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ORIGINAL ARTICLE

An Assessment of Spatio-temporal Land Use/Land Cover Dynamics Using Landsat Time Series Data (2008-2022) in Kuliyapitiya West Divisional Secretariat Division in Kurunagala District, Sri Lanka

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ABSTRACT

The main aim of the study is to detect the changes of land use land cover (LULC) in Kuliyapitiya West Divisional Secretariat division during 2008-2022. Following the download of Landsat images in the study area, several procedures were taken to pre-process the images. This included performing radiometric and geometric corrections to eliminate undesired sensor data and atmospheric noise. The Maximum Likelihood Classification (MLC) was used as the main technique of image post-processing to derive land use maps for the target years. To evaluate the accuracy of outputs 525 ground control points were verified using the Google Earth Pro engine. The classification accuracy of the study was 86% for 2008, 79 % in 2015, and 80 % in 2022. The results showed that over the past 15 years, settlements and built-up areas increased from 20.84% to 28.14% and 0.33% to 2.71%, respectively, whereas coconut lands decreased from 58.3% to 48.6%. The settlement, which showed an increase of land area of 11.9 km^2 throughout the period, was identified as the main land use gainer while coconut was the main land use that lost 15.9 km^2 of its land area over the past fifteen years. The built-up area showed a 3.96 km^2 overall gain during the period due to urbanization and the expansion of the industrial, educational, and service sectors in the study area. The other four land use classes have not undergone any significant changes throughout the relevant time. The study highlights the importance of combining accuracy evaluation and image classification algorithms to gain a more comprehensive understanding of the LULC changes. Hence, our findings could assist decision-makers in land use planning to efficiently guide the sustainable land management.

1 Introduction

Understanding the dynamics of land use and land cover (LULC) is crucial to sustainable resource utilization across various ecosystems. Human activities on land surfaces have resulted in land degradation and it has intensified over the last decade (Rimal et al., 2018; Tiwari and Mishra, 2019). Assessing the reasons and trends of land use dynamics can be effectively done using spatio-temporal LULC change models (Glinskis and Gutiérrez-Vélez, 2019). Land use can be thought of as a conversion or a moving from one type to another because of human activity and environmental factors (Keerthirathna et al., 2019). There may also be a shift in the type of land uses, such as from pasture to farmland, cropland to build-up, or farmland the forest (FAO, 2016). A crucial aspect of the current plan to protect environmental resources, and identify instabilities of nature is the study of LULC dynamics (Rathnayake et al., 2020) . The world's LULC has substantially changed as a result of human development, having negative impacts on both the environment and socioeconomic structure. Thus, in the modern world, accurate identification and change detection are crucial. In order to manage and monitor natural resources, monitoring LULC changes have emerged as an exciting topic of research (Kayet and Pathak, 2015). Utilizing remote sensing technology and multi-temporal data, the most efficient approach to comprehending landscape dynamics at any geographical scale is the

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assessment of LULC (Mishra et al., 2020). Remote sensing techniques and high-resolution spatial data sets are now frequently used to quantify the dynamics of LULC. Only a few of the numerous satellite missions implemented by various countries are freely accessible. Among them, Landsat images are the most popular and freely available data sets (Hu et al., 2016). LULC change studies employ Landsat data because the images are constantly available (Hansen and Loveland, 2012). Satellite remote sensing has the capability to offer precise and reliable data on a large geographical scale, which is suitable for recording both man-made and natural phenomena. Therefore, it serves as an optimal resource for mapping LULC (Kennedy et al., 2015). The website of the United States Geological Survey (USGS) provides easy access to earth observation satellites (Wulder et al., 2019). Geometrically and geographically corrected satellite data are available in the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS). More scholars have recently centered on evaluating the possibilities of satellite data for classifying land uses, tracking land occupancy, and measuring and examining land use changes. Olujide et al. (2018) examined LULC changes in Akure, Nigeria, using Landsat data from the years 1991, 2002, and 2016 through supervised image classification. Iqbal and Iqbal (2018) sought to determine how land use changes over time can be used to stop urban areas from encroaching deeper into agricultural areas from the years 2000 and 2008, in the Rawalpindi division, Punjab, Pakistan. For an urban region called Tirupathi, India, Mallupattu et al. (2013) used RS data to examine LULC trends. Kayet and Patak (2015) in their study, attempted to assess land utilization dynamics in the Saranda forest region, Jharkhand, India for the years 1992, 2005, and 2014. Singh et al. (2019) used RS and GIS tools, and panchromatic images to inspect the dynamics in land usage of Medchalmandal of Medchal district of Telangana, India. The study of Wijesinghe et al. (2023) utilizes RS and GIS techniques to analyze LULC and flood hazard mapping of Neluwa (Sri Lanka), during the Integrated Flood Hazard Vulnerability Modeling. Solórzano et al., (2021) used Sentinel-1 and Sentinel-2 satellites, integrating MS and SAR, in an attempt to categorize land use classes in southeast Mexico. Here, MS+SAR data is processed using the random forest method and U-net techniques. Mishara et al., (2020) used the Maximum Likelihood Classification (MLC) algorithm to assess LULC dynamics in the Rani Khola watershed, Sikkim, during 1988–2018 using Landsat5 (TM) and Sentinel 2A data. Close et al., (2021) examine the applicability of Sentinel-2 to detect land conversion in Wallonia (Belgium) using bi-temporal and multi-temporal Sentinel mosaics. The results revealed that land conversion is very rare in the study area. Feng et al. (2021) forecast the LULC dynamics in Xi'an City, China, using the Markov model and Future Land Use Simulation (FLUS) model with characterizing land use by deriving a complex network model. Yang et al. (2022) proposed a local nearest neighbor (LNN) algorithm to reduce the issues related to the Collaborative Representation (CR) model integrating Tikhonov Regularization (CRT) for LULC changes. Recently Unmanned Aerial Vehicles (UAVs) have also been extensively utilized in LULC mapping and assessment of natural resource (Mishra and Rai, 2021; Mishra et al., 2023).

Since 1990, LULC change detection has been carried out in Sri Lanka using Landsat image products with equal temporal intervals despite the size of the island's fast population expansion resulting in considerable changes in land utilization pattern (Keerthirathna et al., 2019; Mathanraj, 2019). Due to the lack of data, there are no micro-level land use change studies conducted in Sri Lanka in the recent past. Due to socio-economic-induced variables including population increase, industrialization, and urbanization, major changes in land usage may be seen starting in 1990. After the advent of globalization, more researches have been carried out in the Sri Lankan context to detect and examine LULC dynamics using satellite data (Mathanraj et al., 2019; Ratnayake and Ranaweera, 2017). Rathnayake et al. (2020) have utilized Landsat multi-temporal data to examine the changes in land usage throughout Sri Lanka employing three techniques. The MLC technique was applied using Landsat data in a recent study of LULC in the Thalawa Divisional Secretariat Division (DSD) from 1997 to 2020 by Wijesinghe and Withanage (2021).

The aim of this study was to use supervised image classification, a commonly employed machine learning method, to map and measure the LULC in the Kuliyapitiya DSD from 2008 to 2022, using Remote Sensing (RS) data. The study evaluated the changes in LULC by emphasizing the impacts of LULC changes on the sustainable livelihood of the local community, food security, ground water resource, and other environmental system of the study area. There is an identified flaw because no prior research has been undertaken in the same setting using RS techniques in the study area. Previous studies undertaken in the Sri Lankan setting often lacked information on change matrix-based analysis. In the context of RS techniques-based land use change identification, the study acts as a novel research insight that was undertaken in the study area. The downloaded Landsat images were subjected to layer stacking and subsequent subsetting. The images underwent radiometric and atmospheric corrections to eliminate unwanted noise. The process involved utilizing clipped false colour composite images to generate LULC maps. This was achieved by employing the supervised image classification method within the ARC map 10.5 software. The accuracy assessment was completed by conducting a final verification using historical imageries from Google Earth Pro. This method can also be applied to other research endeavours by integrating additional machine learning techniques, such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), to evaluate, visualize, and measure the changes in LULC. Therefore, this study provides decision-makers with valuable information to improve land use planning decisions based on the new insights derived from our findings. Furthermore, the continuous fragmentation of coconut lands gives rise to numerous problems concerning microclimate, groundwater levels, and the livelihood of the local community. Therefore, this work contributes to the sustainable reduction of those concerns. With population growth, coconut and paddy lands were converted into settlements and other land use types in the Kurunegala district during the last two decades. Real estate is one of the major threats to existing coconut lands in Kuliyapitiya West DSD. Maintaining a sufficient amount of coconut, and paddy lands in Kuliyapitiya West DSD is key to sustaining the local livelihood, food safety as well as ecosystem services since the majority of households normally fulfill their paddy rice and coconut requirements from their own paddy lands and small-scale coconut lands. Land use in the Kuliyapitiya West DSD has changed significantly in recent decades. Due to the increase in population and search for suitable habitats, traditional coconut growing areas have been encroached upon by human settlements. Traditional coconut growing areas are declining enormously, thus, appropriate land use planning and policies in the area is the need of the hour. Due to advancements in technology and the availability of freely available spatio-temporal datasets from USGS and other websites, identification and evaluation of land utilization dynamics have become possible.

2 Materials and Methods

2.1 Study Area

Kuliyapitiya West DSD is situated in the Kurunegala district of the northwestern province of Sri Lanka and spans for 164.4 km² (Fig. 1). The area is located within 7.40°-7.55° N and, 79.98°-80.13° E. Paduwasnuwara, Bingiriya and Katupotha DSDs are located in the north, Kuliyapitiya DSD in the east, Udubaddawa DSD in the west, and Pannala DSD in the south direction. Kuliyapitiya West DSD includes 154 villages and 68 Grama Niladari Divisions (GND).

The total population of the area is 87, 820 and the density of the population is 535 persons per km² (Resource-Profile, 2020). Agriculture and allied activities are the main occupations of the inhabitants of the study area. The settlement, areas covered with coconut trees, and paddy fields are the typical land uses of the area. The majority of the population is rural and works in the primary sector. Coconut farming is common in most homesteads, along with paddy fields. Given the prevalence of coconuts and paddy fields as LULC types, there is a significant concern regarding the impacts on the livelihoods of the people in the study area due to changes of these LULCs. This concern has increased in the recent past as a result of coconut land fragmentation with high demand from the real estate sector for settlement expansion purpose (Resource-Profile, 2020). Therefore, the Kuliyapitiya DSD was chosen as the study area because no previous scientific inquiries utilizing RS techniques have been conducted to evaluate LULC changes caused by the above mentioned causes. Furthermore, the growth of built-up area within existing coconut lands poses an additional concern, particularly as a result of government-backed initiatives for expanding educational facilities and industrial complexes.

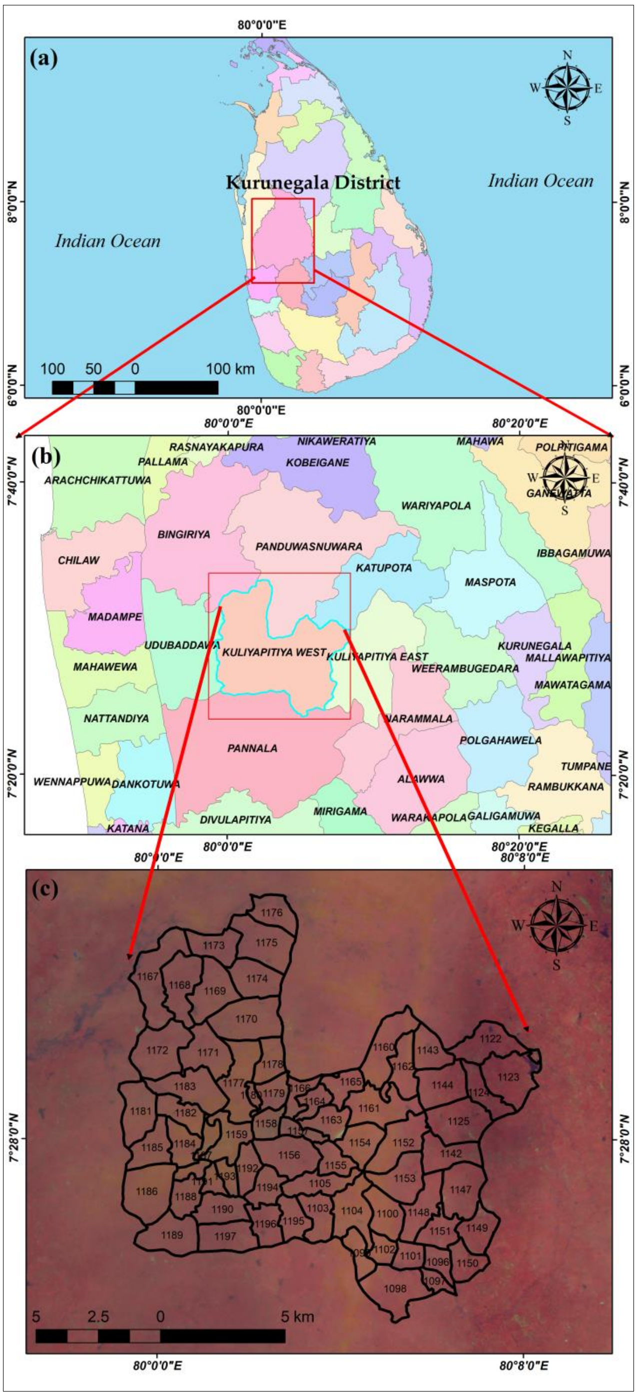

Fig. 1: a. Administrative districts in Sri Lanka, b. Location of Kuliyapitiya DSD, and c. GNDs of Kuliyapitiya West DSD in Landsat8 color infrared (5, 4, 3) composite.

2.2 Data Sources

LULC mapping is one of the principal applications of the Landsat series. Thematic Mapper (TM), Operational Land Imager (OLI), and Enhanced Thematic Mapper Plus (ETM+) are the Landsat satellite images (path 144; row 55) used for the study. All acquired images were level C1 and geometrically adjusted. 15% or less of cloud-free scene data were uploaded from the USGS website (http://earthexploer.usgs.gov) for the research area over three separate periods: 2008, 2015, and 2022 (Table 1). Additionally, the 30-meter spatial resolution OLI sensors from Landsat 8 and 9 are employed in 2015 and 2022, respectively. After acquiring satellite data, Arc Map 10.5 software with the UTM WGS 1984 was used to pre-process and process the data. The Area of Interest (AOI) was derived from the shape file of Survey Department, Sri Lanka, at a scale of 1: 20, 000.

Table 1: Details of the datasets used for the study.

Satellite	Sensor	Date/year of acquisition	Bands used	Spatial resolution	Level of processing
Landsat5	Thematic Mapper (TM)	2008	Visible (B1, B2, B3), NIR (B4) SWIR (B5), TIR (B6), SWIR (B7)	30m	Level 1C
Landsat 8	Thematic Mapper + Enhanced Thematic Mapper (ETM+)	2015	Coastal aerosol (B1) Visible (B2, B3, B4), NIR (B5), SWIR1 (B6) SWIR2 (B7)	30m	Level 1
Landsat 9	Enhanced Thematic Mapper (ETM+) + Operational Land Imager (OLI)	2022	Coastal aerosol (B1) Visible (B2, B3, B4), NIR (B5), SWIR1 (B6) SWIR2 (B7)	30m	Level1

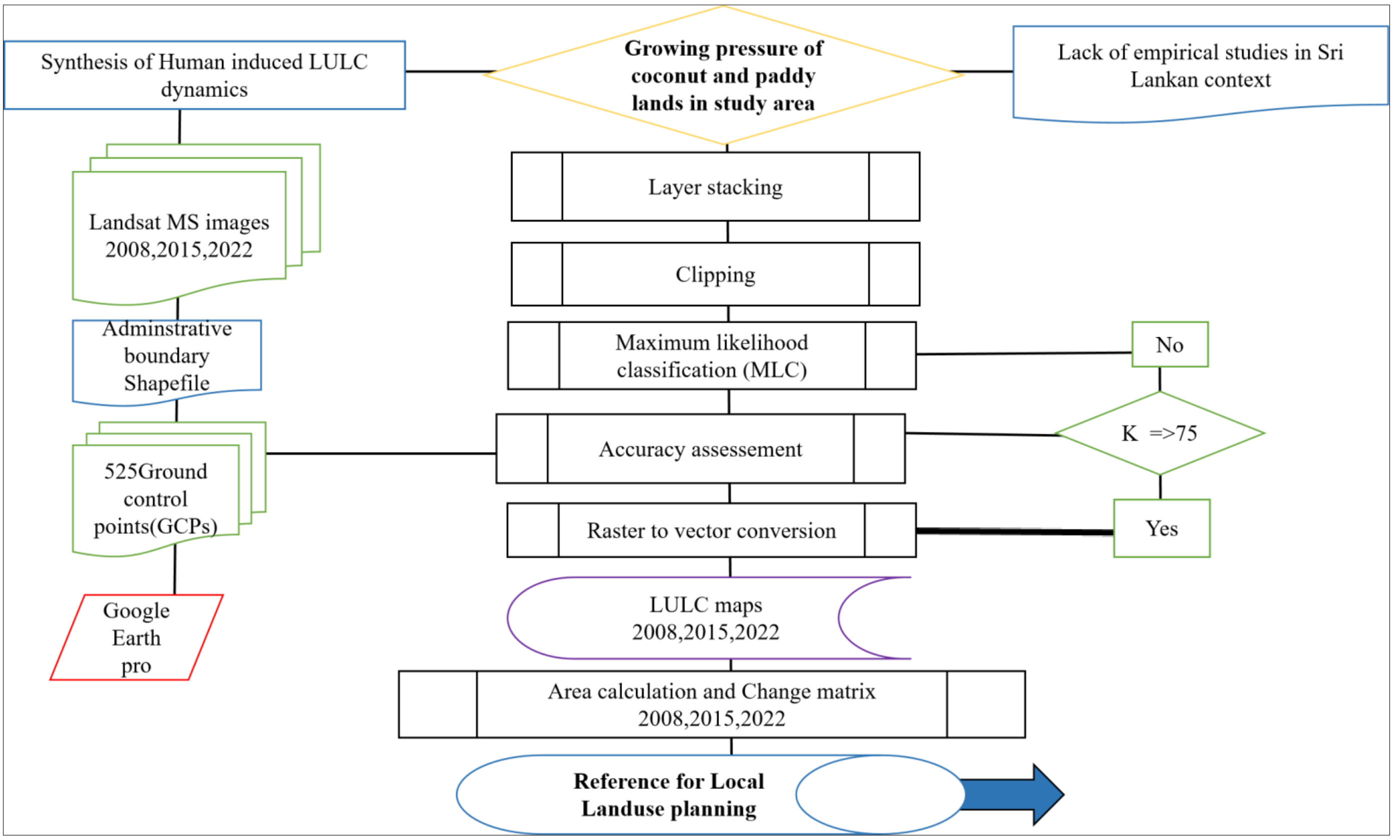

Fig. 2: Methodological flow chart of the study.

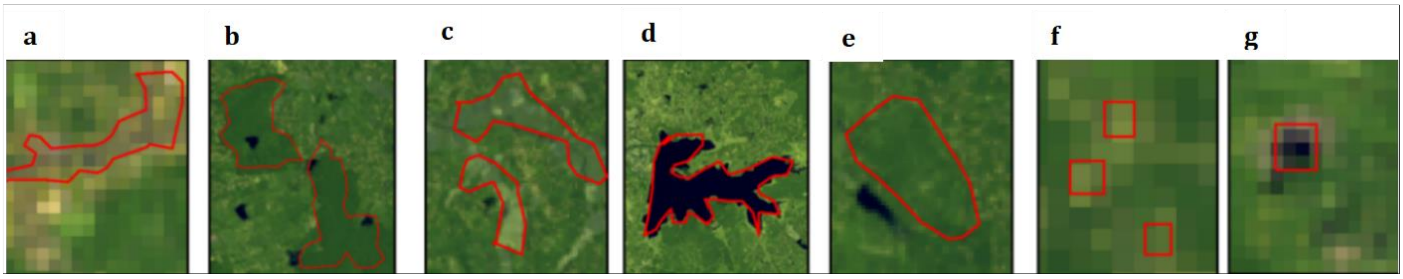

Fig. 3: Signature samples collected from seven land use classes for LULC classification; a. built-up areas, b. forests, c. paddy fields, d. water bodies, e. coconuts, f. settlements, and g. bare lands.

2.3 Methodology

Fig. 2 shows the entire methodological flow chart of the study. The detailed methodology of the study has been discussed below.

2.3.1 Image Pre-processing

After downloading the images, all satellite bands were stacked and each image was sub-set. Then radiometric correction was carried out to remove the unwanted sensor data and atmospheric noise from images. For mapping, a uniform false color composite (FCC) for all years was produced. All images were clipped using the survey department of Sri Lanka's administrative boundary data layer scaled at 1:20, 000 at the very end of the image pre-processing procedure. A semi-automatic classification plugin based on the Dark Object Subtraction (DOS) technique was applied to correct the atmospheric noises. To radiometrically correct the acquired images, DOS was performed coupling with ENVI 5.1 and Arc Map 10.5. The radiometric correction tool in ENVI was utilized by selecting the region of interest (ROI) tool as the parameter for dark object subtraction in the DOS process. The corrected output image files were used for further LULC change analysis. The created maps were validated using Google Earth Pro ground truth verification.

2.3.2 Image Classification

LULC changes were detected through the supervised image classification system that specifies the target land use classes taken into consideration when creating the final maps from Landsat data. A supervised classification algorithm was performed by taking signatures from each LULC class in the study area (Fig. 3).

The ideal number of LULC classes depends on the specifications of a particular research for a particular application (Kaur et al., 2021; Mishra et al., 2020; Saha et al., 2005). Seven LULC classes were selected for mapping the study area as paddy lands, coconuts, settlements, built-up, forests, water bodies, and bare lands.

2.3.3 Image Post-processing

Maximum Likelihood Classification (MLC) algorithm was applied to map all the LULC classes. Due to its ability to utilize labeled data to handle output data, the MLC algorithm in supervised image classification surpasses unsupervised classification approaches in terms of accuracy and consistency, resulting in more precise and reliable outcomes. This takes into account the statistical probability of specific pixel signature classes. Given this context, MLC is the prevailing supervised image classification technique in remote sensing, surpassing other algorithms like Random Forest (RF) and Support Vector Machines (SVM). The availability and simple training process of the MLC have led to its widespread use. It relies upon the likelihood that a pixel is a member of a specific class. MLC is a widely used approach that relies on the Bayesian Equation. This equation is used to calculate the weighted distance or likelihood of an unknown measurement vector. The equation (Mohajane et al., 2018) is as follows:

$$D = \ln(a_c) - [0.5\ln(|Cov_c|)] - [0.5(X - M_c)T(Cov_c - 1)(X - M_c)] \quad (1)$$

Prior to choosing training samples, topographical data from the study area, historical images of the Google Earth Pro engine, and empirical analysis of satellite images were carried out. The minimum number of training samples taken for each class was 25. Choosing ground samples for coconuts and settlements was difficult because of the mixed land use types evident in most areas under those land use classes.

2.3.4 Accuracy Assessment procedure

This is crucial in every LU dynamics identification study to ensure the quality of classified images. In order to measure accuracy, 25 training samples from each class were gathered using the Google Earth Pro ground truth data for selected three years. For each year, 175 ground control points were verified using the historical imagery capabilities of the Google Earth Pro engine. Each point was cross-checked with the ground truth, to ensure whether the sample feature of the classified image was superimposed on the same land use class in the ground. If it was overlaid on the same feature class on the Google Earth Pro image, it was regarded as an accurate classification; if not it was considered as an inaccurate classification. The Kappa coefficient (K) was calculated to assess the agreement between categorized results and actual conditions in order to ascertain the levels of accuracy. Action is initiated for the image if the kappa coefficient is 0.75 or higher. A total of 525 Ground Control Points (25 GCPs each class for one year) were collected randomly to accurately represent the ground truth locations for each class. The below equation was used to calculate the Kappa (Alqurashi and Kumar, 2014).

$$K = \frac{N\sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{k}(x_{i+} \times x_{+i})} \qquad (2)$$

k is the number of rows in the matrix; xii is the number of observations in row i and column i; xi+ and x+i are the marginal totals of row k and column i respectively; and N is the number of observations.

2.3.5 Land Use Change Detection

To correlate the spatial resolution of all subsequent classified results, the LULC map of 2022 was re-sampled at 30 m spatial resolution. At present, several change detection methods have been used by previous researchers (Mishra et al., 2020; Lu et al., 2004). Important data about the geographical distribution of LULC changes are presented by the change matrix (Shalaby and Tateishi, 2007). A change matrix was created from classified images from 2008 to 2015, and 2015 to 2022 to show the changes in land cover in each time period. The change matrix was also created during 2008- 2022 to analyze the overall dynamics in LULC classes between 2008 and 2022.

3 Results

3.1 Status of LULC

Fig. 4 depicts the spatio-temporal LULC changes for seven major classes, including paddy land, coconuts, settlements, built-up, forest, bare land, and water bodies for the years 2008, 2015, and 2022. Table 2 presents the geographical distribution pattern of LULC as performed by supervised image classification. According to the 2008 classification results, the study area was made up of seven different land use classes, including coconut lands (58.34%), paddy fields (15.43%), settlements (20.84%), forests (2.27%), and bare land (2.16%), water bodies (0.60%), and built-up areas (0.33%), respectively. The results of the 2015 classified image show that while built-up areas have increased by 2.24%, paddy lands have grown by up to 18.79% over coconut land, which has fallen by 55.20%. Additionally, settlements grew by up to 21.03%, while bare lands shrank by roughly 0.07%. Other land use classes have not changed significantly during the same time period. However, by 2022, settlements and built-up areas had increased by 28.14% and 2.71% respectively, whereas coconut lands and paddy fields had significantly decreased by 48.64% and 16.69% respectively.

3.2 Accuracy Assessment of Classified Images

Each classified image was subjected to an accuracy assessment, which included calculating the kappa coefficient for the years 2008, 2015, and 2022.

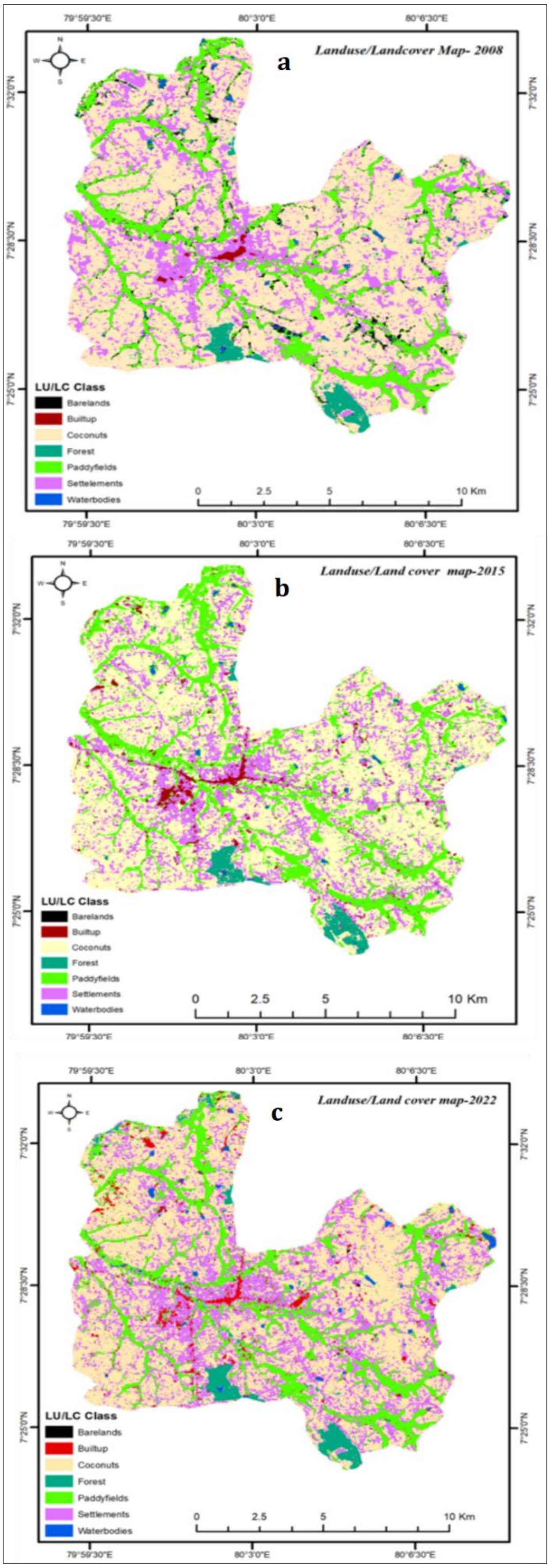

Fig. 4: Land Use Land Cover (LULC) Maps; a. 2008; b. 2015; and c. 2022

Table 2: Results of LULC classification in Kuliyapitiya West DS 2008, 2015, 2022.

Land use class	2008		2015		2022	
	Area (km²)	%	Area (km²)	%	Area (km²)	%
Coconuts	95.83	58.34	90.68	55.20	79.91	48.64
Paddy fields	25.35	15.43	30.87	18.79	27.43	16.69
Settlements	34.24	20.84	34.56	21.03	46.23	28.14
Forest	3.73	2.27	3.61	2.19	4.70	2.86
Bare lands	3.56	2.16	0.22	0.07	0.10	0.06
Water bodies	1.00	0.60	0.64	0.38	1.44	0.87
Built-up	0.55	0.33	3.68	2.24	4.46	2.71
Total	164.26	100	164.26	100	164.26	100

Table 3: Accuracy of Maximum Likelihood classification for 2008, 2015 and 2022.

Land use class	2008		2015		2022	
	Producer's	User's	Producer's	User's	Producer's	User's
Forest	92.5%	100%	92.5%	100%	100%	100%
Paddy	76%	100%	76%	76%	81.4%	88%
Settlements	86.3%	72%	68.9%	80%	61.2%	76%
Coconuts	92%	92%	59.3%	76%	82.6%	76%
Water bodies	100%	100%	96.1%	100%	78%	100%
Built-up	91.6%	88%	85.7%	72%	86.3%	76%
Bare lands	100%	44%	86.6%	52%	100%	48%
Overall accuracy	86.2%		79.6%		80.5%	
Kappa coefficient	0.84		0.76		0.77	

About 25 random points for each land use category in the study area were taken to represent each class in the accuracy evaluation, which is a total of 175 random points. The selected points were then confirmed using the high-resolution Google Earth Pro engine. In general, bare lands had a low user and producer accuracy rate of 44%, 52%, and 48% for each year, making it the most frequently misclassified land use category. With a kappa coefficient of 0.84, the classified 2008 image's overall accuracy was reported as 86.2%, and for the years 2015 and 2022, it was reported that the overall accuracy was 79.6% and 80.5%, respectively. For the years 2015 and 2022, the kappa coefficient was 0.76 and 0.77. Table 3 shows the accuracy of each producer and user across all classes.

3.3 Land Use Changes

LULC has changed tremendously in Sri Lanka over the last few decades. There are only a few remote sensing-based LULC assessment studies available. For example, Colombo Metropolitan Region, which has one of the highest levels of urbanization in the country (Saparamadu et al., 2018) as well as other studies that look at the entire island (Rathnayake et al., 2020; Ratnayake and Ranaweera, 2017). There has not been any prior research done in the study area to evaluate the LULC shift with an emphasis on sustainable utilization of land resources, particularly paddy, and coconut land. Since most of the lowland paddy cultivation areas in the Kuliyapitiya West DSD act as groundwater recharge zones, landfilling and converting these paddy grounds affects negatively to the water resources of the division. The majority of people in the division obtain all of their paddy rice needs through small-scale paddy cultivation. The community's daily paddy requirements have thus been adversely impacted over time by the landfilling of paddy for settlements and the fragmentation of coconut lands for settlements and other purposes. Additionally, most paddy lands are rain-fed and during Yala (one of the paddy cultivation seasons in Sri Lanka from May to August), the study area experiences little rainfall as the DSD is located in the country's intermediate zone, which negatively impacted the harvest of the season. The DSD is lying in Sri Lanka's coconut triangle but recently, coconut land fragmentation has been witnessed by land use change. The fragmentation of small-scale coconut lands and the subsequent increase in the coconut price had a significant negative impact on the livelihood of rural and peri-urban residents. This is because a significant number of households in the DSD continue to rely on their small-scale coconut harvest, which has adversely affected the livelihood of all households, particularly poor households. The recent micro-climate change that raised the surface temperature during the dry season (June–September) had an impact on the rapid development of coconut land fragmentation (Resource-Profile, 2020). A fairly warm climate for urban and peri-urban dwellers in the division will be formed in the future as a result of the worrisome rate of fragmentation of a large number of government-owned coconut lands.

3.3.1 LULC Changes from 2008-2015

Table 4 illustrates the LULC change matrix for the time periods of 2008 to 2015 and LULC changes in the research area throughout the target period. Major changes occurred between 2008 and 2015, including the conversion of 11.6 km² of coconut lands and 4.18 km² of paddy lands into settlement areas as a result of population pressure and the intrusion of new living areas into coconut lands. The conversion of 2.17 km² of settlements into built-up areas as a result of the expansion of new commercial establishments in the Kuliyapitiya town area and urban sprawl along main roads toward Narammala, Pannala, and also Hettipola was also observed. Additionally, during the relevant period, a new industrial establishment called MAS Holding and educational institutions like Wayamba University and University College, the new court complex, and the Shilpa Shalika complex were established in the Megahakotuwa area, where a new built-up area was created. All of those areas were formerly occupied by vast coconut lands. Since the real estate industry's proximity to main roads poses the most threat, up to 4.18 km² of paddy lands of rice fields were turned into settlements between 2008 and 2015. 3.57 km² of paddy fields have also been transformed into coconut lands over the same focus time.

3.3.2 LULC Changes from 2015-2022

Similar changes persisted between 2015 and 2022 (Table 5) in the study area, turning about 11.06 km² of coconut lands and 1.66 km² of paddy fields into settlements, while 1.38 km² of settlement areas were converted into built-up areas following the expansion of the existing built-up area along Meegahakotuwa area. Additionally, a new built-up area appeared in Labuyaya as a result of the establishment of a new industrial firm and the medical faculty of the University of Wayamba. This was also a result of new settlers encroaching on coconut lands due to population pressure. 1.1 km² of coconut lands were also developed into a built-up area. In the Kuliyapitiya West DSD, settlements were created on approximately 22.9 km² of coconut lands and 3.42 km² of paddy fields between 2008 and 2022 (Table 6). As opposed to this, 1.72 km² of villages and 1.25 km² of coconut lands were developed. 0.84 km² of paddy fields were also converted into built-up areas during this time. Some coconut lands were converted to forests in some areas. This is because real estate developers purchased extensive coconut lands and then sold those lands as new settlement areas before the new gazette notification that prohibited the fragmentation of coconut lands. As a consequence, the expansion of new settlements has happened quickly in some areas.

3.3.3 Overall Change of LULC

The overview of LULC changes in the Kuliyapitiya West DSD from 2008 to 2022 is shown in Table 7. The settlement, which showed an increase in land use of +11.99 km² throughout the study time, is the study area's main land use gainer, as shown in Fig. 5. The coconut was the main land use that lost its ground over the past fifteen years, losing 15.92km². The built-up area showed a +3.96 km² overall land use gain during the time period due to urbanization and the extension of the industrial, educational, and commercial service sectors in the study area. Paddy fields and forest cover both grew by 0.97 km² and 2.08 km², respectively, while bare areas lost 3.6 km² over the target period.

Table 4: Land use change matrix 2008-2015.

		Land use 2015 (km²)							
	Class	**Bare lands**	**Built-up**	**Coconuts**	**Forest**	**Paddy fields**	**Settlements**	**Water bodies**	**Grand Total 2008**
Land use 2008 (km²)	**Bare lands**	0.00	0.06	0.64	0.00	2.50	0.29	0.05	3.56
	Built-up	0.00	0.41	0.00		0.00	0.13		0.55
	Coconuts	0.13	0.63	74.17	0.49	3.57	16.78	0.02	95.83
	Forest	0.01	0.01	0.49	3.09	0.00	0.11	0.00	3.73
	Paddy fields	0.01	0.33	3.70	0.00	20.08	1.07	0.14	25.35
	Settlements	0.05	2.17	11.6	0.02	4.18	16.14	0.03	34.24
	Water bodies	0.00	0.03	0.03	0.00	0.51	0.01	0.39	1.00
	Grand Total 2015	0.22	3.68	90.68	3.61	30.87	34.56	0.64	164.30

Table 5: Land use change matrix 2015-2022.

		Land use 2022 (km²)							
	Class	**Bare lands**	**Built-up**	**Coconuts**	**Forest**	**Paddy fields**	**Settlements**	**Water bodies**	**Grand Total 2015**
Land use 2015 (km²)	**Bare lands**		0.00	0.09	0.01	0.01	0.09	0.00	0.22
	Built-up	0.01	1.34	0.36	0.03	0.46	1.38	0.08	3.68
	Coconuts	0.04	1.10	64.80	0.95	5.34	18.34	0.07	90.68
	Forest	0.00	0.00	0.33	3.15	0.00	0.11	0.00	3.61
	Paddy fields	0.00	1.10	3.23	0.37	19.90	5.48	0.76	30.87
	Settlements	0.03	0.83	11.06	0.16	1.66	20.78	0.02	34.57
	Water bodies		0.05	0.01	0.00	0.04	0.02	0.49	0.64
	Grand Total 2022	0.10	4.46	79.91	4.70	27.43	46.23	1.44	164.30

Table 6: Land use change matrix 2008-2022.

		Land use2022 (km²)							
	Class	**Bare lands**	**Built-up**	**Coconuts**	**Forest**	**Paddy fields**	**Settlements**	**Water bodies**	**Grand Total 2008**
Land use 2008 (km²)	**Bare lands**	0.00	0.14	0.45	0.04	2.05	0.74	0.10	3.56
	Built-up	0.00	0.39	0.00		0.01	0.14		0.55
	Coconuts	0.05	1.25	67.54	0.98	2.97	22.91	0.08	95.82
	Forest		0.00	0.32	3.28	0.00	0.11	0.00	3.73
	Paddy fields	0.00	0.84	1.66	0.31	18.58	3.42	0.53	25.36
	Settlements	0.03	1.72	9.85	0.07	3.51	18.81	0.23	34.25
	Water bodies		0.08	0.06	0.00	0.29	0.06	0.47	1.00
	Grand Total 2022	0.10	4.45	79.92	4.70	27.44	46.23	1.44	164.30

Table 7: Gain/Loss of LULC classes during 2008-2022 (km²).

Land use class	**2008-2015**	**2015-2022**	**2008-2022**
Bare lands	-3.34	-0.12	-3.46
Built-up	+3.13	+0.78	+3.91
Coconuts	-5.15	-10.77	-15.92
Forest	-0.12	+1.09	+0.97
Paddy fields	+5.52	-3.44	+2.08
Settlements	+0.32	+11.67	+11.99
Water bodies	-0.36	+0.80	+0.44

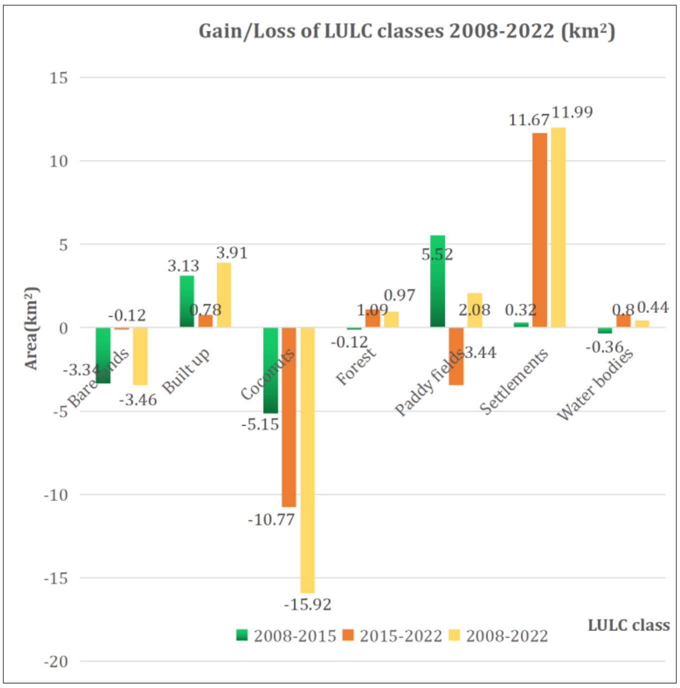

Fig. 5: Gain/Loss of LULC classes in Kuliyapitiya West DS 2008-2022.

4 Discussion

Using multi-temporal remote sensing data from 2008 to 2022, the study sought to identify and assess LULC change patterns in Kuliyapitiya West DSD. The findings showed that over the target period, the settlement area increased by 7.3% while 9.7% of the coconut land was lost as a result of population pressure. According to the study of Saparamadu et al. (2018), considerable land cover changes have also occurred, with over 30% of new construction occurring between 1990 and 2015 and major alterations to wetlands and agricultural lands in the Colombo district. LULC change detection was made, showing a decline in agricultural areas in Talawa DSD from 57% to 43% during 1997-2020 due to settlement and built-up area expansion (Wijesinghe and Withanage, 2021). Mishara et al. (2020) also found that agriculture and forest land have greater pressure from built-up area expansion in Sikkim. The kappa coefficient of our study (0.76-0.84) is essentially compatible with the study of Mishra et al.(2020) which showed an overall accuracy of 85% and 0.81 kappa though they utilized Sentinel 2A data aside from Landsat.

The accuracy level of the open-source satellite data was the main limitation of the study since two land use classes buildup, and settlement areas were mixed in the DSD, especially in the Kuliyapitiya urban area. In this context, it may be essential that ground-based field verification is supplementary to remote sensing data. It will be more helpful to increase the accuracy levels further giving a more realistic view of LULC changes in DSD. Landsat data, at a 30 m spatial resolution does not provide precise details about small features such as settlements, especially in urban areas. Feature extraction was a little bit confusing in those cases. And finally, the accuracy of the results of the LULC assessment was negatively affected by the limited accuracy of assessment samples using the Google Earth Pro engine.

5 Conclusion

Using multi-temporal remote sensing data from 2008 to 2022, the study sought to identify and assess LULC change patterns in Kuliyapitiya West DSD. The findings showed that over the target period, the settlement area increased by 7.3% while 9.7% of the coconut land was lost as a result of population pressure. Since commercial and other service sectors have expanded in response to demand from local urban and rural dwellers built-up area also increased by 2.38%, creating a new built-up area around Meegahakotuwa. From 2008 to 2015, paddy land growth was 3.36%, but by 2022, it had dropped to 2.1%. Water bodies remain untouched at this time. Over the previous fifteen years, forest cover has expanded by 0.59% thanks to urban forests and other conservation measures. Settlement growth took place in rural areas and the town's outskirts as the primary LULC change. A radial pattern of growth with a focus on the town center and Meegahakotuwa area characterizes the built-up area, which is primarily developed along the main roads. The study would be extremely beneficial for the land use planners as they would be able to allocate limited land resources for future urban and settlement growth in the division while maintaining the status quo in the conservation areas and remaining forests. One of the proposed ways to halt the loss of farmland is to find ways to increase the value of the profits generated for the local small landowners who farm on the land. In the context of Sri Lanka's national development strategy, one of the key sectors is tourism and related services. The development of agro-tourism or community-based nature tourism in the study area of Kuliyapitiya West DSD can be shown as an example. . These appear to be a very promising way of developing the study area in terms of environmental, social as well as economic sustainability. Reading traditional topographical maps in the area is less effective than using a GIS and RS integrated strategy to investigate LULC change in both spatiotemporal dimensions. The statistical results will also serve as an additional resource for the division as it makes judgments on how to allocate future land resources.In future study on LULC change detection and mapping, it is recommended to adopt MLC in comparison to other supervised machine learning approaches such as random forest and support vector machine. This would lead to more precise and dependable findings. The study's findings can serve as a framework for future land use and urban planning initiatives in the study area. Planning authorities get benefits from these maps and other generated information as supplemental resources to formulate their planning regulations and standards.

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Author Contributions

Conceptualization, methodology, analysis, writing - original draft preparation, W.K.N.C., P.K., B.C., and writing -review and editing, W.K.N.C., P.K. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

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