Spatio-Temporal Analysis of Land Use/Land Cover Changes in an Ecologically Fragile Area—Alappuzha District, Southern Kerala, India

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Concomitant with careless human interference in the delicate environmental balance, the Earth's surface is witnessing a variety of changes in land use and land cover (LULC). Acquisition of a sound understanding of LULC is an important aspect of maintaining a sustainable, benign, healthy environment. The present work highlights a spatiotemporal study on the LULC features of Alappuzha District, an ecologically fragile area in southern Kerala, a state in South India. The study area faces diverse environmental challenges including decline of landforms, rising sea levels, population expansion and anthropogenic encroachments on the ecological balance. This investigation compiles an audited account of the modifications, in each class of LULC, using geospatial technologies. We interpreted satellite imagery from the Landsat 8 and the Landsat multispectral scanner for the years 1973 and 2017. The LULC aspects were categorized into seven classes: waterbody, waterlogged area, mixed vegetation, built-up land, uncultivated area, paddy field and sandy area. Our findings affirm that the expansiveness of the built-up land area is directly proportional to the growth of the population. Advanced technologies such as remote sensing and geographic information system accentuate alterations in land use patterns over time and the extent to which the changes affect the human population and the natural habitat. We verified the results of our research by assessment of accuracy and ground truth confirmation of the LULC features.

KEY WORDS: Alappuzha, Land use, Land cover, Landsat, Accuracy.

INTRODUCTION

Land cover refers to the spatial distribution of soil, water, vegetation and anthropogenic activities on the surface of the Earth, whereas land use refers to the way humans manage or modify land. The land use and land cover (LULC) of an area are the consequence of socioeconomic undertakings as well as natural changes in the Earth. LULC data support the observed variations and unenviable side effects of impetuous land use, ensued from population overload.

Transformation of land use features such as forests, wetlands, cultivated lands to urban areas increases the impermeable Earth surface areas, which, in turn, alters the hydrologic cycle. These changes increase the rate of surface runoff and reduce replenishment of ground water (James et al.

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1976; Caselles and Lopez Garcia 1989; Moscrip and Montgomery 1997).

Ecological variations in land cover, combined with changes in land use, do not directly result in land degradation. Nevertheless, climate and the ecosystems are adversely affected by thoughtless land use designs, which collectively disrupt the biodiversity, water, release of trace gases and other processes (Riebsame et al. 1994). Comprehensive appraisal of LULC variation is critical for understanding the dynamics of the landscape and to ensure its sustainable management.

Major biodiversity hotspots in India—the Himalayas (Joshi et al. 2004), Northeast India (Lele and Joshi 2009) and the Western Ghats—have endured extensive landscape changes (Kaliraj and Chandrasekar 2012). In particular, Kerala (a state in South India) has seen significant landscape changes, during the last few decades. Toward the latter half of the last century, these changes were clearly associated with socioeconomic changes, triggered by the Land Reform Act 1971.

Nowadays, satellite data of the Earth's resources are available and are relevant and beneficial for studies of LULC transformation (Rawat and Kumar 2015; Shanmugapriya et al. 2016). Satellite imagery has been put to constructive use in multiple domains—forestry, landscape, geology and cartography. Diligent interpretation of satellite images and topographic sheets helped create land use maps of the study area. Satellite images provide synoptic coverage of the Earth surface, on a spatial and time-based scale, which are helpful in deciphering the causes of environmental changes, including coastline water (Misra et al. 2013). Coastal locations have been the preferred destinations of populations, in movement for commercial and other economic reasons. Reddy and Roy (2008) have shown that coastal environments are dynamic ecosystems, profoundly influenced by anthropogenic factors and policies.

Geo-informatics is a powerful tool to monitor the spatial and temporal distribution of changes in land use. Remote sensing (RS) and geographic information system (GIS) tools offer comprehensive insight into the spatiotemporal data of LULC. These methods have been widely accepted for precise discernment by the scientific community (Rawat et al. 2013; Misra and Balaji 2015; Prasad et al. 2018). Kaliraj and Chandrasekar (2012) have demonstrated that a compound data set, consisting of aerial photographs, satellite images and maps, can be used for

the compilation of qualitative and quantitative geodatabases. Investigators in this sector observed that RS techniques have been highly effective for timely, accurate detection of regional and global deviations in LULC phenomena (Wickware and Howarth 1981; Avery and Berlin 1992; Adams et al. 1995; Jaiswal et al. 1999; Petit and Lambin 2001; Jayappa et al. 2006; Amin and Fazal 2012; Kaliraj and Chandrasekar 2012; Mujabar and Chandrasekar 2013). Afify (2011) reported that the Landsat multispectral scanner, the Thematic Mapper (TM) and the Enhanced Thematic Mapper Plus (ETM+) were used in systematic detection of land use changes, worldwide. The appropriate spectral properties of Landsat images deliver enhanced details on LULC variations, unlike the point data collected during in situ surveys by on-site instruments (Muttitanon and Tripathi 2005; Kawakubo et al. 2011; www.landsat.usgs.gov).

Precise data on the recognition and alterations of LULC features have been obtained using recently developed software algorithms (Amin and Fazal 2012; Mohammady et al. 2015). As a matter of fact, the ground that was used as a knowledge engine for clustering the maximum likelihood numbers of pixels in the image was analyzed by MLC in the training of samples of per-pixel signature files (Afify 2011; El-Asmar et al. 2013; Iqbal and Khan 2014). Using the MLC algorithm as a supervised classification technique, the Landsat images offer a nearly perfect assessment of LULC changes. (James et al. 1976; Jensen 1996; Coppin et al. 2004; Lu et al. 2004; Joshi et al. 2011; Amare 2016).

The periodic alteration in land topographies—owing to natural or anthropogenic activities—is defined as LULC transformation (Amin and Fazal 2012; Mamtha et al. 2016). Depending on the requirement of regional habitat and environmental suitability, land endures uninterrupted change from the current practice to the alternative method (Kaliraj et al. 2017).

The main objective of the present work was to determine the factors that contributed to the transformation of each land class and assess the extent of change, in Alappuzha District, an ecologically fragile area in southern Kerala. Over the period from 1973 to 2017, geospatial technologies closely scrutinized the landform degradations in the study area, to derive an audited change in each of the LULC categories.

MATERIALS AND METHODS

Geo-Environmental Setting of the Study Area

Alappuzha, the smallest district of Kerala, was selected for the present study. It is well linked by waterways to different parts of Kerala. Alappuzha is on a landmass, between the wide Arabian Sea and network of rivers flowing into it. It is enclosed between 9°45′ and 9°51′ north latitudes and between 76°1′ and 76°45′ east longitudes, covering an area of 1414 km^2 (or 3.64%) of the state (Fig. 1). The Pathanamthitta and Kottayam districts to the east, Arabian Sea to the west, Ernakulam District to the north and Kollam District to the south (Central Ground Water Board 2013) circumscribe the Alappuzha District. Its population was 2,122,414, according to the 2011 census, with a population density of 1501 inhabitants/km^2, the highest among all districts of Kerala.

The Alappuzha District has a tropical humid climate with an oppressive summer. The annual average rainfall is 2965.4 mm (Central Ground Water Board 2013), and the temperature ranges from 20.5 to 35.5 °C (Indian Metrological Division). Demographically, the Alappuzha District covers both urban and rural settlements. The River Pampa and its tributaries constitute the main drainage system for the district. The drainage density varies between 0 and 6 km/km^2. The slope of the district ranges between 0° and 37.71°, and the elevation varies between 0 and 119 m, above mean sea level.

The predominant land formations of this area are recent alluvium, sub-recent laterites, tertiary sedimentary formations and Archean crystalline formations (charnockite, gneiss). The geomorphology of this area consists of alluvial plain, coastal plain, lower plateau (lateritic), marsh, pediplain and waterbody. The geology includes alkaline rocks, charnockite, migmatite complex, sand and slit, sandstone and clay with lignite and waterbody.

The soil of the area consists of clay, gravelly clay, loam and sandy. The main crops in the district are paddy, coconut, rubber, tapioca, plantains and other banana. The major land use classes of this district include waterbody, waterlogged area, mixed vegetation, built-up land, uncultivated area, paddy field and sandy area. The stream pattern of the study area falls in the fourth order. The main crops in the district are paddy, coconut, rubber, tapioca, plantains and other banana.

Land Use/Land Cover Change Assessment Method

The current study was performed to assess variations in LULC classes, in the Alappuzha District, using geo-informatics and RS. The online portals, Global Land Cover Facility (GLCF) and Earth Explorer, were used to obtain Landsat MSS, with spatial resolution of 60 m, and Landsat 8 images, with spatial resolution of 30 m, for the years 1973 and 2017 respectively. The land use maps were prepared using the RS software: ERDAS IMAGINE 9.2. The images were enhanced, registered, geo-referenced and classified into various through supervised classification of land use types. Later, geometric improvement and data validation were performed using auxiliary data from topographic maps and Google Earth images.

The geometric modification of the imagery resamples the pixel grid to fit to a map projection to other reference image (Kaliraj et al. 2017). In order, to adapt the pixel grids and to remove the geometric alterations, Landsat images were registered and geo-referenced to the Universal Transverse Mercator (UTM), World Geodetic System—WGS 84, 43 N coordinate systems, based on the topographic maps of 1:50,000 scale. To retain the same brightness values of the unaffected pixels, the data were resampled using the algorithm of a nearby pixel. This algorithm takes the preset value of the adjoining pixel and allocates it to the value of the output pixel, thereby relocating the original pixel values, without averaging, so that the subtleties and extremes of the pixel values are not lost (ERDAS Field Guide 1999).

The supervised classification procedure makes a preliminary assessment of areas on the image that delineate land parcels to be mapped. We identified samples of the information classes of interest (i.e., land cover types), in an image. These are called ''training sites.'' In ERDAS Field Guide (1999), training sites are sets of pixels that characterize what needs to be documented as a visible pattern or a prospective land cover class. From the ground truth data, used in this study, the training sites for the signature generation were developed. Each image was based on 50 training sites, to ensure that all spectral classes, representing each LULC category, were sufficiently characterized in the training indicators. The image processing software system was used to develop a statistical characterization of the reflectance, for each information class. This stage, often known as ''signature analysis,'' involves either
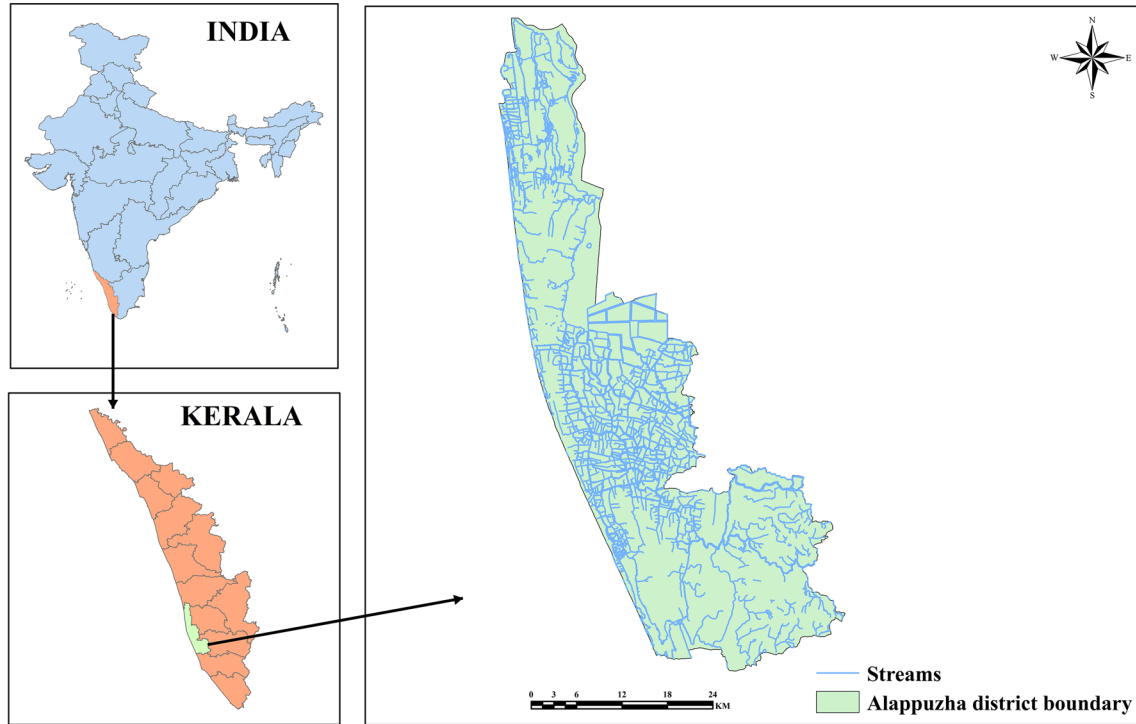
STUDY AREA

Figure 1. Location map of the study area.

the development of a statistic, such as the mean or the range of reflectance, on each image band, or detailed analyses of the mean, variances and covariances over all bands. Once a statistical characterization has been achieved for each information class, the image is then classified by examining the reflectance for each pixel and correlating with the signatures it resembles most (Eastman 2003). Finally, the classified images of the seven LULC classes, namely waterbody, waterlogged area, mixed vegetation, built-up land, uncultivated area, paddy field and sandy area, were then re-coded, clumped and eliminated with the help of ERDAS 9.2 application software. MLC is a statistical decision criterion to assist in the codification of overlapping signatures.

Information on the LULC transformations serves as the vital starting point for the management of coastal resources and assessment of coastal vulnerability. A well-designed methodology was adopted for the current study (Fig. 2). The technical details of Landsat images are given in Table 1.

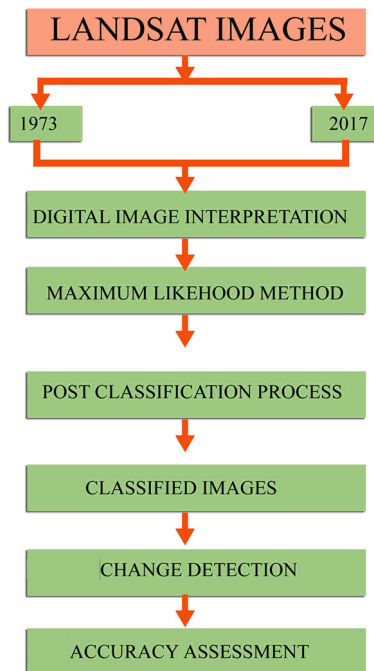The mangroves and their surrounding LULC in Kakinada Bay have been identified, using the

Figure 2. Flowchart of the methodology applied.

supervised MLC classification method of satellite data, from four different times (1977, 1988, 2000 and 2005). A change analysis, conducted among the nine LULC classes, revealed that the various classes had divergent trends of change, through the four decades (1973–2017). The same methodology was adopted in discovery of the LULC alterations.

The accuracy assessment is the essential procedure of feature abstraction from the classified images. Lea and Curtis (2010) reported that accuracy assessment highlights the probable root cause

of faults, in a classified image, thereby improving the accuracy of the interpreted information. The overall accuracy shows how an individual pixel is categorized against the individual land cover situations, attained from the corresponding ground truth data. Bradley (2009) cautioned that none of the image sorting could be assumed complete, until its accuracy has been evaluated. It is significant to certify the accuracy of the materials used in the decision method through the pre- and post-field ground truth confirmation, existing warranty evidence and the statistical study (Foody 2010; Huang and Hsieh 2012).

The standard method for the evaluation of the correctness of a classified image is the "error or confusion matrix" (Ahlqvist et al. 2000; Foody 2002; Mujabar and Chandrasekar 2013). This method allows the comparison of pixels of a classified image to the corresponding pixels of a referenced image, whose class is known (Smith et al. 2003; Szuster et al. 2011). Based on the error of omission and commission, there are three different scales used in the

Table 1. Technical details of Landsat images for the years 1973 and 2017

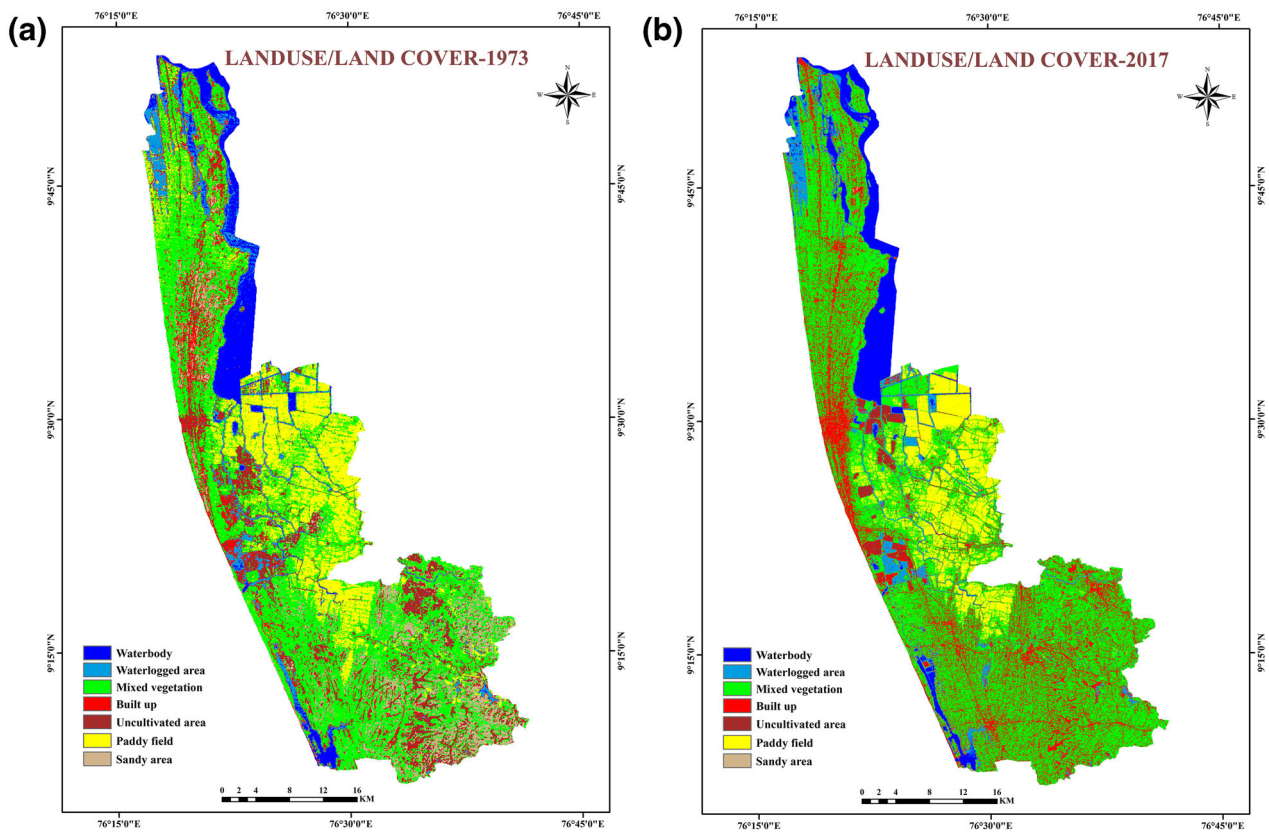| 1973 Images	2017 Images
Path 155 Row 53	Path 144 Row 53
Acquisition date: Feb 10, 1973	Acquisition date: Jan 18, 2017
Path 154 Row 53	Path 144 Row 54
Acquisition Date: Feb 9, 1973	Acquisition date: Feb 3, 2017
60 × 60 m resolution	30 × 30 m resolution

Figure 3. Land use forms in the study area for the years (**a**) 1973 (**b**) 2017.

calculation of the accuracy, in an error matrix: user's accuracy, producer's accuracy and overall accuracy (Coppin and Bauer 1996; Carlotto 2009). The other measurement in the image classification method is the Kappa coefficient, which is used to quantify the classification accuracy required for all elements, including the diagonal ones (Coppin and Bauer 1996; Foody 2010).

In the current study, for the purpose of accuracy assessment, 100 samples were identified, for the years 1973 and 2017. We adopted a stratified sampling method, where a minimum of ten ground truth data points were obtained, from the field, for each LULC class, using a GPS (Global Positioning System) instrument.

RESULTS

The land use maps were prepared by using Landsat MSS for the year 1973 and Landsat 8 ima-

gery for the year 2017 (Fig. 3). The estimated values of the overall accuracy, for the classified images, were 77% and 74%, for the years 1973 and 2017, respectively. The complete Kappa coefficient values were 0.7353 and 0.6926 (Table 2).

The Alappuzha District (1414.24 km^2) includes various classes of land use: waterbody, waterlogged area, mixed vegetation, built-up land, paddy field, sandy area and cultivated land. The total area in km^2 and the percentage for each land use class, for the years 1973 and 2017, were calculated for the analysis (Table 3). The pie chart depicts the area distribution/land utilization, for each land use class in Alappuzha District for 1973 and 2017 (Fig. 4).

The percentage changes of the land use classes, over the period from 1973 to 2017, were computed. From this, it is clear that the built-up land, mixed vegetation and waterlogged area show an increase in their distribution from 1973 to 2017. The yearly changes are represented by a bar chart (Fig. 5). The results computed based on these years are as follows:

Table 2. LULC category-wise assessment of accuracy and statistical parameters for the years 1973 and 2017

LULC class name	Producer's accuracy (%)		User's accuracy (%)		Kappa coefficient	
	Year					
	1973	2017	1973	2017	1973	2017
Waterbody	0.73	0.80	0.80	0.80	0.77	0.77
Waterlogged area	0.64	0.90	0.70	0.90	0.65	0.88
Sandy area	0.80	0.45	0.80	0.45	0.77	0.36
Uncultivated land	0.75	0.64	0.82	0.64	0.78	0.57
Paddy field	0.80	0.73	0.73	0.73	0.69	0.68
Mixed vegetation	0.92	0.85	0.85	0.85	0.82	0.81
Built-up land	0.78	0.80	0.70	0.80	0.66	0.77
Overall classification accuracy	0.77	0.74				
Overall kappa statistics	0.74	0.69				

Table 3. Land use statistics of Alappuzha District for the years 1973 and 2017

| Parameters	Year				Area in changes during 1973 and 2017 (km^2)
	1973		2017		
	Area (km^2)	% of the total area	Area (km^2)	% of the total area	
Waterbody	100.65	7.10	106.21	7.51	5.56
Waterlogged area	78.07	5.50	81.14	5.74	3.07
Paddy field	246.14	17.35	169.14	11.96	− 77.00
Uncultivated land	147.70	10.41	25.08	1.77	− 122.63
Mixed vegetation	620.27	43.73	774.01	54.73	153.74
Built-up land	107.65	7.59	256.78	18.16	149.13
Sandy area	117.93	8.31	1.89	0.13	− 116.04
Total area	1418.42	100.00	1414.24	100.00	

Negative value denotes the decline of area

(a)

(b)
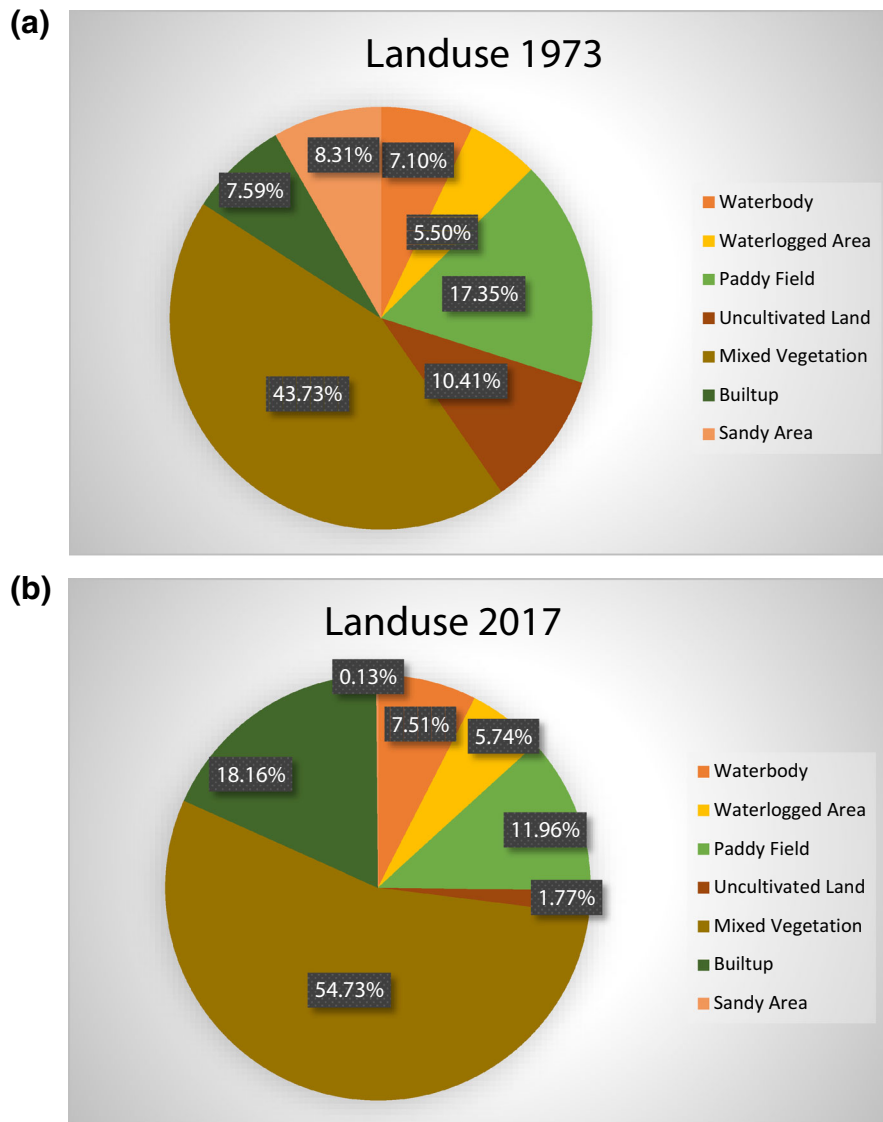
Figure 4. Pie chart showing the land utilization for each land use classes in Alappuzha District for the years (**a**) 1973 (**b**) 2017.

Built-up Land

It is clear from the map that there was an increase in the built-up land area from 6.59% in 1973 to 18.16% in 2017 (Fig. 6a). The census data show that the population of the study area in 1971 was 1,676,076, whereas in 2011 it was 2,122,414, which portrays a demographic growth of close to 27%.

Mixed Vegetation

Mixed vegetation includes residential vegetation such as coconut trees, plantains and other banana, herbs and shrubs. In 1973, the area of mixed vegetation was 620.27 km^2, which increased to 774.01 km^2 in 2017, a 10% increase in the complete land use form (Fig. 6b).
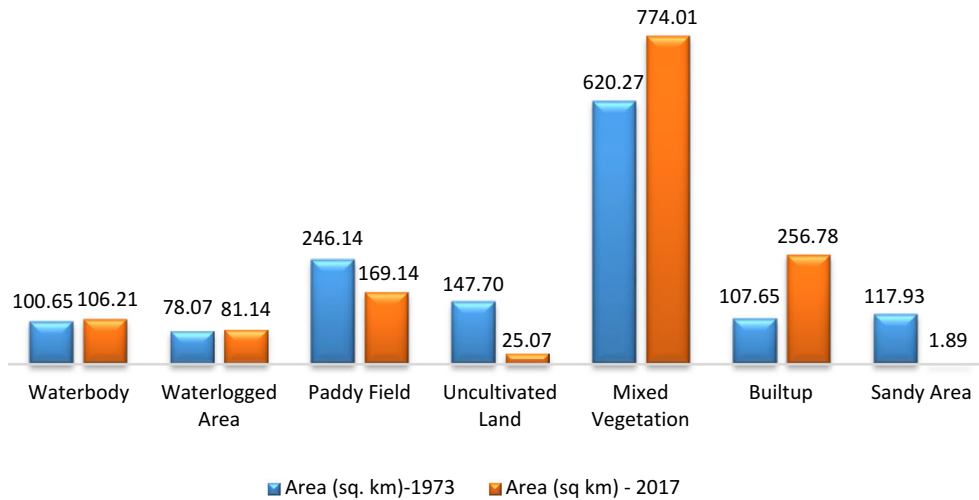
Figure 5. Change in area (km^2) in the years 1973 and 2017.

Paddy Field

There was not much reduction in the paddy field class. In 1973, it was 17.35%, whereas in 2017 it came down to 11.96% (Fig. 6c). Only Kuttanad area is retaining the paddy fields and keeping up the name ''rice bowl of Kerala.'' The paddy fields almost vanished in the southern and northern parts of the district.

Uncultivated Land

The uncultivated land area reduced from 10.41% in the year 1973 to 1.77% in the year 2017, which shows the effect of the mixed vegetation and uncultivated vacant lands being converted to built-up land (Fig. 6d).

Waterbody and Waterlogged Area

There was not much change in the waterbody and waterlogged areas (Fig. 6e and f). It is clear from Figure 6e that there was only a slight increase in the waterbody near the southwestern part of the district. Increase in the waterlogged area was at the outskirts of the city area, near Purakkad. The waterbody and the waterlogged areas enlarged from 100.65 and 78.07 km^2 to 106.21 and 81.14 km^2, respectively.

In this study, a mixture of bands of Landsat images was necessary to abstract the diverse landscape features, such as the coastal part, according to the report on LULC classification (www.landsat.usgs.gov). For instance, the grouping of bands 1, 4 and 5 was categorized for settlements, marshy salt and water bodies in the coastal area. Likewise, the collective image of band 3 and 4 was categorized for forest, cultivable lands and other normal vegetative cover (Chen et al. 2003). An accuracy assessment was performed to assess the reliability of the results.

Yirsaw et al. (2017) studied the ''Land Use/Land Cover Change Modelling and the Prediction of Subsequent Changes in Ecosystem Coastal Area of China'' and reported that built-up land expanded, extensively, at the expense of farmland, wetland and water bodies, validating the findings of our study.

DISCUSSION AND CONCLUSIONS

The accelerated growth of the built-up area, toward 2017, was due to the increasing trends in urbanization. There was a remarkable decrease in the sandy areas and uncultivated lands, during this time; it is clear that this can be attributed to built-up land and mixed vegetation. The sizeable increase in rural-to-urban human migration, toward district centers and the tourism development around Vembanad Lake, resulted in increased built-up land in the prime municipal areas of the Alappuzha District. In the southern part of the district, as well, there was
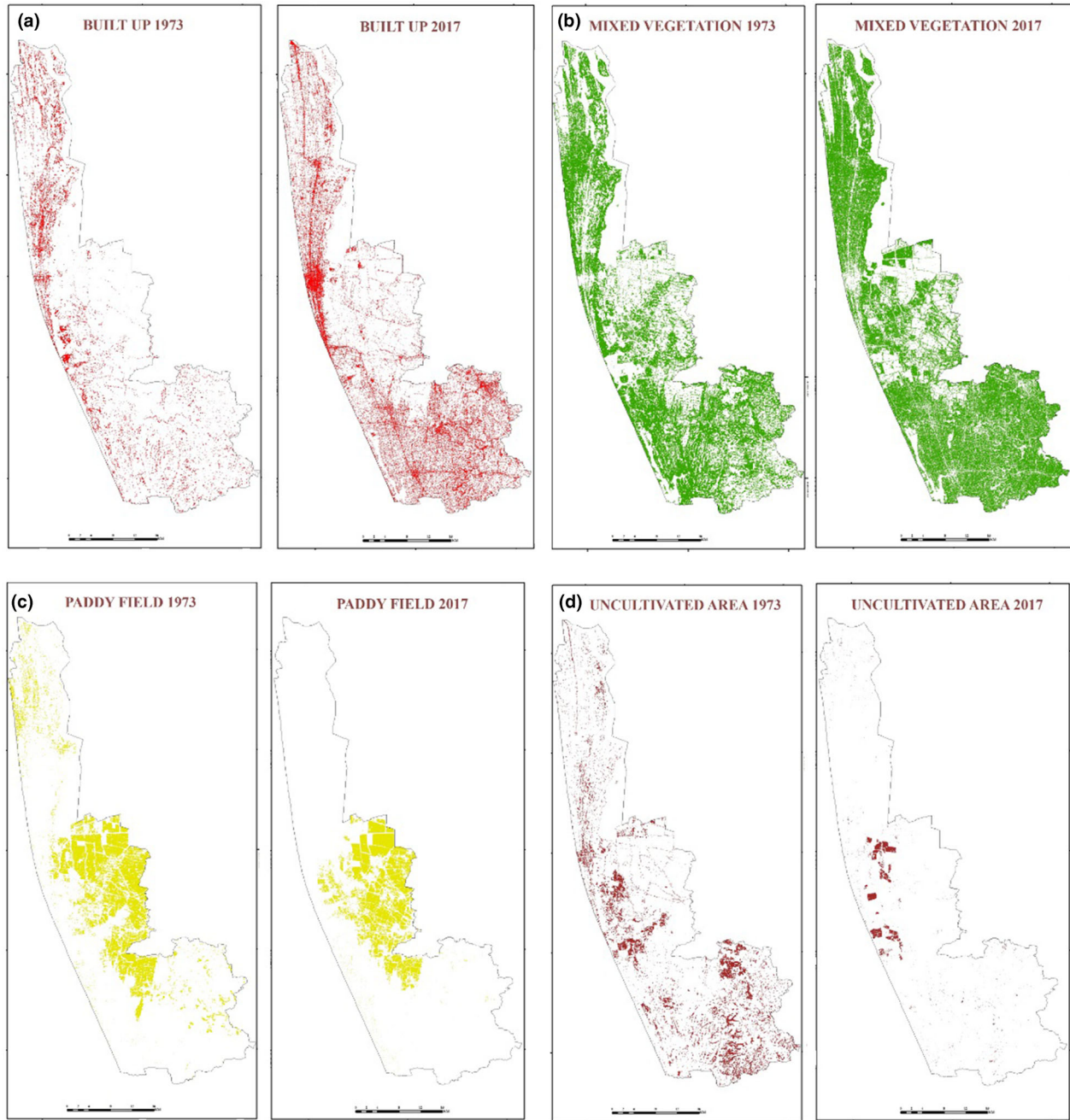
Figure 6. Synoptic view of different land use and land cover pattern (**a**) built-up land, (**b**) mixed vegetation, (**c**) paddy field, (**d**) uncultivated area, (**e**) waterbody, (**f**) waterlogged area.

a significant increase in built-up land, due to noticeable improvements in socioeconomic development. Four of the six municipalities in the Alappuzha District (Alappuzha, Cherthala, Kayamkulam, Mavelikkara, Chengannur and Haripad) are situated in the southern region, which jus-

tifies the rise in population density and built-up land in this region.

The upsurge in the built-up area is directly proportional to the growth of the population, which, in turn, disarrays the delicate environmental balance, by over-usage of natural resources, and exac-
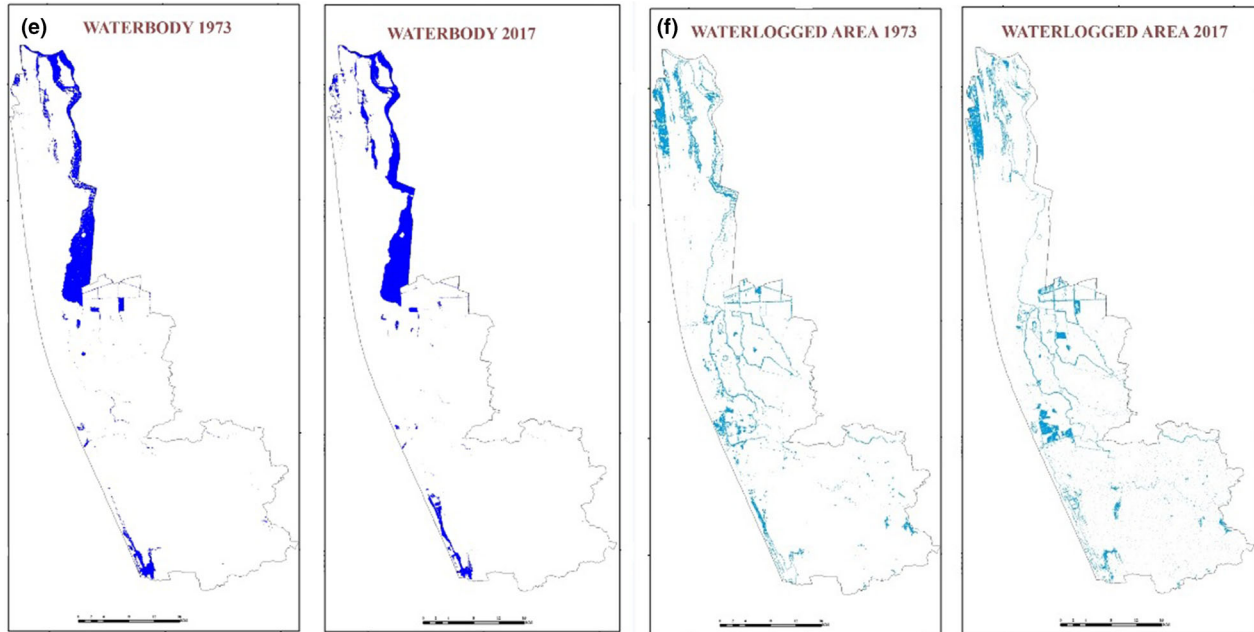
Figure 6. continued.

erbates waste management issues. As human systems are not a closed-loop system, they often negatively affect the ecosystems. The likely outcome will be increased pollution in air, water, land, etc., and loss of biodiversity.

With increases in human population, and the corresponding built-up lands, mixed vegetation also increased, as it is Keralite tradition to have plants, trees, herbs and other home-based cultivation for domestic usage, on their residential premises. This phenomenon was more conspicuous at the southern parts of the district. Based on the plan fund, for the productive segment, under Peoples Plan Campaign, Panchayats (local municipal/village council) promoted vegetable cultivation in their respective areas. Guided by *Grama Sabhas* (a group of native people, mentored by subject matter experts in respective domains), in 2006, a revolutionary movement was launched, across the state of Kerala, to create awareness of the hazardous side effects of pesticides, mainly in vegetables and fruits, which resulted in a decrease in the uncultivated area.

A well-conceived plan for the use of land is inevitable for harmonious ecological balance and sustainable development. A judicious land use plan should be established, focused on control of developed land that encroaches on paddy fields, water-logged area and water bodies. Tenets of ecological protection should be weaved into management of LULC, to preserve eco-friendly biodiversity.

Our work has just begun. We hope to use results of this study to draw the attention of urban and rural planners, toward judicious utilization of natural resources, for short-term gains and long-term self-subsisting development. Additionally, the present transformational findings can be further enhanced by the use of high-resolution satellite imagery, which allows the study of more classes of land use. These satellite images can be compared with aerial photographs of the region, in previous years, to attain a realistic representation of land use/land cover alterations.

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REFERENCES

Adams, J. B., DE Sabol, Kapos, V., Filho, R. A., Roberts, D. A., Smith, M. O., et al. (1995). Classification of multi-spectral images based on fractions of end members: Applications to land-cover change in the Brazilian Amazon. *Remote Sensing of Environment*. https://doi.org/10.1016/0034-4257(94)00098-8.

Afify, H. A. (2011). Evaluation of change detection techniques for monitoring land cover changes: A case study in new Burg El-Arab area. *Alexandria Engineering Journal, 50,* 187–195.

Ahlqvist, O., Keukelaar, J., & Oukbir, K. (2000). Rough classification and accuracy assessment. *International Journal of Geographical Information Science*. https://doi.org/10.1080/13658810050057605.

Amare, S. (2016). Land use/cover change at Infraz watershed by using GIS and remote sensing techniques, northwestern Ethiopia. *International Journal of River Basin Management*. https://doi.org/10.1080/15715124.2015.1095199.

Amin, A., & Fazal, S. (2012). Land transformation analysis using remote sensing and GIS techniques (a case study). *Journal of Geographic Information System, 4,* 229–236.

Avery, T. E., & Berlin, G. L. (1992). *Fundamentals of remote sensing and airphoto interpretation* (5th ed., p. 472). New York: Macmillan Publishing Company.

Bradley, B. A. (2009). Accuracy assessment of mixed land cover using a GIS-designed sampling scheme. *International Journal of Remote Sensing, 30*(13), 3515–3529.

Carlotto, M. J. (2009). Effect of errors in ground truth on classification accuracy. *International Journal of Remote Sensing, 30*(18), 4831–4849.

Caselles, V., & Lopez Garcia, M. J. (1989). An alternative simple approach to estimate atmospheric correction in multitemporal studies. *International Journal of Remote Sensing*. https://doi.org/10.1080/01431168908903951.

Central Ground Water Board. (2013). Ground water information booklet of Alappuzha district, Kerala. http://cgwb.gov.in/District_Profile/Kerala/Alappuzha%20.pdf. Accessed February 20, 2018.

Chen, J., Gong, P., He, C., Pu, R., & Shi, P. (2003). Land-use/land-cover change detection using improved change-vector analysis. *Photogrammetric Engineering and Remote Sensing, 69,* 369–379.

Coppin, P., & Bauer, M. (1996). Digital change detection in forest ecosystems with remote sensing imagery. *Remote Sensing Reviews, 13,* 207–234.

Coppin, P., Jonckheere, I., Nackaerts, K., & Muys, B. (2004). Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing, 25*(9), 1565–1596.

Eastman, J. R. (2003). IDRISI Kilimanjaro guide to GIS and image processing. https://www.mtholyoke.edu/courses/tmillett/course/geog307/files/Kilimanjaro%20Manual.pdf. Accessed February 25, 2018.

El-Asmar, H. M., Hereher, M. E., & El Kafrawy, S. B. (2013). Surface area change detection of the Burullus Lagoon, North of the Nile Delta, Egypt, using water indices: A remote sensing approach. *Egyptian Journal of Remote Sensing and Space Science*. https://doi.org/10.1016/j.ejrs.2013.04.004.

ERDAS Field Guide. (1999) *Earth resources data analysis system* (p. 628). Atlanta, Georgia: ERDAS Inc. http://web.pdx.edu/~emch/ip1/FieldGuide.pdf. Accessed January 12, 2018.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment, 80,* 185–201.

Foody, G. M. (2010). Assessing the accuracy of land cover change with imperfect ground reference data. *Remote Sensing of Environment, 114,* 2271–2285.

Huang, S., Hsieh, H. (2012). The study of the land-use change factors in coastal land subsidence area in Taiwan. In: 2012 International conference on environment, energy and biotechnology (IPCBEE) (Vol. 33, pp. 70–74). Singapore: IACSIT Press.

Iqbal, M. F., & Khan, I. A. (2014). Spatiotemporal land use land cover change analysis and erosion risk mapping of Azad Jammu and Kashmir, Pakistan. *The Egyptian Journal of Remote Sensing and Space Science, 17,* 209–229.

Jaiswal, R. K., Saxena, R., & Mukherjee, S. (1999). Application of remote sensing technology for land use/land cover change analysis. *Journal of the Indian Society of Remote Sensing, 27*(2), 123–128.

James, R. A., Ernest, E. H., John, T. R., Richard, E. W. (1976). Land use and land cover classification system for use with remote sensor data, geological survey professional paper 964. http://www.pbcgis.com/data_basics/anderson.pdf. Accessed February 20, 2018.

Jayappa, K. S., Mitra, D., & Mishra, A. K. (2006). Coastal geomorphological and land-use and land-cover study of Sagar Island, Bay of Bengal (India) using remotely sensed data. *International Journal of Remote Sensing*. https://doi.org/10.1080/01431160500500375.

Jensen, J. R. (1996). *Introductory digital image processing: A remote sensing perspective* (p. 318). Upper Saddle River, NJ: Prentice-Hall.

Joshi, C. M., de Leeuw, J., Van Duren, I. C. (2004). Remote sensing and GIS applications for mapping and spatial modelling of invasive species. In *ISPRS 2004*: *Proceedings of the XXth ISPRS congress: Geo-imagery bridging continents*, 12–23 July 2004. Istanbul, Turkey: International Society for Photogrammetry and Remote Sensing (ISPRS). https://webapps.itc.utwente.nl/librarywww/papers_2004/peer_conf/joshi.pdf. Accessed February 15, 2018.

Joshi, R. R., Warthe, M., Dwivedi, S., Vijay, R., & Chakrabarti, T. (2011). Monitoring changes in land use land cover of Yamuna riverbed in Delhi: A multi-temporal analysis. *International Journal of Remote Sensing, 32*(24), 9547–9558.

Kaliraj, S., & Chandrasekar, N. (2012). Spectral recognition techniques and MLC of IRS P6 LISS III image for coastal landforms extraction along South West Coast of Tamilnadu, India. *Bonfring International Journal of Advances in Image Processing*. https://doi.org/10.9756/BIJAIP.10028.

Kaliraj, S., Chandrasekar, N., Ramachandran, K. K., Srinivas, Y., & Saravanan, S. (2017). Coastal land use and land cover change and transformations of Kanyakumari coast, India using remote sensing and GIS. *Egyptian Journal of Remote Sensing and Space Science, 20*(2), 169–185.

Kawakubo, F. S., Morato, R. G., Nader, R. S., & Luchiari, A. (2011). Mapping changes in coastline geomorphic features using Landsat TM and ETM imagery: Examples in Southeastern Brazil. *International Journal of Remote Sensing, 32*(9), 2547–2562.

Lea, C., Curtis, A. C. (2010). Thematic accuracy assessment procedures: National Park Service Vegetation Inventory, version 2.0. Natural Resource Report NPS/2010/NRR—2010/204, National Park Service, Fort Collins, Colorado, USA. https://www1.usgs.gov/vip/standards/NPSVI_Accuracy_Assessment_Guidelines_ver2.pdf. Accessed February 24, 2018.

Lele, N., & Joshi, P. K. (2009). Analyzing deforestation rates, spatial forest cover changes and identifying critical areas of

forest cover changes in North-East India during 1972–1999. *Environmental Monitoring and Assessment, 156,* 159–170.

Lu, D., Mausel, P., Brondízio, E., & Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing, 25*(12), 2365–2407.

Mamtha, R., Jasmine, N. M., & Geetha, P. (2016). Analysis of deforestation and land use changes in Kotagiri Taluk of Nilgiris District. *Indian Journal of Science and Technology*. https://doi.org/10.17485/ijst/2016/v9i44/105326.

Misra, A., & Balaji, R. (2015). Decadal changes in the land use/land cover and shoreline along the coastal districts of southern Gujarat, India. *Environmental Monitoring and Assessment, 187,* 461.

Misra, A., Murali, R. M., & Vethamony, P. (2013). Assessment of the land use/land cover (LU/LC) and mangrove changes along the Mandovi–Zuari estuarine complex of Goa. *Arabian Journal of Geosciences, 8*(1), 267–279.

Mohammady, M., Moradi, H. R., Zeinivand, H., & Temme, A. (2015). A comparison of supervised, unsupervised and synthetic land use classification methods in the north of Iran. *International Journal of Environmental Science and Technology, 12*(5), 1515–1526.

Moscrip, A. L., & Montgomery, D. R. (1997). Urbanization flood, frequency and salmon abundance in Puget Lowland Streams. *Journal of the American Water Resources Association, 33*(6), 1289–1297.

Mujabar, P. S., & Chandrasekar, N. (2013). Shoreline change analysis along the coast between Kanyakumari and Tuticorin of India using remote sensing and GIS. *Arabian Journal of Geosciences, 6,* 647–664.

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.

Petit, C. C., & Lambin, E. F. (2001). Integration of multi-source remote sensing data for land cover change detection. *Journal of Geographical Information Science*. https://doi.org/10.1080/13658810110074483.

Prasad, G., Vinod, P. G., Shaleena, E. J. (2018). *AIP conference proceedings* (Vol. 1952(1), p. 020028), *international conference on electrical, electronics, materials and applied science*. https://doi.org/10.1063/1.5031990.

Rawat, J. S., Biswas, V., & Kumar, M. (2013). Changes in land use/cover using geospatial techniques: A case study of Ramnagar town area, district Nainital, Uttarakhand, India. *Egyptian Journal of Remote Sensing and Space Science, 16*(1), 111–117.

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.

Reddy, C. S., & Roy, A. (2008). Assessment of three decade vegetation dynamics in mangroves of Godavari Delta, India using multi-temporal satellite data and GIS. *Research Journal of Environmental Science*. https://doi.org/10.3923/rjes.2008.108.115.

Riebsame, W. E., Meyer, W. B., & Turner, B. L. (1994). Modeling land-use and cover as part of global environmental change. *Climatic Change, 28,* 45–64.

Shanmugapriya, E. V., Samhitha, S. V., & Geetha, P. A. (2016). Case study on the landuse pattern of Kanyakumari district using GIS. *Journal of Applied Geology and Geophysics*. https://doi.org/10.9790/0990-0404023641.

Smith, J. H., Stehman, S. V., Wickham, J. D., & Yang, L. (2003). Effects of landscape characteristics on land-cover class accuracy. *Remote Sensing of Environment, 84,* 342–349.

Szuster, B. W., Chen, Q., & Borger, M. (2011). A comparison of classification techniques to support land cover and land use analysis in tropical coastal zones. *Applied Geography, 31*(2), 525–532.

Wickware, G. M., & Howarth, P. J. (1981). Change detection in the Peace-Athabasca delta using digital Landsat data. *Remote Sensing of Environment, 11,* 9–25.

Yirsaw, E., Wu, W., Shi, X., Temesgen, H., & Bekele, B. (2017). Land Use/land cover change modeling and the prediction of subsequent changes in ecosystem service values in a coastal area of China, the SuXi-Chang Region. *Sustainability, 9*(7), 1204p.