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Spatiotemporal Analysis of Land Use and Vegetation Changes in Kasaragod District Using Remote Sensing and GIS: Implications for Sustainable Development

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Abstract

The study presents an in-depth evaluation of spatial and temporal Land Use Land Cover (LULC) modifications and their impacts on environmental and socio-economic dynamics at local scales. Utilizing Remote Sensing (RS) and Geographic Information Systems (GIS) techniques to find out the fluctuations in LULC and vegetational cover from 2000 to 2023 in Kasaragod district of Kerala. Using a supervised classification method on satellite imagery, significant changes were detected in the distribution of various LULC classes. The analysis also included effective strategies for determining vegetation cover using the Normalized Difference Vegetation Index (NDVI) technique, which highlights alterations in LULC and the extent of vegetation cover. LULC classification result indicates that dense vegetation (-63.48%), water body (-41.09%) and barren land (-100.83%) drastically declined while built-up area (82.06%) and mixed crop with settlement (15.66%) significantly increased. NDVI analysis reveals a decrease in dense vegetation (-86.01%) and sparse vegetation (-5.32%), highlighting the importance to protect natural vegetation cover. The trends identified in this research will be valuable for planners and decision-makers in the developmental analysis and future LULC management.

Keywords: Land Use Land Cover, Remote sensing, Geographic Information Systems, Normalized Difference Vegetation Index, Human Wildlife Conflict

1 Introduction

The land is a complex and dynamic mixture of features that includes geology, topography, hydrology, soils, microclimates, and communities of plants and animals that are always interacting, because of weather change and human activity [1]. There is pressure on LULC due to the growing population and increasing socio-economic necessities, unplanned and uncontrollable alterations in

LULC are the outcome of this pressure [15]. Information on LULC, as well as alternatives for optimal utilization, is crucial for selecting, planning, and implementing land use strategies to meet basic human needs and welfare. Additionally, this data is valuable for monitoring how evolving population requirements are impacting land utilization [5]. The LULC classification of an area is an output of natural and environmental factors and their utilization by human throughout time. Deforestation, biodiversity loss, global warming, and a rise in natural disastrous floods are the results of changes in LULC and human/natural processes.

Vegetation mapping aims to identify, describe, and evaluate the relative abundance of the many forms of vegetation that cover the surface of the earth. With the advancement in remote sensing technology, it is now possible to identify and define different phenomena and objects on the Earth's surface without physically visiting the location [4].

The main contribution of this paper is to quantitative mapping and change analysis of the LULC and vegetation cover in the Kasaragod district from 2000 to 2023. Kasaragod has undergone significant LULC transformations driven by socio-economic pressures and developmental activities. These changes contribute to deforestation, biodiversity loss, and escalating Human-Wildlife Conflicts (HWC), highlighting the necessity for spatially informed land-use policies. Remote Sensing (RS) and Geographic Information Systems (GIS) offer robust methodologies for monitoring and analyzing LULC changes. This study fills this gap by employing supervised classification methods and NDVI analysis to quantify LULC changes and assess their environmental impacts.

2 Materials and Methods

2.1 Study Area

Kasaragod, the northernmost district of Kerala, spanning an area of 1992 square kilometers. Kasaragod is geographically framed between North Latitude 12° 02' 25" and 12° 47' 35", and East Longitude 74° 25' 54" and 75° 25' 25". This area falls within the Survey of India toposheet numbers 48L and 48P. The district is enclosed by the Western Ghats to the east, and the Arabian Sea to the west, the northern boundary is shared with the Canara district of Karnataka, and to the south lies the Kannur District [Fig. 1].

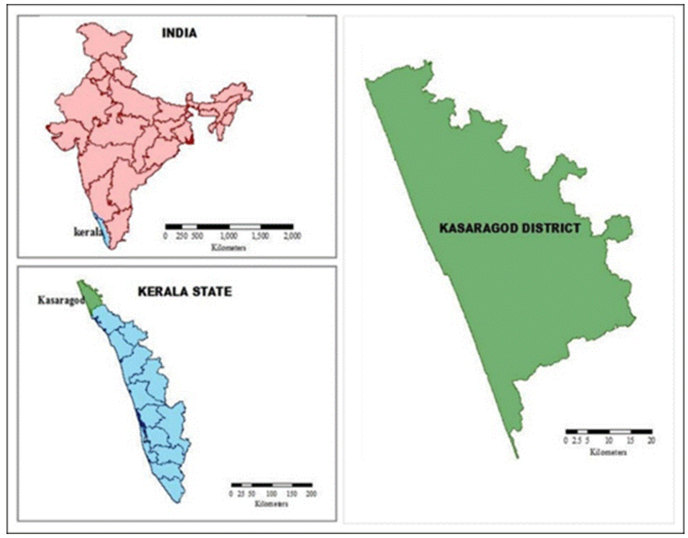


Fig. 1: Study Area Map of Kasaragod

Based on geological properties, the district is naturally separated into the eastern highlands, midlands, and coastal lowlands. The coastal region of the district is covered by coconut and arecanut gardens, while the midland has extensive paddy fields and long stretches of arecanut gardens.

2.2 Data Acquisition and Processing

Indian Remote Sensing (IRS) images acquired between 2000 and 2023 were utilized for the study. Multispectral satellite imageries of LISS III sensor from the Indian Remote Sensing Satellites IRS-1D, RESOURCESAT-1 (IRS-P6), RESOURCESAT-2 (IRS-R2) for years 2000, 2005, 2013 and 2023 were used. IRS data were obtained from the National Remote Sensing Center (NRSC). The 2000–2023 dataset includes four spectral bands and two scenes (Path-Row: 097-064 and 098-065) covering a 141km wide swath with a spatial resolution of 23m.

2.3 Methodology

The study used supervised classification with maximum likelihood and parallelepiped techniques for each dataset. Satellite images were classified, LULC maps generated, and results compared using a pixel-by-pixel change detection matrix. The methodology involved image enhancement, interpretation, classification, NDVI analysis, and LULC and vegetation change detection [Fig. 2]. ArcMap 10 and ERDAS IMAGINE 9.1 software's were used. A detailed LULC map was created from high-resolution satellite images [Table. 1]. The satellite images, each with different spectral bands in .tif format were stacked using the Layer Stack function in ERDAS Imagine, followed by image mosaicking. All topographic sheets were then mosaicked and used as a reference map for georeferencing satellite images [Fig. 3]. Geometric distortions were corrected with the Image Geometric Correction tool, using a polynomial geometric model and UTM WGS 84 north zone 43 projection.

Table 1: Data source specifications for assessing LULC changes in the study area

Sl. No.	Data type	Scale	Purpose
1	IRS – 1D LISS-III of 2000	23.5m	LU/LC map
2	IRS – P6 LISS-III of 2005	23.5m	LU/LC map
3	IRS -R2 LISS-III of 2013	23.5m	LU/LC map
4	IRS -R2 LISS-III of 2023	23.5m	LU/LC map
5	Topographic Sheet (48P/1, 48P/2, 48P/3 & L/15, 48L/14, 48P/4, 48P/6, 48P/7, 48P/8, 48P/11 and 48P/12)	1:50000	Base map
6	Kasaragod District Boundary Shapefile	-	clipping

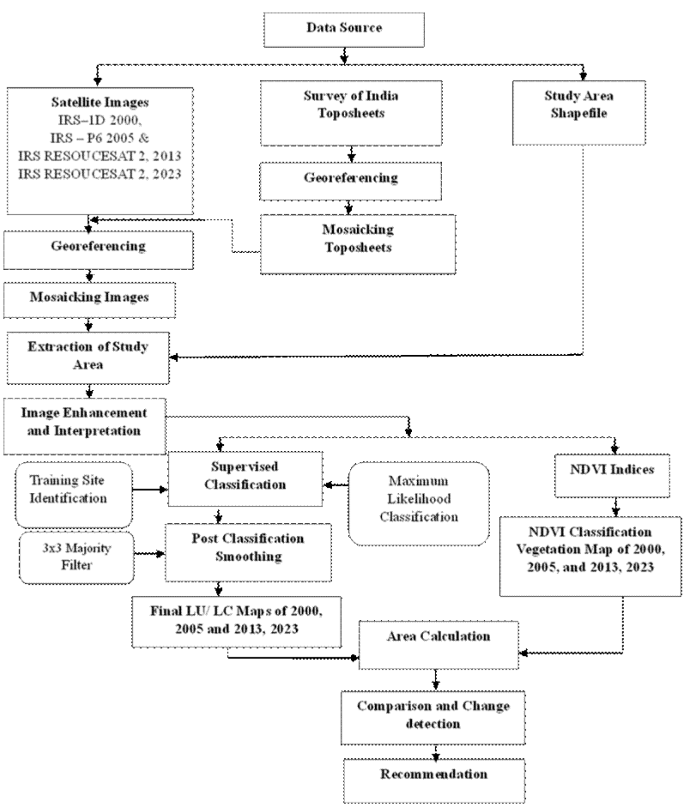


Fig. 2: Flowchart representing the methodology

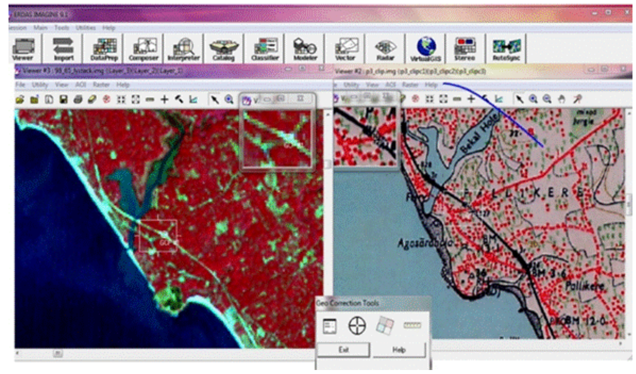


Fig. 3: Georeferencing of satellite images of the study area in ERDAS Imagine Software

2.4 Image Enhancement

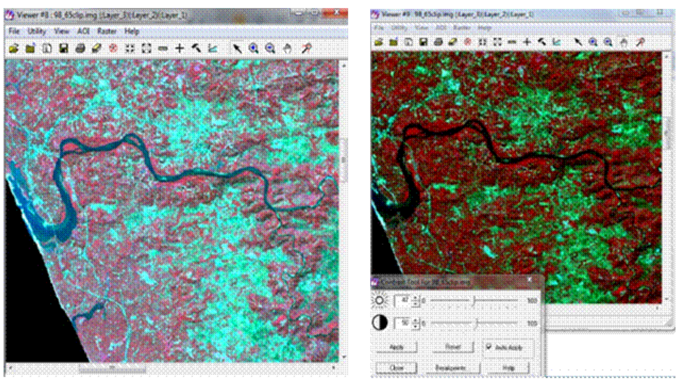
Image enhancement techniques play a critical role in improving the quality of imagery and expanding the scope for accurate image interpretation. In this study, techniques such as brightness/contrast adjustment, edge enhancement, and histogram equalization were employed. The brightness and contrast adjustment functions were applied to enhance the interpretability and perception of the imagery, making the visual data more comprehensible [Fig. 4]. A histogram, which visually represents the brightness levels of an image, provides a deeper understanding of its tonal distribution [Fig. 5]. Through histogram equalization, the intensity values are spread across the full range (0 to 255), where the darkest pixel is assigned a value of 0 (black) and the brightest pixel is assigned 255 [14]. Edge enhancement, another crucial technique used in this study, amplifies intensity differences across features or expands the width of linear features [14]. This adjustment made critical features more distinct and easier to interpret in the imagery [Fig. 6].

2.5 Image Interpretation and Development of an Image Classification Scheme

Image interpretation is a vital tool for performing various LULC classifications, enabling the identification of features such as vegetation, water bodies, built-up areas, and more. In this study, the Indian Scheme of LULC Classification was applied [13] categorizing the study area into six distinct groups [Table. 2].

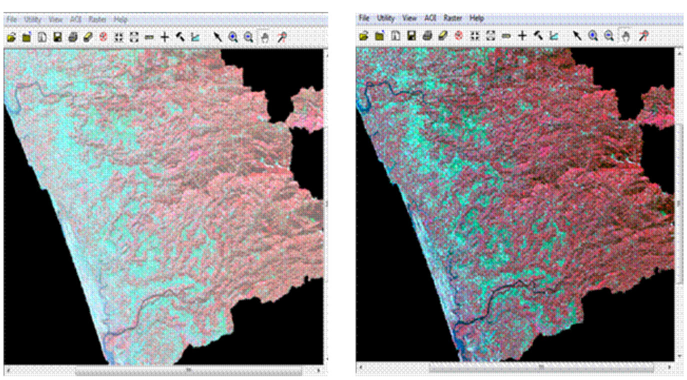
2.6 Image Classification

Image analysis involves identifying groups of pixels with specific spectral properties and determining the features or land cover classes these groups represent [12]. Image classification methods are broadly divided into two categories: supervised classification and unsupervised classification. This study adopted the supervised classification approach, utilizing the parallelepiped algorithm and the Maximum Likelihood Classifier (MLC) to ensure precise categorization of land cover features.



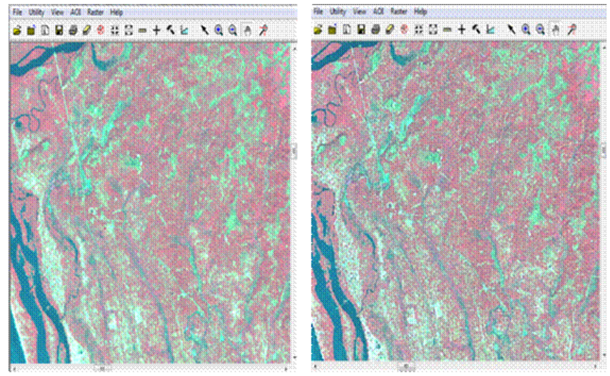
a) b)

Fig. 4: a) Image of the study area a) before applying Brightness/Contrast b) after applying Brightness/Contrast



a) b)

Fig. 5: Image of the study area a) before applying histogram equalization b) after applying histogram equalization



a) b)

Fig. 6: Image of the study area is a) before applying edge enhancement b) after applying edge enhancement

Table 2: Image classification details of the study area

Sl. No.	Class	Description
1	Waterbody	This category comprises areas with surface water, either stored in the form of ponds, lakes, and reservoirs, or flowing as streams, rivers, canals, etc.
2	Dense vegetation	Areas were trees and other vegetation types are predominating canopy cover/ density more than 40%.
3	Plantation and sparse vegetation	Areas under agricultural tree crops planted, they are exhibiting a scattered or continuous pattern. Agricultural plantations are included (such as tea, coffee, rubber, etc.).
4	Mixed crop with settlement	Area by a mix of land use which are dominated by vegetation associated with residential, institutional and recreational areas within the urban built-up areas.
5	Built up land	Human settlement evolved in non-agricultural areas with buildings, transportation and communication infrastructure, utilities related to water, vegetation, and open space.
6	Barren land	Areas of degraded land that can be restored to vegetation with modest effort but are currently underused.

2.7 Maximum Likelihood Classification

Maximum likelihood rule is widely used parametric method in RS and GIS [6, 10]. It based on the principle of determining the probability that a pixel belongs to a specific class. The basic formula assumes that these probabilities are equal in all classes and that the input bands have normal distributions. The equation for the ML/Bayesian classifier is as follows [8]:

D = ln (ac) − [0.5 ln(|Covc|)] − [0.5 (X − Mc) T ($Covc^{-1}$) (X−Mc)]   (1)

Where:

D= Weighted distance

c = A particular class

X = Measurement vector for the candidate pixel

Mc= Mean vector of the sample of class c

ac = Percent probability that any candidate pixel is a member of class c (defaults to 1.0, or is entered from a priori knowledge)

Covc = Covariance matrix of pixels in the sample of class c

|Covc| = Determinant of Covariance of class c (matrix algebra)

$Covc^{-1}$ = Inverse of Covariance of class c (matrix algebra)

T = Transposition function (matrix algebra)

2.8 Parallelepiped classification

The parallelepiped decision rule classifies pixels based on their values compared to upper and lower limits for each band. Each signature (class) has defined limits for all bands. If a pixel's values fall within these limits for all bands, it is assigned to that class [10]. Pixels outside these limits are marked as unclassified. Large rectangles, or parallelepipeds, represent the boundaries of these limits [Fig. 7]. Two image bands, A and B, define the pixel values for training areas based on their maximum and minimum pixel values.

In supervised classification, there are three main steps:

1. Defining Training Sites: spectral signatures are created for each land-use type using the signature editor.

2. Classification: using the training data pixels are categorized into different classes [Fig. 8].

3. Output Production: The final classified image is generated.

This process ensures accurate grouping of pixels into predefined land-use categories.

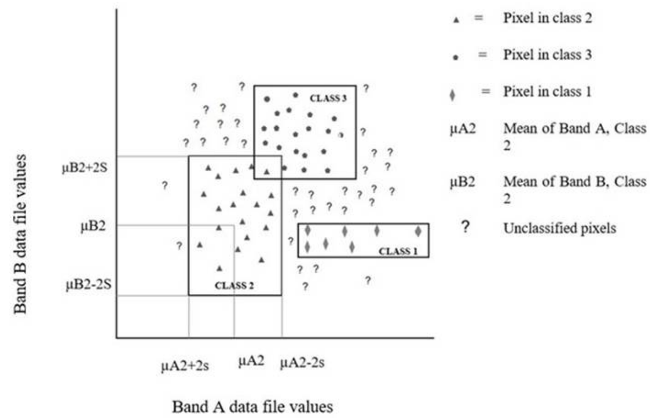
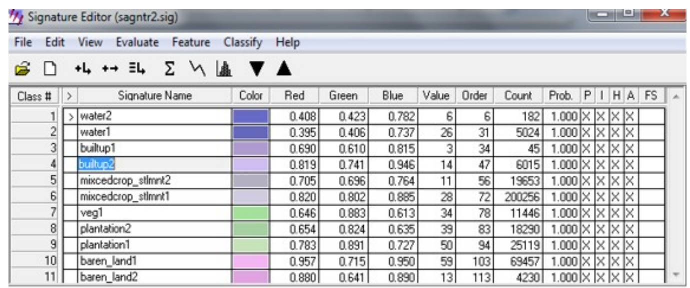


Fig. 7: Parallelepiped classification using two standard deviations as limits



Signature Editor (sagntr2.sig)

File Edit View Evaluate Feature Classify Help

Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1	>	water2		0.408	0.423	0.782	6	6	182	1.000	X	X	X	X	
2		water1		0.395	0.406	0.737	26	31	5024	1.000	X	X	X	X	
3		builtup1		0.690	0.610	0.815	3	34	45	1.000	X	X	X	X	
4		builtup2		0.819	0.741	0.946	14	47	6015	1.000	X	X	X	X	
5		mixcedcrop_stlmnt2		0.705	0.696	0.764	11	56	19653	1.000	X	X	X	X	
6		mixcedcrop_stlmnt1		0.820	0.802	0.885	28	72	200256	1.000	X	X	X	X	
7		veg1		0.646	0.883	0.613	34	78	11446	1.000	X	X	X	X	
8		plantation2		0.654	0.824	0.635	39	83	18290	1.000	X	X	X	X	
9		plantation1		0.783	0.891	0.727	50	94	25119	1.000	X	X	X	X	
10		baren_land1		0.957	0.715	0.950	59	103	69457	1.000	X	X	X	X	
11		baren_land2		0.880	0.641	0.890	13	113	4230	1.000	X	X	X	X	

Fig. 8: Training Areas in ERDAS Imagine software

2.9 Change Detection

In this study, LULC change analysis was identified by employing post-classification change detection method. The Post classification method has been effectively applied by numerous studies in urban areas because of its efficiency in recognizing the location, nature, and rate of change [7]. The following equation was used to calculate the magnitude of change (C) for each class i:

$$Ci = Li - Bi \qquad (2)$$

The percentage change (Pi) in each land use class was determined using [18]:

$$Pi = \frac{Li - Bi}{Bi} \times 100 \qquad (3)$$

Where:

Li = Base image of 2000

Bi = Current image of 2023

2.10 Normalized Difference Vegetation Index (NDVI)

NDVI is a widely used remote sensing method to evaluate the health and productivity of vegetation. It is calculated from the reflectance measurements in the red (RED) and the near-infrared (NIR). NDVI values range from -1 to +1, where higher values (between 0.1 and 1) indicate an abundance of healthy and dense vegetation due to high reflectance in the NIR portion of the electromagnetic spectrum. Bare soil areas correlate with NDVI values closer to zero because of their high reflectivity in both the visible and NIR areas of the electromagnetic spectrum (EMS) [12]. A negative NDVI value indicates non vegetation like water, snow, developments, and barren lands. NDVI method is based on the premise that healthy vegetation has low reflectance in the visible region of the EMS because of chlorophyll and other pigment absorption, but high reflectance in the NIR due to internal reflection by the mesophyll spongy tissue of green leaves [3]. In current study, the NDVI value is calculated according to the following formula.

$$NDVI=(NIR-RED)/(NIR+RED) \quad (4)$$

Where NIR is near infrared reflectance and RED is visible red reflectance. RS satellite imagery utilized band 3 (red) and band 4 (near-infrared).

3 Results and Discussion

3.1 Land Use Land Cover Classification

Prominent changes in LULC classes investigated in this study for 2000, 2005, 2013 and 2023 based on the supervised classification of satellite images [Fig. 9].

The results indicate significant changes in LULC within study area during these periods. In 2000, majority of the study area was covered with plantations and sparse vegetation, representing 60.46% of the total area, followed by mixed crop with settlement with a proportion of 20.43% and barren land at 10.31%. Water body, dense vegetation and built-up land was limited to 2.53%, 3.48%, and 2.79% respectively, of the total area. By 2005, plantation and sparse vegetation covered 56.25% of the area, followed by mixed crop with settlement occupied 23.39%. The result demonstrates the presence of both increased agricultural activities and infrastructural developments. In 2013 plantation and sparse vegetation remained the dominant land cover comprising 51.83% of the total area, showing a decrease compared to the previous years of 2000 and 2005. Mixed crop with settlement expanded significantly, accounting for 26.69% of total land area. The area under water bodies and dense vegetation decreased to 2.23% and 2.63% respectively. The built-up area increased to 7.57% while barren land decreased to 9.05%, indicating that non-vegetated land converted to urban or built-up land. By 2023 plantation and sparse vegetation were still the major land cover, covering an area of 51.17%. Mixed crop with settlement indicates a slight decrease with an area of 24.23% and built-up area significantly increased to 15.55%, the result shows an increasing demand for land from the growing population. The area under water bodies and dense vegetation, covers an area of 1.79% and 2.13% respectively. Barren land covered 5.13%, represents that barren land was increasingly converted to agricultural or built-up land [Fig. 10].

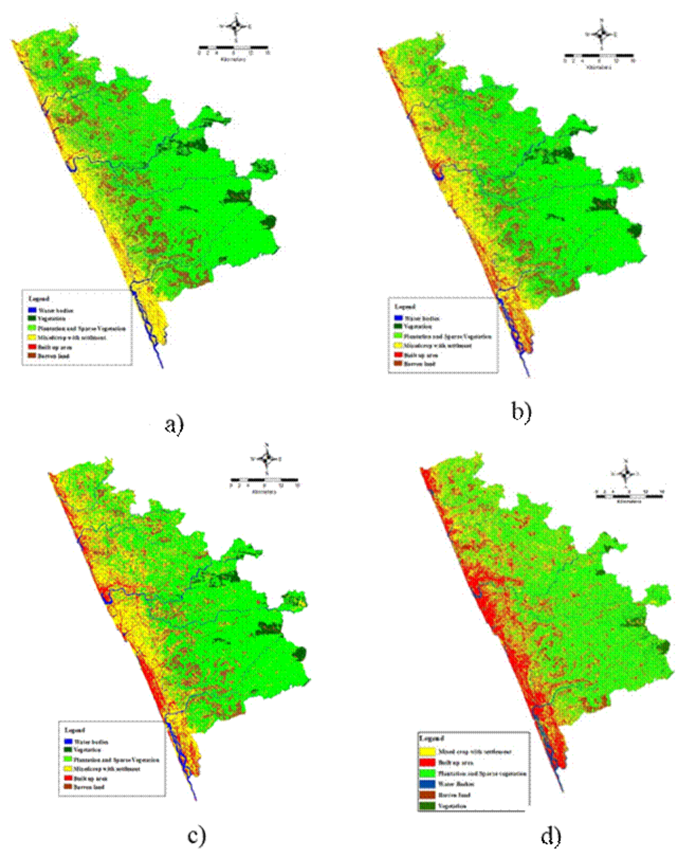


Fig. 9: LULC classification of the study area- a) 2000, b) 2005 c) 2013, d) 2023

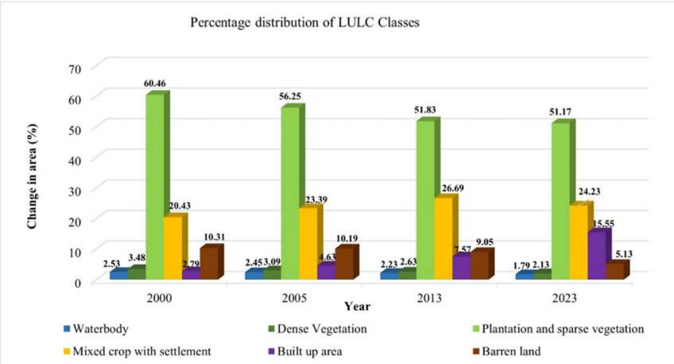


Fig. 10: Percentage Distribution of LULC classes in the Study Area

3.2 Change Detection Analysis of LULC From 2000 to 2023

The change detection analysis highlights significant transformations in LULC over 23 years. Water bodies declined by 14.65 km² (-41.09%) due to conversion into other land uses and changes in water management practice. Dense vegetation decreased by 26.92 km² (-63.48%) due to deforestation, wildfires, and natural disturbances like cyclones [Table. 3]. Mixed crops with settlements increased by 75.58 km² (15.66%), reflecting agricultural growth and urban sprawl, though their extent declined after 2013. Plantations and sparse vegetation showed a net loss of 185.19 km² (-18.17%) due to land conversion. Built-up areas expanded by 254.26 km² (82.06%), driven by residential, commercial, and industrial development particularly in the western plain, which benefits from better connectivity by major highways, railways, water ways, and infrastructure. This concentration has led to rapid urbanization and industrial activities in the area. Barren land shown the most significant loss, declining by 103.08 km² (-100.83%) as it was converted into settlements and agricultural areas. Between 2000 and 2023, barren land, dense vegetation, water bodies, and plantations saw major reductions, while built-up areas and mixed crops experienced notable gains [Fig. 11].

Table 3: Changes in the area under LULC classes of the study area from 2000 to 2023

		Land Use Land Cover Area (Km^2)				Area changed (2023-2000)	
Sl No	Land Use/ Land Cover Type	2000	2005	2013	2023	Km^2	%
1	Waterbody	50.3	48.72	44.46	35.65	-14.65	-41.09
2	Dense Vegetation	69.33	61.71	52.45	42.41	-26.92	-63.48
3	Plantation and sparse vegetation	1204.31	1120.51	1032.51	1019.12	-185.19	-18.17
4	Mixed crop with settlement	407.16	465.91	531.73	482.74	75.58	15.66
5	Built up area	55.59	92.25	150.64	309.85	254.26	82.06
6	Barren land	205.31	202.91	180.21	102.23	-103.08	-100.83

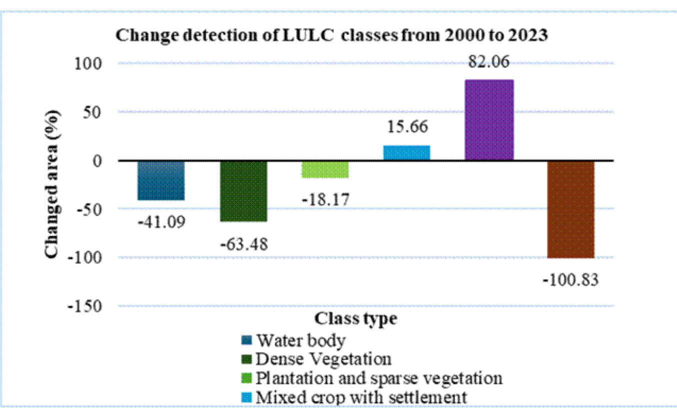


Fig. 11: Area-wise change distribution of LULC classes from 2000 to 2023

3.3 NDVI Classification of Vegetation Map and Change Detection Analysis

The vegetation index calculated using NDVI was applied to analyze vegetation changes from 2000 to 2023 [Fig. 12]. Based on NDVI values, images were classified into three classes: Dense vegetation (NDVI > 0.4), sparse vegetation (NDVI ranging from 0.1 to 0.4), and no vegetation (NDVI < 0.1). The area-wide details for each category are presented in [Table. 4]. In 2000, dense vegetation covered 804.32 km² (40.38%), sparse vegetation accounted for 952.26 km² (47.80%), and no vegetation occupied 235.42 km² (11.82%). By 2005, dense vegetation decreased to 757.42 km² (38.02%), while sparse vegetation and no vegetation increased to 957.38 km² (48.06%) and 277.20 km² (13.92%), respectively. In 2013, dense vegetation further decreased to 652.42 km² (32.75%), with sparse vegetation and no vegetation increasing to 984.63 km² (49.43%) and 354.95 km² (17.82%), respectively. By 2023, dense vegetation significantly reduced to 432.41 km² (21.72%), sparse vegetation declined slightly to 904.16 km² (45.38%), and no vegetation expanded to 655.43 km² (32.90%). These changes highlight significant variations in land use and vegetation cover over the past 23 years. The dense vegetation class showed a considerable decline from 804.32 km² in 2000 to 432.41 km² in 2023, reflecting a loss of -371.91 km² (-86.01%) over the 23-year period [Table. 4]. This decline indicates to factors such as deforestation and urbanization, with forest areas being converted into agricultural land, implying encroachment into forest reserves through cultivation. Sparse vegetation showed an initial increase from 952.26 km² in 2000 to 984.63 km² in 2013, followed by a decrease to 904.16 km² in 2023, resulting in a net loss of -48.10 km² (-5.32%). The no vegetation category expanded consistently, increasing by 420.01 km² (64.08%) during the study period [Fig. 13]. This upward trend due to the factors like urbanization, leading to the transformation of vegetated land into urban infrastructure, including roads, buildings, and residential areas. Additionally, deforestation and soil erosion have further contributed to vegetation loss.

3.4 Human Wildlife Conflict in Kasaragod District 2023

The scarcity of natural prey and food sources often compels wildlife to seek alternative resources, while human-generated food and waste inadvertently attract wild animals, leading to conflict. In regions where human and wildlife populations overlap, such interactions frequently result in physical conflicts and negative consequences, including loss of life, agricultural damage, and habitat destruction. Key drivers of human-wildlife conflict (HWC) include agricultural expansion, human settlement, overgrazing, deforestation, illegal grass collection, and improper waste disposal. This study identified five HWC-affected locations in the Kasaragod district: Delampady, Muliyar, Kuttikol, Bedadka, and Karadka, based on recent reports from local newspapers. Four of these locations lie in the midland region, while Delampady is situated in the Western Ghats [Fig. 14].

Farmers in these HWC zones have reported frequent wildlife incursions, primarily from elephants and wild boars, causing extensive damage to crops and property. Crops such as arecanut, plantains, and coconuts were particularly affected, prompting some farmers to abandon their cultivation [17]. Over the past two decades, elephants from the Karnataka forests have increasingly crossed into the Kasaragod district. A group of 22 elephants has been responsible for recurrent damage, and previous efforts to redirect these herds have been largely unsuccessful. Consequently, many farmers have shifted to alternative income sources, while others have left their agricultural lands fallow [16]. The findings emphasize the need for further research in the HWC zones of Kasaragod to better understand the severity of the issue and develop effective, sustainable mitigation strategies to address the conflict.

Table 4: Area covered by different NDVI classes and change in the area for the years 2000, 2005, 2013, and 2023

NDVI Vegetation Classes	2000		2005		2013		2023		Area changed (2023-2000)	
	Area in km²	Area in %	Area in km²	Area in %	Area in km²	Area in %	Area in km²	Area in %	Km²	%
Dense vegetation	804.32	40.38	757.42	38.02	652.42	32.75	432.41	21.72	-371.91	-86.01
Sparse Vegetation	952.26	47.80	957.38	48.06	984.63	49.43	904.16	45.38	-48.10	-5.32
No vegetation	235.42	11.82	277.20	13.92	354.95	17.82	655.43	32.90	420.01	64.08

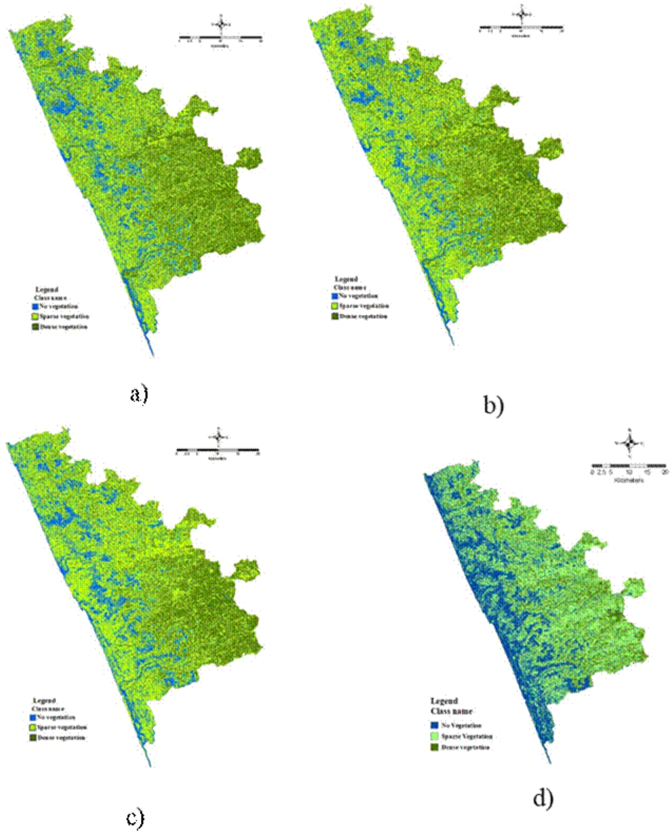


Fig. 12: NDVI classification of the study area- a) 2000, b) 2005, c) 2013, d) 2023

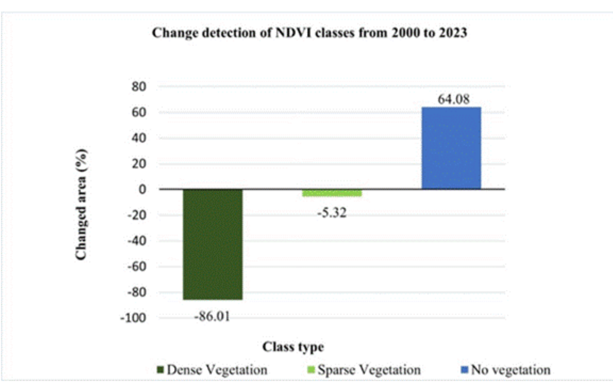


Fig. 13: Area-wise change distribution of NDVI classes from 2000 to 2023

Fig. 14: Human Wildlife Conflict (HWC) buffer zone of the study area in 2023

4 Conclusion

This study utilized RS and GIS techniques to analyze LULC and vegetation changes in Kasaragod district, Kerala, from 2000 to 2023. The findings reveal significant declines in dense vegetation, water bodies, and barren land, coupled with a substantial increase in built-up areas and mixed crops with settlements. Built-up areas expanded by 82.06% over 23 years, reflecting growing population pressure and infrastructural development. NDVI analysis highlighted a drastic reduction in dense vegetation (-86.01%) and a notable increase in non-vegetation areas (64.08%), primarily driven by deforestation, urbanization, and other anthropogenic activities.

The study also identified HWC zones impacted by these LULC changes, emphasizing the need for localized land-use planning to address crop protection and reduce conflict. These results underscore the urgency for sustainable management practices to mitigate urbanization impacts, prevent further deforestation, and conserve agricultural lands and water resources. By providing critical baseline data, this study offers valuable insights for policymakers and planners. Continued monitoring of LULC changes is imperative to support effective policymaking and ensure balanced developmental planning for Kasaragod district, promoting both ecological sustainability and socio-economic growth.

5 Acknowledgements

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6 Disclosure

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