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ORIGINAL ARTICLE

Assessment of land-use and land-cover changes in Pangari watershed area (MS), India, based on the remote sensing and GIS techniques

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Abstract

In this paper, we focus on the assessment of land-use and land-cover change detection mapping to the effective planning and management policies of environment, land-use policy and hydrological system in the study area. In this study the soil and water conservation project has been applied during the five years and after five years what changes have been found in the land-use and land-cover classes and vegetation. In this view, this land-use and land-cover mapping is a more important role to decide the policy for watershed planning and management project in the semiarid region. In an emerging countries, fast industrialization and urbanization impose a significant threat to the natural atmosphere. The remote sensing and GIS techniques are crucial roles in the study of land-use and land-cover mapping during the years of 2007, 2014, and 2017. The main objective of this is to prepare the land-use and NDVI maps in the years of 2008, 2014 and 2017; these maps have prepared from satellite data using the supervised classification method. A normalized difference vegetation index map (NDVI) was done by using Landsat 8 and LISS-III satellite data. NDVI values play a major role in monitoring the vegetation and variation in land-use and land-cover classes. In these maps, four types of land are divided into four classes as agriculture, built-up, wasteland, and water body. The results of study show that agriculture land of 18.71% (158.24 Ha), built-up land of 0.62% (5.31 Ha), wasteland of 40.33% (341.02 Ha), and water body land of 17.39% (147 Ha) are increased. Land-use and land-cover maps and NDVI values show that agriculture land of 22.97% (194.29 Ha), 5.46% (14.59 Ha), and 0.08% (0.22 Ha) decreases during the years of 2008, 2014, and 2017. The results directly indicate that the supervised classification method has been the accurate identified feature in the land-use map classes. This classification method has been given the better accuracy (95%) from spatiotemporal satellite data. The accuracy was also tally with ground-truth and Google earth information. These results can be a very useful for the land-use policy, watershed planning, and management with natural resources, animals, and ecological systems.

Keywords Geospatial · RS · GIS · Satellite data · NDVI

Introduction

In the earth, environment and atmosphere are very sensitivity systems, but the system has been damaged due to various activities by natural and human with one more factor being climate change (Coppin et al. 2004). Land-use and land-cover changes are directly distrusting the natural resources and ecological system balance (Verburg et al. 2004). The study of LULC features such as forestry, wasteland, agriculture lands to wasteland and water body areas rise the resistant of the Earth surface area; these classes have changed the hydrological system, which raise the amount of earth surface runoff and decrease the replacement of groundwater (Caselles and Lopez Garcia 1989; Moscrip and Montgomery 1997). The land-use change classes are being regularly impacted on the ecological, cultivated and biodiversity land, particularly in the dry regions. For example, the LULC monitoring variations have been found due to village-level planning and micro-watershed development, LULC is regularly changed in the land-use and land-cover classes, and all these changes have effect on the surface runoff, decreased groundwater level, water and soil pollutants (Aydinoglu and Gungor 2010 and Pande and Moharir 2014). Thus, the changes of

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LULC pattern have been considered to effect on the groundwater quality contents and climate parameters (Osborne and Wiley 1988; Basnyat et al. 1999; Roth et al. 1996; Chapin et al. 2000, Lu et al. 2004 and Vijith and Satheesh 2007).

Land-use class is a most important to a new inventory regarding the past and current natural resources. These past and current data can be more useful to researchers, land-use policy, and societies (Suresh et al. 2011). The changes of land-use patterns were based on natural and socioeconomic issues driving the strength. These changes are day by day increasing the population rate since the large population has been leading to increase the pressure on the environmental, sustainable practices, and planning of the urban area, agricultural land. One of the major factors is drinking freshwater sources, which those factors subsequently contribute to changes of land-use and land-cover classes and pattern (Pande 2020a and 2020b). Mishra 2017 investigated the runoff and soil loss under various land-use practices through remote sensing and GIS technology, and this study has been helpful to the development of the Himalayan Watershed, India. Hua 2017 studied on the land-use and land-cover change detection impact on the water quality using remote sensing and multivariate statistics analysis.

Satellite technologies have been a more significant role in the geographic mapping, analysis of datasets, storing, capturing, and integrated database; hence, this technology is very important to display the natural resources and ecological information of past and present (Chilar 2000; Donnay et al. 2001; Chan et al. 2001; Selcuk et al. 2003; Lo and Choi 2004; Rogan and Chen 2004; Chander et al. 2009; Fichera et al. 2012; Ceccarelli et al. 2014; Chaitanya Pande 2014; El Bastawesy 2014). Nowadays, so many researchers and scientists studied the land-use and land-cover changes and more significant things that cultivated the land shifted to waste and other lands due to drought situations in the globe surface. Hence, the satellite data and decision-maker software tools should be needed to analysis, report, and regularly monitoring issues related to the ecosystem, water, soil and eco-friendly development, and planning (Hassan 2015). Mona Allam et al. (2018) studied on the land-use and land-cover variation and analysis based on the MLC and NDVI techniques and landsat satellite data in the semiarid and arid regions. Geospatial technologies are more effective technologies for regularly checking the multitemporal classification of variations in the land-cover and land-use classes (Kachhwala 1985; Brondizio et al. 1994; Jensen 2005; Bakr et al. 2010; Ahmad and Quegan 2012). RS and GIS technology have been given a chance to complete the insights like the spatiotemporal data of land-use maps. Those technologies have been globally approved for accurate judgement by scientific society (Prasad et al. 2018; Mishra et al. 2020). Accuracy data and changes of land-cover classes are found by ENVI and ARC-GIS software (Mohammady et al. 2015). As a substance of reality, the ground data were used as an information engine for grouping the signature samples' pixel numbers in satellite images and processed through supervised classification tools (Iqbal and Khan 2014). The important objective of this paper was to enclose the land-use parameters that contribute to the conversion of every land-use class and measure the changes during years of 2008, 2014, and 2017 in the Pangari watershed area.

Objective

(1) To identify of LULC classes and classify using classification methods and satellite images.
(2) To prepare the NDVI and LULC maps for change detection analysis during 2007, 2014, and 2017 years.
(3) To assess the accuracy of LULC classes to understand the error matrix in mapping.
(4) The result of study can be useful to watershed development and land-use policy in the watershed area.

Study area

The Pangari watershed is located in Tq. Mehakar of Buldhana Districts in Maharashtra of India, which lies between 20°4′ 00″ N latitude and 76°6′ 00″ E longitude. The climate of the watershed is humid in the subtropical region. However, coldest months are October to January of the watershed area; the winter seasons of minimum and maximum temperatures were found between 8 to 15 °C, respectively. The watershed area is under the dry land agriculture zone so the total agriculture land depends on the rainwater and groundwater. So, particular agriculture crops are affected and decrease the crop yield production. Hence, land-use change is a very important to the development of hydrological process system and agriculture perspective (Fig. 1). Total annual rainfall is 750 to 900 mm by Dr. PDKV, Akola. The area is situated nearby forest and hilly regions. It is a very critical issues that have been facing LULC in the semiarid region. The clay, gravelly, and sandy soils were observed in the watershed area. The soybean, cotton, sorghum, chickpea, and wheat crops are found in the watershed area. The watershed area farmers are much more familiar with rainfed crops. The waterbody, agriculture, and other vegetation, built-up land, and wasteland area are most important to sustainable development and conserve the natural resources.

Material and methods

LULC classes are classified from satellite images by classification methods. LISS-III and Landsat 8 satellite images with a spatial resolution of 23.5 m and 30 m during the years of 2008, 2014, and 2017 were collected by Bhuvan web-based

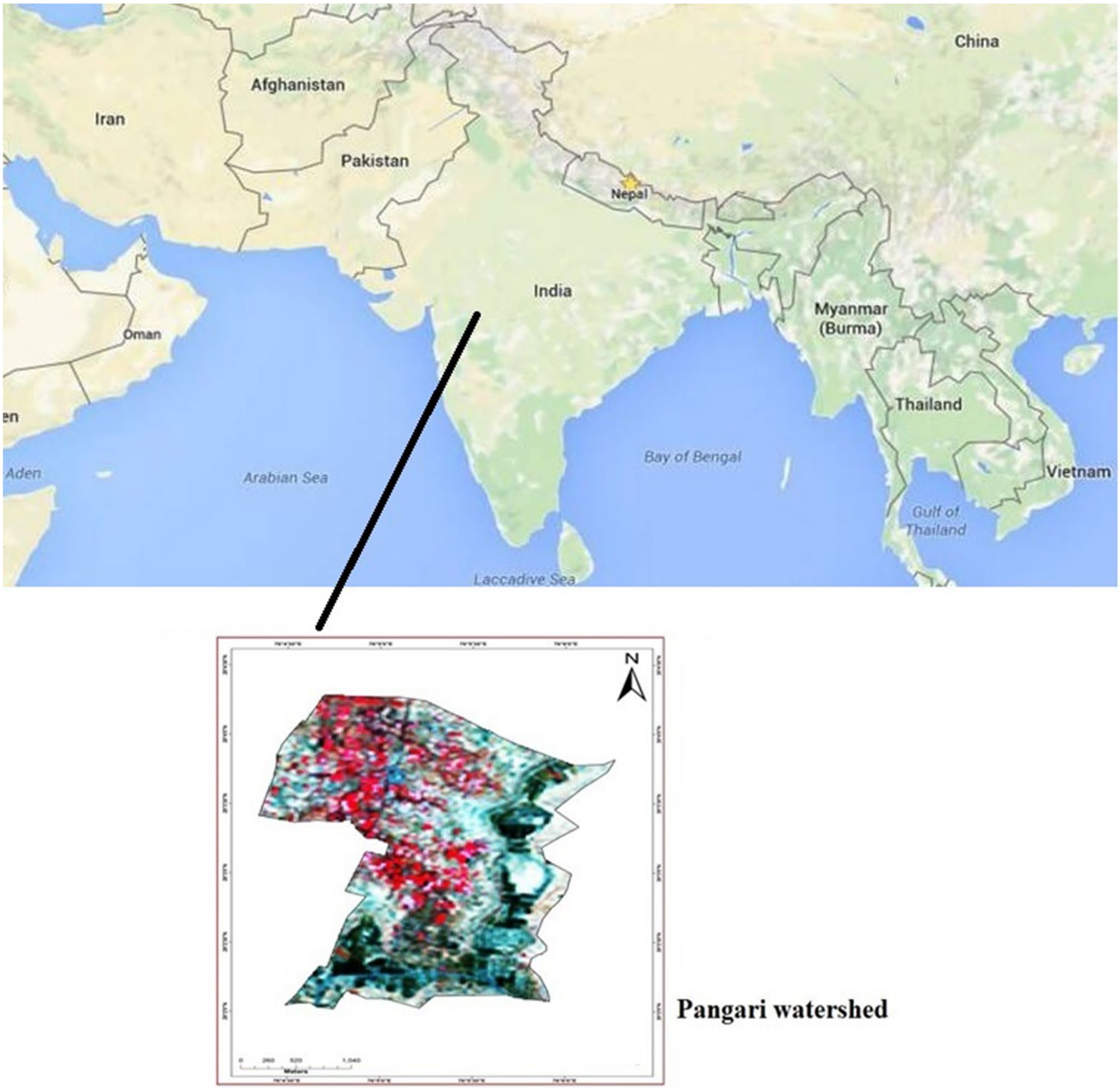


Fig. 1 Location map of Pangari watershed

portals and Earth Explorer sites. These satellite images were calculated by assigning per-pixel signs and dividing the area into four classes on the bases of the specific digital number (DN) values of changed landscape elements. The three years of land-use and land-cover maps were prepared by Arc-GIS 10.3 software. LULC classification methods were done by using the supervised classification method (Table 1). The land-use and land-cover maps were cross-verified with the ground-truth information with high-resolution images. The five classes were classified such as water body, agriculture,

Table 1 Satellite data specifications

Data	Year of acquisition	Bands/colour	Resolution(m)	Source
IRS-LISS-III	2008	Multispectral	23.5	www.bhuvan.in
Landsat ETM$^+$	2014 and 2017	Multispectral	30	www.earthexplore.com

Table 2 Details of land-cover results during years of 2008, 2014, and 2017

Land-use/land-cover classes	2008		2014		2017	
	AREA (Ha)	Area (%)	AREA (Ha)	Area (%)	AREA (Ha)	Area (%)
Wasteland	244.28	28.89	329.50	38.96	341.02	40.33
Built-up land	3.89	0.46	4.63	0.54	5.31	0.62
Agricultural land	597.34	70.64	369.13	43.65	352.53	41.68
Water body	–	–	103.75	12.75	147.04	17.39
Total area	845.53		845.53		845.53	

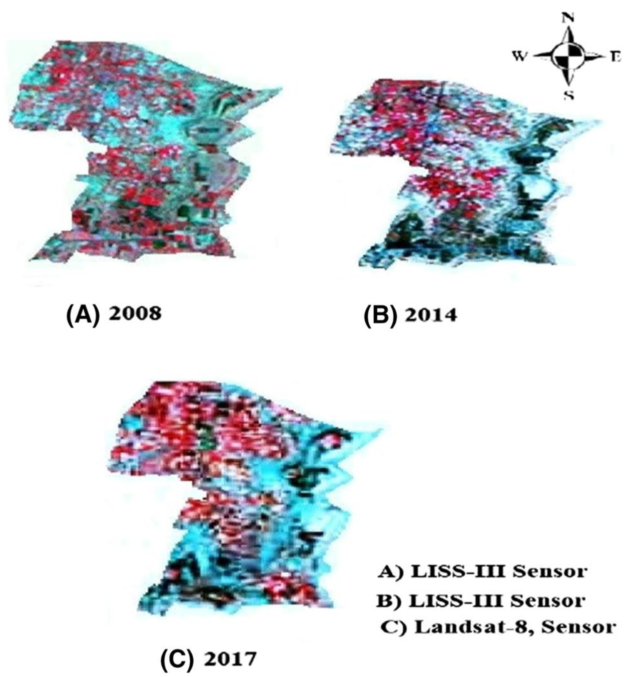


Fig. 2 LISS-III and Landsat images for the study area

other vegetation, built-up land, and wasteland area (Table 2). Land-use and land-cover maps were prepared and cross-checked with ground-truth samples. Another type of information was supplementary data, which added the data from field encounters to check the LULC classes. The information was supplemental. The geographic positioning system gathers and geographically references 100 points of ground truth (GPS).

NDVI (normalized difference vegetation index) maps during the years of 2008, 2014, and 2017 were estimated from LISS-III and Landsat satellite images (Fig. 2). The normalized difference vegetation index (NDVI) maps were measured during the years of 2008, 2014, and 2017 using Raster calculator tools of spatial analysis. The NDVI values were based on the ratio among both bands that are extremely delicate to the green biomass; it is demarcated as.

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{R})/(\mathrm{NIR} + \mathrm{R})$$

NIR is the near-infrared band, and R is the red band. For LISS-III 4 and 2, the NIR and R bands are 4 and 2, respectively, whereas, for Landsat 8 the NIR and R bands are 7 and 4. During the calculation of the NDVI values, the output is shown on greyscale raster map with index ranging from 1 to -1. As per requirements, we can change the colours in NDVI map.

Change detection

Land-use change detection and analysis maps were done by using the supervised classification technique and ArcGIS 10.3 Software. Various satellite image classification is mostly measured by pixels and spectral reflectance of features. These techniques were totally depended on pixels or grids within particular class. The basic concept accepted these chances, which are equivalent to various input bands. However, these techniques required a so-long period for calculation, depending seriously on a regular classification of the data in every input band to over-categorize signatures with comparatively big values of the covariance matrix (Rosenfield and Fitzpatirck-Lins1986; Riebsame et al. 1994; Ruiz-Luna and Berlanga-Robles 2003; Owojori and Xie 2005; Yuan et al. 2005). The smallest estimation period for supervised classification technique is required. This study's effective error matrix and Kappa coefficient techniques have helped to the evaluation of land-use maps, and the accuracy of results was estimated. Therefore, five land-use and land-cover classes such as agricultural land, wasteland, built-up land, and water body were found in respective years. The assessment of land-use and land-cover map methodology is presented in Fig. 3.

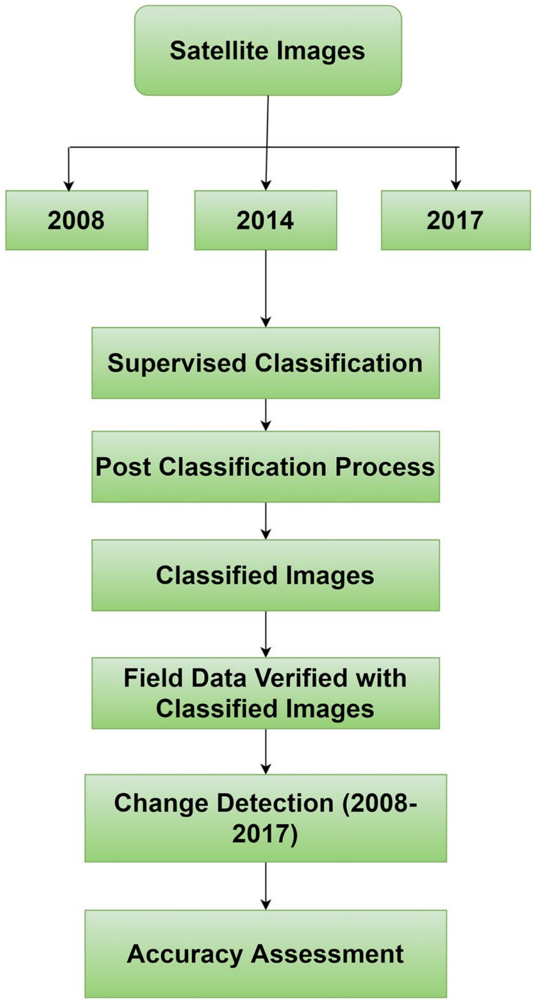


Fig. 3 Flow chart of the methodology

Results and discussions

The final classified land-use maps are shown in Fig. 4a, b and c. Table 4 shows the change matrix for varying areas from one class to another class in between the assigned dates. Moreover, the whole area of land use and land cover was shown in the hectare unit, and fraction of every land-use and land-cover class between various periods is shown in Table 2. The outcome of a supervised classification method discloses general decreases in agricultural land and an increase in waste, built-up, and water body land during the years of 2008, 2014, and 2017. The results of study area have been showed agricultural land changes of land use and land cover in the watershed area (597.34 Ha (70.64%)), (369.13 Ha (43.65%)) (352.53 Ha (41.68)) during years of 2008, 2014, and 2017, respectively. The wasteland, representing the agriculture land, is converted to wasteland in the watershed area (244.28 Ha (28.89%)), (329.50 Ha (38.96%)), (341.02 Ha (40.33)) for 2008, 2014, and 2017, respectively. These areas are insufficient rainfall, and drought condition issues directly affected on the agriculture crops and land-use classes in the area. The remaining two land-use classes (built-up and water body) are denoted as (3.89 Ha (0.46%)), (4.63 Ha (0.54%)) (5.31 Ha (0.62%)) and (0 Ha (0%)), (103.75 Ha (12.75%)) (147.04 Ha (17.39%)) in the years of 2008, 2014, and 2017, respectively. The water body area is increased by 12.75% and 4.64% in 2008 and 2014 years and 2014 and 2017 years mostly increased due to soil and water conservation activities during five projects. The built-up land areas are 0.08 and 1.42% increase due to the population growth in 2008 and 2014 and 2014 and 2017 (Table 2).

Accuracy valuation for the classified images

Therefore, two kinds of correctness were studied in the confusion matrix user and producer accuracies (Table 3). Based on those kinds of classification, the total image classification correctness and overall kappa statistics were measured. While the whole classification accurateness for the separated images is > 85% depended, Anderson et al. 1976 proved that the satisfactory accurateness of sorting should be > 90% and kappa statistics > 0.9. The accurateness calculation of the different land-use maps produced was verified by using classifiers. It has executed depending on the calculation of the error matrix statistics (Pande et al. 2018). As per the outcome, the land-use maps measured different accuracy methods such as overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), and the kappa coefficient (Kc), which are measured by Eqs. 1, 2 and 3.

$$\text{User's accuracy}: A_u = P_{ii}/P_{i+}. \tag{1}$$

$$\text{Producer accuracy}: A_P = P_{ii}/P_{+1}. \tag{2}$$

$$\text{Overall accuracy} = A_o = \frac{\sum_{i=1}^{m} P_{ii}}{n} \times 100. \tag{3}$$

Supervised classification maps

In this paper, past satisfactory accurateness of three thematic maps of land use and land cover based on the supervised classification method is agreed. The results of produced overall accuracies of 97.54, 95.54, and

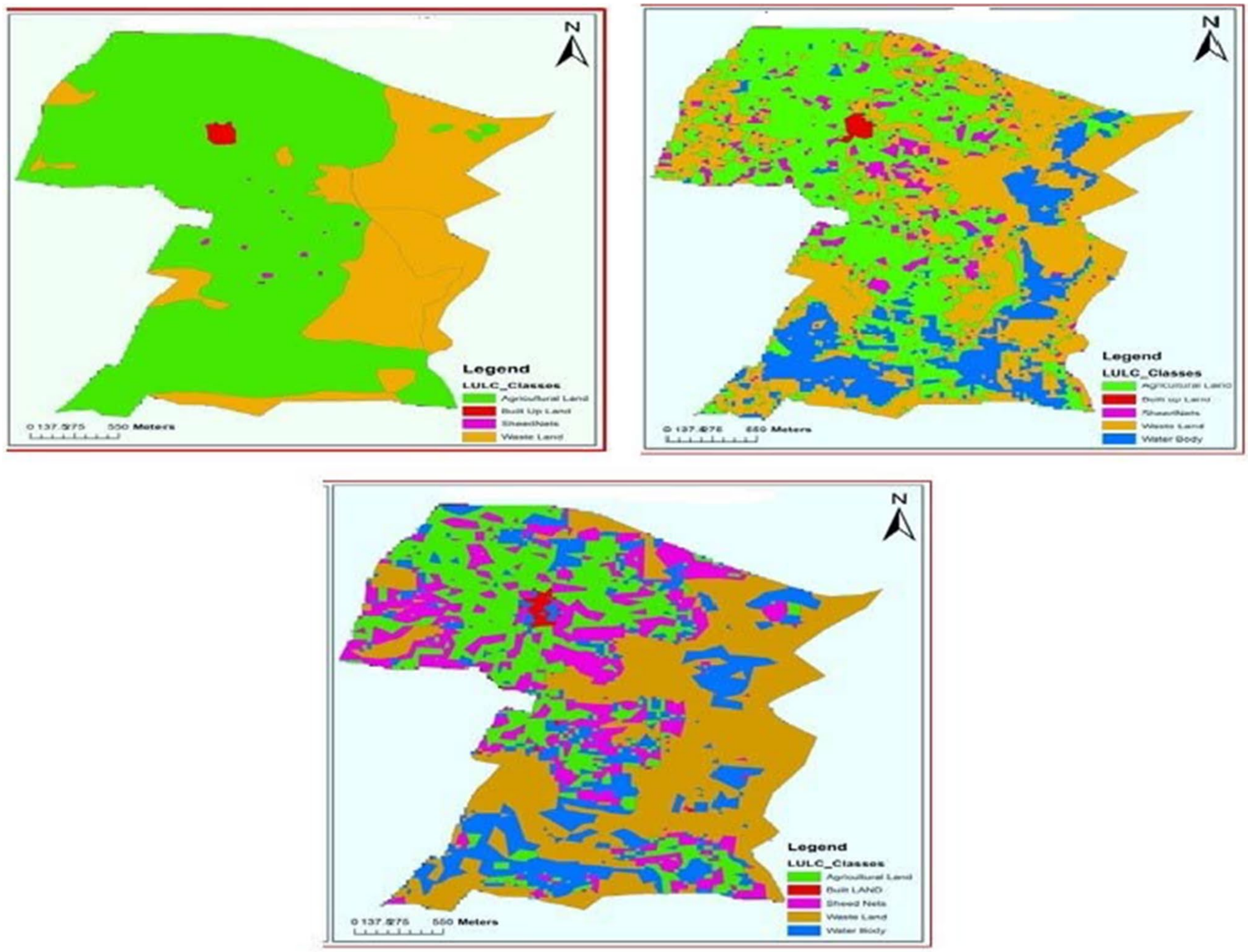


Fig. 4 The classified maps for land-use/land-cover classes (**a**) 2008, (**b**) 2014, (**c**) 2017

Table 3 Matrices error for 2008, 2014, and 2017 classified images depends on the supervised classification method of the study area

Land-use classes	Years								
	Producer's accuracy (%)			User's accuracy (%)			Kappa coefficient (%)		
	2008	2014	2017	2008	2014	2017	2008	2014	2017
Agricultural land	90.23	91.67	93.87	92.54	94	95	0.78	0.73	0.79
Waste land	94.50	95	97	93	94	96	0.89	0.87	0.85
Built-up land	100	100	100	100	100	100	100	100	100
Water body	100	100	100	100	100	100	100	100	100
Overall classification Accuracy	97.54	95.54	93.54						
Overall kappa Statistics	94.32	96.32	97.32						

93.54% during the years of 2008, 2014, and 2017 classified the imageries, respectively; overall, the kappa statistics were > 0.90. The minimum producer accuracy of 90.23% was given to the agriculture land, while the other two land-use and land-cover classes (built-up and water body) had correctness of 100% in 2008 year. The user accuracy results have been indicated for the agricultural land in 2008, 2014, and 2017, which was 92.54%, 94%, and 95% associated with the built-up and waterbody land-use classes, which had correctness of 100% (Table 3). The user accuracy of wasteland was 93%, 94%, and 96% in the years of 2008, 2017, and 2017, respectively. The inspected accuracy for the 2014 classified imageries (Table 3) had almost the same trend as the 2008 classified image with a good determination of agriculture class as the producer accuracy increased to 91.67%, whereas the accuracy of other classes little increased to an average of 97.54%. In this study, results show that user accuracy for built-up and waterbody class's accuracy was 100%, but two classes were changed in the years of 2008, 2014, and 2017, respectively. The agricultural and wasteland were better in all divided data with an accuracy of 95% and 96% during the years of 2017, but the user accuracy of agriculture and wasteland decreased to 92.54% and 93% in the year

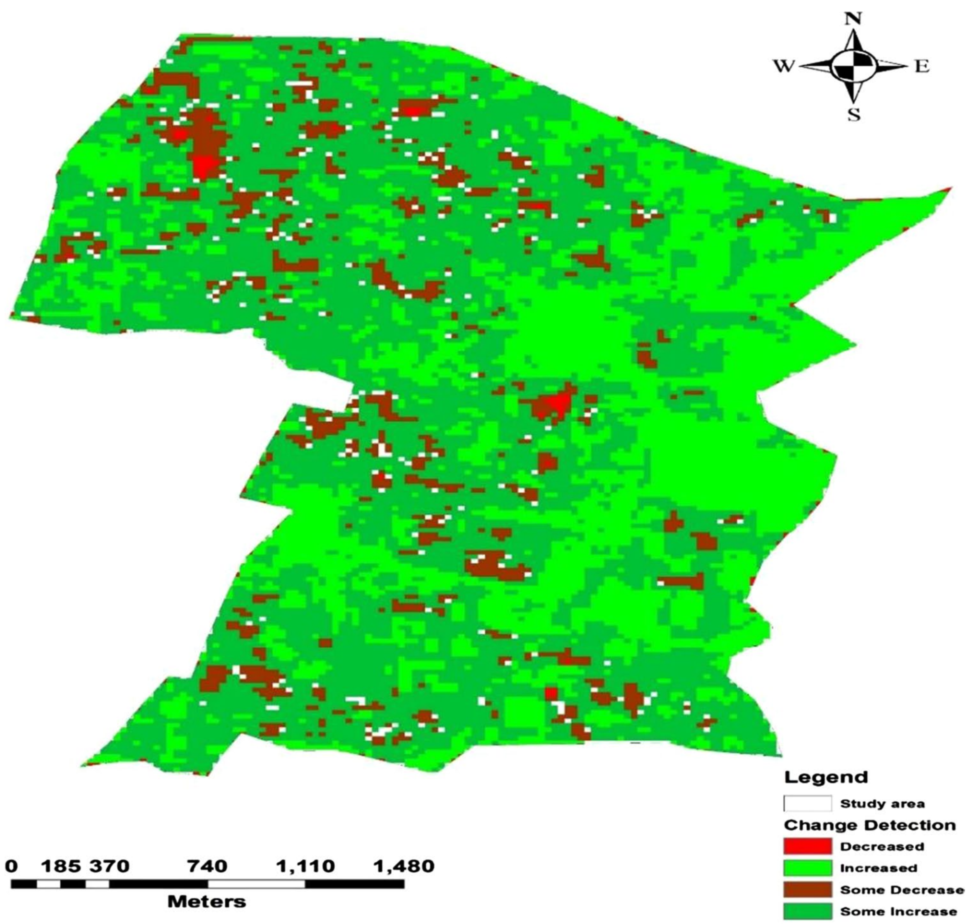


Fig. 5 Change detection map between 2008, 2014, and 2017

Table 4 Details of LULC change detection during 2008–2014, 2008–2017, and 2014–2017

LULC	2008(Ha)	2014(Ha)	Changes	2008(Ha)	2017(Ha)	Changes	2014(Ha)	2017(Ha)	Changes
Wasteland	244.28	329.5	85.22	244.28	341.02	96.74	329.5	341.02	12.02
Built-up land	3.89	4.63	0.74	3.89	5.31	1.42	4.63	5.31	0.68
Agricultural land	597.34	369.13	– 228.21	597.34	352.53	243.81	369.13	352.53	16.6
Water body	–	103.75	103.75	–	147.04	147.04	103.75	147.04	43.29

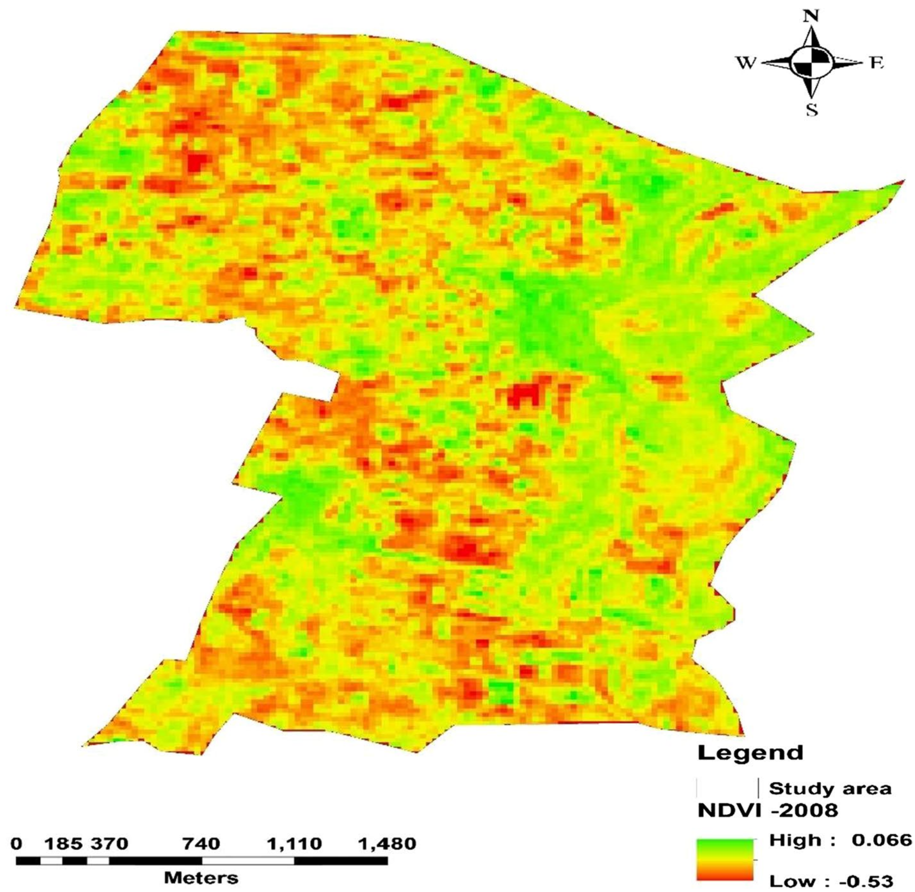


Fig. 6 Normalized difference vegetation index (NDVI) of 2008

of 2008. The 2008 classified image accuracy evaluation (Table 3) shows various classes than the aforesaid divided images as agriculture land-finding producer accuracy was the lowest (90.23%) with an important improvement in the built-up and water body identification (accuracy = 100%).

LULC/Change detection

The study of monitoring the land use and land cover over 9 years (from 2008 to 2017) is concluded; the divided images indicated were employed to identify the variation in the land use and land cover for three time series 2008–2014, 2008–2017, and 2014–2017 (Fig. 5). The change matrix of the land-cover classes in between the allocated time series with the variation area by hectare and percentage is shown in Tables 2 and 4 for supervised classification, respectively.

In this study, three NDVI thematic maps were prepared during years of 2008, 2014, and 2017 in colour scale values between 1 to − 1 (Figs. 6, 7 and 8). The NDVI values > 0 denoted the wasteland, whereas the negative values and the values near about 0 are mostly made from the water body, built land, and bare soil (ESRI, 2019). The NDVI values are indicated to more healthy vegetation. Results have shown that the NDVI values ranged between − 0.53t o 0.066, − 0.35 to 0.11, and − 0.53 to − 0.66 for 2008, 2014, and 2017, respectively. The NDVI maps are more role in the identification of classes of land use during the years of 2008, 2014, and 2017.

Conclusion

Remote sensing and GIS technologies were integrated for analysis and changes in the land-use and land-cover classes (Fig. 9). In this study, supervised classification method was used for identification of land-use classes with

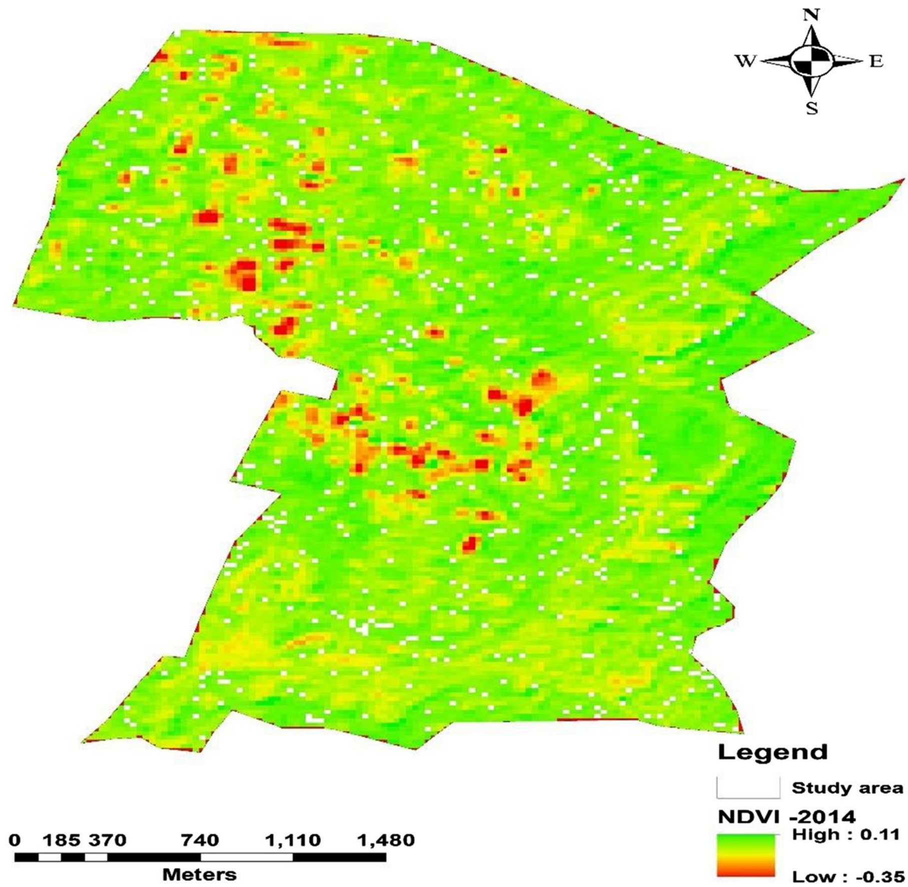
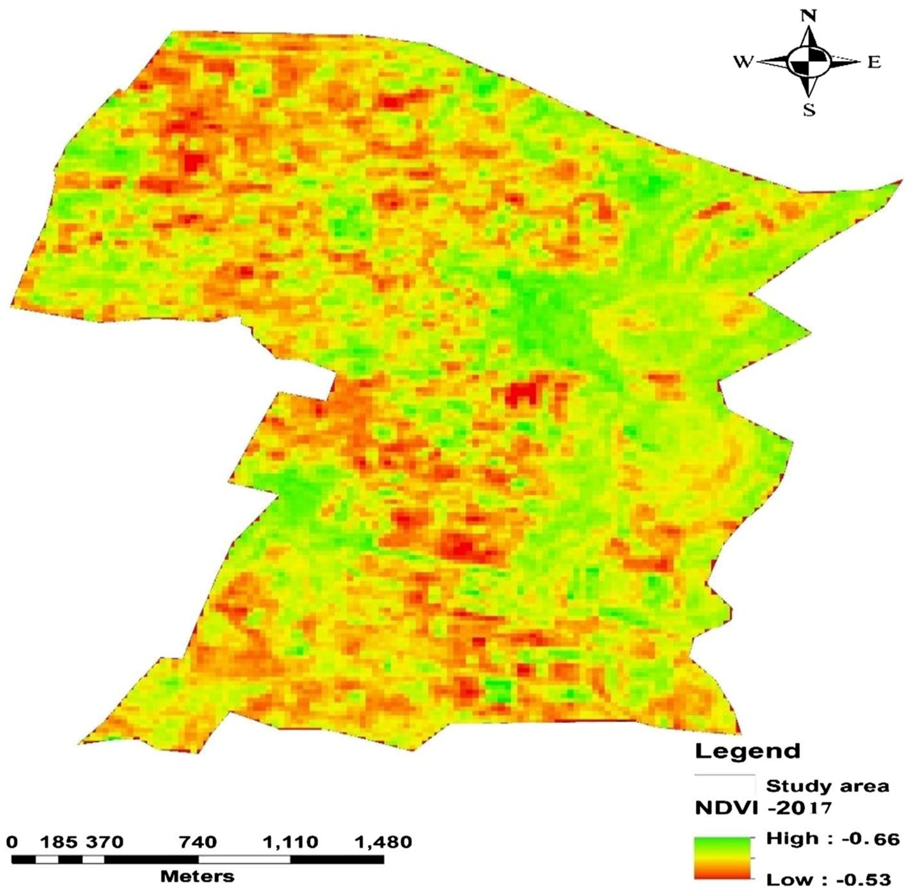


Fig. 7 Normalized difference vegetation index (NDVI) of 2014

the help reference of field data. Two common classification methods (MLC and NDVI) were applied in this study. The NDVI maps were utilized to be found of vegetation conditions in the research. These maps were observed that the agriculture land shows the variation of (597.34 Ha (70.64%)), (369.13 Ha (43.65%)) (352.53 Ha (41.68)) in area. The results of NDVI maps show vegetation analysis ranged in between − 0.53 to 0.066, − 0.35 to 0.11, and − 0.53 to − 0.66 for 2008, 2014, and 2017, respectively. However, the supervised classification method has confirmed to be a good classifier because the overall accuracy is up to 95%. The selected study area is under a rural area so the agricultural land is the main economic source for livelihood. The results of the study area are that it is very useful for the sector of agriculture development and increasing agronomic crops. According to the study, it is also found that the built-up land is increasing due to the human population and as compared to this agriculture land decreased due to environmental factors and human being activities. The present study thus shows that remote sensing and GIS are advanced tools for analysing and quantifying spatial necessary qualifications that traditional mapping technologies cannot otherwise be used. These technologies allow change detection in much less time, at a cheaper cost, and with greater accuracy. Further research is required to examine the water source and supply in the study area and to link the agriculture and drinking water demands with the period to provide a general environmental view of the study area.

Fig. 8 Normalized difference vegetation index (NDVI) of 2017



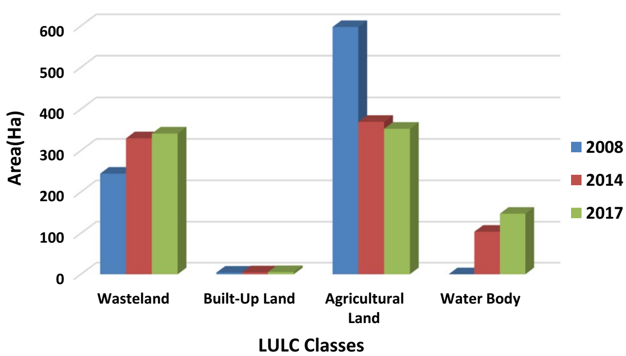


Fig. 9 Summary of land-use and land-cover classes in 2008, 2014, and 2017

Recommendations

This study result can be very much useful for preparation of land-use policy and watershed development project. In the semiarid regions, these types of results can be helpful for understanding the drought conditions and water scarcity.

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We are not used any text form in the already published article and also no any journal submission of paper.

Declarations

Conflict of interest There is no conflict of interest in this paper.

Ethical conduct No ethical text is used in this paper.

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