected regions in Sri Lanka (Fernando et al. 2005, 2008; Gunaryadi et al., 2017; Shaffer et al. 2019). DWC provides "ali-wedi" which are specific firecrackers for elephants, approximately 25 cm long and 2.5 cm in diameter, to farmers in high HEC areas (Fernando et al. 2008).

Acoustic deterrents offer various benefits. They ensure the safety of elephants avoiding any harm to them, are a cost-effective method, and promote ethical and humane treatment of these magnificent creatures. Furthermore, this method has demonstrated promising results in efficiently deterring elephants (Zhang and Wang 2003).

However, there are significant drawbacks associated with using this repellent method. The absence of long-term adverse effects may raise concerns regarding sustainability and long-term effectiveness (Nelson et al. 2003). Furthermore, this method may only be effective over short distances (Shaffer et al. 2019), limiting its practicality in scenarios where elephants need to be deterred from larger areas. These techniques effectively keep elephants away from crops, and short-distance elephant repellents (Thuppil and Coss 2015; Wijayagunawardane et al. 2016). Additionally, the use of this repellent may disrupt the psychosocial well-being and livelihood activities of farmers (Shaffer et al. 2019; Tchamba 1996).

Light-based deterrents

Since ancient times, lighting fires has been a universal method of protecting crops from elephants and other wild animals (Fernando et al. 2008). Farmers may use flaming torches and light to protect ripening crops and deter elephant raids (Davies et al. 2011; Fernando et al. 2005; Shaffer 2010). Fires are also lit around the farms to improve visibility (Sitati and Walpole 2006). Farmers use light-based deterrents to keep elephants away when they detect them, especially at night (Shaffer et al. 2019). This kind of deterrent mitigates HEC as elephants tend to run away from massive fires. Controlling the fire regularly to prevent it from spreading into the surrounding area is a labor-intensive part of this method. Failure to properly manage the fire may destroy crops and surrounding vegetation (Enukwa 2017).

Most wild animals tend to avoid areas with fire (Nelson et al. 2003), making it an effective means of keeping elephants away from crop fields. Additionally, this method is relatively inexpensive (Enukwa 2017). Moreover, the use of fire as a repellent ensures that elephants are not harmed in the process (Fernando et al. 2008).

However, there are several disadvantages associated with using fire as a deterrent. Fire-based deterrents tend to be more effective in the short term but lose efficacy over time (Fernando et al. 2008; Zhang and Wang 2003). Elephants may adapt to the presence of fire or simply move to a different location (Sukumar 1991; Wijesekera et al. 2021), rendering this method less effective in the long run and serve as short-term measures, and their effectiveness may diminish as elephants adjust their behavior or find alternative routes (Shaffer et al. 2019).

Agriculture-based deterrents

Agriculture-based deterrents create barriers to wildlife entering subsistence farmland and consuming or damaging crops (Kolinski and Milich 2021). Farmers discourage elephants by using crops that are less attractive or palatable to elephants (Gross et al. 2017; Santiapillai et al. 2010). With this approach, they use citrus plant species such as orange and lime trees to create bio fences (Fernando et al. 2008; Sajla and Famees 2022). By planting these trees alongside their crops, particularly in the border areas adjacent to elephant habitats, they hope to decrease crop raiding (Dharmarathne et al. 2020).

Agriculture-based deterrents offer several advantages that make them a viable option in mitigating HEC. They are characterized as “low-tech” solutions that can be produced using locally available resources and techniques (Nelson et al. 2003). These deterrents can provide economic benefits to farmers. By implementing strategies such as intercropping or alternative crop cultivation, farmers can compensate for the reduced cultivation of main crops that are susceptible to elephant damage. Diversifying agricultural practices can lead to increased income and economic stability for farmers (Shaffer et al. 2019).

However, there are notable disadvantages associated with agriculture-based deterrents. One significant drawback is the requirement for consistent monitoring and maintenance. These deterrents often necessitate regular check-ups, repairs, and adjustments to ensure their effectiveness. This can impose a labor-intensive burden on farmers or communities already engaged in various agricultural activities.

Elephant watch towers/guard houses

An elephant watch tower, also known as a guard house, is a secure location for surveillance where a person can monitor elephant activities, and take appropriate precautions to prevent loss (Madzimure 2017). Elephant watch towers or guard houses are structures designed to provide elevated observation points for monitoring elephant movements and preventing HEC. Elephant watch towers are constructed in tall trees around six to nine meters high near the forest boundary, using wood, bamboo, a plastic cover, and tin sheeting with an easily climbable ladder (Madzimure 2017; Nakandala et al. 2014). At night villagers use these to detect elephants from a distance (Madzimure 2017; Nakandala et al. 2014).

These structures offer several advantages in mitigating conflicts. They ensure that elephants are not harmed during the monitoring process (Gunaryadi et al., 2017). Additionally, watch towers and guard houses can help minimize damage to crops, property, and infrastructure by providing early warning of elephant presence, allowing for timely intervention and preventive measures (Sugiyo et al. 2016).

However, there are certain disadvantages associated with the use of elephant watch towers. One notable drawback is the potential for these structures to scare away elephants due to their reliance on the fear elephants have towards human presence. Elephants may alter their behavior patterns or avoid areas where watch towers or guard houses are located, potentially impacting their natural movements and habitat use. This can lead to altered migration routes or the concentration of elephants in other areas, which may have broader ecological implications.

Beehive fences

Beehive fences are simple and inexpensive, made without cement and using only locally sourced materials (King 2019). Hives, or dummy hives, are hung every 10 m and linked together in a specific formation so that if an elephant comes into contact with one of the hives or interconnecting wire, the hives all along the fence line will swing open and release the bees (King et al. 2017). Elephants usually get scared of bees because the bees can quickly attack elephants when disturbed (Enukwa 2017; King et al. 2017). At present, Sri Lanka has beehive fences surrounding the small areas of crops in home gardens (Butler 2016).

Using beehives as a method to deter elephants from crop fields offers several advantages. It ensures that elephants are not harmed. Additionally, farmers can also earn by selling so-called “elephant-friendly honey” and bee products (Enukwa 2017; Shaffer et al. 2019), which can serve as an additional source of income for farmers. Moreover, this method is cost-effective, making it easily affordable for farmers (Sugiyo et al. 2016). Moreover, this method is cost-effective, making it easily affordable for farmers (Sugiyo et al. 2016). The implementation of beehives has also proven effective in reducing HEC by minimizing crop destruction (Enukwa 2017).

However, there are some disadvantages associated with the use of beehives as a deterrent method. Elephants may adapt and create new routes to avoid areas with beehives, reducing the effectiveness of this approach. Adequate training and management of the beehives are necessary to ensure their proper functioning and effectiveness (Sugiyo et al. 2016).

Traditional approaches for mitigating HEC have proven to be ineffective in adequately addressing the challenges posed by this complex issue. The limitations and drawbacks associated with these traditional approaches highlight the need for a novel and innovative method to effectively manage and reduce HEC. It is evident that relying solely on the existing techniques is insufficient in providing long-term solutions and achieving sustainable coexistence between humans and elephants. Therefore, researching alternative strategies and adopting a fresh approach becomes imperative to address the existing conflict and ensure the well-being of both human communities and elephant populations.

Methodology

In this review paper, a systematic approach was used to collect and analyze relevant literature on HEC, with a particular focus on the context of Sri Lanka. The methodology can be described in five steps, literature search, initial screening, focused search on Sri Lanka, study selection and data extraction and synthesis. A comprehensive search for relevant papers and data on HEC was conducted using various sources, including Google Scholar, ResearchGate, Scopus, Web of Science, websites, and newspapers. This search aimed to identify peer-reviewed journal papers, books, conference papers, and newspaper articles related to the topic. A total of 573 articles related to HEC were found, including 146 peer-reviewed journal papers.

In the first phase of screening, the focus was on collecting review papers related to HEC to establish a solid foundation for the analysis. The most important and relevant papers were manually filtered from this initial set of review articles, ensuring that this analysis would be grounded in a thorough understanding of the existing literature. In the next phase of the methodology, papers and data specifically related to HEC in Sri Lanka were searched. After identifying a comprehensive set of relevant papers and data, criteria were applied to select the most relevant studies for inclusion in the review. This included considering factors such as the quality of the research, the relevance to research questions, and the contribution of the study to our understanding of HEC in Sri Lanka. For this paper, 152 papers and websites were used including 75 peer-reviewed journal papers.

Key information was extracted from the selected studies, focusing on the aspects most relevant to the research questions. This data was synthesized, organizing it into categories that aligned with research objectives, and enabling a comprehensive and coherent presentation of findings. By employing this systematic and targeted methodology, a diverse range of literature were gathered and analyzed on HEC in Sri Lanka, ensuring that the review paper is both comprehensive and focused on the most critical aspects of the issue.

Results and discussion

This review presents an overview of the history, present status, and traditional approaches to preventing and mitigating HEC in Sri Lanka. Despite various efforts, HEC remains a pressing issue, highlighting the need for innovative strategies that prioritize both human and elephant safety for the long-term conflict resolution.

The major complexes of HEC are multidimensional, involving social, economic, and environmental aspects. They can be divided into several key areas, crop raiding, property damages, human injuries and death, elephant injuries and death, habitat losses and fragmentation, mitigation methods and their challengers and lack of effective policies and regulation.

In Sri Lanka, recorded a distressing number of elephant deaths, reaching a total of 439 in the year 2022. A significant proportion of these deaths were a direct result of HEC. Among these, 60 elephants were tragically killed by humans through gunshot wounds, reflecting the severity of the conflicts between local communities and these majestic creatures. Similarly, 59 elephants met a tragic end due to the use of explosives such as Hakkapatas, indicating the aggressive measures adopted to mitigate the HEC. Furthermore, electrocution caused the demise of 51 elephants, demonstrating the risks posed by the overlap of elephant habitats and human infrastructure. Man-made transportation systems also contributed to elephant mortalities, with 14 elephants dying due to train accidents and another 3 due to road accidents.

In response to the escalating HEC in Sri Lanka in 2022, the government found itself obligated to pay a substantial sum as compensation for the substantial human and property losses. The total compensation sum reached USD 946,553.34 (LKR 345,255,330), reflecting the severity and magnitude of the crisis. This amount was disbursed in recognition of 160 human fatalities, 192 injuries, and a staggering 2,741 instances of property damage caused by elephant encounters.

This enormous financial burden serves as a stark reminder of the urgency and necessity to address and mitigate the ongoing conflict, to not only reduce the cost to human life and livelihood but also to promote sustainable coexistence with the elephant population. These figures starkly underscore the urgent need for effective strategies and policies to mitigate the escalating HEC in Sri Lanka.

To mitigate the HEC, various measures have been employed, ranging from traditional measures like thorn branches and wooden fences to more innovative approaches like beehive fences, elephant watchtowers, guardhouses, and trenches. However, these methods come with their own set of challenges. They can be expensive, require regular maintenance, and often provide only short-term and limited-distance deterrence.

However, there is a lack of generic frameworks that provides a standardized approach to implementation. In Sri Lanka, the correlation between elephant habitats and changes in land cover and land use, especially greenery, has yet to be established due to the lack of up-to-date, detailed information and precise data on forest cover changes. Therefore, identifying the HEC risk zone hotspot map is an essential step in mitigating HEC in Sri Lanka. There is an extremely urgent need for a standard framework to monitor, identify and predict these HEC risk zone hotspots.

This paper suggests that prospects of incorporating satellite data fusion with GIS modeling in future research. This approach can facilitate more effective management and mitigation strategies by providing valuable insights into the spatial distribution of conflict hotspots. Satellite imagery can be used to prepare accurate and updated land use and land cover maps. Combining maps with GIS modeling to analyze elephant habitats and land-use patterns will identify risk zones and hot spots of HEC in Sri Lanka. The information of hotspots will significantly contribute to HEC management by identifying patterns of elephant movements using accurate changes in forest greenery and weather patterns. This information can be used to prioritize areas for intervention and allocate resources more effectively.

Using satellite data and GIS modeling to develop early warning systems can alert communities to the presence of elephants. Such systems will help prevent HEC incidents by giving communities time to take appropriate precautions and reduce negative interactions between humans and elephants.

Furthermore, integrate satellite data and GIS modeling into the development of adaptive management strategies and land use planning. This will help ensure that future infrastructure projects, agricultural expansion, and other development initiatives consider the spatial dynamics of HEC, minimizing potential conflicts. This approach can contribute to the development of targeted, effective, and sustainable strategies for mitigating HEC, ultimately promoting a more harmonious coexistence between humans and elephants in the region.

Conclusion

Sri Lanka is home to 10% of Asian elephants and 2% of the world's elephant population. The estimated elephant population divided by the land area, elephant density of India and Thailand, is 0.0008 and 0.006 respectively, while Sri Lanka's density is 0.088. However, their numbers have dwindled, with around 5,787 elephants in 2011. Elephant habitat loss, degraded forage, reduced corridors connectivity between forest areas, and a significant decline in elephant populations relative to their historical size and range have been caused by new human settlements and expansion of agricultural land use due to the rapid increase of rural human population.

Elephants confront more frequently with humans and people have attempted to kill elephants with explosives, poisoned foods, and gunfire. As a result, human and elephant deaths have increased in the last 30 years. From 1991 to 2021, there were 5,954 elephant deaths, and 2,111 human deaths. The highest number of elephant deaths, with 407 incidents was recorded in 2019. In HEC mitigation efforts, Sri Lanka spent USD 2.47 million on electric fences in 2019 and 2020, with a total length of 4,756 km, as part of HEC mitigation measures. The DWC also spends annually on elephant thunders, compensations to affected people, capturing and, translocating elephants, and drives elephants from villages into the forest. Also, traditional mitigation methods attempt to limit elephant movement into agricultural areas by using barriers such as thorn branches, wooden fences, beehive fences, elephant watchtowers, guardhouses, and trenches.

This article reviewed HEC's history, status, and traditional prevention and presently practicing mitigation methods. A variety of specific mitigation measures are used, but there are no generic frameworks to implement. HEC management has to be integrated into a long-term land use planning that recognizes elephants as an economic and cultural asset. Using high spatial resolution satellite data and GIS modeling to develop early warning systems can alert communities about movement of elephants according to the seasonal fluctuation of greenery of feeding grounds. Such systems will help prevent HEC incidents by giving communities time to take appropriate precautions and reduce negative interactions between humans and elephants. To find sustainable solutions to HEC, scientists, wildlife managers, policymakers, wildlife enthusiasts, government authorities, and local communities must actively work together.

Recommendation

Authors of present study suggest applying a satellite data fusion with GIS modeling to identify risk zones of HEC in Sri Lanka. Satellite remote sensing has the capability to classify land cover types with high accuracy and this fact has proven by thousands of researches throughout the world (Xie et al. 2008). GIS applies to integrate land cover data with other spatial data layers such as elephant movement records, HEC recorded spots, seasonal variations on vegetation, spatial distribution of human activities, and climatic data. Different land cover classification methods including random forest classifier and support vector machine will be used to classify land cover types to produce the most accurate land cover maps (Qin and Liu 2022) to obtain high accuracy in forest boundaries. GPS data can be used to observe, identify, and record the routes and movements of elephants and integrate field observations with GIS database. Through the GIS data analysis, it will be possible to reveal elephant movement routes, corridors, and entry points into human settlements or crop fields. The resulting HEC zone and elephant hot spots were then visualized on a map using GIS software. This system will inspire researchers to find new ways to protect people and elephants.

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Declarations

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3.3 Links and implications

The two publications presented in Chapters 3 and 4 are linked by their collective investigation of the complex relationship between humans and elephants in Sri Lanka. The initial article is a thorough study of the historical context and status of HEC, indicating the multifaceted factors contributing to this continuing challenge. HEC tends to occur in or near elephant-friendly habitats. Thus, identifying such habitats is critical for investigating HEC, for which it is important to define elephant-friendly forest cover in maps. In line with this, in the second article, Sentinel-2 satellite data are used to map forest cover in southeast Sri Lanka. This spatial analysis provides essential insights into the dynamic landscape, revealing a deep understanding of the geographical elements that substantially impact human-elephant interactions.

Combining these studies constructs a coherent description of issues surrounding HEC and its mapping, with historical insights complemented by current spatial analysis. This helps to provide a comprehensive knowledge of the complications surrounding the HEC in Sri Lanka. The first article lays the foundations by describing the historical context and presenting the current challenges. The second article extends this narrative into spatial dynamics by mapping and analysing forest cover using modern technology. These two articles offer a comprehensive perspective, enriching the HEC discourse and developing an advanced knowledge of its complexities in the Sri Lankan context.

CHAPTER 4: PAPER 2 – APPLICATION OF SENTINEL-2 SATELLITE DATA TO MAP FOREST COVER IN SOUTHEAST SRI LANKA THROUGH THE RANDOM FOREST CLASSIFIER

4.1 Introduction

This chapter is an exact copy of an article published in 2022 in the *Journal of Advances in Engineering and Technology*, *1*(1), pp. 1-10.

This article investigates the usefulness of RF classification in producing an enhanced-quality forest cover map for Sri Lanka using Sentinel-2 satellite data. The detailed methodology, which includes a thorough examination of the RF classification, provides valuable insights into processing and analysing satellite data for accurate forest cover mapping. Furthermore, the analysis of Sentinel-2 satellite data highlights the potential for innovative approaches to LCLU management by using RS technology for environmental monitoring. As RF classification offers precision in mapping forest cover, the findings are more reliable and applicable to environmental management. NDVI is a powerful tool for monitoring forest cover and can provide valuable insights into forest ecosystems' health, dynamics, and trends. Therefore, NDVI is used to assess the accuracy of RFC and is employed only as a supplementary tool to validate the presence of forested areas. Furthermore, the discussion extends to the potential future applications of these satellite-based methodologies for guiding further studies and developing long-term LCLU strategies. This study helps improve present forest cover mapping procedures while laying the framework for developing cutting-edge environmental monitoring and resource management methodologies.

4.3 Links and implications

The link between the two articles presented in Chapters 4 and 5 is firmly established through the common approach of classifying Sentinel-2 satellite imagery using RF classification. In the initial study, RF classification is applied to analyse Sentinel-2 satellite imagery through SNAP software, providing a robust framework for accurate land cover analysis and identifying forest cover.

This original study sets the stage for the article presented in Chapter 5, *"Greenery change and its impact on HEC in Sri Lanka: A model-based assessment using Sentinel-2 imagery."* Building upon the foundational work presented in Chapter 4 and this study extends the procedure by incorporating three LCLU classification methods: RF, SVM, and OBIA. The research expands beyond forest mapping, investigating the complex relationship between greenery changes and HEC. Essentially, the sequential relationship between these articles emphasises the evolutionary progression of research, from initial forest cover mapping to a broader analysis of the dynamic relationship between environmental changes and HEC.

CHAPTER 5: PAPER 3 – GREENERY CHANGE AND ITS IMPACT ON HUMAN-ELEPHANT CONFLICT IN SRI LANKA: A MODEL-BASED ASSESSMENT USING SENTINEL-2 IMAGERY

5.1 Introduction

This chapter is an exact copy of an article published in 2023 in the *International Journal of Remote Sensing*, *44*(16), p.p. 5121–5146.

This study focused on a comprehensive analysis throughout Sri Lanka, exploring the complex relationship between greenery changes and HEC. This article demonstrates the dynamic landscape of Sri Lanka, concentrating on the complex interaction between greenery alterations and HEC through a model-based assessment using Sentinel-2 imagery. Using three advanced classification methods, RF, SVM, and OBIA, LCLU is classified into various categories, considering the complexity of Sri Lanka's woody vegetation.

The study highlights the effectiveness of supervised classification with machine learning algorithms. It achieves high precision in classifying LCLU, with RF emerging as the most effective method, offering insights into the spatial dynamics of HEC. Through a comprehensive analytical approach, the investigation uncovers the correlation between changes in greenery and their impact on the frequency and intensity of human-elephant encounters. This spatial distribution reveals a connection between HEC and human-altered landscapes adjacent to forest reservations and patches. Identifying high-risk areas for HEC enables strategic governmental interventions, potentially designating these regions as protected areas.

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Greenery change and its impact on human-elephant conflict in Sri Lanka: a model-based assessment using Sentinel-2 imagery

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ABSTRACT

Human-elephant conflict (HEC) is a significant conservation issue for Asian elephants (*Elephas maximus*) and an environmental and socioeconomic crisis in elephant range countries, including Sri Lanka. Approximately 14,897 HEC incidents were recorded in Sri Lanka between 2015 and 2021. In this study, we present a Sri Lanka-wide analysis to explore the impact of greenery change on HEC. Our sources were official government data, and land use and land cover maps developed using Sentinel-2 satellite imagery. We applied the support vector machine (SVM), random forest (RF), and object-based image analysis classifications to classify land cover into six categories. This classification scheme also considered the differences observed in Sri Lanka's woody vegetation, consisting of forest, open forest, paddy fields, homestead gardens, and other crops. Analysis of the accuracies of the three types of classifiers confirmed that the supervised classification with two machine learning algorithms, RF and SVM, delivered a higher level of precision in land cover classification. RF was the best option, with a 97.34% overall accuracy and a 0.94 kappa coefficient, while SVM recorded a 94.68% overall accuracy and a 0.89 kappa coefficient. According to the findings, most HEC incidences were recorded in open forests (54%), while 62% were recorded within 2 km of the forest edge. Results indicated that HEC coincides with the human-occupied changed landscape adjacent to forest reservations and patches. The findings could be valuable for HEC management by identifying areas where elephants are most likely to conflict with humans, and the government may declare these as protected areas. Also, we propose an early warning system as an effective approach that helps detect and monitor elephant herds' movement. Therefore,

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implementing long-term land use planning is crucial for protecting the forest and natural habitats, restoring elephant habitats, and mitigating HEC by minimizing human encroachment and promoting sustainable land use practices.

1. Introduction

1.1. Human elephant conflict and land cover and land use changes in Sri Lanka

Human-elephant conflict (HEC) is an interaction between humans and elephants in which one species harms the other (Nguyen, Phan, and Chun-Hung 2022). HEC has been defined as 'any disagreements or contentions related to destruction, loss of life or property, and interference with the rights of individuals or groups that are directly or indirectly related to elephants' (KenyaWildlifeService 1994). It is also a significant conservation issue for Asian elephants (*Elephas maximus*). Also, it is considered one of the critical environmental and socioeconomic crises (Cabral de Mel et al. 2022) in 13 Asian countries: Bangladesh, Bhutan, Cambodia, China, India, Indonesia, Laos, Malaysia, Myanmar, Nepal, Sri Lanka, Thailand and Vietnam (Figure 1) (Fernando and Pastorini 2011).

This conflict arises due to the expanding overlap of human settlements and agricultural activities with the natural habitats of elephants, leading to conflicts and negative interactions between humans and elephants (Gunawansa et al. 2023). The phrase highlights the significant concern posed by HEC, emphasizing its importance in the context of Asian elephant conservation efforts. The Sri Lankan elephant (*Elephas maximus maximus*) has been listed as an endangered species by the International Union for the Conservation of Nature (IUCN 2020), which emphasizes the urgent need for conservation efforts to protect the remaining population and its habitat (Williams et al. 2008).

Inadequately managing elephant migrations and movements can lead to their encroachment into human settlements (Hossain et al. 2023), resulting in insecurity and restriction of freedom of movement due to the potential safety risks. Competition between humans and elephants for space and water has caused deaths and injuries and destroyed crops and infrastructure (Entekhabi et al. 2012). Furthermore, climate changes, deforestation, land degradation, increasing socioeconomic demands, and a growing population impose stress on land use (Yeshey et al. 2023), resulting in elephant attacks on humans (Zhang and Wang 2003). Land cover and land use (LCLU) changes are noted as one of the most significant environmental issues worldwide (Zarandian et al. 2023). Therefore, over the past decade, HEC has become a critical environmental issue in elephant-inhabiting countries, including Sri Lanka, with the intentional killing of elephants in retaliation for human actions such as habitat destruction and ivory poaching (Rathnayake et al. 2022).

The conflict between elephants and humans has been a concern throughout history. The rural population in Sri Lanka has increased significantly from 8.25 million in 1960 to 17.98 million in 2021 (WorldBank 2023). Potential causes and contexts of HEC in Sri Lanka include the change in land cover due to changes in land use with respect to the expansion of human territories, the growth of rural populations, and the loss of elephant habitats for elephants (Anuradha et al. 2019).

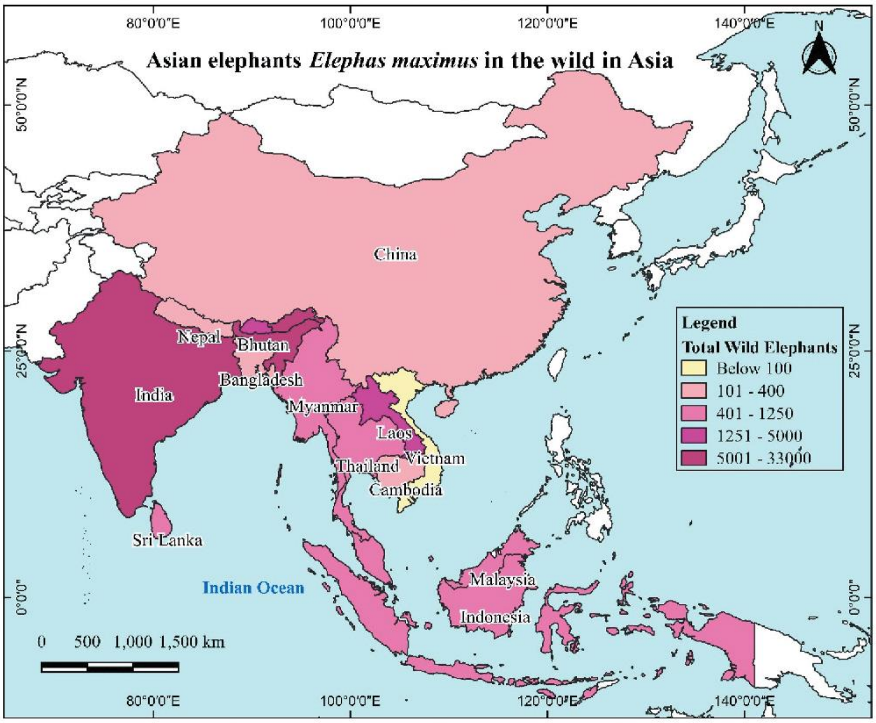

Figure 1. Map of elephant-ranging countries in Asia showing the total numbers of wild elephants: Coordinate reference system (CRS); (WGS 84/UTM zone 44N) (Sukumar 2006).

These contributing factors are primarily responsible for the worsening situation. Most current HEC mitigation tools lack the flexibility to accommodate the ecological needs of elephants and are ineffective in reducing HEC in the long term (Cabral de Mel et al. 2022). The maps in Figure 2 visualize the HEC in Sri Lanka from 2015 to 2021.

The distribution of government hospitals, HEC zones, and road networks in Sri Lanka has been strategically planned to ensure accessible healthcare services and efficient transportation throughout the country. Government hospitals are strategically located in different regions, including urban centres and rural areas, to address the healthcare requirements of the population effectively. Figure 3 illustrates the locations of hospitals in Sri Lanka and the existing road network.

Transporting a patient to a hospital after an elephant attack can be particularly challenging for several reasons. First, many of these attacks occur in remote areas, making access to transportation difficult. Additionally, the potential danger posed by elephants in the area can delay transport and put the safety of patients and medical personnel at risk. Moreover, it can be more challenging to access transportation at night, further delaying the patient's access to medical care. If the patient is seriously injured, the situation can become even more critical, as the nearest hospital may be too far to transport the patient in time.

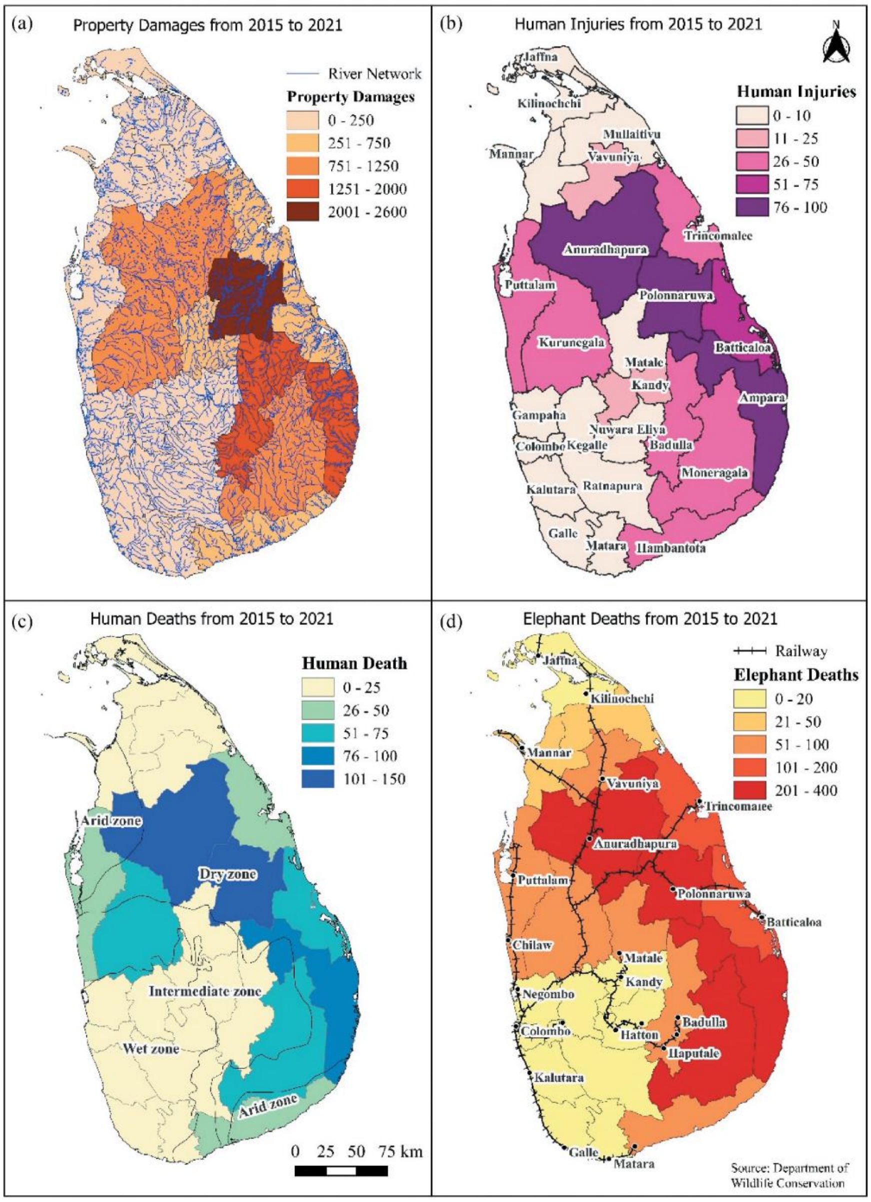

Figure 2. Distribution of four types of HEC incidents in Sri Lankan districts (a) property damage (2015–2021); (b) human injuries (2015 – 2021); (c) human deaths (2015–2021); (d) elephant deaths (2015–2021). Source: Department of Wildlife Conservation.

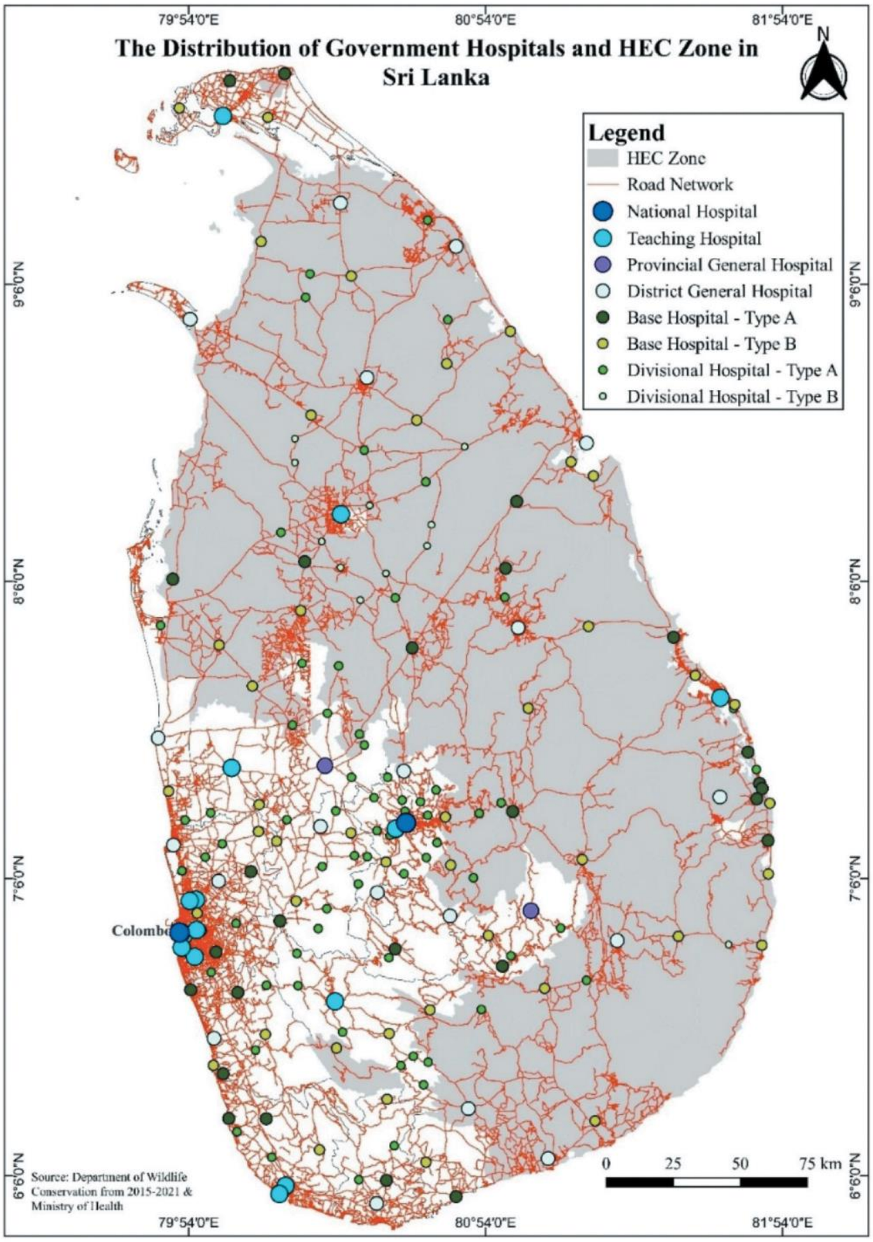

Figure 3. Distribution of the government hospitals, HEC zone and road network of Sri Lanka (MOH 2023).

The overall HEC level in the country during 2015–2021 in relation to administrative districts was most recorded in the dry zone, with the highest number in Polonnaruwa district with 3,105 incidents (Figure 4). Climate zones have been overlaid to understand the regional distribution of each type of HEC. Much of the habitat area of elephants also coincides with areas of infrastructure such as road and rail networks. Elephant habitat also coincides with many rice-cultivated areas, irrigation tanks, forests, and reservoirs in Sri Lanka (Rathnayake et al. 2022).

According to HEC data from the Department of Wildlife Conservation (DWC) of Sri Lanka, 14897 HEC incidents have been recorded in the last seven years. A total of 2,173 elephants and 708 humans lost their lives during this period. Remarkably, human deaths have doubled since 2015. Since 2003, 11405 incidents of property damage have been recorded due to HEC, and human injuries are more frequent, with 610 confirmed incidents. Property damage, which represents more than 72% of all HEC reports, has increased by more than 128% since 2015.

Considering the 2015 to 2022 period, there is some data fluctuation, but overall, the trend is increasing. In 2021, improvised explosive devices (Hakkapattas) were responsible for 69 elephant deaths; 64 were killed by electrocution, 45 were shot, six died in train accidents, and four were poisoned with toxic chemicals. Furthermore, in 2020, 69 elephants lost their lives due to these explosive devices, 66 were electrocuted, 46 were shot, three died in a train accident, and two were poisoned, highlighting the need to implement more effective measures to prevent such tragic incidents.

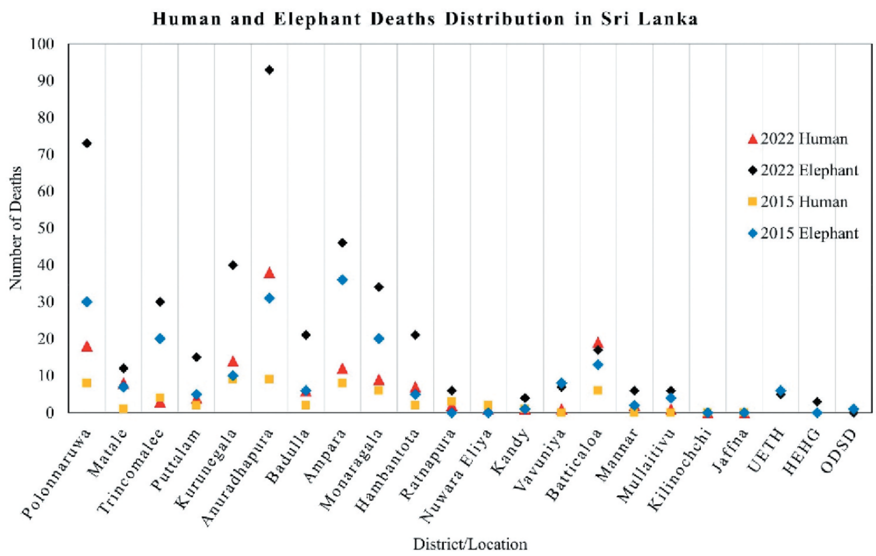

Figure 4. Number of human and elephant deaths in districts, Udawalawe Elephant Transit Home (UETH), Horowpothana Elephant Holding Ground (HEHG), and Other Divisional Secretariat Divisions (ODSD) during the last seven years. Source: Department of Wildlife Conservation.

Elephants require a large area to meet their intake of about 150 kg of plant matter per day (Samansiri and Weerakoon 2007) and reproductive requirements. Changes in and around forest areas, both natural and artificial, directly impact elephant habitats (Anuradha et al. 2019). Behaviours will change with the greenness of the land cover as it alters in wet and dry conditions. As a result, an accurate forest map is vitally needed to track or estimate elephant populations. The size of an elephant's home range varies depending on the availability and nature of the habitat (Marshal et al. 2010). Therefore, to identify HEC hotspots, an accurate forest map must be integrated with a GIS database.

Large-scale forest cover losses in Sri Lanka have increased in recent decades due to the breakdown of sustainable agriculture (Perera and Tsuchiya 2009; Perera et al. 2012; Ranagalage et al. 2020). When the British Empire took control in 1843, about 90% of Sri Lanka was covered by forests (Lindström 2011). From 2010 to 2019, the forest loss rate was dramatically high, which can be associated with the rapid infrastructure development of the country (Ranagalage et al. 2020; Sudhakar Reddy et al. 2016). In 2010, the World Food and Health Organization ranked Sri Lanka as the country with the fourth highest rate of deforestation (Jayasundara 2023; Perera 2021).

Due to rapid forest degradation, humans and elephants frequently come into contact with each other, with losses for both species. Crop fields and settlements have been particularly vulnerable hotspots where frequent HECs occurred. The situation will become more complicated in the near future because Sri Lankan elephants have a very limited area due to the country being an island.

1.2. Research objectives

HEC is one of the critical environmental issues in Sri Lanka; its relationship with LCLU change has not been established due to the lack of updated detailed forest cover changes in Sri Lanka. Therefore, creating an HEC hotspot map is essential to mitigate HEC in Sri Lanka. In this study, we aim to develop a satellite data fusion approach with GIS modelling to produce an accurate LCLU map to identify HEC risk zones in Sri Lanka.

2. Materials and methods

2.1. Study area

Through a detailed investigation of existing HEC records, the largest forest region in southeast Sri Lanka and its surrounding area was selected as the study area. This area of approximately 5,836 km^2 (Figure 5) encompasses 14 divisional secretary's divisions (DSDs, also known as divisional secretariats; these constitute the country's third administrative level) across four administrative districts: Badulla, Hambantota, Monaragala, and Rathnapura.

These areas mainly account for national parks, agricultural lands, forests, and villages with perennial vegetation. The study area includes four large national parks: Udawalawe, Lunugamvehera, Bundala, Ussangoda, and Yala. Udawalawa is a popular spot for viewing elephants, and Yala National Park covers a large part of the selected area. In addition, the study area includes Wirawila Tissa, Madunagala Sanctuary, and Ridiyagama Safari Park. The majority of the study area falls into dry and arid zones, which both experience

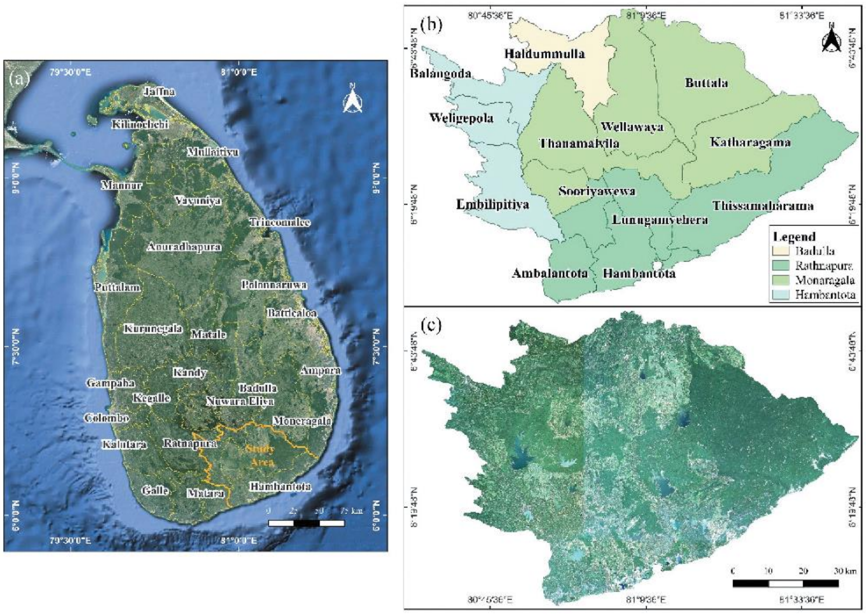

Figure 5. Location of the study area: (a) District map of Sri Lanka; (b) Divisional secretary's divisions of the study area; (c) Sentinel-2 image mosaic of the study area. Coordinate reference system (CRS) (WGS 84/UTM zone 44N).

a significant dry period from May to September. The northeast monsoon rains appear in most parts of Sri Lanka, including the dry zone, from December to February.

2.2. Sentinel-2 satellite data

The Sentinel-2 satellite system was developed by an industrial consortium led by Astrium GmbH (Germany). Astrium SAS (Marshal et al.) is responsible for the MultiSpectral Instrument (MSI). The MSI works passively by collecting sunlight reflected from the Earth. Sentinel-2 products by the European Space Agency (ESA) and the European Union, as part of the Copernicus Program, have contributed to effectively monitoring the Earth's surface (ESA 2023a). The primary goal is to offer high-resolution satellite data for various applications such as land monitoring, emergency management, security, climate change analysis, and marine studies. LCLU data encompass a range of categories, including residential areas, roads, forests, and agricultural areas (ESA 2015). The free and open access policy to Copernicus Sentinel data provides users with a large volume of consistent and complete data (Mitraka et al. 2020).

The Copernicus Open Access Hub (previously known as Sentinels Scientific Data Hub) provides complete, free, and open access to Sentinel-1, Sentinel-2, Sentinel-3, and Sentinel-5P user products. Sentinel data products are made available systematically and freely to all data users, including the general public and scientific and commercial users, through https://scihub.copernicus.eu/.

Sentinel-2 satellite data have the potential to improve forest classification at medium to large scales due to their 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 satellite revisit frequency is 10 days, and the combined constellation revisits frequency is 5 days (ESA 2023b).

The Sentinel-2 mission is made up of twin polar-orbiting satellites (Sentinel-2A and Sentinel-2B) in the same orbit, phased at 180° to each other (ESA 2015). For the bottom-of-atmosphere data (Level 2A) (Pádua et al. 2022) products that have been used in this study, the atmospheric correction has already been applied (ESA 2023c). Sentinel-2 product data are relatively high resolution, using the data processing software SNAP developed by the ESA. Table 1 summarizes the characteristics of the Sentinel-2 satellite data used in this study.

2.3. HEC data acquisition

HEC incidents data were obtained for seven years (2015–2022) from DWC Sri Lanka. DWC is the custodian of reported HEC incidents in Sri Lanka (Department of Wildlife Conservation 2023). The HEC data are reported under four main categories: human deaths, elephant deaths, human injuries, and property damage. These incidents have been documented with location information, wildlife region, DSD, district, and the incident's date (or year). Elephant deaths and property damage reporting depend entirely on the community alerting the DWC headquarters or the nearest regional wildlife office if any incident has occurred. Human deaths and injuries are more accurately documented because they are confirmed through a police investigation or medical records.

2.4. Satellite data classification schemes and classification systems

Remote sensing technology has been widely used to extract land cover/use information efficiently, as it can repeatedly obtain data for a large area (Hossain and Chen 2019). Remote sensing classification is a complex process that requires the consideration of factors such as spatial resolution, classification algorithms, and training data. The main steps of image classification are the determination of a suitable classification system, the selection of training samples, image pre-processing, feature extraction, the selection of appropriate classification approaches, and accuracy assessment (Lu and Weng 2007).

Today, machine learning (Aburas et al.) algorithms have been widely chosen to classify satellite images for mapping the Earth's surface (Avci et al. 2021). A suitable classification system and sufficient training samples are prerequisites for successful classification. This study used RF, SVM, and OBIA classification systems and six classification schemes.

2.4.1. Classification schemes and reference data collection

The dominant land cover types of the study area have been characterized and classified by the proposed classification schemes. The classification scheme was based on the study's primary objective, which is to identify the forest and the open forest. The land cover classification scheme developed for the study is summarized in Table 2.

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

Satellite	Processing Level	Cloud Cover Percentage	Tile Number Field	Date of Acquisition
Sentinel-2A	Level-2A	5.75	T44NNN	22.01.2022
Sentinel-2A	Level-2A	13.78	T44NMM	22.01.2022
Sentinel-2A	Level-2A	0.38	T44NMN	22.01.2022
Sentinel-2A	Level-2A	13.33	T44NNM	22.01.2022

Table 2. LCLU use category and definitions.

LCLU category	Definition
Forest	Trees and bushes, covered by natural, newly forested, or planted forests
Open forest	Moderately tall trees and a reasonably 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, non-built-up 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

Figure 6 shows examples for each LCLU category class, representing the wide range of variations in the foremost classes. As explained below, existing land cover maps were used for the spatial stratification of reference pixels and benchmarking the performance of the proposed mapping process.

Spatial stratification refers to the process of dividing a study area into smaller, more homogeneous units based on certain characteristics. Reference pixels are within the study area for which the land cover type is known with a high degree of accuracy. These pixels are typically selected based on ground truth data. Reference pixels are used to train the classification algorithm and to assess the accuracy of the resulting land cover map.

Benchmarking the performance of the proposed mapping process involves comparing the resulting land cover map to existing land cover maps and assessing its accuracy. This can be done using metrics such as overall accuracy, kappa coefficient, and user's and producer's accuracy. Benchmarking helps to identify areas of the map that may require further refinement. It aids in ensuring that the resulting map is reliable and accurate.

Land cover classification requires representative, precise, and robust reference data. In this classification, ground truth data were collected through the information gathered from field observations and reference to Google Earth high-resolution data to implement a protocol to ensure the high quality of the reference data.

2.4.2. Support vector machine

An SVM is a nonparametric image classification algorithm that consists of a collection of related regression and classification learning algorithms (Saini and Ghosh 2018; Yousefi et al. 2022). SVMs are supervised learning algorithms based on statistical learning theory heuristic algorithms (Srivastava et al. 2012). The SVM often provides more robust classification results from highly variable spectral information than the most popular supervised classification methods (Cervantes et al. 2020). The SVM may achieve high classification accuracy using a small training sample set (Foody and Mathur 2004; Zheng et al. 2015). The SVM consists of four kernel types. Linear, radial basis function,

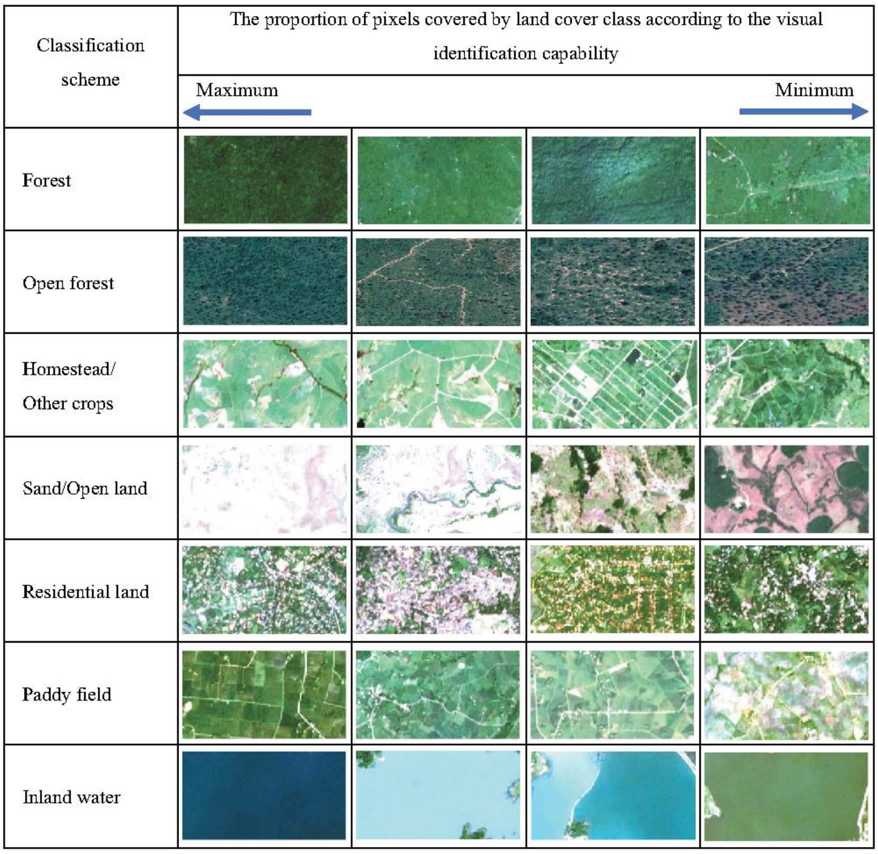

Figure 6. Examples of the target LCLU classes showing the ranges of classification scheme distribution. These are ordered by LCLU proportion cover of a pixel. From left to right: maximum to minimum cover to still be assigned to the class.

sigmoid, and polynomial kernels are commonly used to classify remote sensing data (Chabalala, Adam, and Ali 2022).

An SVM, a popular and accurate technique for satellite image classification, is widely used in remote sensing (Mountrakis, Im, and Ogole 2011; Yousefi et al. 2022). Therefore, determining the optimal values of the penalty parameter in the SVM method is essential. This is done by considering the different land cover types and the corresponding surface land reflectance in arid and humid regions (Thanh Noi and Kappas 2018).

We performed supervised classifications using the SVM algorithm in the open-source Orfeo Toolbox (OTB) software through https://www.orfeo-toolbox.org/otb-release-8-1-0/ (De Luca et al. 2019). The algorithms implemented in OTB were applied in this work through QGIS software. The OTB version used was 8.1.0 and interfaced with QGIS 3.22. With the SVM, we used a linear kernel type with a model type based on a C value equal to one. For the classifications, 50% of the field samples were used as training data and 50% for validation.

2.4.3. Random forest

RF is an ensemble classifier that comprises a large number of decision trees created by randomly chosen predictors from randomly selected data that are a subset of the training dataset, and the final classification/prediction decision is made based on a majority vote (Adugna, Xu, and Fan 2022; Belgiu and Drăguţ 2016). The Random Forest Classifier (RFC) is an ensemble machine learning algorithm used successfully in land cover classification in remote sensing (Adugna, Xu, and Fan 2022; Marissiaux and Defourny 2018). The RFC produces multiple decision trees using a randomly selected subset of training samples and variables (Belgiu and Drăguţ 2016). Due to its higher classification accuracy, this classifier has gained popularity in the remote sensing community (Jin et al. 2018).

For this study, Sentinel-2 imagery was processed using ESA SNAP version 9.0.0 software developed by ESA https://step.esa.int/main/download/snap-download/. Sentinel-2 imagery-corrected 10 m spectral bands were used in this classification. The identification of land covers was carried out by referring to Google Earth Pro. For the RF model, defining two important adjustable parameters was necessary. The first denotes the number of predictors tested at each decision tree node split (mtry), and the second illustrates the number of decision trees runs at each iteration (ntree) (Chabalala, Adam, and Ali 2022; Tatsumi et al. 2015). In this study, the RF model was optimized, and the model accuracy was maximized using these two primary parameters, set as mtry 3200 and ntree 50.

2.4.4. Object-based image analysis

OBIA is defined as a subdiscipline of GIS devoted to partitioning remote sensing imagery into meaningful image objects and assessing their characteristics through spatial, spectral, and temporal scales (Hay and Castilla 2006). The key steps in OBIA are segmentation and classification (Blaschke 2010). Segmentation is a method of partitioning an image into a set of separate regions that are intended to correspond to meaningful landscape units of varying sizes based on spectral and geographic features (Nasir et al. 2022) such as colour, texture, shape, size, and grey value (Kazemi Garajeh et al. 2022). The quality of the segmentation stage directly affects the results of the OBIA approach for remote sensing image analysis (Hossain and Chen 2019).

In this study, the OBIA classification of the Sentinel-2 image was performed using the Orfeo Toolbox 8.1.0 plugin and QGIS 3.22. The 'Mean-Shift' segmentation algorithm in the OTB plugin was used to segment the image and convert pixels with similar characteristics into a polygon (Zaki et al. 2022). Extensive trial-and-error experiments were conducted to determine the optimal image segmentation parameters, which took around one and a half hours. The optimal parameter settings used for the OTB plugin are 15 for spatial radius, five for range radius, and one for minimum segment size. Training samples were used for land cover classification and testing samples were used for land cover map evaluation. Based on the average spectral value of pixels in each polygon from the image segmentation, the training samples were then used to classify each land cover imagery using a linear SVM kernel type.

2.5. Accuracy assessment

To determine the best outcome of the mapping process, accuracy assessment is a fundamental step in remote sensing image processing. This is used to quantify the

Table 3. Rating criteria for Kappa coefficient.

Kappa coefficient	Strength of agreement
<0.00	Poor
0.00–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.00	Almost perfect

error and uncertainty that might be involved (Rwanga and Ndambuki 2017). The accuracy assessment results verify the image classification quality (Nasir et al. 2022). First, a confusion matrix (an error matrix) is usually used as the quantitative method to calculate image classification accuracy. This allows us to assess the overall accuracy, as well as the accuracy of the producer and the user. In one recent study, this approach was applied to evaluate the accuracy to determine the validity of classification algorithms (De Luca et al.). For the present study, a measure of validation of each classified map was provided by constructing a confusion matrix between the training areas and the maps. Then, the accuracy assessment process estimated overall accuracy (OA), Kappa coefficient (KC), user accuracy (UA), and product accuracy (PA) using Equations one to four, presented below, based on the confusion matrix. Table 3 shows the categorization of the Kappa coefficient (Rwanga and Ndambuki 2017).

$$OA = \frac{Total\,number\,of\,corrected\,classified\,pixels}{Total\,number\,of\,reference\,pixels} \times 100 \tag{1}$$

$$PA = \frac{Number\,of\,correctly\,classified\,pixels \in \,aclass}{Number\,of\,training\,pixels \in \,that\,class} \times 100 \tag{2}$$

$$UA = \frac{Number\,of\,correctly\,classified\,pixels \in \,aclass}{Total\,number\,of\,pixels\,classified \in \,that\,class} \times 100 \tag{3}$$

$$KC = \frac{Total\,number\,of\,sample \times \,Total\,number\,of\,corrected\,sample - \sum(column\,total \times \,row\,total)}{(Total\,number\,of\,sample)^2 - \sum(column\,total \times \,row\,total)} \tag{4}$$

A manual process was used to complete an accuracy assessment and construct a confusion matrix for performance evaluation. For this evaluation, 186 ground truth data pixels were randomly selected. Google Earth imagery offers a clear view of LCLU features with details and can be utilized for field verifications when in situ field observation is not practically possible. This study used Google Earth imagery as the primary ground truth data collection source. Figure 7 shows the flow chart of the methodology applied in this study.

3. Results

Once the Sentinel-2 image was classified using the SVM, RF, and OBIA methods, the accuracy assessment for these maps was conducted. The classifiers were executed using

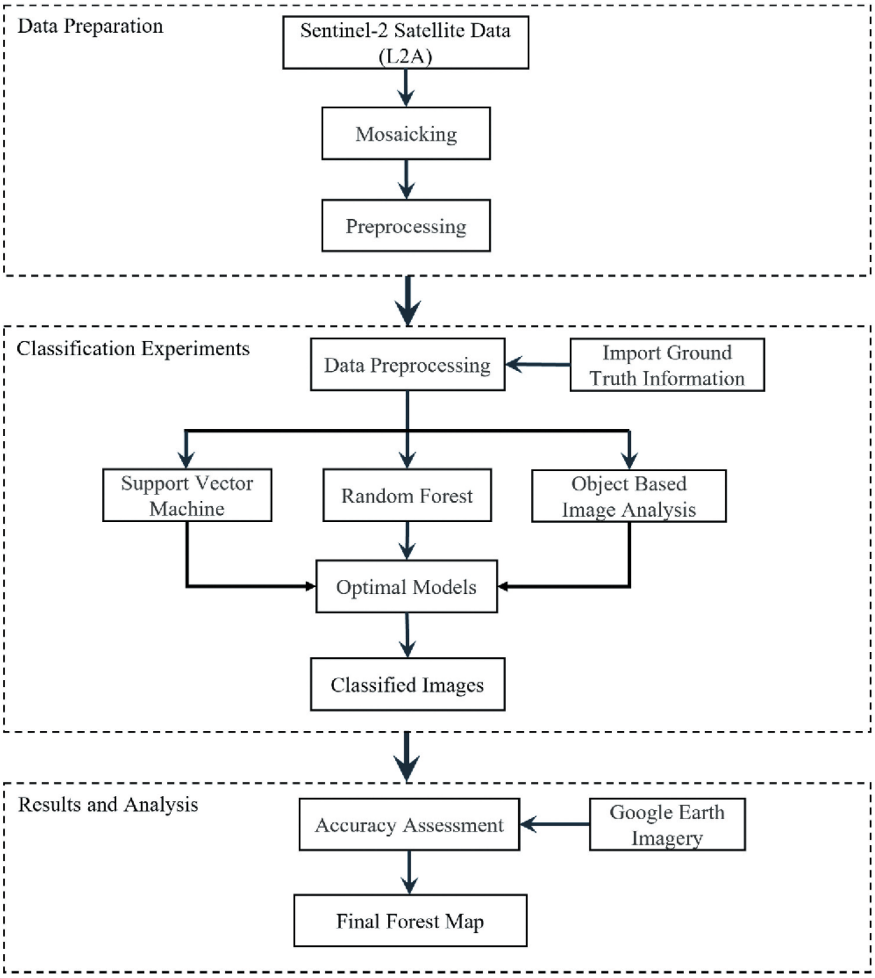

Figure 7. The schematic framework of the methodology applied in the present study.

the optimum parameter values to determine the best model for each classification method. Then a confusion matrix was computed to evaluate the overall accuracy and Kappa coefficient. This section presents the current study's findings, which utilized Sentinel-2 processed data to prepare land cover maps featuring six distinct LCLU categories.

3.1. *Support vector machine*

Figure 8 illustrates the classification of the results obtained from SVM. Forest and tree species are mainly distributed in the east and northwest of the study area. Most broadleaf tree species are found in natural forests, representing 44.8%.

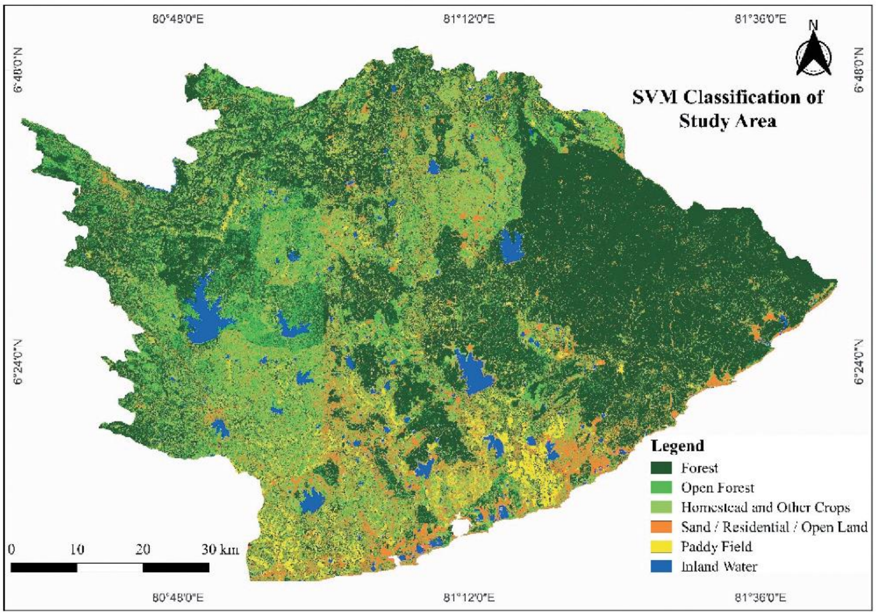

Figure 8. Map of the land cover classification using SVM classification. The Sentinel-2 image was taken on 22nd January 2022.

It has been observed that the high-density forest (forest) class achieved more accuracy than the low-density forest (open forest). The open forest and homestead, and other crop pixels are as misclassified as each other, resulting in low accuracy. All classification schemes generally have good accuracies, ranging from 79% to 100% (Table 4).

3.2. Random forest

Figure 9 illustrates the utilization of RF for the generation of LCLU map. In the RF classification, almost all classes have more than 95% PA, except for homestead and

Table 4. The confusion matrix for SVM classification includes the user's (UA) and producer's (PA) accuracies.

Classification scheme	Forest	Open forest	Homestead and other crops	Sand/Residential/ Open land	Paddy field	Inland water	UA%
Forest	87	3	1	0	0	0	95.60
Open forest	1	19	1	1	0	0	86.36
Homestead and other crops	1	2	24	0	0	0	88.89
Sand/Residential/ Open land	0	0	0	19	0	0	100.00
Paddy field	0	0	0	0	17	0	100.00
Inland water	0	0	0	0	0	10	100.00
PA%	97.75	79.17	92.31	95.00	100.00	100.00	

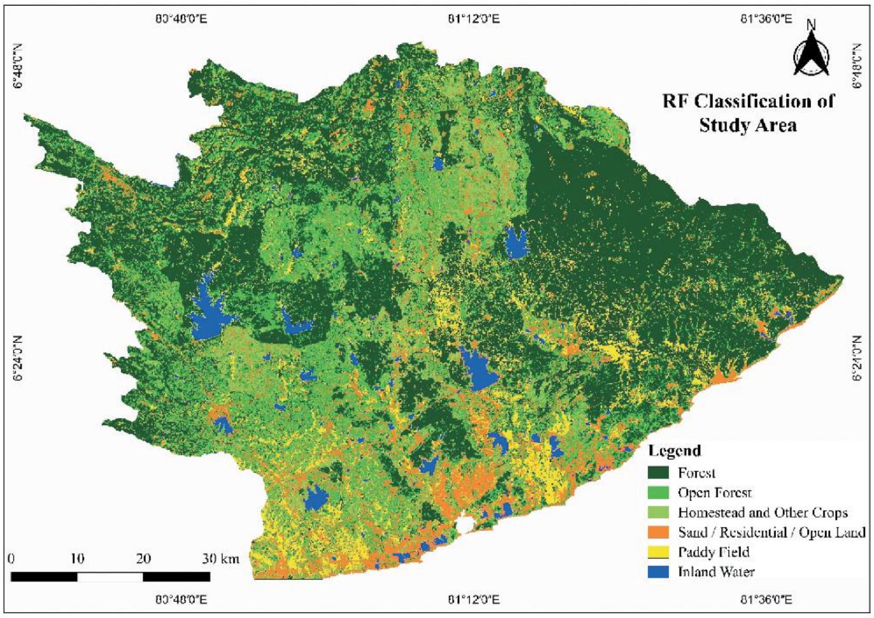

Figure 9. Map of the land cover classification using the RF classification.

other crops (Table 5). Generally, each classification scheme's accuracy shows that RF can classify well.

3.3. Object-based image analysis

OBIA was used to create the land cover map (Figure 10). Some paddy fields have been misclassified as inland water, homestead, and other crops. According to Table 6, the UA values for the open forest, paddy field, homestead and other crops were less than 60%.

As summarized in Table 7, the SVM and RF methods achieved significantly higher land cover classification accuracy. However, when comparing the Kappa coefficient, the SVM and RF method's performances are almost perfect. According to this study, the RF

Table 5. Confusion matrix for RF classification and including user's and producer's accuracies.

Classification scheme	Forest	Open forest	Homestead and other crops	Sand/Residential/ Open land	Paddy field	Inland water	UA%
Forest	88	0	1	0	0	0	98.88
Open forest	0	24	1	1	0	0	92.31
Homestead and other crops	1	0	23	0	0	0	95.83
Sand/Residential/ Open land	0	0	1	19	0	0	95.00
Paddy field	0	0	0	0	17	0	100.00
Inland water	0	0	0	0	0	10	100.00
PA%	98.88	100.00	88.46	95.00	100.00	100.00	

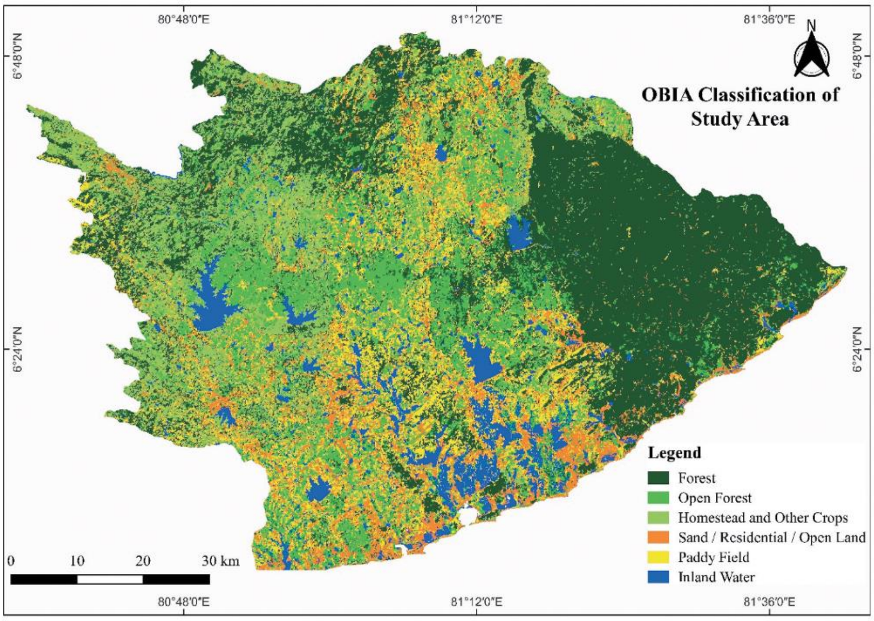

Figure 10. Map of land cover classification using the OBIA classification.

Table 6. Confusion matrix for OBIA classification, including user's and producer's accuracies.

Classification scheme	Forest	Open forest	Homestead and other crops	Sand/Residential/ Open land	Paddy field	Inland water	UA%
Forest	66	1	2	0	0	0	95.65
Open forest	7	14	4	0	8	0	42.42
Homestead and other crops	8	5	16	0	0	0	55.17
Sand/Residential/ Open land	1	0	1	16	0	0	88.89
Paddy field	7	4	3	1	5	0	25.00
Inland water	0	0	0	3	4	10	58.82
PA%	74.16	58.33	61.54	80.00	29.41	100.00	

Table 7. Overall accuracy and Kappa coefficient of the SVM, RF, and OBIA classification.

Classification method	Overall accuracy %	Kappa coefficient
SVM	94.68	0.89
RF	97.34	0.94
OBIA	68.62	0.51

technique generated the highest performance, and the OBIA technique performed moderately compared to the other two methods.

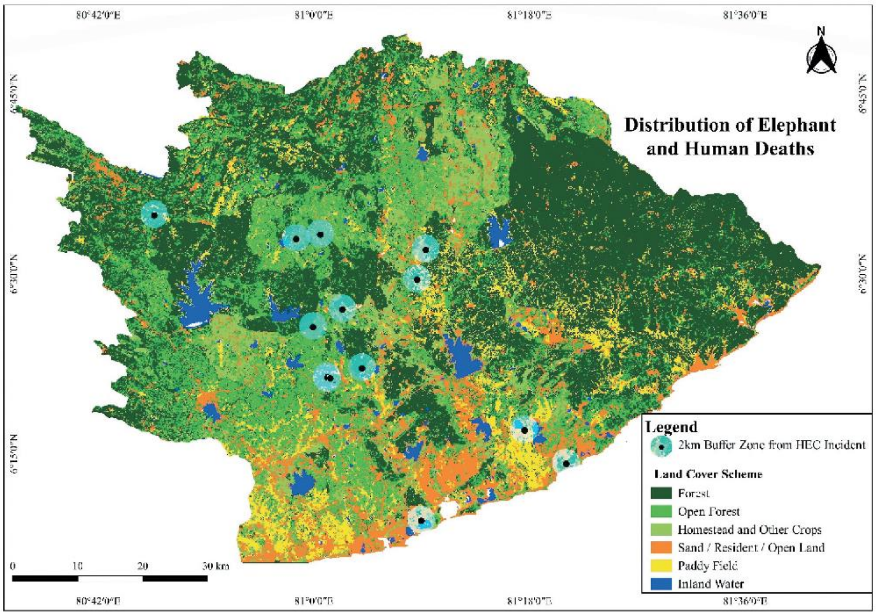

Figure 11. The distribution of elephant and human deaths in the study area with a 2km buffer for HEC incidents in 2021. This 2022 land cover map was produced using RF classification.

3.4. Influence of land cover changes on HEC

The study revealed that areas near forests, paddy fields, homesteads, and other crops are hotspots for HEC incidents. This finding confirms elephants' preference for productive vegetation. The highest accuracy outcome for the 2022 land cover map produced using RFC supports this conclusion. This analysis was carried out by examining human and elephant records in 2021. We found that most HEC incidents (54%) were recorded in the open forest area, while 62% were recorded within a 2 km buffer zone of forest boundaries (Figure 11). In the study area, the distance from inland water sources had a less significant relationship (with 38% of incidents close to the inland water sources) with the occurrence of HEC.

3.5. Assessment of forest cover based on vegetation indices

Vegetation indices calculated from satellite images are straightforward and efficient methods for quantitative and qualitative assessments of vegetation cover, vitality, and growth dynamics (Omia et al. 2023; Pesaresi et al. 2020). Normalised difference vegetation index (NDVI) is one of the widely used indices to detect multitemporal vegetation greenery (Aburas et al. 2015), and NDVI results are presented in Figure 12. In Sentinel data, the red band corresponds to the B4 band, and the near-infrared (NIR) band corresponds to the B8 band. The calculated NDVI values ranged from 0.938 to −0.992 in January 2022, with the higher values indicating forest, low positive values characterizing sparse vegetation,

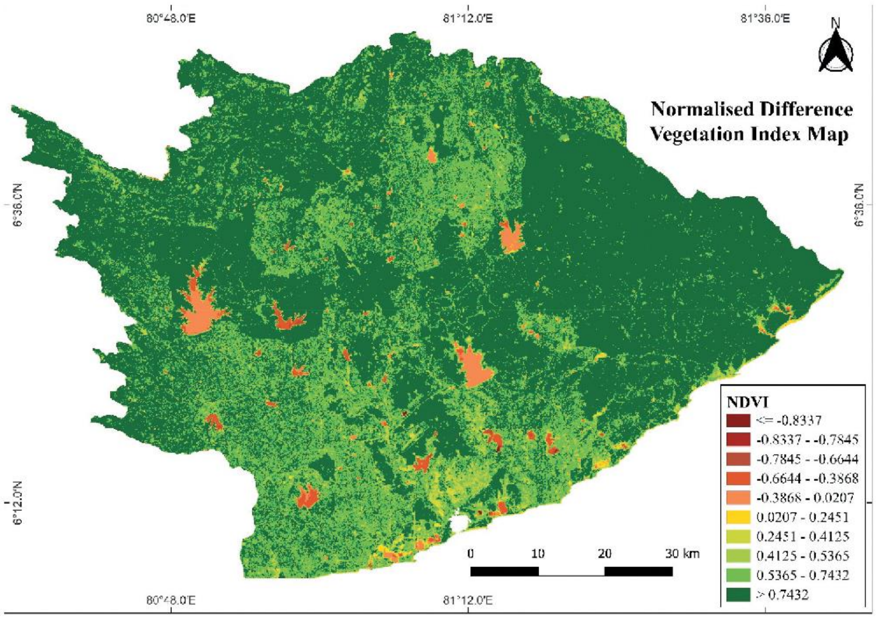

Figure 12. NDVI results of the study area.

and negative values representing water. In this study, NDVI was used to validate the forest area classified by RFC.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{5}$$

4. Discussion

Due to changing socio-ecological and environmental pressures, Sri Lanka's rapid land cover change has created an altered interface for human-wildlife interactions. Understanding these shifts is crucial to mitigate repeated negative interactions escalating conflict between people and elephants. Large herbivores such as elephants require extensive home ranges for food and, thus, a large area of suitable habitat to meet their survival and reproduction needs. Data from the World Food and Health Organization has ranked Sri Lanka as the country with the fourth highest rate of deforestation. Likely, Sri Lanka's higher elephant density of around 0.1 elephants/km^2 compared to the 0.01 elephants/km^2 in India is due to its smaller size and significant elephant population. Sri Lanka and India have different elephant densities due to the contrasting land sizes of the two countries. Sri Lanka, a relatively small island nation compared to India, has a concentrated elephant population within a smaller land area. With a smaller land area, Sri Lanka's elephant population is concentrated in a smaller space, leading to a higher density of elephants per unit area.

When the food quantity for elephants in the reserve habitat does not match the elephant population's expansion rate, this causes problems. To solve this problem, elephants must move outward to find new habitats and gradually go towards farm villages outside the reserve to feed, which leads to the potential risk of HEC. Simultaneously, multiple development goals, such as agriculture and transportation, affect elephant habitats overlapping with human activities. Expanding cash crop cultivation areas and highway construction projects contribute to this impact. Consequently, the migration and communication of elephant populations are disrupted. In other words, human activities continue to encroach on the living spaces of elephants in different ways. Sri Lanka had approximately 5,787 elephants in 2011, and the range has been shrinking in the dry zone in recent decades. Furthermore, elephants are not able to find an additional area to feed due to the country being an island.

Annual HEC incidents have increased in line with the changes in LCLU patterns in rural Sri Lanka. Furthermore, the occurrence of HEC in the study area was closely linked to higher average NDVI values, suggesting the link between the greenery of the vegetation and HEC incidents. About 54% of HEC incidents were recorded in open forests, while 62% were recorded within 2 km of the forest boundary. According to DWC reports, 51% of elephant deaths occurred in Sri Lanka in 2021 due to explosives, electrocution, gunfire, train accidents, and toxic chemicals. Therefore, identifying the HEC risk zone hotspot map is essential to reduce HEC in Sri Lanka.

The hotspot map will significantly contribute to the management of HEC by identifying elephant movement patterns by accurately monitoring changes in forest greenery and weather patterns. This information can be used to prioritize areas for intervention and allocate resources more effectively in planning and land use management. Additionally, developing early warning systems can notify communities of the presence of elephants. Such systems will help prevent HEC incidents by providing communities sufficient time to take appropriate precautions and reduce negative interactions between humans and elephants. The government may declare these as protected areas, establish electrical fences or buffer zones to separate human settlements from elephant habitats, and implement other measures to reduce HEC.

Recent advances in remote sensing, including the availability of high-resolution data such as Sentinel-2 satellite images, have enabled free data access for various environmental monitoring applications. Among other applications, machine learning algorithms are widely employed in land cover mapping. Satellite data classification, RF, and SVM are commonly used algorithms due to their distinct advantages and strengths, which make them suitable for various tasks with higher classification accuracy. RF is known for its robustness to noise, handles ability to high-dimensional data, and capability to capture non-linear relationships. On the other hand, SVM performs well with limited training samples, can handle complex decision boundaries, and is robust to overfitting. Depending on the specific characteristics of the land cover classification problem, the selection of RF or SVM can lead to accurate and reliable classification results.

Support vector machine, random forest, and object-based image analysis are the three classification algorithms utilized for land cover classification. SVM and RF have gained prominence as methods for detecting changes in land cover. All three were utilized with Sentinel-2 satellite image data and evaluated. The error matrix technique was used to assess the accuracy, calculating the overall accuracy, Kappa coefficient, producer's accuracy, and user's accuracy of classified maps. The overall accuracy of RF and SVM ranged between 94.68% and 97.34%, with a Kappa coefficient of 0.89 to 0.94. On Sentinel-2 satellite imagery, the highest accuracy (97.34%) was achieved by RF.

The Sri Lankan elephant is the country's largest land animal, requiring forest and other vegetation patches to survive. Therefore, the details of existing forest maps are expected to be periodically evaluated to accurately identify forests and forest patches. The data produced by this study on forest greenery changes and HEC data will be evaluated to determine possible locations where elephants are roaming.

The proposed method in this study has some limitations in real-world application, particularly concerning the accuracy of the classification. Some potential limitations include data quality, availability, and training data representativeness. The accuracy of satellite data classification heavily relies on the availability and quality of input data. Although good results for land cover classification can be obtained from Sentinel-2 imagery, it is difficult to obtain enough clear Sentinel-2 images on rainy and cloudy days. The accuracy of the classification model depends on the representativeness and quality of the training data. If training data does not adequately capture the variability and characteristics of target land cover classes, classification accuracy may be compromised. This may have a negative impact on classification accuracy.

The research methodology adopted in this study will apply to other regions dealing with similar human-wildlife conflict (HWC), 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. Flexibility in scaling can ensure that the method remains effective and feasible. Furthermore, regions sharing similar characteristics in terms of HWC, including the presence of specific species and comparable habitats, enhance the applicability of the methodology. An adaptable and adjustable research methodology that will accommodate different contexts and conditions holds a higher potential for applicability. Considering these factors and conducting assessments before adapting the method for successful implementation and achieving desired outcomes in various regions.

5. Conclusions

HEC has significantly increased in the past seven years, doubling human and elephant deaths. Changes in LCLU, human territories expansion, rural population growth, and elephant habitat loss are primary contributing factors to this issue's worsening. While various methods have been applied to address this matter, it remains unresolved. There is a lack of research exploring the connection between greenery changes and HEC hotspots. As an initial step, in this study, we investigated the utilization of Sentinel-2 satellite imagery for LCLU classification in Sri Lanka to monitor changes in greenery. We also analysed the relationship between the greenery of changes in land cover and HEC hotspots, highlighting the importance of satellite data as a significant tool for mapping areas of potential conflict with human activities.

Remote sensing has emerged as a powerful tool for monitoring changes in LCLU, providing crucial information for environmental management and conservation planning. This study evaluates the effectiveness of random forest, support vector machine, and object-based image analysis classification methods in producing LCLU maps using Sentinel-2 satellite data. An accuracy assessment was conducted using 188 randomly selected ground truth points. The ground truth data were gathered through field observation and Google Earth high-resolution data. The overall classification accuracies of the RF, SVM, and OBIA classifiers were 97.34%, 94.68%, and 68.62%, respectively, with Kappa coefficients of 0.94, 0.89, and 0.51, indicating strong agreement between ground truth and classified data. These findings suggested that RF and SVM are efficient and accurate approaches for classifying Sentinel-2 satellite imagery to produce LCLU maps.

Based on the LCLU map created using the RF classifier and existing records of human and elephant interactions, we found that HEC occurrences were closely related to open forest areas and forest boundaries. Most HEC incidents (54%) were recorded in the open forest area, while 62% were recorded within 2 km of forest boundaries. The findings of this study highlight the potential value of using Sentinel-2 satellite data to monitor greenery changes in relation to LCLU.

The findings of this study can be used to mitigate HEC and promote coexistence between humans and elephants. Also, the results could be valuable for managing HEC by identifying areas where elephants are most likely to come into conflict with humans. The government may declare these as protected areas, establish electrical fences or buffer zones to separate human settlements from elephant habitats, and implement other measures to reduce HEC. Furthermore, the findings of this research could be helpful to both public and private stakeholders involved in elephant conservation efforts. By understanding the patterns and drivers of HEC, stakeholders can develop targeted interventions to reduce the risk of conflict.

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5.3 Links and implications

The connection between the two articles presented in Chapters 5 and 6 is their united approach to tackling the prevalent issue of HEC in Sri Lanka. High-resolution Sentinel-2 satellite imagery was a key tool for identifying areas where human activities intersect with elephant habitats. Both studies employed machine learning algorithms, specifically RF and SVM classifiers, alongside Sentinel-2 satellite imagery for a thorough examination of how changes in greenery affect the dynamics of HEC.

The methodology is consistent with both articles. The created LCLU map effectively pinpoints critical hotspots for HEC incidents in Sri Lanka. Additionally, NDVI values were utilised for both studies to quantify changes in vegetation cover, clearly depicting alterations in greenery within the study area.

Paper 4, presented in Chapter 6, further enhances the methodology to generate a comprehensive forest map. This map, coupled with a detailed analysis of HEC, enables the identification of high-risk zones. Both research efforts underscore the potential of integrating remote sensing and GIS in mitigating HEC.

CHAPTER 6: PAPER 4 – IDENTIFYING HUMAN-ELEPHANT CONFLICT HOTSPOTS THROUGH SATELLITE REMOTE SENSING AND GIS TO SUPPORT CONFLICT MITIGATION

6.1 Introduction

This chapter is an exact copy of the published article in 2024 in the *Remote Sensing Applications: Society and Environment*, 35.

This study addresses a pressing issue of HEC in regions where elephants and humans coexist, specifically focusing on Sri Lanka. Integrating remote sensing and GIS analysis, changes in LCLU are examined, utilising Sentinel-2 satellite data to identify potential conflict areas. The research, conducted in two forest-dominated regions of southeast Sri Lanka from 2021 to 2022, uses high-resolution Sentinel-2 imagery to detect proximity areas of human activities and elephant habitats.

Monthly changes in vegetation cover were quantified using NDVI values derived from MODIS data. These identified regions are suitable for elephants to frequently forage in. Furthermore, using KDE, high-density areas were identified 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. The process revealed varying levels of HEC risk, from very high to low.

The study employs the RF and SVM classification methods for LCLU classification. The LCLU map, created using the RF classifier, indicated that all identified hotspots for very high and high HEC risks are closely aligned with forest boundaries.

6.2 Published paper

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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.

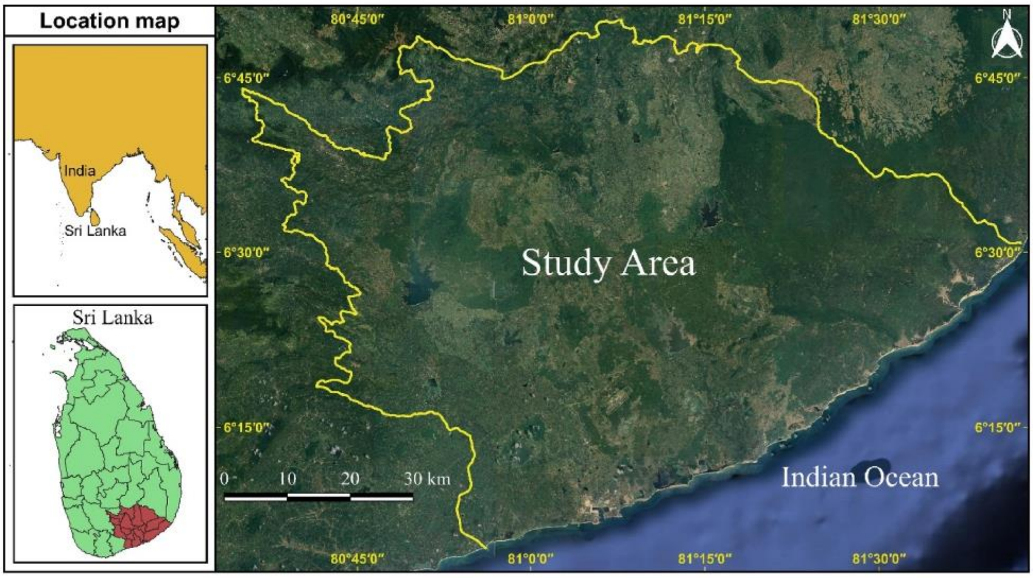

Fig. 1. Map of the study area.

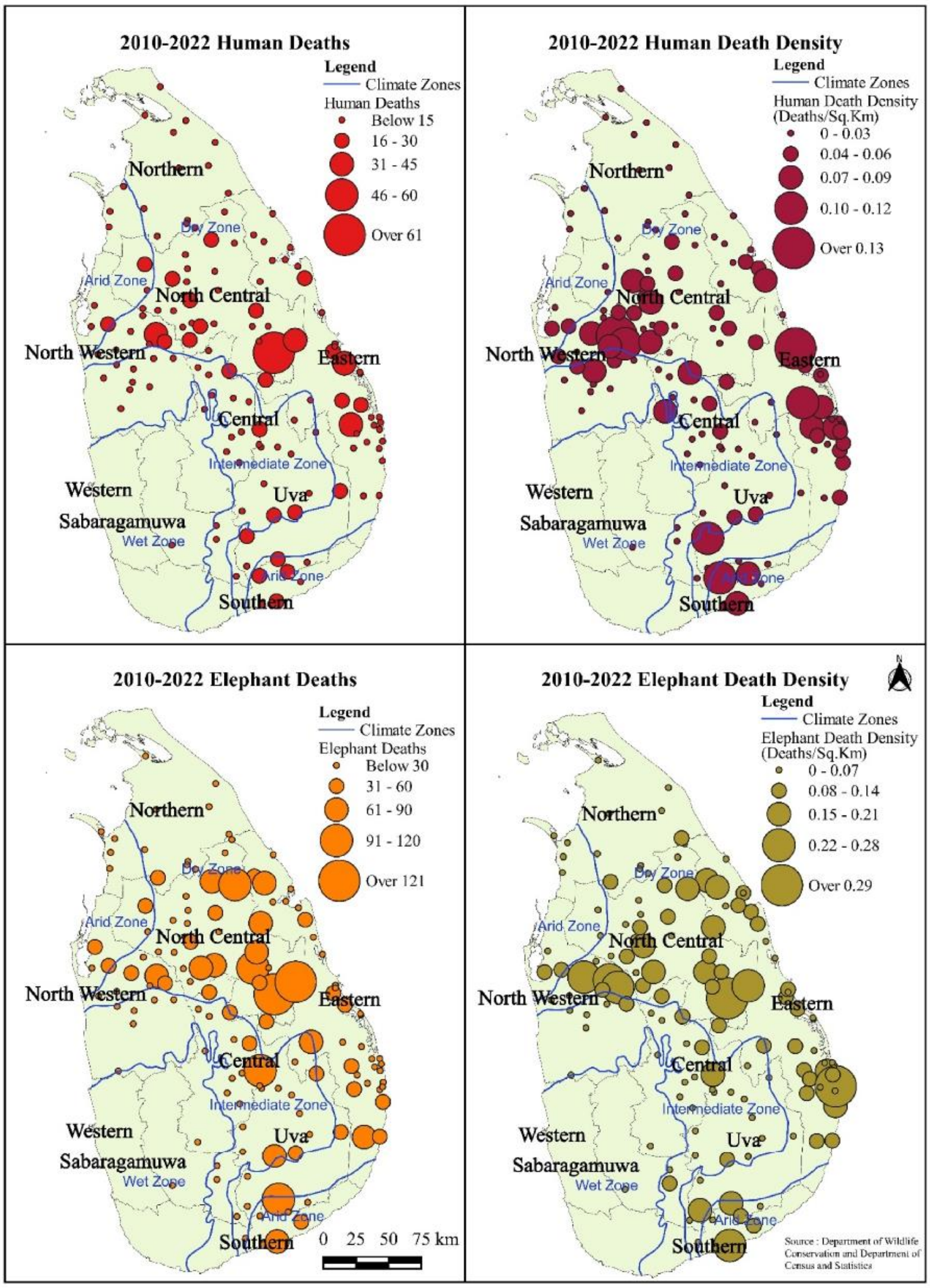

Fig. 2. Comparative analysis of elephant and human deaths and densities in Sri Lanka from 2010 to 2022.

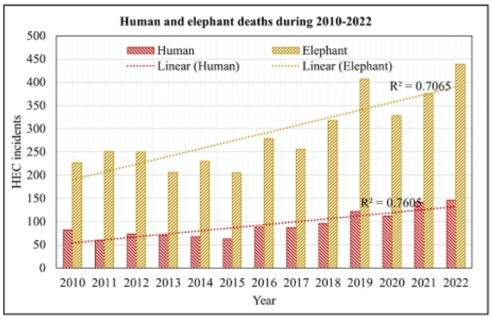

Fig. 3. Temporal trend of human and elephant deaths reported from 2010 to 2022.

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.

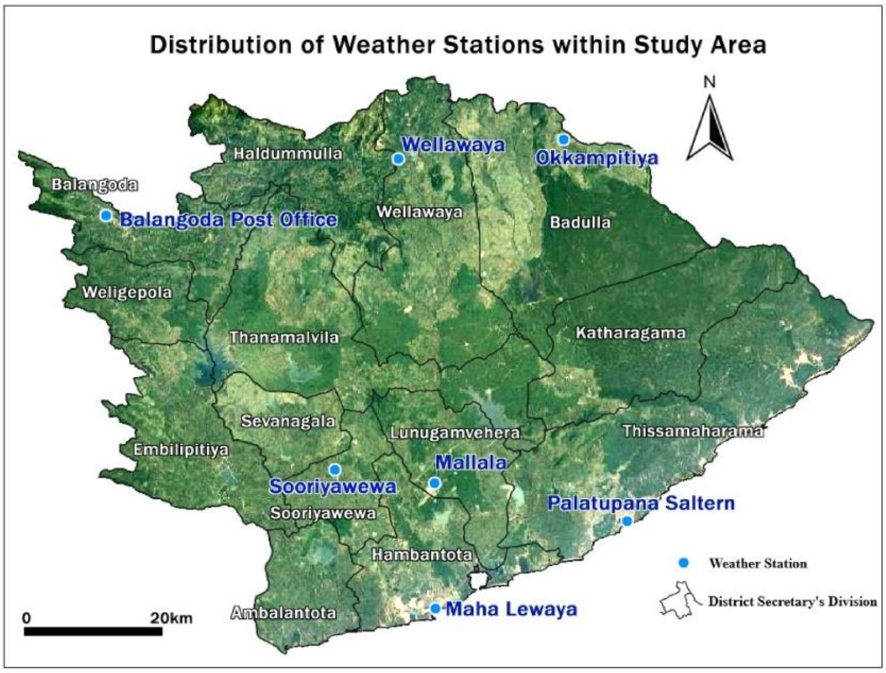

Fig. 4. Distribution map of weather stations within the study area.

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

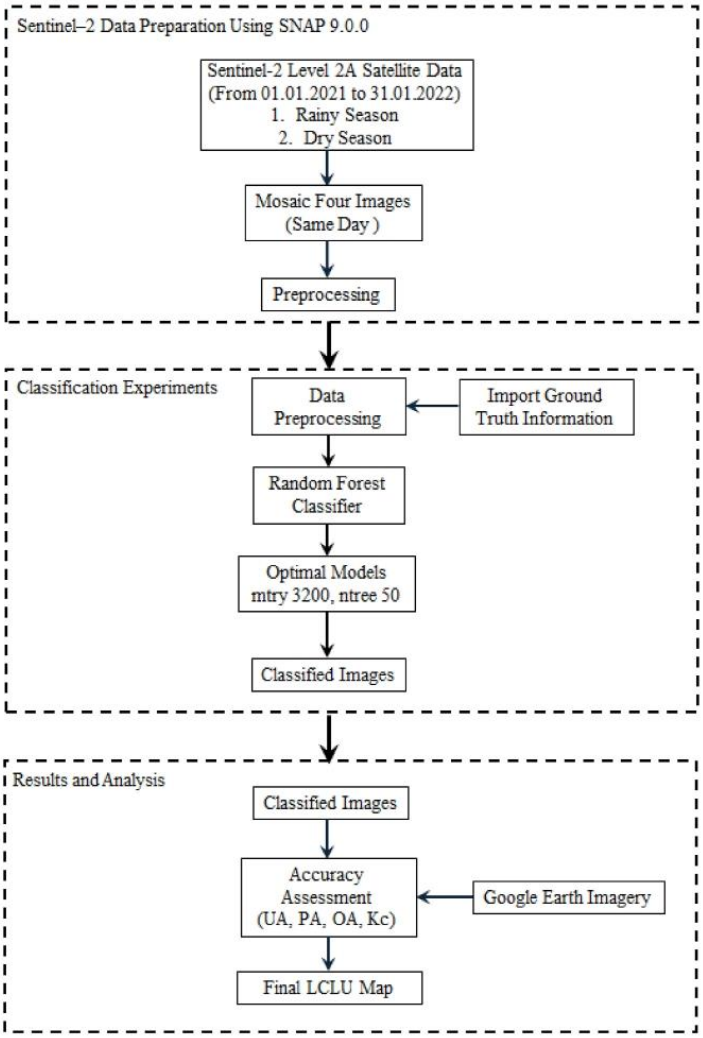

Fig. 5. Workflow diagram of the RF classification process.

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.

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} = \frac{B2 - B1}{B2 + B1} \quad (1)$$

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.

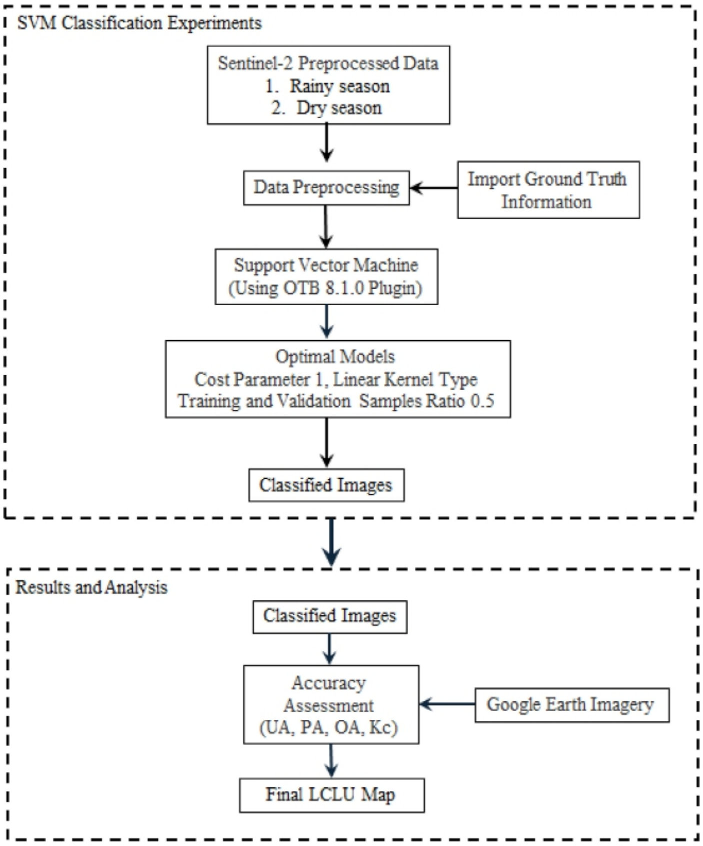

Fig. 6. Workflow diagram of the SVM classification process.

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.

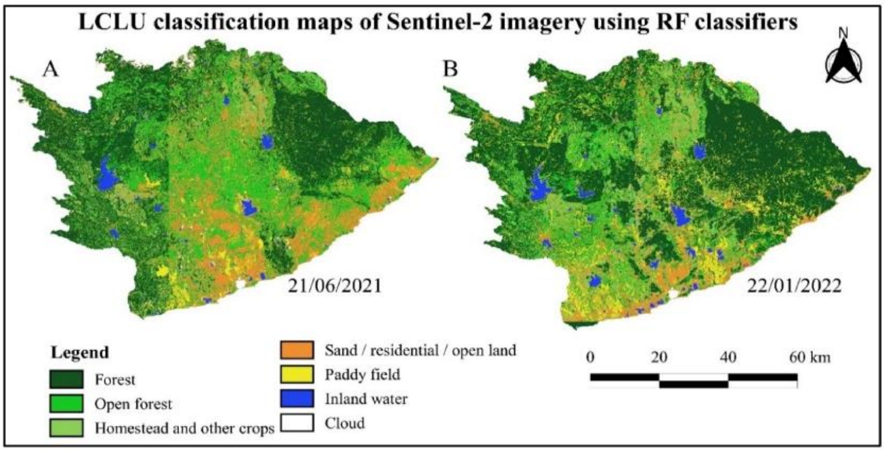

Fig. 7. LCLU classification maps of Sentinel-2 imagery using RF classifiers for 2021 to 2022.

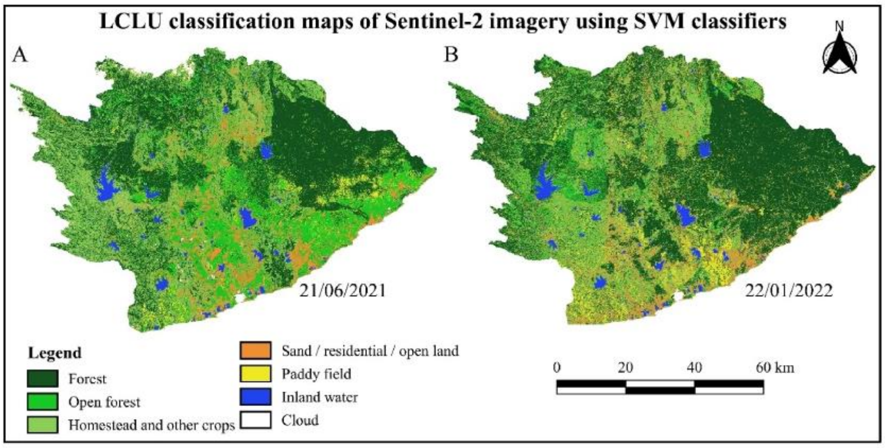

Fig. 8. LCLU classification maps of Sentinel-2 imagery using SVM classifiers for 2021 to 2022.

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

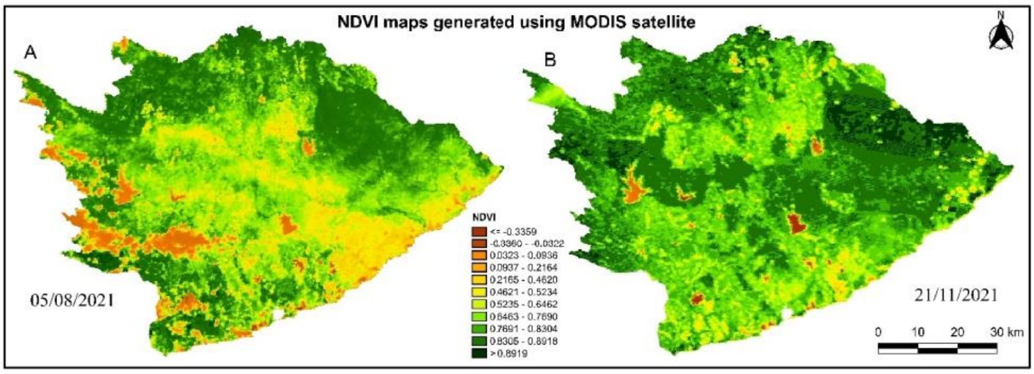

Fig. 9. NDVI results of the study area: (a) NDVI map in the dry season; (b) NDVI map in the rainy season.

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.

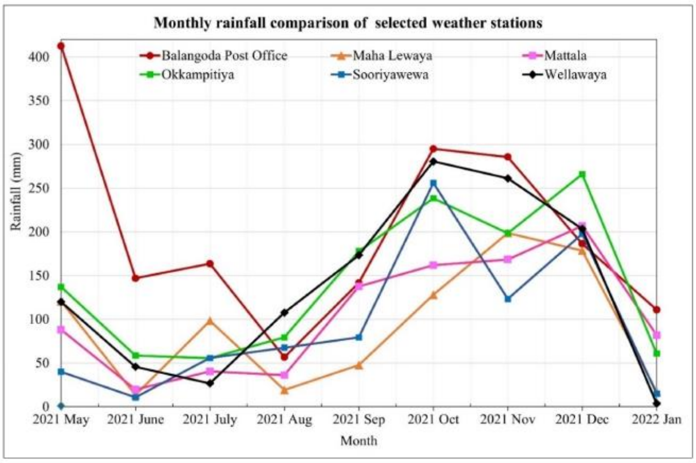

Fig. 10. Monthly variation of rainfall from May 2021 to January 2022.

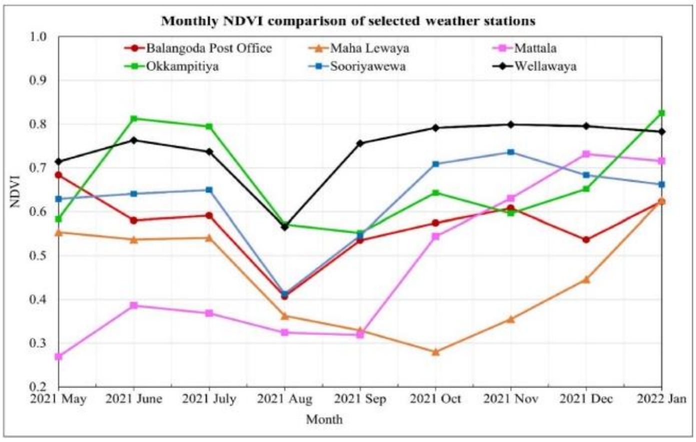

Fig. 11. Monthly variation of NDVI from May 2021 to January 2022.

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-

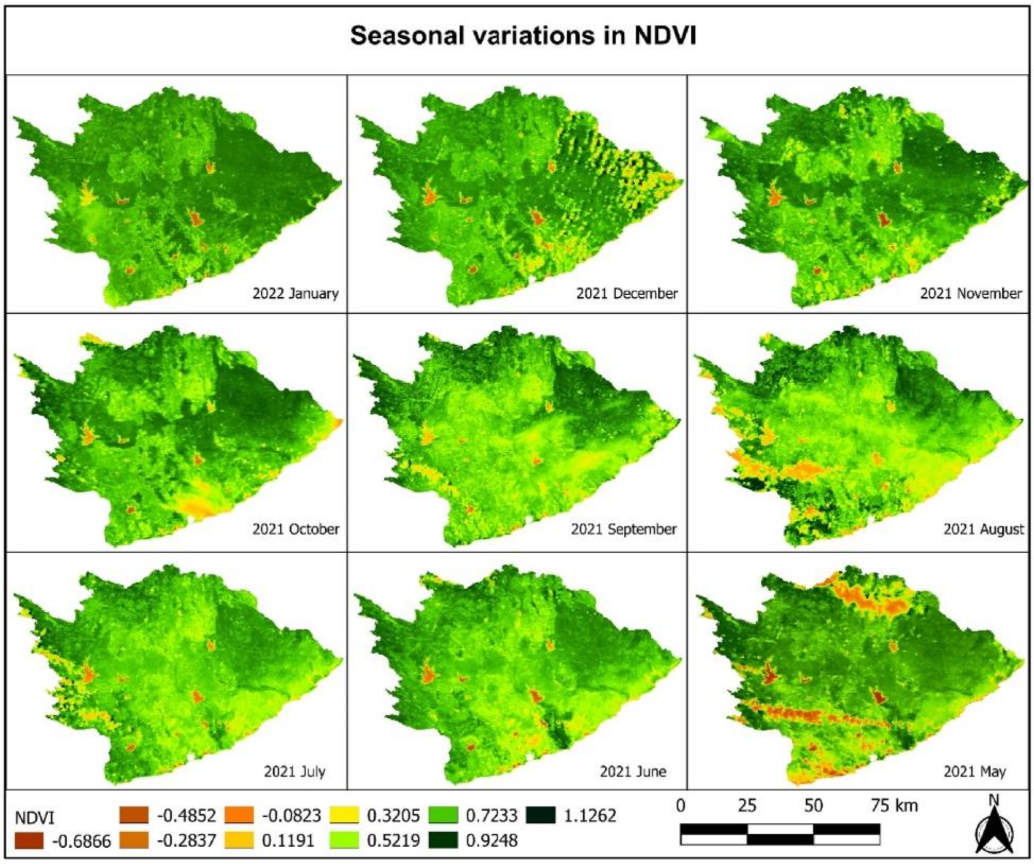

Fig. 12. Monthly seasonal variations in NDVI from May 2021 to January 2022.

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

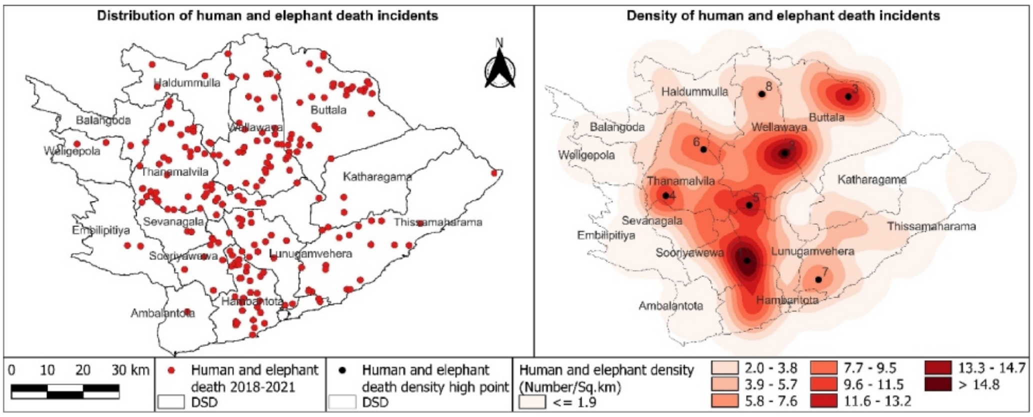

Fig. 13. (a) Distribution of reported human and elephant death incidents from 2018 to 2021; (b) The density of human and elephant death incidents per km^2 within the study area.

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.

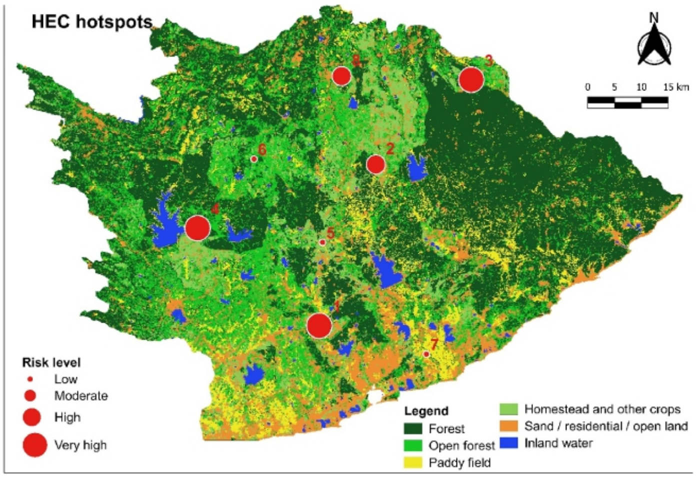

Fig. 14. HEC hotspots and their risk level.

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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CHAPTER 7: DISCUSSION AND CONCLUSION

7.1 Discussion

HEC has emerged as a critical socio-economic and conservation challenge within elephants' range in Sri Lanka and other countries. This is driven by competition between humans and elephants for space and resources. Sri Lanka hosts a considerable population of wild elephants, with a higher elephant density than India, of approximately 0.1 elephants/km^2 compared to 0.01 elephants/km^2.

The expansion of the human populations into previously undisturbed areas and the consequent reduction in elephant habitats have heightened the frequency of encounters between humans and elephants. These encounters often result in crop damage and property destruction. Data collected from 2015 to 2022 revealed the severity of the issue, with 18,409 reported incidents of HEC. Human and elephant deaths have doubled since 2010, while property damage has increased by over 238 percent since 2015 and accompanies a significant portion of the 14,145 deaths caused by HEC. This study's focus on accurately identifying high-risk areas is crucial for safeguarding elephant populations and the well-being of local communities.

The primary objective of this study has been to utilise GIS and satellite data fusion for the precise identification and demarcation of areas in Sri Lanka at high risk of HEC. By analysing conflict patterns, exploring the factors in the environment and landscape contributing to these incidents, and creating models to predict zones of potential future conflicts, the researcher seeks to effectively address the ongoing challenges of HEC as a precursor for their mitigation.

The research area, approximately 5,836 km^2, was marked by dense forests, open forests, paddy fields, and tropical crop cultivations, particularly in two rich, biodiverse, forest-dominated regions in southeastern Sri Lanka. Notably, Udawalawe National Park was identified as hosting an elephant population of 804 to 1160, indicating an exceptionally high density of 1.02-1.16 elephants/km^2. Utilising the advanced technologies of remote sensing and GIS facilitated a detailed analysis of spatial patterns and environmental factors contributing to HEC. These tools proved instrumental in identifying patterns, trends, and zones at high risk for HEC.

The study relied on Sentinel-2 L2A imagery with less than 14 percent cloud coverage and MODIS satellite data with minimal cloud coverage. Six distinct LCLU classification schemes were identified, employing supervised classification methods through RF and SVM algorithms. SNAP 9.0.0 and QGIS 3.28 software with OTB 8.1.0

plugin tools were used in the classification process. The training sites were carefully selected using various sources, including Google Earth, field data, existing knowledge, and public datasets. The RF classification algorithm was optimised, and model accuracy was maximised by setting two main parameters, mtry at 3200 and ntree at 50. The SVM classification was implemented with a linear kernel-type algorithm with settings of 1 for cost parameters. These parameter settings enhanced the accuracy of both models. LCLU classification was undertaken with a balance between training and validation samples, maintaining a ratio of 0.5 percent for effective model validation. The optimisation of the RF model and the SVM classification through specific parameter settings resulted in high model accuracy. These were further validated by confusion matrices using 188 randomly selected points. The RF classifier achieved an accuracy of 97.31 percent, and the SVM classifier reached 94.62 percent, highlighting the reliability and precision of these methods for LCLU mapping.

Additionally, NDVI analysis provided insights into vegetation health and its correlation with rainfall patterns, indicating significant fluctuations in vegetation cover corresponding to rainfall levels. During the dry season from May 2021 to August 2021, the recorded rainfall level was less than 150mm. During 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 NDVI values exceeding 0.6.

The KDE technique identified high-density areas of human and elephant death presence, pinpointing eight specific geographic points of heightened death density for humans and elephants. A spatial weight matrix was used for HEC hotspot identification. 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, proximity to forest areas from these points was measured using an LCLU map. Weights between 0 and 0.5 were assigned based on the proximity of these points to the forest.

Additionally, based on NDVI, the impact of changes in greenery on incident occurrences was considered, and weights were assigned from 0 to 0.2 accordingly. HEC hotspots were assigned into four distinct risk categories: very high, high, moderate, and low. Very high and high-risk hotspots were located near forest boundaries where LULC changes have impacted elephant habitat suitability.

The analysis underscored the significant relationship between LCLU changes and HEC, especially in areas where human activities have altered the natural landscape.

Despite these promising results, limitations exist related to the availability and quality of satellite data, the representativeness of training data, and the challenges of applying the methodology in different regions. To ensure the effectiveness and feasibility of this study's methods across diverse settings, future applications in areas experiencing similar human-wildlife conflicts should consider key factors: scalability, similar characteristics, and adaptability.

The proposed method in this study has several limitations when applied in real-world applications. The availability and quality of input data heavily influence the accuracy of satellite data classification. In turn, the accuracy of the classification model depends on the representativeness and quality of the training data. Thus, classification accuracy can be compromised if training data do not adequately capture the variability and characteristics of target LCLU classes. Although satisfactory results for LCLU classification can be obtained, it is difficult to get enough clear images on rainy and cloudy days.

This study's methodology will be applied to other regions dealing with similar HEC, considering scalability, similar characteristics, and adaptability. The ability to scale up or down is essential for its applicability to different areas, ensuring that the methodology remains effective and feasible.

7.2 Conclusion

The study presented in this thesis emphasises the importance of addressing the escalating HEC in countries such as Sri Lanka, where the coexistence of humans and elephants is severely impacted by rapid population growth, agricultural expansion, infrastructure development, and the consequences of climate change. Particularly in rural and semi-urban areas where human settlements and elephant habitats overlap, the challenges intensify, harming both human and elephant communities.

Sri Lanka has a high population density of elephants and humans combined at 0.088 per km^2. This has given rise to significant conservation, socio-economic, and political challenges. The multifaceted impacts of HEC, including human and elephant deaths, crop raiding, and property damage, underscore the urgency of addressing this complex problem. Over the past 15 years, Sri Lanka has experienced the second-highest annual number of human deaths and the highest per capita death rate from HEC globally, showcasing the alarming severity of the issue.

HEC data from the DWC of Sri Lanka indicates 18,409 HEC incidents from 2015 to 2022, with 3,771 elephants and 1,208 humans losing their lives between 2010 and 2022. The Sri Lankan elephant (*Elephas maximus maximus*) is included on the IUCN Red List of Threatened Species.

Traditionally, various methods have been used to mitigate HEC: physical barriers, acoustic, light-based and agricultural deterrents, elephant watch towers, and beehive fences. The Sri Lankan government has responded by establishing electric fences, problem elephant translocation, and elephant corridors. Despite these efforts, the need for innovation remains. The main strength of this study is its proposed and validated HEC high-risk zone identification method, which integrates GIS and satellite data fusion techniques.

Remote sensing and GIS analysis have been successfully combined to monitor changes in greenery correlated with HEC incidents. Using Sentinel-2 satellite data and the machine learning classifiers of RF and SVM, high overall accuracy was achieved of 97.31 percent and 94.62 percent, respectively, with Kappa coefficients peaking at 0.95 and 0.90, respectively. This underscores the effectiveness of RF and SVM for LCLU classification.

This study used monthly MODIS data extractions to monitor and closely track variations in forest greenness using NDVI values derived from MODIS data. This process identified areas suitable for elephants to forage in frequently. For HEC hotspot detection, the KDE technique was used based on high incident density. This process involved assigning weight to conflict incidents within a 5 km radius, considering their proximity to the forest, and evaluating greenery changes using NDVI values. This method revealed four levels of HEC risk ranging from very high to low. Notably, three very high-risk and two high-risk HEC hotspots were situated close to forest boundaries.

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 potential exists to implement the same methodologies in other HEC zones in Sri Lanka and other countries with HEC. This would readily assist in effective resource allocation, community awareness development, data-driven decision-making, and research. As presented in this study, integrating remote sensing and GIS in HEC mitigation significantly contributes to ongoing efforts to foster a harmonious coexistence between humans and elephants in Sri Lanka and other regions facing similar challenges.

7.3 Limitations of the current study and recommendations for future research

7.3.1 Limitations

7.3.1.1 Cloud coverage

This study has faced a substantial constraint due to cloud coverage, which affects the accuracy and resolution of satellite data. Data acquisition became particularly challenging on rainy and cloudy days, and minimal cloud coverage is essential for obtaining precise, high-quality satellite images and accurately identifying LCLU features. Sri Lanka, a tropical region, is susceptible to cloud interference. It is thus important to consider the temporal restrictions imposed by cloud coverage. To address this challenge, researchers must explore alternative data sources or periods with minimal cloud interference.

7.3.1.2 Electric fences

A significant limitation of the study arises from the reliance on electric fences as a mitigation strategy for HEC in Sri Lanka. These barriers may disrupt natural wildlife movement patterns, affecting elephant migration and access to essential resources. Consequently, the locations of electric fences must be carefully evaluated during the data fusion process to enable precise identification of high-risk zones to prevent potential misinterpretations.

7.3.1.3 LCLU classification challenges

The researcher encountered a significant challenge in accurately classifying different land types. Alterations to the landscape during and after harvest create difficulty in accurately distinguishing these areas. For accurate classification, it is necessary to correctly identify without misclassification, such as water-filled paddy fields as water sources, the ripening stage of crops as forest, and the harvested stage as open land. However, this introduces complexity as seasonal changes in harvesting can affect precision. Overcoming these challenges is vital to maintaining the study's accuracy and ensuring reliable findings to address HEC in Sri Lanka.

7.3.2 Recommendations for future research

7.3.2.1 Generalisation

The study specifically focused on Sri Lanka, which may raise a concern about the developed methodology's direct applicability to other regions with differing environmental and socio-economic characteristics. Sri Lanka's unique context may not fully represent the complexities present in other areas. Future research efforts could explore the adaptability of the developed approach in diverse contexts, considering the need for customised strategies to address the complexities of HEC in different geographical and socio-economic settings.

7.3.2.2 Improved data collection system

Improving data collection is crucial for future research on HEC in Sri Lanka. Achieving this involves the integration of on-the-ground reports in real-time, facilitated by the development of user-friendly mobile apps. Establishing a system for real-time reporting, possibly through community engagement with mobile apps, would help people respond to conflict events quickly. It is also essential to regularly verify the accuracy of reported incidents through community engagement and cross-referencing with diverse data sources. Embracing these data-gathering methods through continuous monitoring and adaptation strategies based on real-time data can significantly enhance our understanding and management of HEC in Sri Lanka.

7.3.2.3 Strengthen hotspot identification

Additional criteria, such as proximity to human settlements, water holes, and crops, should be incorporated to improve accuracy and enhance HEC hotspot identification. Proximity to human settlements is due to elephants often entering these areas, leading to conflicts. Water holes are vital because elephants require regular access to water, making areas near these sources prone to elephant activity. Crops are a major attractant for elephants, resulting in frequent crop-raiding incidents. Each of these factors can be weighted based on their influence on HEC. Based on the total weight of the calculated HEC risk levels, early warning systems can be developed to alert communities about potential elephant activity and mitigate the HEC conflict.

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