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Evaluation of Land Use and Land Cover Transformation and Urban Dynamics Using Multi-Temporal Satellite Data

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ABSTRACT. Assessment of Land use and land cover (LULC) transformations at different spatial levels is crucial in several areas, including protection of the environment, resource utilization, planning and sustainability. The present work is an attempt to carry out a detailed study of LULC transformations and to analyze urban areas in Srinagar city (India) using multi-temporal Landsat satellite data for the year 1995 to 2019. Seven different LULC classes were delineated for the selected periods by a supervised method using maximum likelihood classifier algorithm in ERDAS Imagine 14. The findings indicate that over the specified periods substantial changes have occurred in terms of LULC. Overall seven categories were identified and, throughout studies, three trends of LULC change were observed (1) continuous expansion of the area under the class of built-up, barren, horticulture (2) agriculture, water and marshy class are continuously decreasing (3) increase (1995–2010) and decrease (2010–2019) in forest classes between two periods. During the study period, in built-up (+), horticulture (+), agriculture (–) water (–) and marshes (–) most significant changes have been observed, referencing to change in percentage within each class, the maximum variability was observed in built-up (148.07%), horticulture (40.87%), marshes (–58.37%), water (–22%) and agriculture (–35.38%). For quantitative assessment changes Land Consumption Rate (LCR) and Land Absorption Coefficient (LAC) were introduced. The overall research scenario shows that the LULC transition in the city is very evident. The rapid change of LULC in the ecologically sensitive Srinagar city is driven mainly by anthropogenic sources and has a negative environmental influence.

Keywords: LULC, multi-temporal, Maximum Likelihood Classifier (MLC), urban.

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1. Introduction

Land use and land cover are two progressing words which symbolize differently in the contemporary world. Land use usually refers to a series of human-led operations aimed at obtaining products and/or benefits by using land resources. Typically, not evident directly from the imagery, whereas the Land cover is generally described as vegetation (natural or plant) or made man structures (e.g. Buildings) currently happening on the surface of the earth (Kanianska 2016). The rate of human-induced spatial and temporal alteration to land surface change is primarily in LULC are unprecedented and intrusive that they have significantly changed a significant part of the planet, impacting important dimension of Earth's System (Ojima et al. 1994, Lambin et al. 2001, Foley et al. 2005). The evaluation of LULC change has become a prerequisite for and interrelation between various aspects of natural and man-made environments (Herold et al. 2002, Bender et al. 2005, Mendoza et al. 2011, Hegazy and Kaloop 2015). LULC change on the earth's surface is a crucial indication of change represented by urban growth (Jat et al. 2008, Dewan and Yamaguchi 2009, Byomkesh et al. 2012, Dewan et al. 2012, Liu et al. 2014), displacement of farmland (Ali 2006, Du et al. 2014), desertification (Xiulian 2017), loss of cultivated land (Döös 2002), destruction of habitat (Mucova et al. 2018), and the loss of the natural vegetation (Kong and Nakagoshi 2006, Singh and Javeed 2020). These losses have a direct impact on the earth's environment such as climate change, unregulated development, land-losses, wetland destruction and wildlife habitats (Sun et al. 2013, Lin and Yu 2018). In United Nation SDGs 11th goal "Sustainable Cities and Communities" focuses on reduction of the adverse per capita environmental impact of cities. Moreover, due to its frequently immanent negative effect on the status and credibility of the functioning of the environment, LULC changes in land management requires further attention (Quintas-Soriano et al. 2016).

Considering the increased stress on natural resources because of population increases and developments of cities, LULC research focuses on understanding (1) where the transformation occurs (2) what form of land cover transforms (3) which type of land cover conversion taking place (4) the Land transition rate or amount (5) driving factors and the causes of the related change (Loveland and Acevedo 2006). To evaluate where and why LULC changes occur, frameworks typically require an empiric measurement system against some historic transition trend, and then applies the trends for subsequent ventures (Brown et al. 2000). The future transformation patterns will also be an imperative dimension of those investigations, mostly derived through simulation modeling. Nowadays we can identify Spatial and temporal LULC transitions with satellite-based sensors through the advancement of science and technology. Remote sensing has been the most effective method in recent years to observe the spectrally sensitive changes of the earth (Qadir and Singh 2019). The recognition of LULC changes after and before classification methods fall into remote sensing data (Shalaby and Tateishi 2007). A pre-classification method is used to produce maps to classify areas of change or no changes in LULC by multiple Remote Sensing Images (Ghebrezgabher et al. 2016). In contrast, in the post-classification approach, two classified remotely sensed time images are compared to produce maps which show change over time between and within LULC classes. It, therefore, encourages researchers and urban planners to track LULC changes and urban spread areas throughout cities and their nature (Xu et al. 2013, Hassan et al. 2015). The NASA Landsat mission was launched in 1972 and is the longest-running EO program in the world and continues to provide global coverage with a wide spectrum of low to high resolution statistics (Helmer et al. 2000, Lu and Weng 2004, Gao and Zhang 2009). These satellites driven data prove to be extremely consistent throughout the world and relevant for the monitoring, evaluation and identification of land-use change (Gumma et al. 2011, Lu et al. 2012, Jia et al. 2014, Kumar and Acharya 2016). The rate of growth in urban areas in comparison to rural areas is higher because of the lack of basic rural infrastructure (Mehmood et al. 2016). Massive rural-urban migration, rapid growth, creates challenges for residents, urban design, urban development, and management systems, such as over-population, and disputes over land use. In addition, the results of agricultural land, unplanned living areas, expensive arable ground and developer assumptions about land costs and public adulteration of the atmosphere will be reduced (Jensen 2004, Vizzari 2011, Wilson and Chakraborty 2013).

The present study evaluates the LULC changes and urban development in Srinagar city between the periods from 1995–2010–2019 using multi-temporal satellite data. This work aims to (1) identify the main LULC class classification scheme in the city of Srinagar, (2) LULC classes change trajectory during the study period, (3) determining urban class and to assess spatial growth pattern along with Land Consumption Rate (LCR) and Land Absorption Coefficient (LAC).

1.1. Study Area

Srinagar city lies in the central part Kashmir valley in northern India, the only largest city and the largest urban settlement in the Himalayan mountain chain. It is the main center of political, social and economic interaction and represents an active area of urban development. The river Jhelum flows through the center of the city and finally merging into the popular Dal Lake towards the east side of the city. Both the Jhelum and the Dal Lake are important places for visitors, ecological service providers and revenue earners to the local population. The physico-geographical structure of the region illustrates its spatial variability, with large agricultural fields in the south and west and high-level mountains in the north-east and eastern direction, at an average altitude of 1580 m. These geological characteristics have greatly influenced the settlement's development, contributing to major population growth in the plains and less towards the mountains. The city represents a moderate landscape of hills, lakes, orchards, wetlands and beautiful lush green gardens. The city's urban set-up consists primarily of commercial, agricultural, residential and administrative units. The environmental scenario in Srinagar city has changed enormously, as with other parts of the country. The exponential increase in population and the development of infrastructure, connectivity and other areas have significantly altered the urban ecological conditions and has damaged the fundamental environmental functionality.

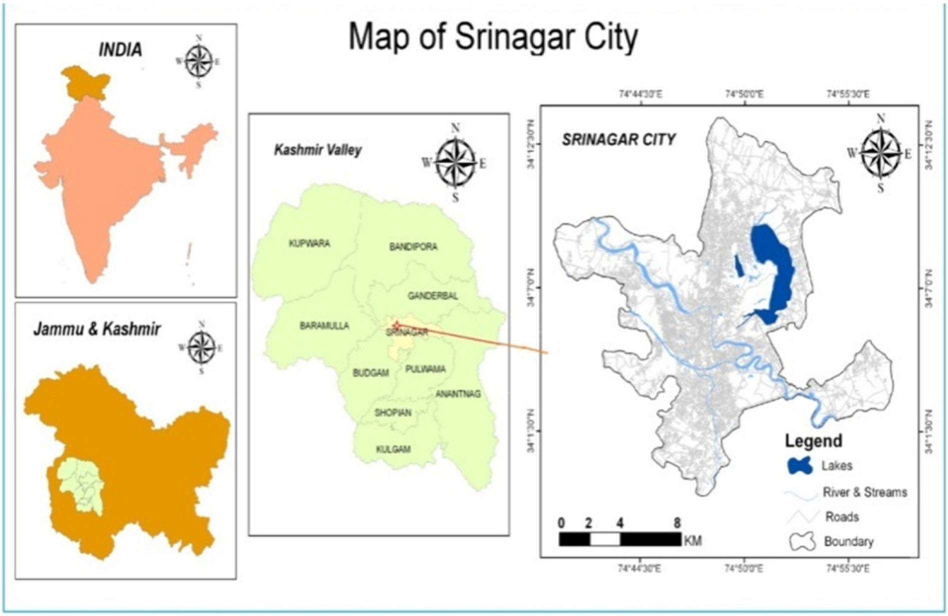

Fig. 1. *Study Area.*

2. Methodology and Dataset

The urban expansion and land-use related transition studies need spatio-temporal data for assessment of LULC dynamics over time. Data of at least two time periods for comparison is required for tracking LULC transition. In the analysis, the images were selected based on their spatial resolution compatible (30 m). Landsat data with images sufficiently compatible with previous missions enable the assessment of regional and global LULC transition in the long term (Irons et al. 2012). Thus, Landsat TM satellite images were used in 1995, Landsat 7 ETM+ for the year 2010 and in Landsat 8 OLI for 2019 (cloud-free scene) to analyze LULC data sets are acquired from the U.S. Earth Explorer TM and Landsat Geological Survey (USGS). Table 1 provides the sensor specifications of various Landsat. In the present study, all images were classified into thematic maps by adopting supervised classification approach (maximum likelihood algorithm). Supervised Image classification intends automatically to categories into specific LULC class pixels of a shared range of reflectance (Addink et al. 2012, Huth et al. 2012, Lillesand et al. 2015, Tarantino et al. 2015, El Garouani et al. 2017). The assignment of per-pixel signatures were analyzed from the satellite data based on the digital number value of various landscape components. A total of seven LULC classes (Level I) were classified in light of (Anderson 1976) proposed system, i.e. agriculture, horticulture, marshes, built up the dense forest, barren and water body for detail (Table 2). A unique identification was assigned to every class and a distinctive color was assigned to separate it from each other. Training samples have been obtained for each of the predefined LULC class by identifying polygons around testing sites and signatures were reported on the basis of the pixels closed within polygons for each land cover class. Generation of signature file from Landsat 5 TM 1995, Landsat 7 ETM+ 2010, and Landsat 8 OLI 2019 was performed to analyze the separability of the selected bands in the LULC class using the scatter plot techniques. The satisfactory spectral signature indicates that the land covers are mapped with "minimal confusion" (Gao and Liu 2010).

Table 1. *Sensor Specifications.*

Landsat 5 (TM)		**Landsat 7 (ETM+)**		**Landsat 8 (OLI)**	
Acquisition date: October 1995		**Acquisition date: October 2001**		**Acquisition date: October 2019**	
Band (µm)		Band (µm)		Band (µm)	
Band 1 – Blue	0.45–0.52	Band 1 – Blue	0.433–0.453	Band 2 – Blue	0.452–0.512
Band 2 – Green	0.52–0.60	Band 2 – Green	0.450–0.515	Band 3 – Green	0.533–0.590
Band 3 – Red	0.63–0.69	Band 3 – Red	0.525–0.600	Band 4 – Red	0.636–0.673
Band 4 – Near Infrared (NIR)	0.76–0.90	Band 4 – Near Infrared (NIR)	0.630–0.680	Band 5 – Near Infrared (NIR)	0.851–0.879
Band 5 – Near Infrared (NIR)	1.55–1.75	Band 5 – Near Infrared (NIR)	1.55–1.75	Band 6 – short infra-red (swir)	1.57–1.65
Row/path: 149/36					
Cloud cover: below 10%					

Source: (http://earthexplorer.usgs.gov/).

Table 2. *LULC Classification Scheme.*

Classes	**Description**
Agriculture	Land for Rabi and Kharif cultivations, most of them included in this section are rice, mustard, maize and vegetables.
Built-up	The category includes residential, commercial, industrial, highway and other pavements.
Barren	The class include rocks, exposed surfaces that remain unvegetated throughout the year
Forest	The class includes coniferous forest scattered across the mountains
Horticulture	Apple, Pear, Walnut, almond and Cherry orchards dominate this group primarily
Marshes	This group consists of wetlands, Aquatic plantation (permanent or seasonal) and other naturally submerged areas.
Water	This category covers open water sources like lakes or rivers

The overall methodology adopted for this research is summarized in Fig. 2. In order to extract urban areas Boolean technique were applied.

Some techniques of post classification are used to enhance up the whole LULC classification and remove the noise. The filter used here is the majority filter 3 X 3 neighborhood. Raster calculator is used to measuring the LULC figure for both percentage and area (km^2). Also, Garmin Oregon 750 GPS was used for field visits to rectify ambiguous spots and to verify the LULC classifications. The methodology adopted in the current research describes the urban change dynamics, with area extension and statistical methods for evaluating the LCR and LAC.

2.1. Accuracy Assessment

The accuracy assessment with classification data becomes a key component of the change detection process. In order to determine the information quality obtained from results, 1995, 2010 and 2019 accuracy assessment was performed. A stratified random accuracy assessment approach for various LULC groups was used in the area. Overall accuracy was 86.42%, 87.85% and 90.20% respectively for the years 1995, 2010 and 2019. A non-parametric kappa test was conducted to calculate the classification accuracy as it accounts Rows, columns and diagonal element in the confusion matrix (Rosenfeld and Fitzpatirck-Lins 1986). Kappa coefficient, the robust indicator of the accuracy agreement between predefined producer ratings and user-assigned ratings. It is calculated by a formula the equation for κ is

$$\kappa = \frac{pr(a) - pr(e)}{1 - pr(e)} \tag{1}$$

where $pr(a)$ is the relative observed agreement among raters, and $pr(e)$ is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly category (Gwet 2002, Viera and Garrett 2005).

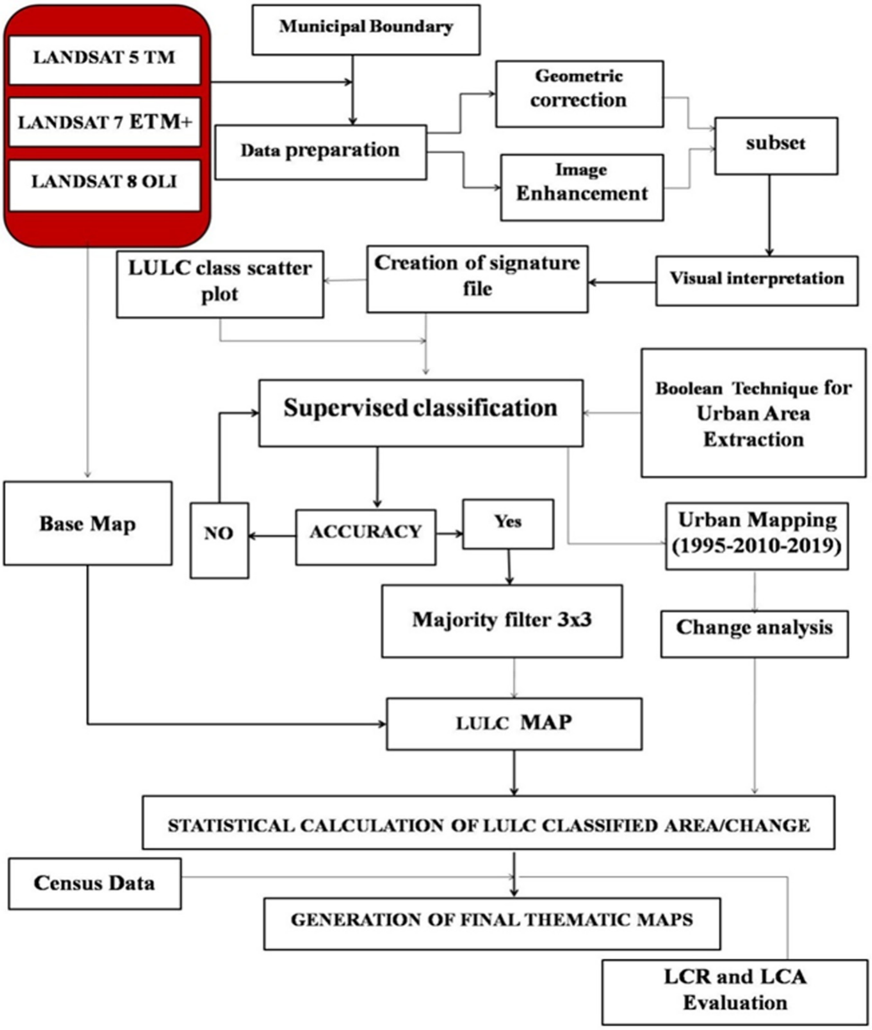

Fig. 2. *The methodology adopted for the study area.*

2.2. Evaluation of LCR and LAC

LCR is a compact measurement, which means that the city is progressively spatially expanding. When the LCR value is high, it implies crowdedness and when it is low, it indicates free open areas. Whereas the LAC is an indicator of changes in urban land use for each population growth unit. It illustrates how new land is used to build up and how people are expanding their periphery.

The formula for LCR and LAC is given below:

$$LCR = \frac{A}{P} \tag{2}$$

where A = Areal extent of the city in (ha) and P = Population

$$LAC = \frac{A_2 - A_1}{P_2 - P_1} \tag{3}$$

where A_1 and A_2 = Areal extents in (ha) for the initial and final years, and P_1 and P_2 = Population statics for the initial and final years, respectively (Yeates and Garner 1976).

3. Results

3.1. Evaluating of Training Sample Signatures

Table 3 present the respective classification accuracy evaluation error matrix tables. Statistically, error matrices were used to compare reference data and classified results. To evaluate the spectral signatures obtained from LULC training samples using scatter plot techniques for the LULC bands selected bands. The spectral signature is selected for detailed study from images of 1995, 2010 and 2019. A unique identification was assigned to every class and a distinctive color was assigned to separate it from each other, as, agricultural area yellow, barren land is dark brown, Horticulture is orange, marshes are pink, the forest is dark green, water is blue and built-up areas presented in red. The signatures obtained from training sample for the 1995 Landsat 5 TM image (Fig. 3(a)) generates scatter plot that shows better results for the band separability and an excellent analysis of the spectral characteristics in the different class areas. It depicts that majority of lace classes are separated reasonably. In the band 1–2, 1–3 entire loss classes are well distributed and supported. It is observed that among all the classes built up area is well separated in all the bands. Scatter plot for the 2010 Landsat 7 ETM+ image (Fig. 3(b)) indicated low to moderate separability in all classes of LULC. Whereas Marshes and forest classes are not separated perfectly, in the band 1–5, and shows low separation, while in bands 1–2 and 1–3 signatures indicated fairly separability. Scatter plot in the 2019 Landsat 8 OLI image (Fig. 3(c)) indicated best separability in all classes of LULC from reasonably separated. Particularly in the 1–2 and 1–3 band, all the land use classes are well separated. However in the 1–4 signatures indicated fairly separability and 1–5 is low separation results, Built-up area is separated perfectly in all the bands (Rahman 2016, Squires 2002).

Table 3. *Accuracy of LULC maps obtained from satellite data for the selected periods.*

(a) Sum of diagonal = 605; Total = 700; Overall accuracy = 86.42%; Kappa coefficient, $\kappa = 0.84$.

Landsat 5 TM 1995									
LULC	**A**	**B**	**M**	**BU**	**H**	**DF**	**W**	**RT**	**UA**
A	**80**	3	5	5	5	2	0	100	80.00
B	2	**90**	1	2	2	2	1	100	90.00
M	4	2	**80**	2	5	2	5	100	80.00
BU	2	3	3	**90**	2	0	0	100	90.00
H	5	1	1	5	**85**	3	0	100	85.00
DF	0	2	3	2	3	**90**	0	100	90.00
W	0	0	5	3	2	0	**90**	100	90.00
CT	93	101	98	109	104	99	97	700	
PA	86.02	89.11	81.63	82.57	81.73	90.91	93.75		
A	**80**	3	5	5	5	2	0	100	80.00

(b) Sum of diagonal = 615; Total = 700; Overall accuracy = 87.85%; Kappa coefficient, $\kappa = 0.85$.

Landsat ETM+ 2010									
LULC	**A**	**B**	**M**	**BU**	**H**	**DF**	**W**	**RT**	**UA**
A	**80**	5	5	5	5	0	0	100	80.00
B	2	**90**	0	5	2	1	0	100	90.00
M	4	2	**80**	5	5	2	2	100	80.00
BU	5	0	0	**90**	5	0	0	100	90.00
H	5	0	0	3	**90**	2	0	100	90.00
DF	5	2	0	3	0	**90**	0	100	90.00
W	0	0	3	2	0	0	**95**	100	95.00
CT	101	99	88	113	107	95	97	700	
PA	79.21	90.91	90.91	79.65	84.11	94.74	97.94		
A	**80**	5	5	5	5	0	0	100	80.00

(c) Sum of diagonal = 630; Total = 700; Overall accuracy = 90.02%; Kappa coefficient, $\kappa = 0.88$.

Landsat 8 OLI 2019									
LULC	**A**	**B**	**M**	**BU**	**H**	**DF**	**W**	**RT**	**UA**
A	**85**	2	3	5	5	0	0	100	85.00
B	2	**90**	0	5	2	1	0	100	90.00
M	2	3	**85**	2	3	0	5	100	85.00
BU	3	0	0	**95**	2	0	0	100	95.00
H	5	0	0	3	**90**	2	0	100	90.00
DF	3	2	0	3	2	**90**	0	100	90.00
W	0	0	5	0	0	0	**95**	100	95.00
CT	100	97	93	113	104	93	100	700	
PA	85.00	92.78	91.40	84.07	86.54	96.77	95.00		
A	**85**	2	3	5	5	0	0	100	85.00

Diagonal colored numbers indicate correctly classified samples for each LULC class, A: agriculture, M: marshes, BU: built-up, B: barren, DF: dense forest, H: horticulture, W: water, RT: row total, CT: Column total, UA: user's accuracy, PA: producer's accuracy.

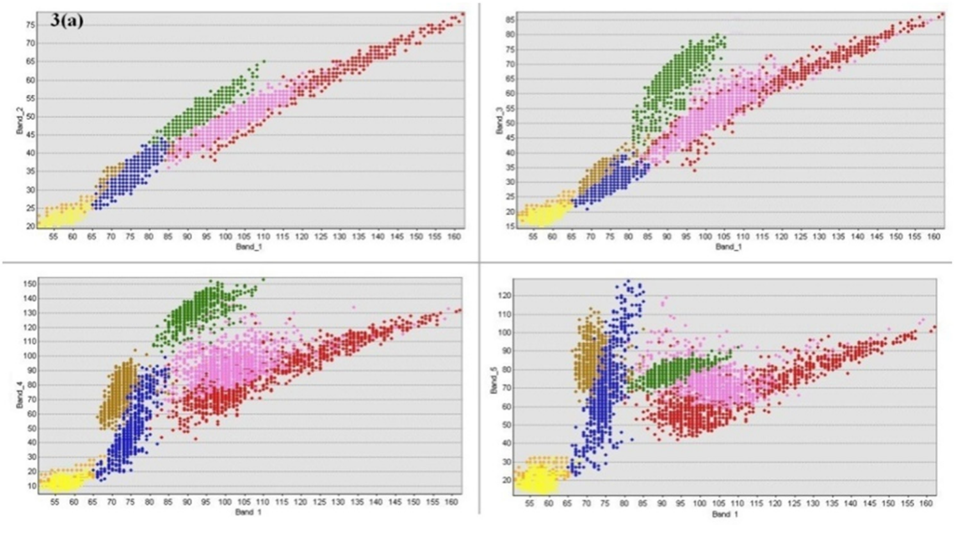

Fig. 3(a). *Scatter plot for the year 1995 using Lansdsat 5 TM.*

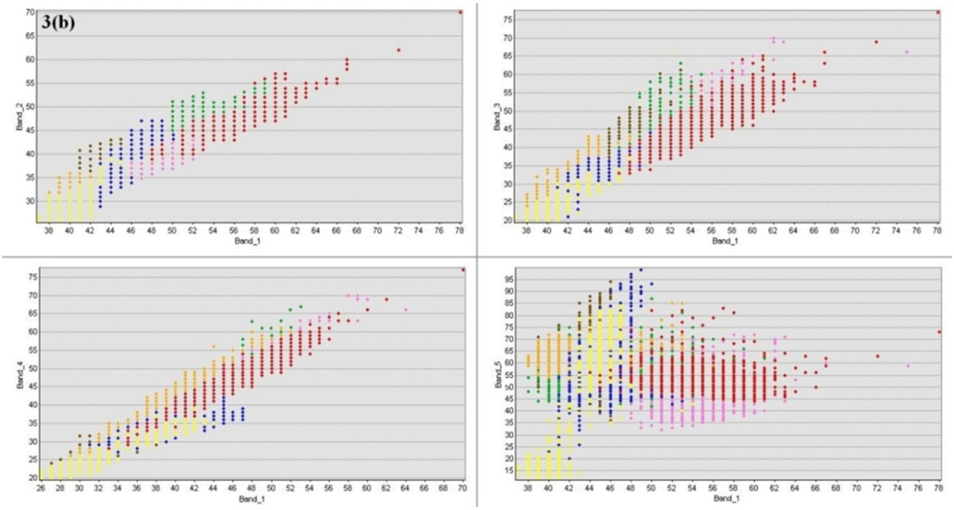

Fig. 3(b). *Scatter plot for the year 2010 Lansdsat 7 ETM+.*

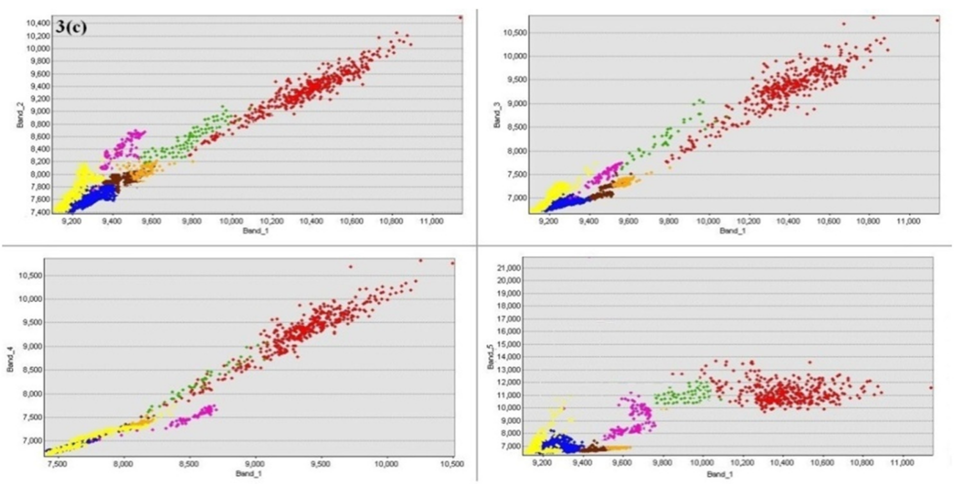

Fig. 3(c). *Scatter plot for the year 2019 using Lansdsat 8 OLI respectively.*

Agriculture *Barren* *Marches* *Built up* *Horticulture* *Dense forest* *Water body*

3.2. LULC Status of Srinagar City in the Year 1995

The 1995 LULC classified map (Fig. 4(a)) consisted of seven classes, i.e. agriculture, horticulture, dense forests, water body, barren, built-up, and marshes. The majority of the area in 1995, i.e. 121.90 km^2, comprising 41.68% of the study area was under agriculture shown in Table 4(a). The total area under water class comprises approximately 7.89% of the total land. Whereas Horticulture and built up comprise approximately 12.38% and 17.61%, respectively. LULC statistics show that the study area was less subject to anthropogenic influences in 1995, as the area was dominated by a higher number of natural classes (Fig. 4(a), Table 4(a)).

Table 4(a). *LULC status of Srinagar city in the year 1995.*

LULC category	Area (km^2)	(%)
Agriculture	121.90	41.68
Barren	7.24	2.47
Built Up	36.20	12.38
Dense Forest	5.61	1.92
Horticulture	51.50	17.61
Marshes	46.96	16.06
Water	23.09	7.89

3.3. LULC Status of Srinagar City Year 2010

The 2010 LULC classified map (Fig. 4(b)) consisted of seven classes, i.e. agriculture, horticulture, dense forests, water body, barren, built-up, and marshes. The majority of the area in 2010, i.e. 90.12 km^2, comprising 30.81% of the study area was under agriculture shown in Table 4. The total area under water class comprises approximately 6.42% of the total land. Whereas Horticulture and built up comprise approximately 21.82% and 23.63%, respectively. LULC statistics of 2010 show that the built-up, horticulture are dominated classes after agriculture. Table 4 revealed that area under the forest class has shown growth and marshes have decreased to almost half in this period (Fig. 4(b), Table 4(b)).

Table 4(b). *LULC status of Srinagar city in the year 2010.*

Land use/cover category	Area (km^2)	(%)
Agriculture	90.12	30.81
Barren	8.38	2.86
Built Up	77.9	26.63
Dense Forest	6.87	2.35
Horticulture	63.83	21.82
Marshes	26.61	9.10
Water	18.79	6.42

3.4. LULC Status of Srinagar City Year 2019

The 2019 LULC classified map (Fig. 4(b)) consisted of seven classes, i.e. agriculture, horticulture, dense forests, water body, barren, built-up, and marshes. Table 4(c) shows that in 2019 most of the areas dominated by built-up and subsequently by the horticultural and agricultural classes. The built-up area in 2019 consists of 89.81 km^2 (30.70%) of the study area. The total area under water class comprises approximately 6.16% of the total area. Whereas Horticulture and agriculture comprise approximately 24.30% and 26.85%, respectively. Marshes, dense forest shows a decrease in the area during this period. LULC statistics show that the study area subject to anthropogenic influences in 2019, as the area is dominated by a built up (Fig. 4(c), Table 4(c)).

Table 4(c). *LULC status of Srinagar city in the year 2019.*

Land use/cover category	**Area (km^2)**	**(%)**
Agriculture	78.53	26.85
Barren	9.12	3.12
Built Up	89.81	30.70
Dense Forest	4.94	1.69
Horticulture	72.54	24.80
Marshes	19.55	6.68
Water	18.01	6.16

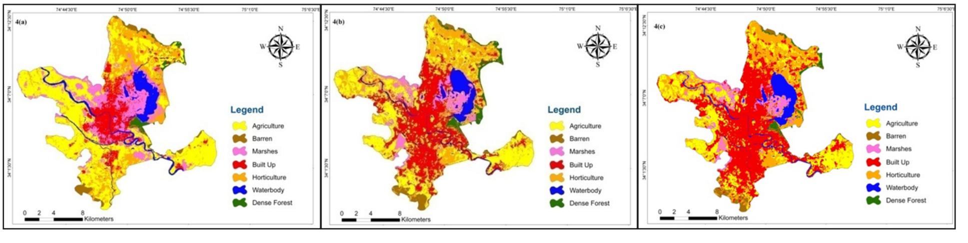

Fig. 4(a). *LULC Map of Srinagar city in the year 1995, (b) LULC Map of Srinagar city in the year 2010, (c) LULC Map of Srinagar city in the year 2019.*

3.5. LULC Change Detection from the Year 1995–2019

Land use Land cover change on the Earth's surface is an essential indicator in understanding the dynamics between human and the environment. This understanding is significant for the efficient use of resources and better decision making (Lu et al. 2004, Seif and Mokarram 2012). Change detection was performed from classified maps from Landsat 5 TM (1995), Landsat 7 ETM+ (2010) and Landsat 8 OLI (2019). A general scenario of the significant changes taking place in the Srinagar city was extracted by analyzing the respective maps for 24 years. Table 5 shows very clearly that, from 1995 to 2019, the LULC pattern in the city underwent major changes. Agriculture showed a decrease in area from 121.50 km^2 in 1995 to 90.12 km^2 in 2010 which further decreases to 78.53 km^2 in 2019 and reveals that during 1995–2010, the maximum loss of agriculture was observed. Total agriculture land decreased by 43.37 km^2 for 24 years. While horticulture and built upon the other hand shows a remarkable trend due to their conversion. Horticulture showed an increase in area from 51.50 km^2 in 1995 to 63.83 km^2 in 2010 which remarkably shows a further increase in the area to 72.54 km^2 in 2019 which reveals that majority of horticulture land increased during 1995–2010. Total growth of horticulture land increased by 21.04 km^2 for 24 years. Built-up class also shows an increase around the city and the majority of the area under this class shows a significant increase during the period 1995–2010. Based on the findings, the built up registered an increase of 41.70 km^2 in (1995–2010) and a remarkable additional increase of 11.92 km^2 in (2010–2019). Built-up showed a total growth of 53.61 km^2 during 24 years. Water body exhibited a decreasing trend, resulting in a decrease in the area of water spread from 23.09 km^2 in 1995 to 18.79 km^2 in 2010 and decrease further in 2019 to 18.01 km^2 with a net decrease of 0.96% during 24 years. From 1995 to 2010, an area of about 4.30 km^2 gradually shrunken from water body class showing a maximum reduction in the area as compared to 0.78 km^2 shrinkage from 2010–2019.Second major changes were observed in Marshes, 16.05% of the land was under Marshes which reduced up to 9.10% in 2010 and further went down to 6.68% in 2019. From 1995 to 2019, the maximum change in area was observed, i.e., about 6.62 km^2 of the area under marshes and was reduced as to 27.41 km^2 from 2010 to 2019.During the selected period, the forest was observed to be revealing two change patterns i.e., the forest area shows increase i.e., 1.91–2.35% from 1995 to 2010, and a decrease to 1.6% of the total area from 2010 to 2019 (Fig. 4(a), 4(b), 4(c)). Barren areas show an increasing trend during 24 years results revealed land has gradually increased to 1.14 km^2 in 1995–2010 and further increased to 0.74 km^2 in 2010–2019.

Table 5. *LULC Status of Srinagar city in 1995–2019.*

Class Name	1995	2010	2019	Area change (1995–2010)	Area change (2010–2019)	Net change (1995–2019)
Agriculture	121.9	90.12	78.53	–31.78	–11.59	–43.37
Barren	7.24	8.38	9.12	1.14	0.74	1.88
Built Up	36.2	77.9	89.81	41.70	11.91	53.61
Dense Forest	5.61	6.87	4.94	1.26	–1.93	–0.67
Horticulture	51.5	63.83	72.54	12.33	8.71	21.04
Marshes	46.96	26.61	19.55	–20.35	–7.06	–27.41
Water	23.09	18.79	18.01	–4.30	–0.78	–5.08

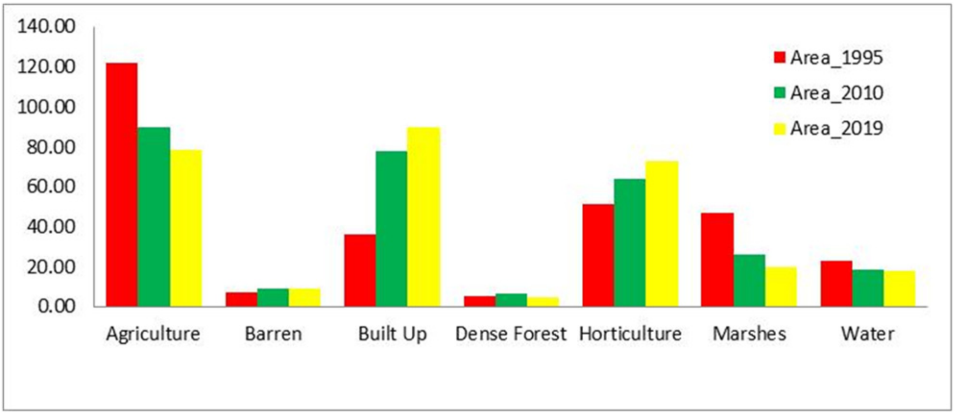

Fig. 5(a). *Area under different LULC classes (1995–2019).*

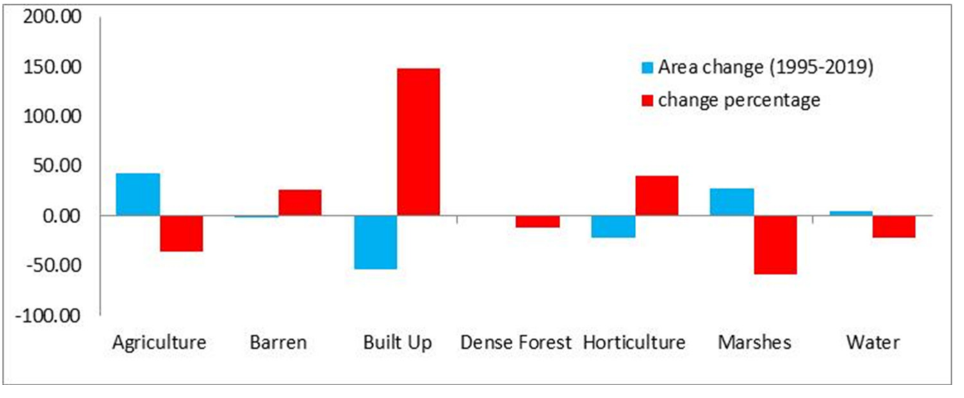

Fig. 5(b). *Changes within each LULC class (1995–2010–2019).*

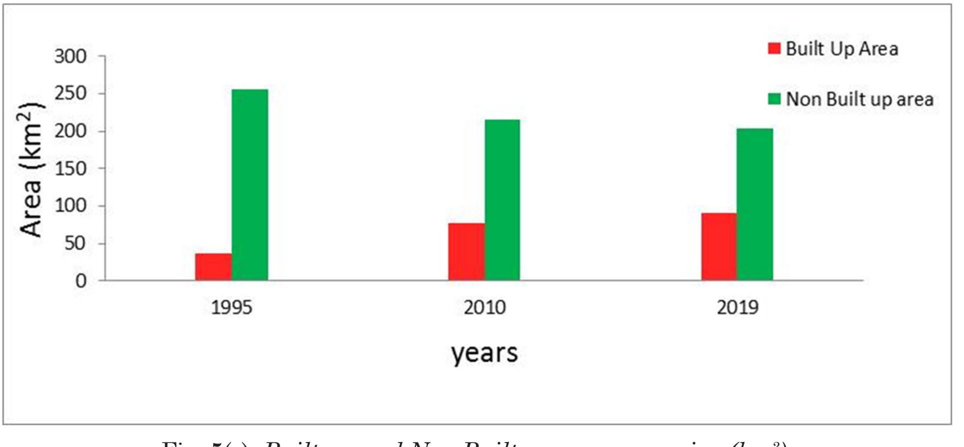

Fig. 5(c). *Built up and Non Built up area expansion (km²).*

3.6. Population Growth and Built-up Land Expansion

As the summer capital, Srinagar city is major commercial hub in the Kashmir valley and also a major tourist destination. Srinagar city underwent a rapid growth of population from 1901 to 2011 (Kuchay and Bhat 2014). In order to link demographic change to the built-up development in the study area, data from the Census of India for 1991–2001–2011 were collected and the built-up area were delineated from the Landsat satellite imagery for 1995–2010–2019. Population data analysis shows that the population of Srinagar city grew by about 58.6 percent over the period from 1991 to 2011 and built-up over the years from 1995 to 2019 grew by about 148.1 percent (Table 6). It reveals this within a 24-year cycle. This indicates that within 24 years, the built-up areas surpassed by about 250 percent that of population growth.

Table 6. *Trend of population growth and built up expansion (area in km²).*

Year	Population	% growth (1991–2011)	Years	Built up	% growth (1995–2019)
1991	800,723		1995	36.2	
2001	995,806		2010	77.89	
2011	1,269,751	58.6	2019	89.81	148.1

Urban areas have been identified using a Boolean approach by defining as a precondition based on study area knowledge. Classes falling in the urban group were assigned a value of 1 and all other classes as 0.Urban maps prepared from satellite data for reference years 1995, 2010, and 2019, respectively. The study indicates the progressive growth of the current space in the built-up area of the city of Srinagar. Non Built up areas that include rest of LULC class accounts about 87.62%,73.37% & 69.30% in 1995, 2010 & 2019 respectively (Fig. 6(a)–(c)), registering a change of about 16.27% (1995 to 2010) and 5.55% in (2010–2019) as shown in Fig. 7(a)–(c). The urban/built-up areas had a perceptible increase, from 12.37% (36.20 km^2) of the total land in 1995 to 26.62% (77.89 km^2) 2010, and further expands to 30.70% (89.81 km^2) of the total land in 2019 as illustrated in Fig. 8(a)–(c). Table 8 shows the overall 53.61 km^2 growth of the built-on region between 1995 and 2019, spatial dynamic changes based on satellite data between 1995–2010 and 2010–2019 indicated a rise of 41.69 km^2 in the first period (1995–2010) and of 11.92 km^2 in the second period. LCR for the years 1995, 2010, and 2019 is 0.0045, 0.0070, and0.00078, respectively (see Table 8). It shows an increase during the period 1995–2010 and further shows a slight increase during 2010–2019.current research revealed that the maximum urban area in this region was occupied during and before 1995–2010. LAC for the periods 1995–2010 and 2010–2019 is 0.021 and 0.004; respectively (see Table 8). The period between 2010 and 2019 witnessed a decrease in the rate at which the rapid expansion of the city was going as against 1995 and 2010. For instance, the built-up land increased by 4170 (ha) in 1995–2010 and only 1191 (ha) in 2010–2019. This is also evident in the drop observed in the land absorption coefficient from 0.021 to 0.004 between 2010 and 2019. The result reflects that the population began to expand across the city during the period 1995–2010–2019 and relocated to the outskirts of the city for better living in an open space away from the densely populated region.

Table 7. *Built-up area and other classes with the respective years.*

LULC	1995		2010		2019	
	Area (km^2)	(%)	Area (km^2)	(%)	Area (km^2)	(%)
Built Up	36.20	12.37	77.89	26.62	89.81	30.70
Non Built up area	256.3	87.62	214.6	73.36	202.69	69.29
Increased Built Up areas (in km^2)	**1995–2019**		**2010–2019**		**1995–2010**	
	53.61		11.92		41.69	

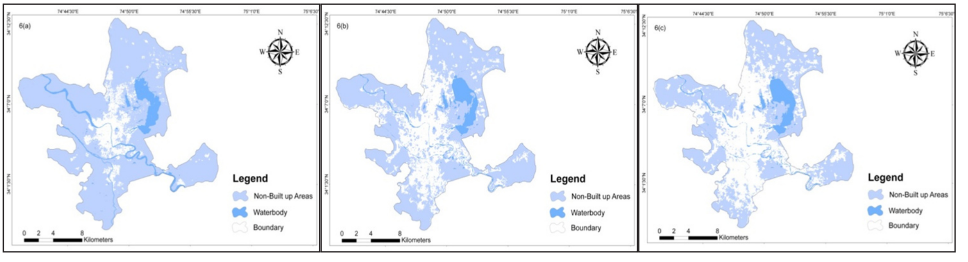

Fig. 6(a). *Non-Built up areas in 1995, (b) Non-Built up areas in 2010, (c) Non-Built up areas in 2019.*

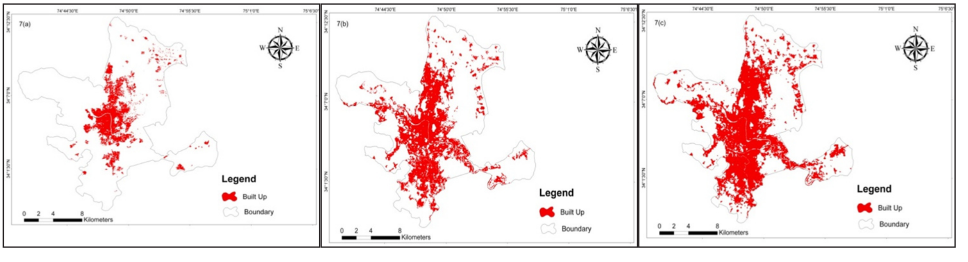

Fig. 7(a). *Showing Built up areas in 1995, (b) showing Built up areas in 2010, (c) showing Built up areas in 2019.*

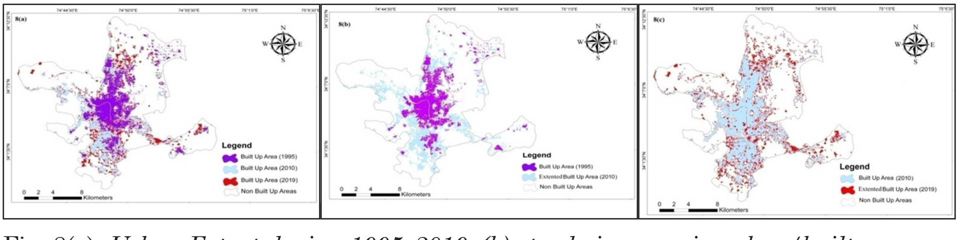

Fig. 8(a). *Urban Extent during 1995–2019, (b) steady increase in urban/built-up areas in Srinagar city from (1995-2010), (c) steady increase in urban/built-up areas in Srinagar city from (2010–2019).*

Table 8. *LCR for selected period and LAC.*

Year	LCR (ha/person)	Year	LAC (ha/person)
1995	0.0045	–	–
2010	0.0070	1995–2010	0.021
2019	0.0078	2010–2019	0.004

4. Conclusion

The Current patterns in urban planning have the most direct environmental effects on the environment, land, infrastructure, urban area composition and design and therefore quality of life. The urban areas of Srinagar have progressively grown over the last few years. Being located in the center of the Kashmir Valley, a large proportion of non-built areas are intended to convert into built-up areas. The population development trends will have an obvious effect on national parks and land use areas unless any conservation strategy is resolved. The study indicates rapid growth in urban/constructed developments leading to drastic land and land use transition, as seen from rapid reductions in agriculture, marshes, river and forestry areas. The result shows a rapid growth in built-up/urban area between 1995 and 2010 while the periods between 2010 and 2019 witnessed slight increase. Horticulture is a LULC class which, after transformation, grows extensively in the entire city after built up. The horticultural land area has increased from 17.61% to 21.79%, and 24.80% respectively in 1995, 2010 and 2019. Forest class revels two change patterns, i.e., the area under forest category shows a progressive growth, i.e., 1.92% to 2.30% in (1995–2010) and a decrease in forest cover from 2.30% to 1.69% in (2010–2019). The open water area has been limited to almost half. The agriculture, water body are the most stressed natural resources in the study area due to climate changes and anthropological effects. The valley's lakes and rivers exhibit major morphological modifications and declines due to massive human activity and variations in water budgets. It is concluded that the findings of the study will give political leaders an insight into the understanding of land use scenario and improvements in land use and the development of environmental friendly policy in the city of Srinagar.

References

Ali, A. M. S. (2006): Rice to shrimp: Land use/land cover changes and soil degradation in Southwestern Bangladesh, Land use policy, 23(4), 421–435.

Anderson, J. R. (1976): A land use and land cover classification system for use with remote sensor data, US Government Printing Office, Washington, DC.

Bender, O., Boehmer, H. J., Jens, D., Schumacher, K. P. (2005): Using GIS to analyse long-term cultural landscape change in Southern Germany, Landscape and urban planning, 70(1–2), 111–125.

Brown, D. G., Pijanowski, B. C., Duh, J. D. (2000): Modeling the relationships between land use and land cover on private lands in the Upper Midwest, USA, Journal of Environmental Management, 59(4), 247–263.

Byomkesh, T., Nakagoshi, N., Dewan, A. M. (2012): Urbanization and green space dynamics in Greater Dhaka, Bangladesh, Landscape and Ecological Engineering, 8(1), 45–58.

Dewan, A. M., Yamaguchi, Y. (2009): Land use and land cover change in Greater Dhaka, Bangladesh: Using remote sensing to promote sustainable urbanization, Applied Geography, 29(3), 390–401.

Dewan, A. M., Yamaguchi, Y., Rahman, M. Z. (2012): Dynamics of land use/cover changes and the analysis of landscape fragmentation in Dhaka Metropolitan, Bangladesh, GeoJournal, 77(3), 315–330.

Döös, B. R. (2002): Population growth and loss of arable land, Global Environmental Change, 12(4), 303–311.

Du, S., Shi, P., Van Rompaey, A. (2014): The relationship between urban sprawl and farmland displacement in the Pearl River Delta, China, Land, 3(1), 34–51.

Foley, J. A., et al. (2005): Global consequences of Land Use, Science, 309(5734), 570.

Gao, J., Liu, Y. (2010): Determination of land degradation causes in Tongyu County, Northeast China via land cover change detection, International Journal of Applied Earth Observation and Geoinformation, 12(1), 9–16.

Gao, Y., Zhang, W. (2009): LULC classification and topographic correction of Landsat 7 ETM+ imagery in the Yangjia River Watershed: the influence of DEM resolution, Sensors, 9(3), 1980–1995.

Ghebrezgabher, M. G., Yang, T., Yang, X., Wang, X., Khan, M. (2016): Extracting and analyzing forest and woodland cover change in Eritrea based on Landsat data using supervised classification, The Egyptian journal of Remote Sensing and Space Science, 19(1), 37–47.

Gumma, M. K., Thenkabail, P. S., Hideto, F., Nelson, A., Dheeravath, V., Busia, D., et al. (2011): Mapping irrigated areas of Ghana using fusion of 30 m and 250 m resolution remote-sensing data, Remote Sensing, 3(4), 816–835.

Gwet, K. (2002): Kappa statistic is not satisfactory for assessing the extent of agreement between raters, Statistical Methods for Inter-Rater Reliability Assessment, 76(1), 378–382.

Hassan, M. S., Mahmud-Ul-Islam, S., Rahman, M. T. (2015): Integration of remote sensing and GIS to assess vulnerability of environmental degradation in North-Western Bangladesh, Journal of Geographic Information System, 7(05), 494.

Hegazy, I. R., Kaloop, M. R. (2015): Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt, International Journal of Sustainable Built Environment, 4(1), 117–124.

Helmer, E. H., Brown, S., Cohen, W. B. (2000): Mapping montane tropical forest successional stage and land use with multi-date Landsat imagery, Int J Remote Sens, 21(11), 2163–2183.

Herold, M., Scepan, J., Clarke, K. C. (2002): The use of remote sensing and landscape-metrics to describe structures and changes in urban land uses, Environment and Planning A, 34(8), 1443–1458.

Huth, J., Kuenzer, C., Wehrmann, T., Gebhardt, S., Tuan, V. Q., Dech, S. (2012): Land cover and land use classification with TWOPAC: Towards automated processing for pixel- and object-based image classification, Remote Sensing, 4(9), 2530–2553.

Jensen, J. R. (2004): Digital change detection, In Introductory Digital Image Processing: A Remote Sensing Perspective; Prentice-Hall: Upper Saddle River, NY, USA, 467–494.

Jia, K., Wei, X., Gu, X., Yao, Y., Xie, X., Li, B. (2014): Land cover classification using Landsat 8 operational land imager data in Beijing, China, Geocarto Int, 29(8), 941–951.

Kanianska, R. (2016): Agriculture and its impact on land-use, environment, and ecosystem services, Amjad Almusaed (Ed.), Landscape ecology – The influences of land use and anthropogenic impacts of landscape creation, Intech, The Netherlands, 124.

Kong, F., Nakagoshi, N. (2006): Spatial-temporal gradient analysis of urban green spaces in Jinan, China, Landscape and urban Planning, 78(3), 147–164.

Kuchay, N. A., Bhat, M. S. (2014): Urban sprawl of Srinagar city and its impact on wetlands – A spatio-temporal analysis, International Journal of Environment and Bioenergy, 9(2), 122–129.

Kumar, R., Acharya, P. (2016): Flood hazard and risk assessment of 2014 foods in Kashmir Valley: a space-based multisensor approach, Nat Hazards, 84(1), 437–464.

Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., et al. (2001): The causes of land-use and land-cover change: Moving beyond the myths, Global Environmental Change, 11(2), 261–269.

Lillesand, T., Kiefer, R. W., Chipman, J. (2015): Remote sensing and image interpretation, Wiley, New York.

Lin, Q., Yu, S. (2018): Losses of natural coastal wetlands by land conversion and ecological degradation in the urbanizing Chinese coast, Scientific reports, 8(1), 1–10.

Liu, Y., Chen, J., Cheng, W., Sun, C., Zhao, S., Pu, Y. (2014): Spatiotemporal dynamics of the urban sprawl in a typical urban agglomeration: a case study on Southern Jiangsu, China (1983–2007), Frontiers of earth science, 8(4), 490–504.

Loveland, T. R., Acevedo, W. (2006): Land cover change in the Eastern United States, US Geological Survey,

https://landcovertrends.usgs.gov/east/regionalSummary.html, (accessed: 1 Sept 2018).

Lu, D., Weng, Q. (2004): Spectral mixture analysis of the urban land-scape in Indianapolis with Landsat ETM+ imagery, Photogram Eng Remote Sens, 70(9), 1053–1062.

Lu, D., Mausel, P., Brondizio, E., Moran, E. (2004): Change detection techniques, Int J Remote Sens, 25(12), 2365–2407.

Lu, D., Hetrick, S., Moran, E., Li, G. (2012): Application of time series Landsat images to examining land-use/land-cover dynamic change, Photogrammetric Engineering and Remote Sensing, 78(7), 747–755.

Mehmood, R., Mehmood, S. A., Butt, M. A., Younas, I., Adrees, M. (2016): Spatiotemporal analysis of urban sprawl and its contributions to climate and environment of Peshawar using remote sensing and GIS techniques, Journal of Geographic Information System, 8(2), 137–148.

Mendoza, M. E., Granados, E. L., Geneletti, D., Pérez-Salicrup, D. R., Salinas, V. (2011): Analysing land cover and land use change processes at watershed level: a multitemporal study in the Lake Cuitzeo Watershed, Mexico (1975–2003), Applied Geography, 31(1), 237–250.

Mucova, S. A. R., Leal Filho, W., Azeiteiro, U. M., Pereira, M. J. (2018): Assessment of land use and land cover changes from 1979 to 2017 and biodiversity & land management approach in Quirimbas National Park, Northern Mozambique, Africa, Global Ecology and Conservation, 16, e00447.

Ojima, D. S., Galvin, K. A., Turner, B. L. (1994): The global impact of land-use change, BioScience, 44(5), 300.

Qadir, J., Singh, P. (2019): Land use/cover mapping and assessing the impact of solid waste on water quality of Dal Lake catchment using remote sensing and GIS (Srinagar, India), SN Applied Sciences, 1(1), 25.

Quintas-Soriano, C., Castro, A. J., Castro, H., García-Llorente, M. (2016): Impacts of land use change on ecosystem services and implications for human well-being in Spanish drylands, Land Use Policy, 54, 534–548.

Rahman, M. T. (2016): Detection of land use/land cover changes and urban sprawl in Al-Khobar, Saudi Arabia: An analysis of multi-temporal remote sensing data, ISPRS International Journal of Geo-Information, 5(2), 15.

Rosenfeld, G. H., Fitzpatirck-Lins, K. (1986): A coefficient of agreement as a measure of thematic classification accuracy, Photogramm Eng Remote Sens, 52(2), 223–227.

Seif, A., Mokarram, M. (2012): Change detection of gil playa in the northeast of Fars province, Iran Am. J. Sci. Res, 86, 122–130.

Shalaby, A., Tateishi, R. (2007): Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the Northwestern coastal zone of Egypt, Applied Geography, 27(1), 28–41.

Singh, P., Javeed, O. (2020): NDVI Based Assessment of Land Cover Changes Using Remote Sensing and GIS (A case study of Srinagar district, Kashmir), Sustainability, Agri, Food and Environmental Research.

Squires, G. D. (Ed.) (2002): Urban sprawl: Causes, consequences, & policy responses, The Urban Institute.

Sun, C., Wu, Z. F., Lv, Z. Q., Yao, N., Wei, J. B. (2013): Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data, International Journal of Applied Earth Observation and Geoinformation, 21, 409–417.

Tarantino, E., Novelli, A., Aquilino, M., Figorito, B., Fratino, U. (2015): Comparing the MLC and Java NNS approaches in classifying multi-temporal Landsat satellite imagery over an ephemeral river area, Int J Agric Environ Inf Syst (IJAEIS), 6(4), 83–102.

Viera, A. J., Garrett, J. M. (2005): Understanding inter-observer agreement: the kappa statistic, Fam Med, 37, 360–363.

Vizzari, M. (2011): Peri-urban transformations in agricultural landscapes of Perugia, Italy, Journal of Geographic Information System, 3(2), 145.

Wilson, B., Chakraborty, A. (2013): The environmental impacts of sprawl: emergent themes from the past decade of planning research, Sustainability, 5(8), 3302–3327.

Xiulian, B. (2017): Analysis of Desertification Situation Using Remote Sensing and GIS – A Case Study in Ongniud Banner, Horqin Sandy Land.

Xu, L., Li, Z., Song, H., Yin, H. (2013): Land-use planning for urban sprawl based on the CLUE-S model: A Case study of Guangzhou, China, Entropy, 15(9), 3490–3506.

Yeates, M., Garner, B. (1976): The North American City, Harper & Row Publication, New York.

Procjena korištenja zemljišta i preobrazbe zemljišnog pokrova i urbane dinamike koristeći viševremenske satelitske podatke

SAŽETAK. Procjena korištenja zemljišta i preobrazbe zemljišnog pokrova (LULC) na različitim prostornim razinama važna je u nekoliko područja uključujući zaštitu okoliša, iskorištavanje prirodnih izvora, planiranje i održivost. U ovom radu pokušava se provesti detaljna studija LULC preobrazbi i analizirati urbana područja u gradu Srinagar (Indija) koristeći viševremenske satelitske podatke Landsat za razdoblje od 1995. do 2019. godine. Iscrtano je sedam različitih LULC klasa za odabrano razdoblje uz pomoć nadzirane metode koristeći algoritam klasifikatora najveće vjerojatnosti u ERDAS Imagine 14. Rezultati ukazuju na to da su se u određenim razdobljima dogodile znatne promjene u smislu LULC-a. Svih sedam kategorija je identificirano te su kroz studije promatrana tri trenda izmjene LULC-a (1) stalno širenje područja u klasi izgrađenosti, neplodnosti, hortikulture (2) poljoprivreda, vode i močvarno tlo se stalno smanjuju (3) porast (1995–2010) i smanjenje (2010–2019) u klasi šuma između dva razdoblja. Tijekom razdoblja provođenja studije, u klasi izgrađenosti (+), hortikulture (+), poljoprivrede (–) voda (–) i močvarnog tla (–) opažene su najznačajnije promjene izražene u postocima unutar svake klase, najveća varijabilnost je uočena u klasi izgrađenosti (148,07%), hortikulture (40,87%), močvarnog tla (–58,37%), vode (–22%) i poljoprivrede (–35,38%). U svrhu kvantitativne procjene promjena uvedene su stopa korištenja zemljišta (LCR) i koeficijent apsorpcije zemljišta (LAC). Sveukupan istraživački scenarij pokazuje da je LULC tranzicija u gradu vrlo očita. Brze izmjene LULC-a u ekološki osjetljivom gradu Srinagaru vođene su uglavnom antropogenim izvorima te imaju negativan utjecaj na okoliš.

Ključne riječi: *LULC, viševremenski, klasifikator najveće vjerojatnosti (MLC), urbani.*

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