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Elucidation of change detection techniques for land use and land cover mapping using the geospatial approach: a case study in Berhampore Block, Murshidabad district, West Bengal, India

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Abstract

Consistent and appropriate change detection of topographic features offers the framework for evaluating the links and interconnections between anthropogenic and natural processes for sustainable resource management. This investigation seeks to reveal the present land use/land cover and their transition pattern between 2009 and 2019 utilizing Landsat TM and Landsat 8 OLI imagery through the process of change detection techniques. ArcGIS v 10.8 and ERDAS Imagine v14 were utilized to interpret satellite imagery and analyze quantifiable information for land-use change estimation of the research region, Berhampore block. Maximum Likelihood Classifier (MLC), Raster-based analysis, Vector-based analysis, and Image Differencing have been used to evaluate the results of the transformation during the study period. The result indicates that during the period of 2009 and 2019, built-up, vegetation, and barren land have been increased while agricultural land and water bodies have been decreased. Finally, the study would also recommend the policymakers to keep an eye on the prevailing situation of present land use and land cover in order to preserve existing plants, prevent the uneven expansion of the built-up area, and protect the natural ecosystem.

Key words: Land use and land cover, pixel-based overlay, Maximum likelihood classifier algorithm, Berhampore, Image differencing.

Introduction

Change detection is defined as "the technique of finding differences in the status of an object or phenomenon by watching it at different times" (Singh, 1989). In simple words, the change detection procedure includes recognizing the changes of spatial location, assessing the transformation, and evaluating the change detection accuracy. Though detecting changes in satellite imagery is a complicated and time-consuming task, researchers have spent a great deal of time and effort creating various change detection approaches because it is a hot topic of research, with innovative approaches being created regularly. The detection of change in land use (LU) and land cover (LC) is significant because of their functional applications in a wide range of fields, notably degradation of forest, estimation of damage, disaster monitoring, rapid urbanization, planning, and land management, and so on. Land cover, in simple terms, refers to "the physical qualities of the surface of the earth as reflected in the arrangement of flora, water, soil, and other physical properties of the land, including those resulting from human activities such as settlement. The way humans and their habitat have used land is referred to as land use" (Rai et al., 2015). Land use and land cover change (LULCC) is a ubiquitous, fast-moving, and important mechanism, possibly the much more visible kind of worldwide environmental transformation because these emerge at different temporal and regional scales that are directly significant to people's everyday lives (CCSP, 2003).

The significant alterations in the contemporary situation of the earth's surface appear to be the result of human operations. Variations in the land area affect the energy, water, and biogeochemical processes on a local, national, and worldwide level, and such variations will eventually have an impact on the viability of environmental assets and socio-economic processes (Vescovi et al., 2002). Several cities in developing nations are confronted with the challenge of substantial urban growth as a result of the massive expansion in the human population and their activities. Due to increasing urbanization, the extent of arable land, forest, and water bodies has diminished, and also found declination in air and water quality in rising temperature and surface run-off signifies comprehensive environmental destruction (Mondal and Das 2018). That's why LULCC detection and their future trend assessment on a spatio-temporal scale is crucial for a deeper knowledge of landscape dynamics, as well as for optimizing natural asset use and reducing environmental effects on the government, non-government, and scientific communities (Dewidar 2004).

LULCC detection using remotely sensed imagery has been a matter of significant research efforts around the world (Rawat et al., 2015). Ahmadizadeh et al., 2014 had used an artificial neural network (ANN) and a post-classification technique to track land-use change in Birjand, Iran, and found that the ANN was extremely effective at classifying Landsat imagery with acceptable classification accuracy. Zaidi et al., 2017 applied the normalized differencing vegetative index (NDVI) and semi-supervised image classification to detect a change in the Kuantan Drainage Basin, Malaysia.To depict the urban expansion and its effect on agricultural fields and forestry in the Rawalpindi division, Iqbal et al., 2018 employed a vegetation index of differencing via an object-based and supervised classification model. Birhane et al.,2019 utilized a post-classification change detection approach to display the impact of geomorphologic variability on land use land cover (LULC) change in the Hugumburda national forest prioritized region, and discovered that rugged terrain, greater elevations, and a northeast facet were significant topographic features in controlling LULC changes. To get a quantitative knowledge of the spatial and temporal patterns of LULC, Alawamy et al.,2020 wielded a maximum likelihood supervised classification and post-classification comparison approach. Bhattacharjee et al., 2020 for categorization and validation of change detection of satellite images in a Northeastern wetland ecosystem of Bangladesh, used the normalized difference vegetation index (NDVI) and the modified normalized difference water index (MNDWI), followed by an unsupervised classification strategy and a post-classification comparison method.

Tewabe et al., 2020 applied classification comparisons of land cover statistics to study the periodic patterns of land-use trends and indicate significant movement of forestland to farmland and residential areas in the Lake Tana Basin, North West Ethiopia. Hao et al., 2021, used the maximum likelihood classification method and three-dimensional graphics to analyze the spatial dynamics of land cover on the Tibetan plateau, and he also stated that the change detection approach is now centered on three-dimensional dynamic change rather than the two-dimensional one that conventional LULCC detection methods detected. Vivekananda et al., 2021 had tried a post-classification contrast methodology based on the MLC technique to authenticate land-use variations by a survey of the topographical map of India and satellite imagery of different time frames and he also claimed that the post-classification contrast technique would have the best accuracy of classification. Li et al., 2021 employed an object-based and multi-temporal image analysis approach to detect LULC changes in the Tiaoxi watershed, and explained how this combination technique provides a robust and adaptable strategy to Land cover change monitoring that aids emergency response and government administration. Numerous researchers in India have conducted land use/land cover studies, particularly utilizing remote sensing data. Rahaman, et al.,2020 used Maximum Livelihood techniques with the combination of LST, NDVI, NDWI, and LAI (Leaf area index) to show the impact of LULC on the environment of Barddhaman district, West Bengal, India, and found that LST-NDVI and NDVI-NDWI have negative correlations, whereas LST and NDWI have no relationship.

Thakur et al., 2020 used the MLC pixelbased image analysis method to achieve variations on a pix el basis to investigate the LULC change on forest ecosystems, and he discovered that the Normalized difference Moisture index (NDMI) is positively associated with the enhanced vegetation index (EVI) and the Normalized difference vegetation index (NDVI). He also added that compared to other satellite vegetation indices, NDVI and EVI combined with NDMI seems to be the optimum indicator for monitoring vegetation/LULC dynamics. In addition, numerous techniques such as "spectral mixture analysis" (Adams et al., 1995; Roberts et al., 1998; Ustin et al., 1998), "the Li-Strahler canopy model" (Macomber and Woodcock 1994), "chi-square transformation" (Ridd and Liu 1998), "fuzzy sets" (Metternicht 1999, 2001), "artificial neural networks (ANN)"(Gopal and Woodcock 1996, 1999; Abuelgasim et al. 1999; Dai and Khorram 1999) and "multi-temporal composite image change detection"(Carmelo et al., 2012; Eastman and Fulk, 1993), "maximum likelihood classifier"(Islam et al.,2018; Kumar et al.,2012) "raster-based analysis", "vector-based analysis" and "image differencing"(Afify et al., 2011; Amin et al.,2017; Hoque et al.,2017) also used in different times by different scholars. Furthermore, there is no such thing as an ideal change detection technique, and it is questionable that one would ever be produced. But, despite the fact that they are among them, remote sensing and geographic information systems (GIS) are a powerful weapon for obtaining fast and reliable knowledge on landscape patterns and variations. Terrain transformations can be researched in a short amount of time frame and at a minimal expense using geospatial techniques (Vivekananda, 2021). In the current research, the Maximum likelihood classification approach (MLCA) has been adopted with the combination of Raster-based analysis, Vector-based analysis, and Image Differencing technique to generate multi-temporal land-use and land cover categorization, to highlight how the Berhampore block has changed and remain unchanged between the period of 2009 and 2019.

Study Area

The investigated region, Berhampore Block, situated at 24º 06ˈN and 88º 15ˈE, is an administrative division in Berhampore subdivision, Murshidabad district of West Bengal state, India. It is surrounded on the north by Murshidabad Jiaganj C.D Block, on the east by Hariharpara C.D Block, on the south by Beldanga C.D Block, and on the west by Nabagram C.D Block. The study area is comprised of an area of 314.19 square kilometers with 1 Panchayat Samiti, 17 Gram panchayats, 317-gram sansads (village Council), 144 Mouzas, and 124 inhabited villages. The Headquarters of this C. D Block is at Berhampore. Physio-graphically, the area lies in the long narrow river valley that is the Ganges Bhagirathi basin, split into two natural physiographic regions by the Bhagirathi river- On the west side, Rarh, and on the east side, Bagri. The elevation of this Block is 22 meters. Climatically, the study region enjoys tropical wet and dry climates, annual mean temperature is approximately 27℃ and receives roughly 1600 mm of rain each year on average. In terms of demographic point of view, Berhampore block has a total population of 378,830, with 94,861 men and 86,466 women. The decadal population growth from 2001 to 2011 was 17.95% in the study area (2011 census). Berhampore had a total population of 288,728 literates, with males accounting for 153,930 and females accounting for 134,798(2011 census). The gender disparity was 6.18 percent. The main religion of this C.D block is Muslim. Agricultural activities are still the primary occupation of this region. The map of study area is shown in figure 1

Materials and Methods

Database

Two separate periods were chosen for the exploration of varying types and patterns of land use and land cover in this study. The two multi-spectral satellite images of the same month, one is taken in 2009 from TM (Landsat Thematic Mapper) and another is obtained in 2019 through Operational Land Imager (OLI) by using United States Geological Survey (USGS) (http://earthexplorer.usgs.gov). Before the change analysis, all satellite imagery was generated and pre-processed using ArcGIS version 10.8 software and ERDAS Imagine version 14. The table 1 shows an overview of all Landsat images.

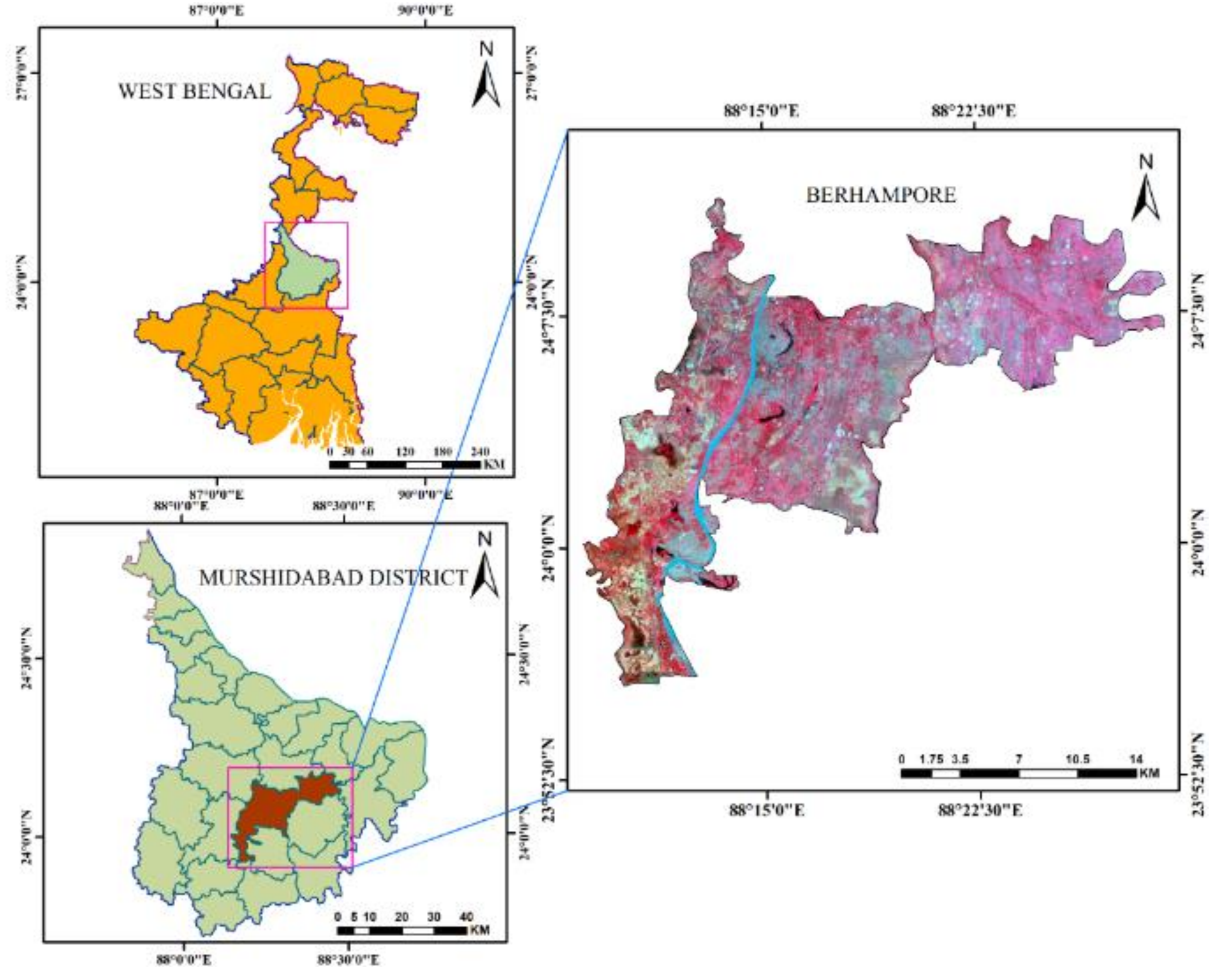

Figure 1: *Base map of the investigated region*

Table 1

Comprehensive information on the satellite imagery used during this investigation

Sr.no.	Satellite	Sensor	Path/Row	Acquisition Date	Spectral Band(s)	Spatial Resolution(m)	Wavelength (µm)
							(µm)
1.	Landsat-5	TM	138/043	01/10/2009	1	30	0.45-0.52
			139/043	24/10/2009	2	30	0.52-0.60
					3	30	0.63-0.69
					4	30	0.76-0.90
					5	30	1.55-1.75
2	Landsat-8	OLI/TIRS	138/043	30/11/2019	1	30	0.43-0.45
			139/043	21/11/2019	2	30	0.45-0.51
					3	30	0.53-0.59
					4	30	0.64-0.67
					5	30	0.85-0.88

Change Detection Technique

After downloading the satellite imagery, the images were improved spectrally and radiometrically during the pre-processing period. After that improved image were used for supervised classification using the maximum likelihood classifier (MCL) technique, with signatures gathered using the spectral response pattern of each land cover class as a reference. The density slicing technique was also used to capture the threshold pixel of a few classes. Then both the prepared land use/land cover imagery was overlapped after classification to determine pixel-based changes in the mainland cover classes. Then, both images were also compared in arc map using the raster calculator. After converting the raster LULC images into the vector, changes in Land use/Land-cover classes were evaluated utilizing vector data analysis techniques such as union, intersect, and symmetrical difference. Now, the above-discussed techniques used for showing change detection of land use and land cover elaborated in a broader perspective:

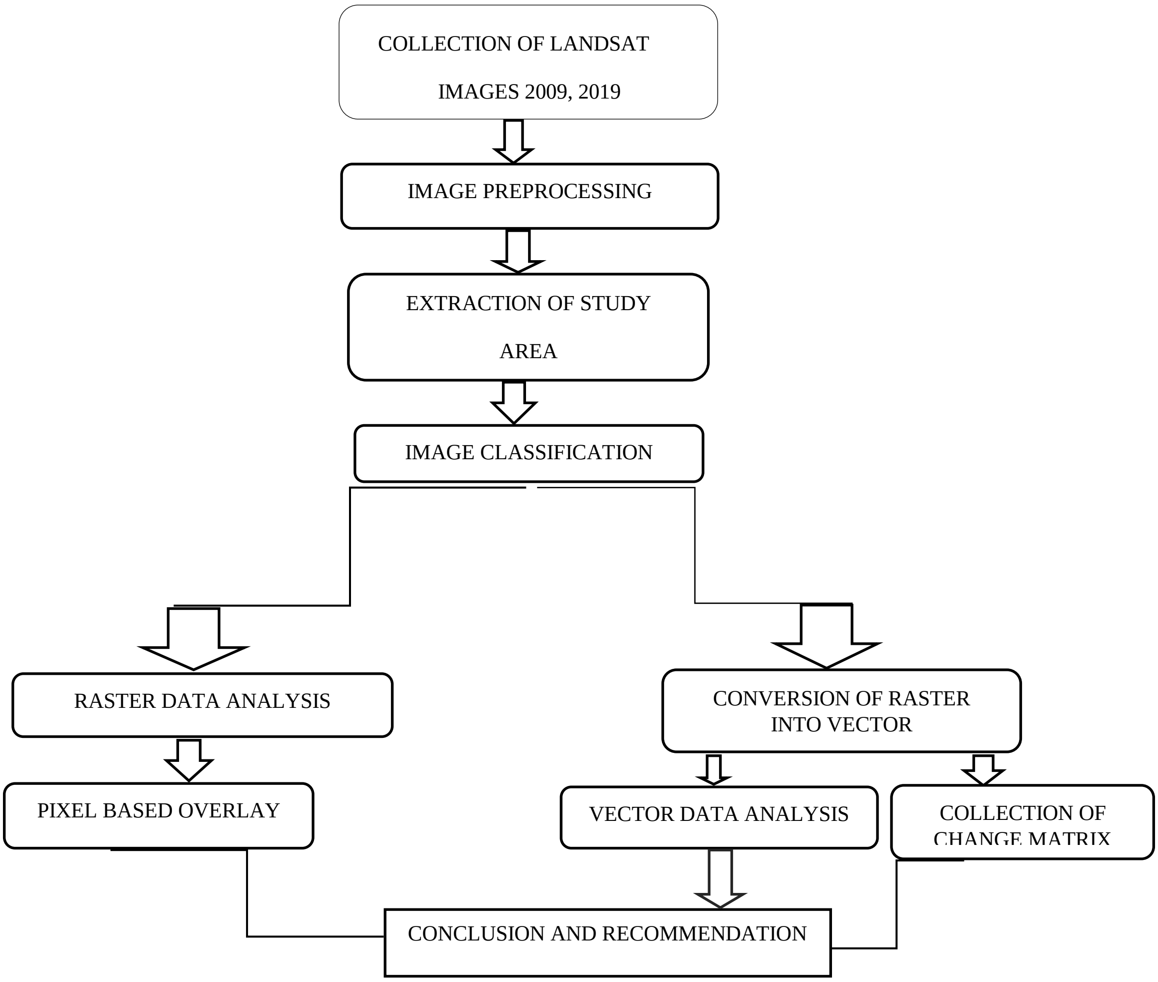

Figure 2: *Data analysis flowchart*

Preprocessing

In this process, the nearest neighbour approach was used to resample imagery from two separate years. Layer stacking was used for all of the bands. A few preprocessing enhancing techniques, such as histogram equalization and Pixel resample, were used to make it useful for future research. The required area was cut off with the subset tool, and the boundary polygon was converted from shape file to AOI to subset the image (Area of interest). The region was clipped based on the AOI, which was utilized to detect the properties of different band combinations.

LULC Classification Technique

The satellite imagery was processed appropriately and classified for further utilization. The maximum likelihood technique for supervised classification, the most popular approach for analyzing remote sensing image data, requires a collection of firsthand observations, aerial image interpretation, map assessment, and field survey to recognize and locate land cover types that are pre-defined, was employed in this study (Jensen, 2005). It is founded on the notion that the allocation of pixel values in each class is roughly characterized by a normal distribution whose parameters are digital values in each of the image's spectral bands. In general, most of a class's training pixels possess identical properties and are thus grouped in an extended cluster across space. The number of training pixels with the same value reduces as the distance from the cluster's centre grows. When categorizing unknown pixels, the Maximum likelihood classifier algorithm (MLCA) considers the grouping's variability and covariance, as well as the spectral response outline. Land utilization and land cover maps for the years 2000 and 2020 were created using these techniques for five classes depicted in figure 3.

Table 2

Land utilization and land cover classification

Land use/ cover class	Explanations
Agricultural land	It includes mono and multiple cropped area, irrigated area, and fellow land.
Barren land	Bare or exposed soil cover and open space.
Built-up area	Built-up territory in cities and rural areas, and residential, economic, and industry areas, as well as places with exposed soil due to natural or anthropogenic activities.
Water-bodies	River systems, lake, perennial surface water, reservoirs, and manmade water bodies
Vegetation	Land with scant or exposed flora, scrub, bushes, and aquatic plants.

Post-processing

After making categorization, a post-processing procedure must be employed. Post-classification enhances the outcome and supports us in the verification of our findings. To complete the post-processing stage, the current effort included class recoding and accuracy assessment was prepared. The recode option assigns a new class value number to any or all classes, resulting in the creation of a new thematic raster layer with the new class numbers. The accuracy assessment helps us to compare specific pixels in the thematic raster layer to known-class reference pixels. This is a method for comparing the classification to ground truth data that is well-organized. In this project, we're looking for accuracy and the reliability of the current work was assessed via Google Earth as the ground truth data. We can also say that the post-processing technique, in remote sensing helps to reduce the effect of atmospheric, sensor, and ambient variables' error one by one from already prepared multi-temporal images, also come up with a comprehensive matrix of transformed information.

Analysis Based on Raster Data

Raster based analyses is a method of change detection in which each pixel of land use land cover (LULC) map for two time periods are analyzed by overlapping both the images. In this study, a technique which is based on comparison of pixel was used to generate change information on a pixel-by-pixel basis and therefore analyze variations more effectively using "from, to" information (Rawat et.al).

Analysis Based on Vector Data

For calculating change detection, vector-based analyses enable the continuous evaluation of numerous image bands. The concept underlying this technique is that an individual pixel with changing values throughout time will be found in significantly various locations in the feature space (Jensen, 2005). The values of the pixel are represented as spectral band vectors, and the change vector (CV) is computed by deducting vectors for all pixels at various dates (Malia,1980). The magnitude of change refers to the size of the change vector, while the direction of change reflects the type of change. On the other hand, vector analysis may also be developed on changed data.

Image Differencing

In the image differencing method, the digital number (DN) values of two spatially enumerated images, attained at different periods, are deducted through pixel with pixel and band by band. If the difference between the digital number values is found zero that means there is no change between the images. In any case, if changes occur, that time it would be positive or negative. Sometimes, in this method, the differences can be found even when changes have not happened over the surface of the earth. Because of this reason, accurate registration of imagery and exact radiometric circumstances are never taken for satellite imagery, recorded at various dates.

Change Matrix

A change matrix is a technique that depicts the spatial pattern of alterations in LULC (Shalaby and Tateishi, 2007). Using this method, land utilization and land cover changes in the year of 2009 and 2019 was created by utilizing classified images of these two periods and the altered or change matrix was used to estimate overall changes in LULC classes.

Findings and Discussions

Identification of land utilization classification and evaluation of change using multi-temporal satellite data from 2009-2019

It was believed that the outcomes of the Berhampore block land-use modeling would offer information on the aerial pattern of land-use classification as well as assessment and quantification of LULC changes throughout the last ten years (Islam et al.,2018). Figure 3 depicts land use maps which were generated from various Landsat images. The horizontal significance of different land use classifications in 2009 and 2019, as well as their changing patterns across different periods, are demonstrated in table 3 and table 4. To fulfill the objective of this paper, satellite data were downloaded from USGS. The detailed various vector and raster data were created, interpreted, and analyzed. The maximum likelihood technique of supervised classification was used to create a land use /land cover map (Lu et al.,2004). The classified images are highlighted in figure 3.

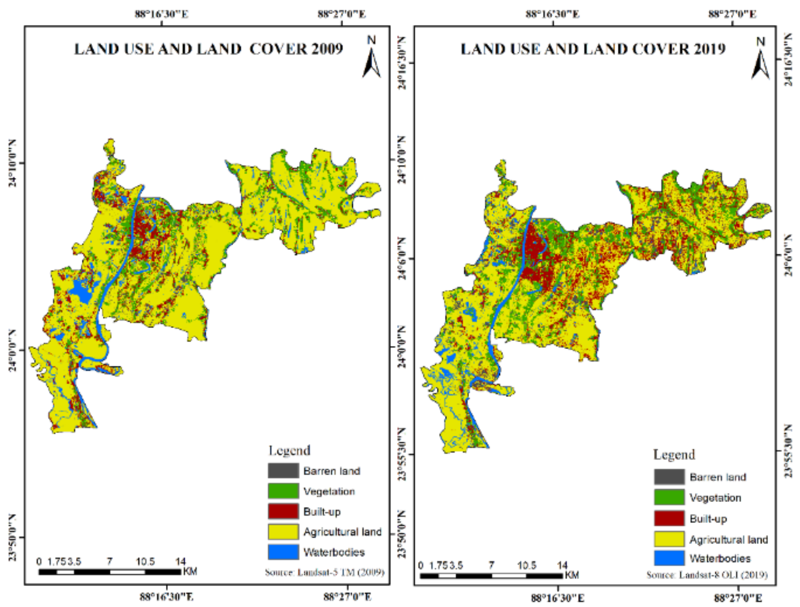

Figure 3: *Land Utilization and Land Cover*

From figures 3(A) and (B), it is found that most of the cover of land in the present area of research is covered mostly by agriculture and settlement, followed by vegetation. Some of its areas is also covered by water bodies and barren land. But the area covered by each class has a wide disparity in both the years.

Table 3: Dynamic pattern of each land utilization and land cover class

		Area (In Sq. Km.)		
Sr.no.	Class name	2009	2019	Change
1	Agricultural Land	220.51	181.44	-39.07
2	Barren land	6.37	13.82	7.45
3	Built-up	32.04	53.27	21.23
4	Vegetation	45.86	62.1	16.24
5	Waterbodies	28.53	22.68	-5.85

From table 3, it has been observed that area covered by agriculture has seen a decreasing trend, most of its area is converted into settlements as it is seen that the area under settlement has taken a great leap. The classes having a positive growth are settlement and vegetation and barren land. The area under the water body is also found to be decreasing. The changing pattern of the various land cover and land use classes can be shown precisely with the help of a change matrix. Change matrix calculates the area-wise change of land cover in the different time period.

Table 4

Change matrix of land use land cover

LULC 2019 (Square Kilometers)		LULC 2009(Square Kilometers)					
		Agricultural land	Barren land	Built-Up	Vegetation	Waterbodies	Grand Total
	Agricultural land	155.04	2.85	8.65	6.87	8.03	181.44
	Barren land	9.69	1.80	0.54	0.38	1.41	13.82
	Built-Up	28.22	0.82	15.15	6.94	2.14	53.27
	Vegetation	21.09	0.78	6.77	30.93	2.53	62.1
	Waterbodies	6.47	0.12	0.93	0.74	14.42	22.68
	Grand Total	220.51	6.37	32.04	45.86	28.53	333.31

After generating the land use land cover images for 2009 and 2019, both the images were overlaid and pixel-wise change was analyzed. The maps were created by overlapping each concerned land cover class keeping rest of the classes as hollow and increasing their transparency. From the classification, it was found that the land cover classes which have seen the maximum changes are agriculture, settlement, and vegetation. To find out the changed and unchanged area of each land cover class, a pixel-based overlay technique was used. The result of the latter was shown in figure 4.

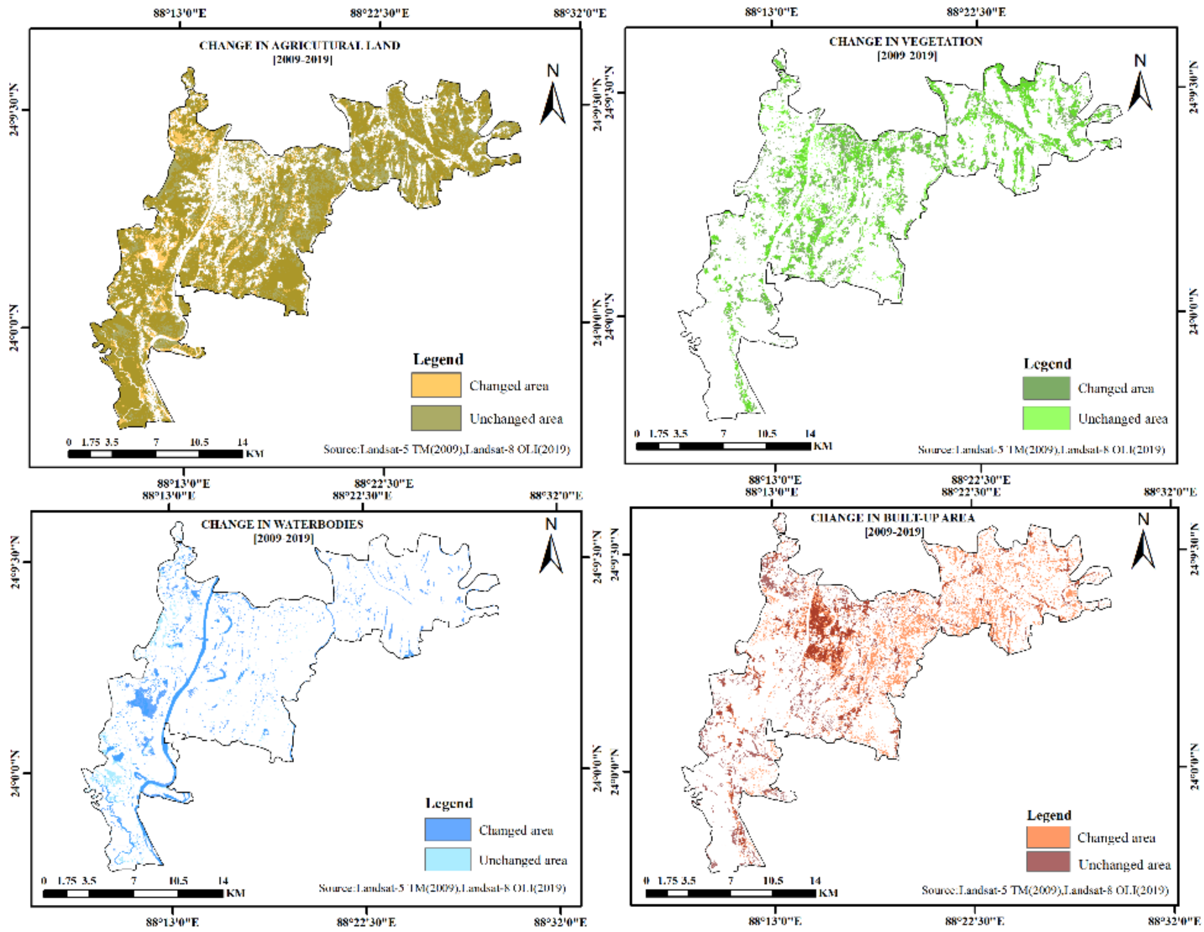

Figure 4: *Pixel Based Overlay or Raster data analysis*

To find out the changed and unchanged area, vector data analyses were also used. Vector data analyses use the geometric object of point, line, and polygon. The accuracy of analyses depends on the accuracy of these objects in terms of location and shape. There are many vector data tools available in ArcGIS like buffer, union, intersect, symmetrical difference, dissolve, update, etc. Some of these tools use bullion connectors and, or and zor. Vector data analyses have come up to be one of the most efficient yet simplest techniques to visualize the changes in the different temporal periods. Vector data analyses are comprised of various tools which work using the Boolean operators. For vector data analyses the images have to be converted into shape file format which is further used for various types of analyses. In the present work vector data analyses tools such as intersect, symmetrical difference, select, and clip were used to show the changes of major land cover classes. The final output is shown in figure 5.

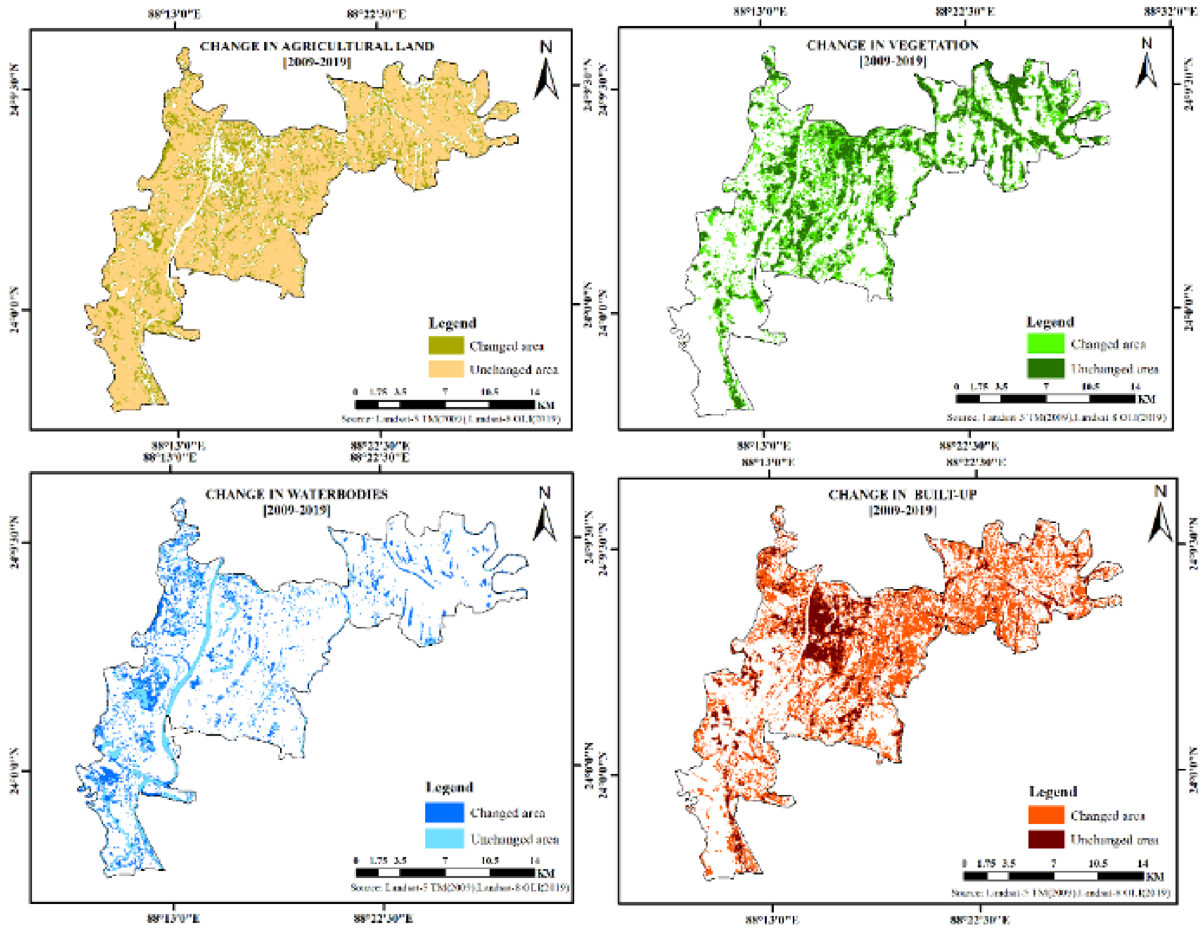

Figure 5: *Vector Data Analysis*

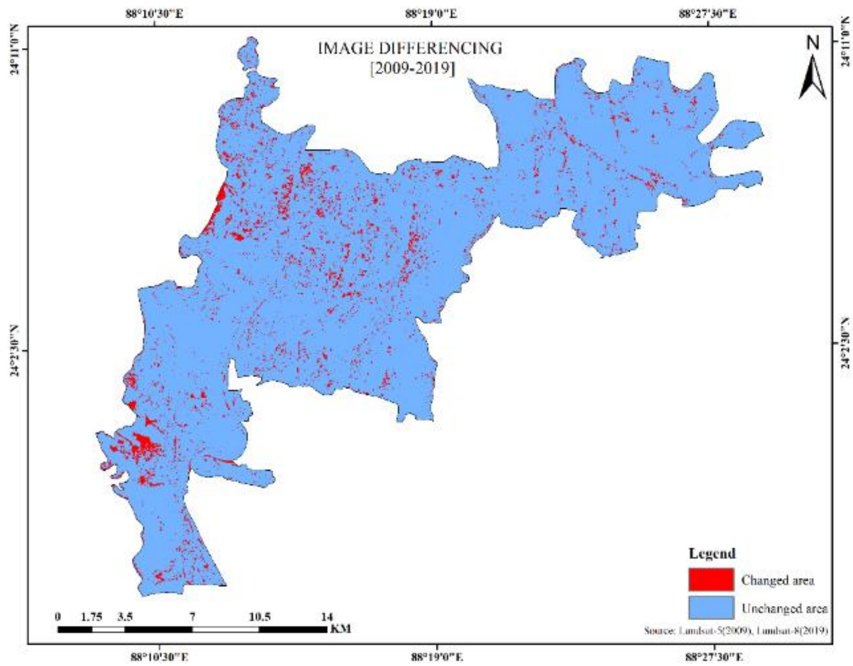

Figure 6: *Image Differencing*

Image differencing techniques are based on multivariate statistics to detect changes in a variety of ways. Cells are classified by utilizing image differencing based on spectral variations prior and posterior the events (Myint.et.al 2008). Image differencing involves the detraction of co-registered images from two separate dates, then applying a threshold value to create an image that depicts changes in land utilization and land cover. As previously stated, standard deviation values are commonly used to define threshold values. The percentage of no change may be enhanced if the standard deviation is lower. The best way to choose the right criterion is to consider how accurate it is to classify pixels as change or no change. The mean with a set of standard deviations can be used to establish the change/no change criterion values, or they can be determined proactively using a monitor and operator-controlled image processing software which is efficient for level slicing. Despite the fact that, this is a simple technique, it just identifies altered areas rather than defining the sorts of changes from one category to the next.

Conclusions

The investigation, which was carried out in one of the Murshidabad District's development blocks, West Bengal (India), shows that multi-temporal satellite imagery can help to quantify spatio-temporal features that are otherwise impossible to define it using traditional mapping methods (Rawat at al.,2015). The analysis finds that vegetation is the most common and major land cover in the studied area. Afforestation efforts between 2009 and 2019 increased the area under vegetation from 45.86 square kilometers to 62.1 square kilometers. The second important classification i.e., built-up land consumption, has increased from 32.04 square kilometers to 53.27 square kilometers in the research region, owing mostly to the expansion of the Berhampore town area throughout the study period. Then, agriculture is the third most prevalent land cover, with an area of 181.44 square kilometers, down from 220.51 square kilometers due to the transformation to vegetation, barren terrain, and built-up regions. In addition, the size of the waterbody shrank rapidly from 28.53 square kilometers to 22.68 square kilometers. Techniques include pixel-based overlay, raster-based analyses, vector-based analyses, image differencing, and image classification scheme enable change detection in less time, at a cheaper cost, and with greater precision. It can be inferred from this research that remote sensing and geographical information systems possess superlative approaches for monitoring the patterns of development and growth in any area.

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