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MONITORING SPATIO-TEMPORAL DYNAMICS OF LAND USE/LAND COVER CHANGES USING REMOTE SENSING AND GIS – A CASE STUDY OF ERNAKULAM DISTRICT, INDIA

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Abstract. Urbanisation is presently one of the most serious environmental challenges, spreading at unprecedented rates and intensifying across all countries, with far-reaching implications for ecosystems, biodiversity, and human well-being. Rapid increases in activities such as urbanisation, socioeconomic activity, and environmental change create changes in land use and land cover. Therefore, it is essential to comprehend LULC change to assess its effects on hydrology. The study reveals that the agricultural land area reduced from 56.53% in the year 2006 to 50.41% in the year 2016, which shows the urbanisation and the conversion of the vacant lands to the build-up lands. It is clear from the data that there was an increase in the built-up area from 8.27% in the year 2006 to 14.80% in the year 2016. In 2006, the area under the water body class was 189.19 km^2. Also, the wasteland area reduced from 1.77% in the year 2006 to 0.87% in the year 2016, which shows the effect of the vacant land being converted into built-up areas. The purpose of this study was to evaluate land use/land cover changes in Kerala's Ernakulam district using remote sensing and geospatial information system (GIS) techniques. This research includes LULC classification and accuracy assessment. The LULC classification had overall accuracy (OA) of 81.49%, 81.87%, and 82.79% respectively. The overall kappa coefficient was 0.75, 0.75, and 0.77 respectively for the year 2006-06, 2011-11, and 2016-16.
Keywords: *land use/land cover, remote sensing, geospatial information system (GIS), overall accuracy, kappa coefficient*

Introduction

Land cover refers to the surface cover of lands such as vegetation, water, urban infrastructure, and bare land, and land use refers to the purpose for which the land serves like recreation, wildlife habitat, or agriculture (Coffey, 2013). For worldwide monitoring studies, resource management, and planning operations, identifying, defining, and mapping land cover is critical (Treitz, 2004). Land cover identification gives a baseline against which monitoring operations (Change detection) can be carried out and also, gives information on the ground cover for baseline thematic maps (Mishra et al., 2020). It is crucial to understand the distinction between land cover and land use, as well as the information that each may provide. Land cover is one of the properties assessed using remote sensing methods, from which land use can be inferred, particularly with ancillary data (Roy and Roy, 2010; Pal and Ziaul, 2017; Siddhartha and Mukherjee, 2019)

Urbanization is a spatial phenomenon involving population increase, structural transformation, and the continued expansion of built-up regions that has a direct influence on the land use land cover (LULC) of urban landscapes (Fan et al., 2017). It is important to realise that urbanisation is not a disaster, but rather a need (Siddhartha and

Mukherjee, 2019; World Economic Forum, 2018). The positive impacts of urbanisation can only be accomplished if cities are economically viable and capable of providing long-term economic growth (Hammer et al., 2011). When it comes to Kerala, the state's urbanisation and settlement pattern are distinct. Kerala has an urban-rural continuum with a reasonably uniform distribution of housing units, as well as an urban-rural settlement pattern (Firoz et al., 2014). Rapid urbanisation has had a significant impact on the local and regional socio-ecological system, resulting in diminishing biodiversity, elevated city temperature, loss of productive agriculture, and fragmented wildlife habitat (Aithal and Ramachandra, 2016).

Changes in land use characteristics such as wetlands, forests, and cultivated land in urban areas increase the impermeable regions of the Earth's surface which result in the disruption in the hydrologic cycle (El Garouani et al., 2017). Satellite data on the Earth's resources are now available, and it is important and useful for studies of LULC transformation (Selçuk et al., 2003; Kadhim et al., 2016; Lo et al., 2004).

Remote sensing imageries and techniques are frequently utilised to analyse urban development and sprawl all over the world (Congalton, 1991; Campbell and Wynne, 2011). Researchers and decision-makers can use remote sensing data to track changes in a field of long-term interest without much on-site field monitoring. With the emergence of Geographical information systems (GIS) and remote sensing, land use/cover mapping has provided a helpful and comprehensive method for improving area selection of agricultural, urban, and/or industrial areas of a region (Jensen, 2005; Muzein, 2006). With the introduction of high spatial resolution satellite images and more advanced image processing and GIS technologies, land use/land cover trends are now being monitored and modelled on a more regular and consistent basis. Land use/cover mapping has become one of the most significant uses of remote sensing, with remote sensing being frequently utilised to update land use/cover maps (Bakker et al., 2004).

Validation of accuracy assessment is an important phase in the processing of remote sensing data (Gautam and Chennaiah, 1985). It determines the user's information value of the generated data (Borak et al., 2000) The overall accuracy of the classified image is determined by comparing how each pixel is categorised to the specified land cover conditions generated from the ground truth data (Chen and Wang, 2010; Cohen et al., 2017). Producer's accuracy measures errors of omission, which is a measure of how well real-world land cover types can be classified. User's accuracy measures errors of commission, which represents the likelihood of a classified pixel matching the land cover type of its corresponding real-world location (Mironga, 2004; Mohajane et al., 2018; Manandhar et al., 2009).

This study attempts to map out the status of land use/cover of Ernakulam district in view to determine the land consumption rate and the change that has occurred over the last few years using geospatial techniques. This research is anticipated to provide useful information for the decision-makers and planners to develop strategies for sustainable LULC management and environmental planning policies.

The methods

Geo-environmental setting of the study area

The study focuses on the Ernakulam district located almost in the middle of Kerala State and on the coast of the Arabian Sea. The district lies between the longitude of 76° 16' 48.00" and latitude of 9° 58' 48.00" N and spans an area of about 3068 km². The

district is bounded on the North by Thrissur district, on the south by Kottayam and Alappuzha districts, and on the east by Idukki district and the Arabian Sea lies all along the western boundary of the district. The district is split into three distinct sections: highland, midland, and lowland, which are comprised of hills and forests, plains, and the coastline, respectively. A part of the Western Ghats forms the hilly or eastern portion. The midland is primarily flat land with natural drainage systems such as backwaters and canals. The low land region makes up 20% of the overall area.

There is a tropical humid climate in the area, with a long hot season and plenty of seasonal rain. The hot season from March to May is followed by the South-West Monsoon season from June to September and the North-East Monsoon season from October to November/mid-December. From the end of December until the beginning of February, the weather is usually dry. The district receives on an average 3450 mm of annual rainfall. About 67% of the rainfall is due to the south-west monsoon. This district's seacoast is fully within Cochin taluk, and Cochin port, a large natural harbour, is also inside this taluk.

About 30% of the area is urban where about 49% of the district's population lives (Census, 2011). In all development initiatives, the population parameter acts as the foundation. One of the goals of all types of planning is to provide the highest level of benefit to the maximum number of people. The land use pattern reflects the district's characteristics in terms of growth, development, and activity pattern. It also indicates the amount of land suitable for future development in an informal way. *Figure 1* shows the location of the study area.
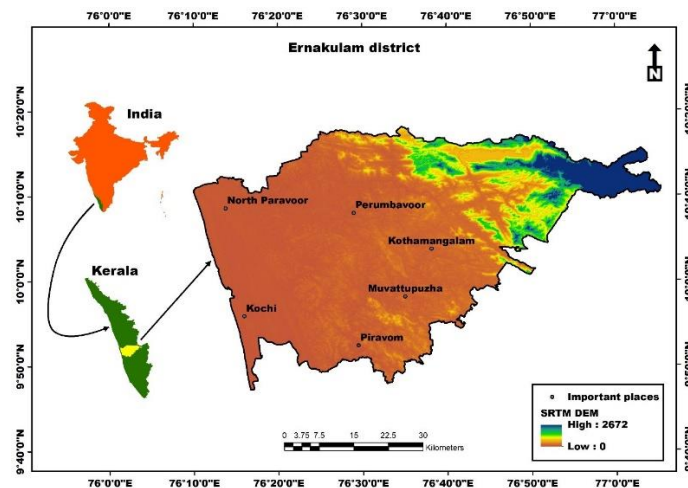

Figure 1. *Location of the study area*

Data acquisition and processing

The current study used geo-informatics and Remote Sensing to analyse differences in LULC classes in the Ernakulam District. Remote sensing (RS) is the science of acquiring and analysing information about objects or phenomena from a distance (Lu and Weng, 2007; Hogland et al., 2013; Rwanga and Ndambuki, 2017). To avoid cloud cover, the images were taken during the dry season (Durieux et al., 2003). Satellite images are subjected to image pre-processing to minimize distortions caused by the

sensor, the sun, the atmosphere, and the topography. This is to improve the image component's quality and interpretability for remote sensing analysis (Kar et al., 2018).

Cloud-free and haze-free satellite images were georeferenced and corrected during the pre-processing stage concerning the UTM zone 43 N (Universal Transverse Mercator) based on the WGS84 (World Geodetic System) datum (Ganaie et al., 2021). The data were resampled using the methodology of a nearby pixel to keep the same brightness values of the unaffected pixels. This approach allocates the present value of the adjacent pixel to the value of the output pixel, relocating the original pixel values without averaging and preserving the subtleties and extremes of the pixel values. A representative ground truth data set is required in remote sensing research to correlate this reflectance attribute with the object, train classifiers, and allow accurate automated categorization.

Image classification

Image classification is one of the most effective methods of processing satellite image data. An image is classified based on the actual classes it represents on the ground or earth's surface as it helps detect, identify, and classify its different features (Srivastava et al., 2012; Kalra et al., 2013). In remote sensing, image classification can be categorized into supervised and unsupervised techniques. Here in this study, we adopted the supervised classification using a maximum likelihood classifier (MLC) which is one of the most widely used supervised classification algorithms due to its availability and simple training process. This method classifies satellite image pixels based on their probability of occurrence. It assumes equal probabilities for all classes and normal distributions for all input bands.

The image classification procedure involved the generation of 150 training samples for each satellite image using the region of interest (ROI) tool in ENVI 5.3 image processing software. To successfully classify land use/land cover spectral classes, this method was done. In addition, we validate the prepared map with the existing maps obtained from the authorised agencies in the study area and Google Earth maps.

Landsat imageries for the years 2006, 2011, and 2016 for the study area were obtained from the online portals, Global Land Cover Facility (GLCF), and Earth Explorer with a spatial resolution of 30 m. The images were enhanced, registered, geo-referenced, and classified into various land use types using supervised classification (Lillesand et al., 2015; Onur et al., 2009). Later, using supplementary data from topographic maps and Google Earth photos, geometric improvement, and data validation was performed.

Aggregated the classes of LULC shapefile into 5 broad classes named Agricultural Land, Built-Up, Forest, Wastelands, and Waterbodies. Then, assigned 5 classes a unique integer/number value. Converted shapefile to raster of pixel 5 m spatial resolution *Figure 2a, b,* and *c*. The pictures were improved, registered, geo-referenced, and categorised into different land use categories using supervised classification. The supervised classification procedure makes a preliminary assessment of areas on the image that delineate land parcels to be mapped (Prasad and Ramesh, 2019). Supervised Maximum Likelihood Classification Technique (MLCT) is adopted to generate different categories of LULC maps of the study area.

Additionally, to improve the accuracy level and to reduce errors in maximum likelihood classification, the Landsat images of the study area were categorised and the points were chosen from various parts of the study area and were verified using Google

Earth's latitude and longitude. The Validation/accuracy was performed into QGIS using the GRASS tool kappa. The per-class area was calculated in QGIS using the tool 'Raster layer unique values report' for the years 2006, 2011, and 2016.
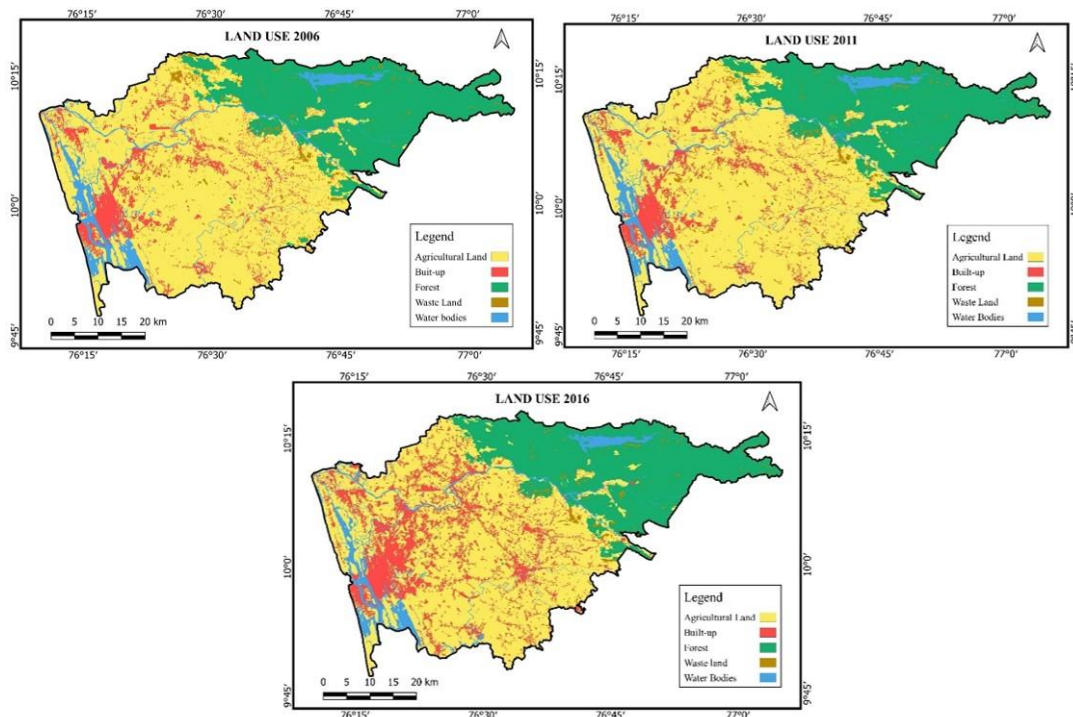

Figure 2. Land use land cover – (a) 2006, (b) 2011, (c) 2016

Accuracy assessment

The accuracy assessment is a necessary step in the feature abstraction process from classified images (Maxwell et al., 2021). The accuracy assessment involved the determination of thematic or classification accuracy (Maxwell and Warner, 2020; Borana and Yadav, 2017). For the thematic accuracy, 100 points are chosen on the map and the same is displayed in the image using the "Accuracy Assessment Tool" in ERDAS Imagine software. The field verification of randomly selected points is also done. The value is derived by overlaying these ground truth locations on the land use land cover map.

Accuracy assessment was done through ERDAS imagine with a ground control point of Google Earth Pro software and GPS ground data sets (Ragheb and Ragab, 2015; Aguilar et al., 2020). A classified image or change detection map needs to be compared against reference data, assumed to be true, to assess its performance and quantify its accuracy (Mengistu and Salami, 2007; Guler et al., 2007). The process had used to estimate the accuracy of image classification by comparing the classified map with a reference map. Therefore, a full accuracy assessment needs to include the report on Overall accuracy, User Accuracy, and Producer Accuracy had investigated using the Kappa coefficient. User Accuracy quantifies the error of commission while Producer Accuracy quantifies the error of omission. The user and producer accuracies, on the other hand, differed amongst LULC classes and study areas (Morales-Barquero et al., 2019; Nutini et al., 2013).

$$User\ Accuracy = \frac{Number\ of\ correctly\ classified\ pixles\ in\ a\ class}{Total\ number\ of\ pixles\ in\ a\ class} \qquad (Eq.1)$$

$$Producers\ Accuracy = \frac{Number\ of\ correctly\ classified\ pixles\ in\ a\ class}{Total\ number\ of\ pixles\ in\ all\ classes} \qquad (Eq.2)$$

$$Overall\ Accuracy = \frac{Total\ number\ of\ all\ correctly\ classified\ pixles}{Total\ number\ of\ pixles\ in\ all\ classes} \qquad (Eq.3)$$

Another method that quantifies classification accuracy is Kappa statistics; it measures the chance agreement (Kadhim et al., 2016; Vitousek, 1992). It is more efficient than the overall accuracy of satellite images. To achieve high overlay accuracy for better results, the satellite imageries were geo-referenced and rectified. Kappa coefficient (k), a discrete multivariate technique (Rawat and Kumar, 2015), was used to assess the accuracy of the results found through analysis of Landsat 5, 7, and 8 data (Rawat and Kumar, 2015; Msofe et al., 2019). Kappa (k) is a statistical tool used widely to assess the accuracy of derived maps (Dame et al., 2019). Kappa statistics, which measures chance agreement, is another approach for quantifying categorization accuracy. It is more efficient than the overall accuracy of satellite images.

$$Cohen's\ Kappa\ (k)\ = \frac{(P0 - Pe)}{(1 - Pe)} \qquad (Eq.4)$$

where P_0 is observed accuracy and P_e is change agreement.

The kappa coefficient varies from 0 to 1, where 0 means agreement equivalent to chance; 0.1 to 0.20 means slight agreement; 0.21 to 0.40 means fair agreement; 0.41 to 0.60 means moderate agreement; 0.61 to 0.81 means substantial agreement; 0.81 to 0.99 means near-perfect agreement or good performance; and 1 means perfect agreement (Ferreira et al., 2019).

LULC change detection

The significance of change detection is determining which land-use class is transitioning from one to the other. Change detection was conducted utilising the most common and accurate change detection method, post-classification comparison (PCC) (Du et al., 2017). While reducing the difficulty of radiometric calibration between images of various dates, post-classification comparison explains the nature of changes between study periods (Mallupattu and Sreenivasula Reddy, 2013; Bhat et al., 2017).

The most commonly used land change detection methods include change vector analysis, image overlay, principal component analysis, classification comparisons of land cover statistics, image rationing, and the differencing of normalized difference vegetation index (NDVI) (Han et al., 2009; Muttitanon and Tripathi, 2005).

$$Change\ percentage\ (\%) = \frac{Present\ LULC\ area - Previous\ LULC\ area}{Previous\ LULC\ area} X100 \qquad (Eq.5)$$

The final and initial LULC areal coverage were compared using the above procedure to get the LULC change in percentage (%). The capacity to measure temporal impacts using multi-temporal data sets is essentially what it is all about (Singh, 1989). Several researchers have attempted to solve the challenge of change detection by using digits.

Approaches for digital change detection can be generally classified by *Equation 1* analysis techniques used to delineate areas of significant alterations and *Equation 2* the data transformation procedure (if any). In this study, the land use statistics of the Ernakulam district for the years 2006-06, 2011-11, and 2016-16 were detected by applying the post-classification comparison method. This approach was used in this study because of its simplicity and ability to compare two images from two distinct sensors and time (Alphan et al., 2009). It is important to note that most change detection algorithms need good spatial alignment of the two pictures (Dewidar, 2004; Mengistu and Salami, 2007; Guler et al., 2007). A well-designed methodology was adopted for the current study.

Results

The land use maps were prepared using Landsat images for the years 2006, 2011, and 2016. Changes in land use/cover are a major driver of global change, with significant implications for many international policy issues. The Ernakulam district encompasses a wide range of land uses: agricultural land, built-up, forest, wastelands, and water bodies. For the analysis, the total area and percentage for each land-use class for the years 2006, 2011, and 2016 were computed. From 2006 to 2016, the percentage changes in land use classifications were calculated. It is apparent from this that the built-up land has increased in value from 2006 to 2016 (*Tables 1* and *2*).

Table 1. Land use statistics of the Ernakulam district for the year 2006, 2011, and 2016

LULC class	2006		2011		2016	
	Area (km²)	% Cover	Area (km²)	% Cover	Area (km²)	% Cover
Agricultural land	1728.33	56.53	1746.57	57.11	1541.00	50.41
built up	252.93	8.27	246.09	8.05	452.28	14.80
Forest	832.65	27.24	830.15	27.14	850.73	27.83
Wastelands	54.11	1.77	46.60	1.52	26.64	0.87
Waterbodies	189.19	6.19	189.00	6.18	186.07	6.09
Total area (km²)	3057.20		3058.40		3056.71	

Table 2. Dynamics of LULC change between 2006 and 2016 (km²)

LULC class	LULC change 2006-2011		LULC change 2011-2016		LULC change 2006-2016	
Agricultural land	18.24	0.58	-205.57	-6.7	-187.33	-6.12
Built up	-6.84	-14.80	206.19	6.75	199.35	6.53
Forest	-25.00	-0.10	20.58	0.69	18.08	0.59
Wastelands	-7.51	-0.25	-19.96	-0.65	-27.47	-0.9
Waterbodies	-0.19	-0.01	-2.93	-0.09	-3.12	-0.1

The study area's land use and land cover categories exhibited both positive and negative growth in the area of total geographical area. The agricultural area occupies an area of 56.33% in 2006, it could be shown a slightly positive trend in 2011 around 57.11%. Whereas the rest of the classes showed a negative trend. A negative value denotes the decline of the area. During the study period, all the categories showed both

positive and negative growth in the total geographical area. The agricultural land occupies an area of 57.11% in 2011, got reduced to 50.41% in 2016. The agricultural land area reduced from 56.53% in the year 2006 to 50.41% in the year 2016, which shows the urbanisation and the conversion of the vacant lands being converted to the build-up lands (*Fig. 3a*).
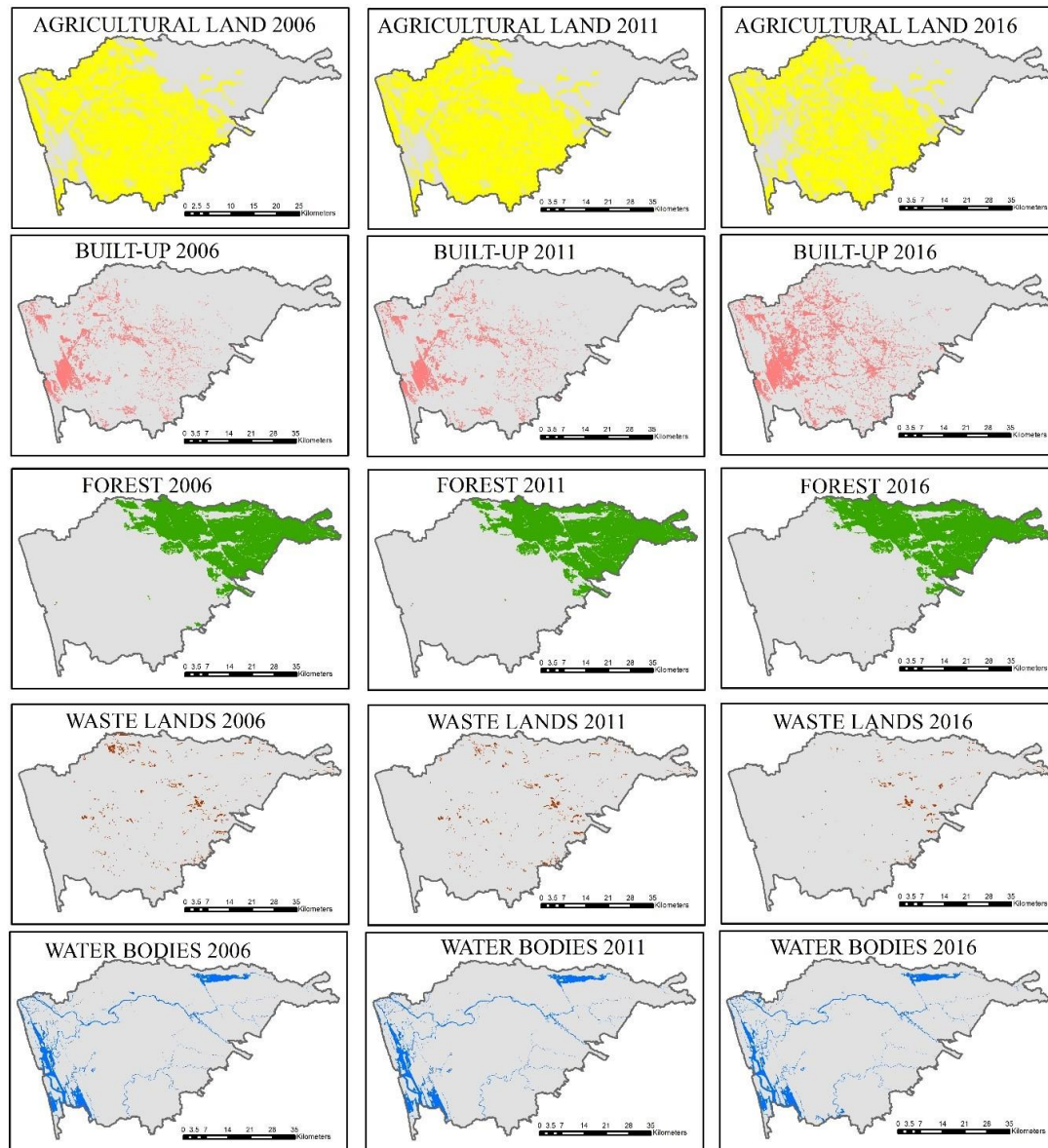

Figure 3. *Synoptic view of different land use and land cover pattern. (a) Agricultural land (b) built-up (c) forest (d) waste lands (e) water bodies*

The spatio-temporal changes of the built-up area have a significant impact on the reclamation of wetlands. In this study, the built-up area represents both rural and urban built-up along with the mining/industrial area. It is clear from the data that there was an increase in the built-up area from 8.27% in the year 2006 to 14.80% in the year 2016 (*Fig. 3b*). The census data show that the population of the study area in 2001 was 3,105,798, whereas in 2011 it was 3,282,388 which portrays demographic growth.

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Forests are thick canopies of trees. Forest in the study area represents the deciduous (Dry/Moist/Thorn), evergreen/semi-evergreen, a forest plantation, littoral/swamp forest (Mangrove/Forest Water Swamp), and scrub forest. In the study area, it was clear that there was an increase in the forest area from 27.24% in the year 2006 to 27.83% in the year 2016 (*Fig. 3c*). During the research period, there was no encroachment due to human activity, deforestation, agriculture, or plantation. The wasteland area reduced from 1.77% in the year 2006 to 0.87% in the year 2016, which shows the effect of the vacant land being converted into built-up areas. In the waterbody and waterlogged regions, there was little change (*Fig. 3d*). Water bodies include lakes/ponds, Reservoir/tanks, and rivers/streams. The area under the water body class was reduced from 189.19 km^2 which is 6.19% in 2006 to 6.09% in 2016 (*Fig. 3e*).

The results from the accuracy assessment showed an overall accuracy of 81.49%, 81.87%, and 82.79% respectively in the years 2006, 2011, and 2016. In the year 2016, Users' accuracy ranged from 74.26% to 95.83% while producer's accuracy ranged from 74.19% to 95.83%. The producer's accuracy reflects the accuracy of prediction of the particular category and the user's accuracy reflects the reliability of the classification to the user. The wasteland was found to be more reliable with 95.83% of the user's accuracy (*Table 3*).

The overall kappa coefficient was 0.75, 0.75, and 0.77 respectively for the year 2006-06, 2011-11, and 2016-16 (*Table 4*).

Table 3. *The producer's accuracy and user's accuracy matrix for the years 2006, 2011, 2016*

LULC class	Producer's accuracy (%)			User's accuracy (%)		
	2006	**2011**	**2016**	**2006**	**2011**	**2016**
Agricultural land	89.30	89.74	81.59	74.22	74.47	81.19
Built up	64.81	66.96	81.45	79.55	81.05	74.26
Forest	93.90	93.98	95.83	92.77	91.76	92.00
Wastelands	80.00	80.77	74.19	94.12	95.45	95.83
Waterbodies	75.00	74.29	77.00	89.29	89.66	85.56

Table 4. *The kappa coefficient per class matrix for the years 2006, 2011, and 2016*

LULC class name	Kappa coefficient		
	2006	**2011**	**2016**
Agricultural land	0.59	0.59	0.70
Built up	0.74	0.76	0.67
Forest	0.91	0.90	0.90
Wastelands	0.94	0.95	0.96
Waterbodies	0.87	0.87	0.82

Discussion and conclusion

The rate of urbanisation and land being converted is astounding. Urbanization exacerbates the conflict between land and water development. The study demonstrated the value of remote sensing and geographic information systems (GIS) in mapping and identifying urban LULC dynamics on both spatial and temporal scales. Multi-temporal

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Landsat data has also been shown to accurately detect urban LULC changes despite their moderate. The current urbanisation trend has the most visible environmental effects on the surrounding ecosystems, land resources, urban form and pattern, and therefore quality of life. It has also been observed that some sort of urbanisation is taking place in the region's protected zones. Rapid urban/built-up expansions resulted in substantial changes in land use and cover, as seen by steep reductions in the agricultural, wasteland, and water bodies.

Increased built-up land stemmed from a significant rise in rural-to-urban people's migration toward district centres. In addition, the expansion of the tourism industry, as well as the noticeable improvements in socio-economic development, has contributed to this rise in the built-up area. Between 2006 and 2016, the built-up area expanded dramatically. It was 8% in 2006 and increased to 14% in 2016. The increase in the built-up area is directly proportional to population growth. As a result of the overuse of natural resources, the delicate environmental balance is disrupted, and waste management difficulties are exacerbated. Because human systems are not closed-loop, they frequently have detrimental consequences for ecosystems.

In 2006 the percentage of agricultural land was 57% and in 2016 it was 50%. A large agricultural land was converted to non-agricultural land in the year 2016. As per the 2011 census, Ernakulam became Kerala's most urbanised district with a 68.07% urban populace. Various human activities had resulted in significant changes in the studied area's land use/land cover. Information on the LULC pattern dynamics over a period is vital to the effective management of an area. The effectiveness of the use of remote sensing and GIS integration for mapping and detecting LULC changes in the Ernakulam district was demonstrated in this study.

For a harmonic ecological balance and long-term development, a well-thought-out land-use strategy is required. A judicious land use plan should be put in place, with a focus on controlling developed land that encroaches on paddy fields, waterlogged areas, and water bodies. To sustain eco-friendly biodiversity, ecological preservation tenets should be woven into LULC management. The findings and analysis of the study imply significant policy implications for various urban planning activities for sustainable land-use/cover practices in the Ernakulam district. However, in future research, the use of high-resolution temporal data, as well as the integration of the study's zoning rules and development plans, might assist to increase the accuracy of the findings, planning for urban utilities, assessing the environmental consequences of urban sprawl, and preserving socio-environmentally significant regions are all essential tasks. Land cover changes and population growth need to be examined in greater depth in future research. By utilizing demographic data, we can gain an understanding of the long-term dynamics of LULC change and how it holistically impacts sustainable development.

REFERENCES

[1]   Aguilar, M. A., Jiménez-Lao, R., Nemmaoui, A., Aguilar, F. J. (2020): Geometric accuracy assessment of deimos-2 panchromatic stereo pairs: sensor orientation and digital surface model production. – Sensors 20(24): 1-17.

[2]   Aithal, B. H., Ramachandra, T. V. (2016): Visualization of urban growth pattern in Chennai using geoinformatics and spatial metrics. – Journal of the Indian Society of Remote Sensing 44(4): 617-633.

[3]   Alphan, H., Doygun, H., Unlukaplan, Y. I. (2009): Post-classification comparison of land cover using multitemporal Landsat and ASTER imagery: the case of Kahramanmaras, Turkey. – Environmental Monitoring and Assessment 151(1-4): 327-336.

[4]   Bakker, W. H., Grabmaier, K. A., Huurneman, G. C., Meer, F. D. van der, Prakash, A., Tempfli, K., Gieske, A. S. M., Hecker, C. A., Janssen, L. L. F., Parodi, G. N., Reeves, C. V., C.Weir, M. J., Gorte, B. G. H., Horn, J. A., Kerle, N., Pohl, C., Ruitenbeek, F. J. van, Woldai, T. (2004): Principles of Remote Sensing. – The International Institute for Geo-Information Science and Earth Observation (ITC), Enschede.

[5]   Bhat, P. A., Shafiq, M. ul, Mir, A. A., Ahmed, P. (2017): Urban sprawl and its impact on landuse/land cover dynamics of Dehradun City, India. – International Journal of Sustainable Built Environment 6(2): 513-521.

[6]   Borak, J. S., Lambin, E. F., Strahler, A. H. (2000): The use of temporal metrics for land cover change detection at coarse spatial scales. – International Journal of Remote Sensing 21(6-7): 1415-1432.

[7]   Borana, S. L., Yadav, S. K. (2017): Accuracy assessment of land cover classification in Jodhpur City using remote sensing and GIS. – International Journal of Advanced Research in Computer and Communication Engineering 6(10): 220-224.

[8]   Campbell, J. B., Wynne, R. H. (2011): Introduction to Remote Sensing. 5th Ed. – Guilford, New York.

[9]   Chen, Z., Wang, J. (2010): Land use and land cover change detection using satellite remote sensing techniques in the mountainous Three Gorges Area, China. – International Journal of Remote Sensing 31(6): 1519-1542.

[10]   Coffey, R. (2013): The Difference Between "Land Use" and "Land Cover". – Michigan State University Extension, East Lansing, MI.

[11]   Cohen, W. B., Kauffman, J. B., Guild, L. S. (2017): Detection of deforestation and land conversion in Rondônia, Brazil using change detection techniques. – International Journal of Remote Sensing: 731-750.

[12]   Congalton, R. G. (1991): A review of assessing the accuracy of classifications of remotely sensed data. – Remote Sensing of Environment 37(1): 35-46.

[13]   Dame, J., Schmidt, S., Müller, J., Nüsser, M. (2019): Urbanisation and socio-ecological challenges in high mountain towns: insights from Leh (Ladakh), India. – Landscape and Urban Planning: 189-199.

[14]   Dewidar, K. M. (2004): Detection of land use/land cover changes for the northern part of the Nile delta (Burullus region), Egypt. – International Journal of Remote Sensing 25(20): 4079-4089.

[15]   Du, C. W. B., Cui, X., Zhang, L. (2017): A post-classification change detection method based on iterative slow feature analysis and Bayesian soft fusion. – Remote Sensing of Environment: 241-255.

[16]   Durieux, L., Machado, L. A. T., Laurent, H. (2003): The impact of deforestation on cloud cover over the Amazon arc of deforestation. – Remote Sensing of Environment 86(1): 132-140.

[17]   El Garouani, A., Mulla, D. J., El Garouani, S., Knight, J. (2017): Analysis of urban growth and sprawl from remote sensing data: case of Fez, Morocco. – International Journal of Sustainable Built Environment 6(1): 160-169.

[18]   Fan, C., Myint, S. W., Rey, S. J., Li, W. (2017): Time series evaluation of landscape dynamics using annual Landsat imagery and spatial statistical modeling: evidence from the Phoenix metropolitan region. – International Journal of Applied Earth Observation and Geoinformation 58: 12-25.

[19] Ferreira, L. M. R., Esteves, L. S., de Souza, E. P., dos Santos, C. A. C. (2019): Impact of the Urbanisation process in the availability of ecosystem services in a tropical ecotone area. – Ecosystems 22(2): 266-282.

[20] Firoz, M., Banerji, H., Sen, J. (2014): A methodology to define the typology of rural urban continuum settlements in Kerala. – Journal of Regional development and Planning 3(1): 49-60.

[21] Ganaie, T. A., Jamal, S., Ahmad, W. S. (2021): Changing land use/land cover patterns and growing human population in Wular catchment of Kashmir Valley, India. – GeoJournal 86(4): 1589-1606.

[22] Gautam, N. C., Chennaiah, G. C. (1985): Land-use and land-cover mapping and change detection in Tripura using satellite Landsat Data. – International Journal of Remote Sensing 6(3-4): 517-528.

[23] Guler, M., Yomralioglu, T., Reis, S. (2007): Using Landsat data to determine land use/land cover changes in Samsun, Turkey. – Environmental Monitoring and Assessment: 155-167.

[24] Hammer, S., Kamal-chaoui, L., Robert, A., Plouin, M. (2011): Cities and Green Growth: A Conceptual Framework. – OECD Regional Development Working Papers 2011/08. OECD Publishing, Paris. http://dx.doi.org/10.1787/5kg0tflmzx34-en.

[25] Han, J., Hayashi, Y., Cao, X., Imura, H. (2009): evaluating land-use change in rapidly urbanizing china: case study of Shanghai. – Journal of Urban Planning and Development 135(4): 166-171.

[26] Hogland, J., Billor, N., Anderson, N. (2013): Comparison of standard maximum likelihood classification and polytomous logistic regression used in remote sensing. – European Journal of Remote Sensing 46(1): 623-640.

[27] Jensen, J. R. (2005): Introductory Digital Image Processing. A Remote Sensing Perspective. 3rd Ed. – Prentice Hall, Upper Saddle River.

[28] Kadhim, N., Mourshed, M., Bray, M. (2016): Advances in remote sensing applications for urban sustainability. – Euro-Mediterranean Journal for Environmental Integration 1(1): 1-22.

[29] Kalra, K., Kumar Goswami, A., Gupta, R. (2013): A comparative study of supervised image classification algorithms for satellite images. – International Journal of Electrical 1(10): 2320-2084.

[30] Kar, R., Obi Reddy, G. P., Kumar, N., Singh, S. K. (2018): Monitoring spatio-temporal dynamics of urban and peri-urban landscape using remote sensing and GIS. A case study from Central India. – Egyptian Journal of Remote Sensing and Space Science 21(3): 401-411.

[31] Lillesand, T., Kiefer, R. W., Chipman, J. (2015): Remote Sensing and Image Interpretation. – Wiley, Hoboken.

[32] Lo, C. P., Jinmu Choi (2004): A hybrid approach to urban land use/cover mapping using Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images. – International Journal of Remote Sensing 25(14): 2687-2700.

[33] Lu, D., Weng, Q. (2007): A survey of image classification methods and techniques for improving classification performance. – International Journal of Remote Sensing 28(5): 823-870.

[34] Mallupattu, P. K., Sreenivasula Reddy, J. R. (2013): Analysis of land use/land cover changes using remote sensing data and GIS at an urban area, Tirupati, India. – The Scientific World Journal: 1-7.

[35] Manandhar, R., Odehi, I. O. A., Ancevt, T. (2009): Improving the accuracy of land use and land cover classification of Landsat data using post-classification enhancement. – Remote Sensing 1(3): 330-344.

[36] Maxwell, A. E., Warner, T. A. (2020): Thematic classification accuracy assessment with inherently uncertain boundaries: an argument for center-weighted accuracy assessment metrics. – Remote Sensing 12: 1905.

[37] Maxwell, A. E., Warner, T. A., Guillén, L. A. (2021): Accuracy assessment in convolutional neural network-based deep learning remote sensing studies—part 2: Recommendations and best practices. – Remote Sensing 13: 2591.

[38] Mengistu, D. A., Salami, A. T. (2007): Application of remote sensing and GIS inland use/land cover mapping and change detection in a part of south western Nigeria. – African Journal of Environmental Science and Technology 1(5): 99-109.

[39] Mironga, J. M. (2004): Geographic information systems (GIS) and remote sensing in the management. – Applied Ecology and Environmental Research 2(1): 83-103.

[40] Mishra, P. K., Rai, A., Rai, S. C. (2020): Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India. – Egyptian Journal of Remote Sensing and Space Science 23(2): 133-143.

[41] Mohajane, M., Essahlaoui, A., Oudija, F., Hafyani, M. El, Hmaidi, A. El, Ouali, A. El, Randazzo, G., Teodoro, A. C. (2018): Land use/land cover (LULC) using Landsat data series (MSS, TM, ETM+ and OLI) in Azrou forest, in the central middle atlas of Morocco. – Environments MDPI 5(12): 1-16.

[42] Morales-Barquero, L., Lyons, M. B., Phinn, S. R., Roelfsema, C. M. (2019): Trends in remote sensing accuracy assessment approaches in the context of natural resources. – Remote Sensing 11(19): 1-16.

[43] Msofe, N. K., Sheng, L., Lyimo, J. (2019): Land use change trends and their driving forces in the Kilombero Valley Floodplain, Southeastern Tanzania. – Sustainability 11(2): 505.

[44] Muttitanon, W., Tripathi, N. K. (2005): Land use/land cover changes in the coastal zone of Ban Don Bay, Thailand using Landsat 5 TM data. – International Journal of Remote Sensing 26(11): 2311-2323.

[45] Muzein, B. S. (2006): Remote Sensing a GIS for Land Cover/Land Use Change Detection and Analysis in the Semi-Natural Ecosystems and Agriculture Landscapes of the Central Ethiopian Rift Valley. Thesis Report. – Technische Universität Dresden, Fakultät Forst-, Geo- und Hydrowissenschaften: Institut für Photogrammetrie und Fernerkundung, Dresden.

[46] Nutini, F., Boschetti, M., Brivio, P. A., Bocchi, S., Antoninetti, M. (2013): Land-use and land-cover change detection in a semi-arid area of Niger using multi-temporal analysis of Landsat images. – International Journal of Remote Sensing 34(13): 4769-4790.

[47] Onur, I., Maktav, D., Sari, M., Kemal Sönmez, N. (2009): Change detection of land cover and land use using remote sensing and GIS: a case study in Kemer, Turkey. – International Journal of Remote Sensing 30(7): 1749-1757.

[48] Pal, S., Ziaul, S. (2017): Detection of land use and land cover change and land surface temperature in English Bazar urban centre. – Egyptian Journal of Remote Sensing and Space Science 20(1): 125-145.

[49] Prasad, G., Ramesh, M. V. (2019): Spatio-temporal analysis of land use/land cover changes in an ecologically fragile area—Alappuzha District, Southern Kerala, India. – Natural Resources Research 28: 31-42.

[50] Ragheb, A. E., Ragab, A. F. (2015): Enhancement of google earth positional accuracy. – International Journal of Engineering Research and Technology 4(1): 627-630.

[51] Rawat, J. S., Kumar, M. (2015): Monitoring land use/cover change using remote sensing and GIS techniques: a case study of Hawalbagh block, district Almora, Uttarakhand, India. – Egyptian Journal of Remote Sensing and Space Science 18(1): 77-84.

[52] Roy, P. S., Roy, A. (2010): Land use and land cover change in India: a remote sensing & GIS perspective. – Journal of the Indian Institute of Science 90(4): 489-502.

[53] Rwanga, S. S., Ndambuki, J. M. (2017): Accuracy Assessment of land use/land cover classification using remote sensing and GIS. – International Journal of Geosciences 8(4): 611-622.

[54] Selçuk, R., Nisnci, R., Uzun, B., Yalçin, A. (2003): Monitoring land use changes by gis and remote sensing technique: case study of Trabzon. – 2nd FIG Regional Conference, Morocco.

[55] Siddhartha, K., Mukherjee, S. (2019): Cities Urbanisation and Urban Systems (Settlement Geography). – Kitab Mahal Publication, New Delhi.

[56] Singh, A. (1989): Review article: Digital change detection techniques using remotely-sensed data. – International Journal of Remote Sensing 10(6): 989-1003.

[57] Srivastava, P. K., Han, D., Rico-Ramirez, M. A., Bray, M., Islam, T. (2012): Selection of classification techniques for land use/land cover change investigation. – Advances in Space Research 50(9): 1250-1265.

[58] Treitz, P. (2004): Remote sensing for mapping and monitoring land-cover and land-use change. – Progress in Planning 61(4): 267.

[59] Vitousek, P. M. (1992): Global environmental change: an introduction. – Annual Review of Ecology and Systematics 23: 1-14.

[60] World Economic Forum (2018): The Global Risks Report 2018. 13th Ed. – World Economic Forum, Geneva.