JGISE Vol. 4 No. 1 (2021), pp. 71 - 80 | https://doi.org/10.22146/jgise.64857

JGISE
Journal of Geospatial Information Science and Engineering
ISSN: 2623-1182 | https://jurnal.ugm.ac.id/jgise

Monitoring land encroachment and land use and land cover (LULC) change in the Pachhua Dun, Dehradun District Using Landsat images 1989 and 2020

Rahul Thapa[1], Vijay Bahuguna[2]

[1] Research Scholar at D.B.S (P.G) College, Dehradun (Uttarakhand), India.
[2] Assistant Professor at D.B.S (P.G) College, Dehradun (Uttarakhand), India.

Corresponding Author: Rahul Thapa **| Email:** Rahulthapa126@gmail.com

Diterima (*Received*): 22/03/2021 Direvisi (*Revised*): 16/05/2021 Diterima untuk Publikasi (*Accepted*): 03/06/2021

ABSTRACT

Remote sensing and G.I.S help acquire information on changing land use and land cover (LULC), and it plays a pivotal role in measuring and monitoring such local and global changes. The present analysis has been executed on Landsat 5 TM, 1989 and Landsat 8 OLI/TIRS, 2020 images of Pachhua Dun, including Dehradun & Mussoorie urban agglomeration. The present study aims to detect the land encroachment or area of change; rate of change and monitoring spatio-temporal variation in LULC change between 1989-2020 using change detection technique, supervised maximum likelihood classification, and *Overall accuracy & Kappa Coefficient (K)* was applied as an accuracy assessment tool. The results derived from the change detection analysis exhibits that the highest growth rate was recorded in built-up areas +247.75% (110 km^2) and revealed the annual rate of change of 3.55 km^2. or 7.99%, the highest among all LULC class during the overall study period of 31 years. The result also found that among all LULC class, the most significant LULC conversion took place from agricultural land to built-up areas followed by open/scrubland and vegetation/forest cover; approximately 69.9km^2 of the area under agricultural land was found to be converted into built-up areas. At the same time, 38.9 km^2 area of vegetation/forest cover and 36.3 km^2 of the area of open/scrubland have converted into agricultural land. Rising anthropogenic influence and unsustainable land-use practices in the study area have led to a large-scale human encroachment and rapid transformation of the natural landscape into the cultural landscape. This analysis provides the essential long-term Geospatial information related to LULC change for making optimum decision-making process and sustainable land-use planning in the Pachhua Dun-Dehradun District, Uttarakhand, India.

Keywords**:** LULC; Change detection; supervised classification; Accuracy assessment; Maximum likelihood classification.

© Author(s) 2021. This is an open access article under the Creative Commons Attribution-ShareAlike 4.0 International License (CC BY-SA 4.0).

1. Introduction

In general, the land use land cover (LULC) definition splits the Earth's surface into two categories: land use and land cover. (Donnay, Barnsley, and Longley 2000). The LULC modifications must be studied in order to plan and manage natural resources properly. Remote sensing and GIS techniques and software provide robust tools for acquiring timely satellite data of change in LULC with accuracy (Arveti, Etikala, and Dash 2016; Lu et al. 2004; Mamun and Mahmood 2013). GIS and remote sensing have covered a wide range of applications in environments, integrated eco-environment assessment, and agriculture (Mallupattu and Sreenivasula Reddy 2013).

The use of satellite data has recently expanded to take advantage of the growing amount of spatial data available in combination with GIS to help in analysis. Amidst, humans have caused remarkable changes (Birhane et al. 2019), but LULC change and its resources have been widely used for socio-cultural, spiritual, and material needs. Furthermore, such changes in LULC can be ascribed to several depending on the climatic, socio-economic and political conditions(Kafi, Shafri, and Shariff 2014). LULC changes indicates the environmental changes generated by anthropogenic and natural consequences (Rawat and Kumar 2015; Santosa, 2015). However, the primary factor determining the LULCC and its size and patterns are population growth, and such changes are dynamic and continuous in nature. The expansion of Urban and sub-urban areas demands more land and promotes rural areas' transformation to the urban area(Farooq and Ahmad 2008; Mohan et al. 2011; Xiaoqing and Jianlan 2007).

Therefore, LULC change analysis report plays a crucial role in the optimum utilization and management of natural resources (Vivekananda, Swathi, and Sujith 2020).

The recent decades have witnessed the extensive array of improvements achieved in the field of LULCC methods and techniques, and various LULCC mapping have been applied, along with change detection all over the globe(Jin et al., 2013, 2017; Kun et al., n.d.; Lv et al., 2018; Mishra et al., 2020; Phiri & Morgenroth, n.d.; Wu et al., 2018; Zhang et al., n.d.; Zhu & Woodcock, 2014). There are numerous methods and technique are available for detecting LULC change and its assessment. The change detection technique detects gaps in its composition by analysing a phenomenon or an object at a particular time interval(Lu et al. 2004).The Change Detection in LULC is the measure of the separable Data Layout and noticeable change in information that can lead to more visible insight into the subtle process enclosing LULCC that the data observed from the usual changes(Singh et al. 2013). It has emerged as an essential process for urban development, monitoring and management of natural resources. Therefore, the simple Change Detection method is seldom adequate in itself; it is crucial to have up-to-date and accurate LULC change data to understand and assess the environmental consequences of such change(Giri, Zhu, and Reed 2005; Srivastava et al. 2012a).

The following details must be given for good change detection technique research: (1) the spatial distribution of changed types; (2) the change rate and change in the area; (3) the change trajectories for the land cover class; (4) classified image accuracy assessment using the change detection results (Lu et al. 2004). Whereas various supervised classification has become the most extensively used LULC classification method in Remote sensing & G.I.S helps in identifying significant changes in LULC classes(Gašparović, Zrinjski, and Gudelj 2019; Huang, Davis, and Townshend 2002; Verma et al. 2020), which creates decision surface based on the means of covariance of each classification class (Richards n.d.; Srivastava et al. 2012b). In Image classification, the supervised classification method accompanied by Maximum likelihood classification or algorithm (MLC) is popular among scholars, as it is based on the possibility that a pixel belongs to a particular class; however, in our case, the result obtained using MLC method have produced few miss-classifications between different LULC classes in the study area. Hence, we applied the *interactive supervised classificatio*n technique as it has created more accurate and satisfactory result.

The present study aims to detect the area of change and rate of change using change detection technique & analysing the spatio-temporal variation in LULC change between 1989-2020. The result was obtained using multiple satellite datasets of Landsat images of Landsat-5, 1989; and Landsat-8, 2020 in Pachhua Dun, Dehradun district, Uttarakhand (India).

2. Map of the Study area

The current research was performed in Pachhua dun as shown in Figure 2.1. It includes two blocks, i.e., Vikasnagar C.D Block and Sahaspur C.D Block and Dehradun & Mussoorie Urban Agglomeration. The longitudinal extent of the study area is 77°34'30"E to 78°10'30''E, whereas the latitudinal extent of the study area is 30°13'30''N to 30°32'30"N. The total area covered by the study area is 931.3 km^2; and its elevation range varies from 362m to 2320m. The Lowest elevation was found in Vikasnagar C.D block, and the highest elevational point was found in Mussoorie range.

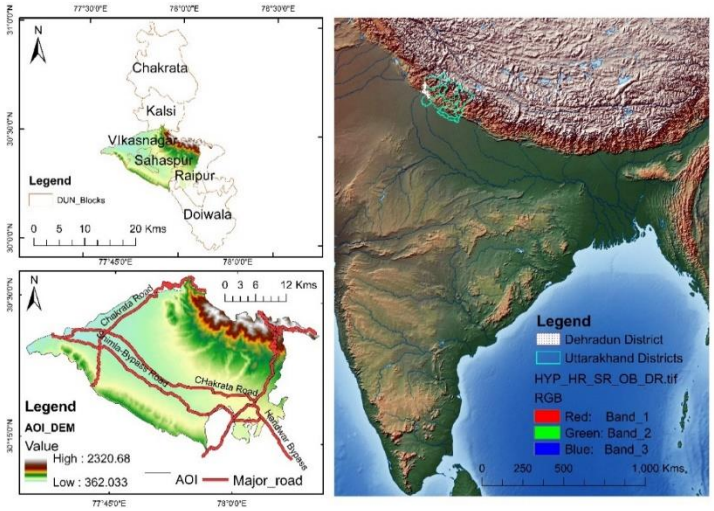

Figure 2.1. Location of the study area (Pachhua Dun-District Dehradun)

3. Data and Methodology

To assess the 31 year of LULC change of the Pachhua dun, the Landsat-5, 1989, and Landsat 8 , 2020 satellite images was used. Primarily both sensors (OLI & TM) of Landsat images was used to monitor change and mapping LULC change using five LULC class of viz., agricultural land (AL), the Built-up areas (BUAs), Open/Scrubland (O/SL), Vegetations/ Forest cover (V/FC), Water bodies (WB) of the Pachhua dun, Dehradun district.

3.1 Method and techniques of image classification.

3.1.1. Maximum likelihood supervised classification schemes and Change Detection.

To analyse the LULC change, the most widely used supervised MLC method was applied. With an aim to ease the image classification using change detection, the study area was grouped into five categories Each LULC classification class was arranged into alphabetic orders, i.e., the AL, BUAs, O/SL; V/FC & WB. The classified *.tiff* was converted into polygon *shp.* The accuracy assessment was executed on the both images of Landsat 5, 1989 and Landsat 8, 2020 using Google Earth and ArcMap. Although, few *similar spectral responses w*as also evident in the

selected training samples of BUAs, ephemeral rivers bed contained bare/land rock, gravels and conglomerate (under Water bodies). The timely and accurately applied change detection technique over the Eath's surface gives us more refined analysis that helps us understand human and natural phenomena' interaction patterns. Therefore, to monitor and manage natural resources and urban development, change detection has become a critical process(Hassan et al. 2016). Figure 4.2 and 4.3 shows the LULC map of the area of change (AOC) between 1989-2020.

3.2 Accuracy Assessments

In any image classification initiative, accuracy assessment plays a crucial role. Its goal is to calculate the effectivity of the sampled pixels in the right LULC groups. (Rwanga and Ndambuki 2017). it is implemented using Overall accuracy (OvAc), and Kappa coefficient(K) obtained from the error matrix of LULC class(Clevers 2009; Liu, Frazier, and Kumar 2007). The obtained result is given in Table 3.1. The ratio between correctly classified training pixels and the total number of pixels as given in Eq. (1)

$$OvAc = \frac{OvAc \sum_{a=1}^{u} c_{aa}}{Q} \times 100\% \quad (1)$$

Where, U represents the total number of training class and Q represents the total number of training pixel. Along with the minimum acceptable OvAc of 85%. However, to obtain more accurate and robust accuracy assessment results, the kappa (K) was implemented along with an OvAc assessment.

Table 3.1 : Statistical summary of accuracy assessment of LULC map.

LULC Class	User%	Producer %	User%	Producer %
Agricultural Land	75.96	75.24	87.42	88.59
Built-Up Areas	64.39	87.63	88.29	89.50
Open/Scrub Land	83.82	71.25	72.22	72.22
Vegetation/Forest Cover	92.16	87.85	96.17	97.10
Water Bodies	85.00	80.00	84.68	80.15
Overall Accuracy	*79.42%*		*87.46%*	
Kappa (K)	*74.08%*		*84.04%*	
Commission errors	*20.35%*		*14.24%*	
Omission errors	*19.73%*		*14.75%*	

3.2.1 Accuracy assessment using Kappa Coefficient

The relationship is determined by (K) between two sets of the categorical dataset when correcting the agreement between the groups for chance (Jenness and Wynne 2005), (K) report the relationship between the reference data and classified map (Lillesand, Kiefer, and Chipman 2015). The kappa strength of agreement on a scale where 0.00 indicates poor agreement or no correlation in the classification, whereas a (K) of 1 represents perfect agreement. Kappa coefficient can be measured using the formula given in Eq. (2).

$$K = \frac{n\sum_{i=1}^{p} x_{ii} - \sum_{i=1}^{p}(x_{i+} \times x_{+i})}{n^2 - \sum_{i-1}^{p}(x_{i+} \times x_{+1})} \quad (2)$$

Where, $\sum x_{ii}$ = Total number elements of the error matrix; $\sum x_{+1}$= $\sum$ of column *i; and* $\sum x_{i+}$ = $\sum$ of row *i, and* n = Total number of training pixels, and p = Number of classes.

The error matrix has then been generated to represent the results from comparing the LULC categories' reference class labels with the actual results (Stehman and Czaplewski 1998). The OvAc and (K) results obtained after the accuracy assessment of LULC change using error matrix and MLC algorithms is given in Table 3.1. The estimated OvAc and (k) value was 79.42% and 74.08% for the Landsat 1989 image. And as per the kappa strength of agreement, it is a *substantial agreement.* Whereas the Kappa coefficient value and Overall accuracy of Landsat 8, 2020 image was 84% and 87.46%, and it is turn out to be an almost perfect agreement under the kappa strength of agreement class. After the Accuracy assessment, the LULC change matrix and map were produced using ArcGIS to understand the status of LULC change and its magnitude rate of change for 1989-2020. The percentage of change (PC) and Magnitude of change (MC), and Annual Rate of Change (ARC) of the classified image was calculated using the following equations (Eqs 3-6).

$$MC(km^2) = A_i - A_f \quad (3)$$

$$PC\ (\%) = \frac{A_i - A_f}{A_i} \times 100 \quad (4)$$

$$ARC\ (km^2.year^{-1}) = \frac{A_i - A_f}{n} \quad (5)$$

$$ARC\ (\%) = \left(\frac{A_i - A_f}{A_i \times n}\right) \times 100 \quad (6)$$

Where, A_f is the class area in km^2 at the final time and A_i is the class area in km^2 at the initial time, and n is the number of years of the study period.

4. Result and Discussion

4.1. Conversion matrix of LULC map

To prepare LULC map, the satellite images of Landsat 5-1989 & Landsat 8-2020 were taken and processed. Table 4.1-4.3 and Figure 4.1-4.3 demonstrate the final result obtained from the change detection analysis of each LULC class area of interest. The classification was intended to create a 31-year LULC change and to compare the

change in surface temperature. The supervised MLC technique was applied for analysing and mapping the LULC change, as each LULC class expresses the proportion of the total area of the satellite image covered by it. Therefore, it offers an insight into the overall area's composition.

The change detection was applied to estimate the land-use conversion in percentage and km^2. This finding is consistent with several other previous studies carried out in the Dehradun District (Agarwal, Soni, and Rawat 2019; Deep and Kushwaha 2020; Iortyom, Semaka, and Abawua 2020; Maithani 2020; Mishra, Kumar, and Nikam 2019; Nijagunappa et al. 2007; Sawant, Prakash, and Mishra 2021; Sharma and Bagri 2020; Tiwari and Khanduri 2011; Tripathi, Pingale, and Khare 2019), highlighting the LULC change and its impact. The rapid spatial expansion of BUAs or urban activities in the study area may result in further loss in agricultural land, thus leading to accelerating sustainability risks and the threat of livelihoods, as agricultural growth stimulates non-agricultural activities in the rural regions, and it would be beneficial for those with little or no agricultural land or other assets.

4.2. LULC change and Land encroachment among each LULC class

To understand the land encroachment among each LULC class during the last three decades, a change detection matrix or error matrix (Table 4.1) was produced, which showed that:

(i) Among all LULC class, the open/scrub land has witnessed large-scale human encroachment, and about 53.36% or 38.9km^2 of open/scrub land area has been converted into agricultural land, 24.8 km^2 or 34% into built-up areas, and 9.05% or 6.6 km^2 into vegetation/forest cover.

(ii) About 27.22% or 69.9 km^2 agricultural land area was converted into built-up areas, 11.64% 29.9 km^2 into vegetation/forest cover, and 1.48% into open/scrub land.

(iii) 6.89% or 36.3 km^2 area of vegetation/forest cover found to be converted into agricultural land, 3.49% or 18.4 km^2 area into built-up areas.

(iv) 46.20% or 14.4 km^2 area of water bodies found to be converted into built-up areas (primarily at the banks of Asan river and its tributaries, it is a westward flowing ephemeral river, flows through Sahaspur to Vikasnagar C.D blocks 23.43% (7.1 km^2) into agricultural land, and 8.25%(2.5 km^2) into open/scrub land.

Table 4.1. LU/LC change matrix illustrating the land encroachment in sq. km of the study area

		Year 2020					
	LULC	**AL**	**BUAs**	**O&SL**	**V&FC**	**WB**	**Total**
Year 1989	**AL**	152.9	69.9	3.8	29.9	0.3	256.8
	BUAs	13.5	26.9	0.9	2.6	0.5	44.4
	O&SL	38.9	24.8	2.2	6.6	0.4	72.9
	V&FC	36.3	18.4	0.4	471.3	0.5	526.9
	WB	7.1	14.4	2.5	0.9	5.4	30.3
	Total	*248.7*	*154.4*	*9.8*	*511.3*	*7.1*	931.3

Table 4.2. Area an amount of change in different LULC categories

	1989		**2020**		**1989-2020**	
LULC Class	**Area in km^2**	**Area in %**	**Area in km^2**	**Area in %**	**Area in km^2**	**Area in %**
AL	256.8	27.57	248.7	26.70	-8.1	-0.87
BUAs	44.4	4.77	154.4	16.58	110	11.81
OSL	72.9		9.8	1.05	-63.1	-6.78
VFC	526.9	56.58	511.3	54.90	-15.6	-1.68
WB	30.3	3.25	7.1	0.76	-23.2	-2.49

Table 4.3. Statistical description of area and amount of change in different LULC change categories in the of study area during 1989-2020

LU/LC Cover Categories	1989	2020	Rate of Change		Annual rate of Change	
	Area Km²	Area Km²	Area km²	Area %	Km² .year⁻¹	%.year⁻¹
AL	256.8	248.7	-8.10	-3.15	-0.26	-0.10
BUAs	44.4	154.4	+110.00	+247.75	+3.55	+7.99
O/SL	72.9	9.8	-63.10	-86.56	-2.04	-2.79
V/FC	526.9	511.3	-15.60	-2.96	-0.50	-0.10
WB	30.3	7.1	-23.20	-76.57	-0.75	-2.47
Total Area	931.3	931.3	-	-	-	-

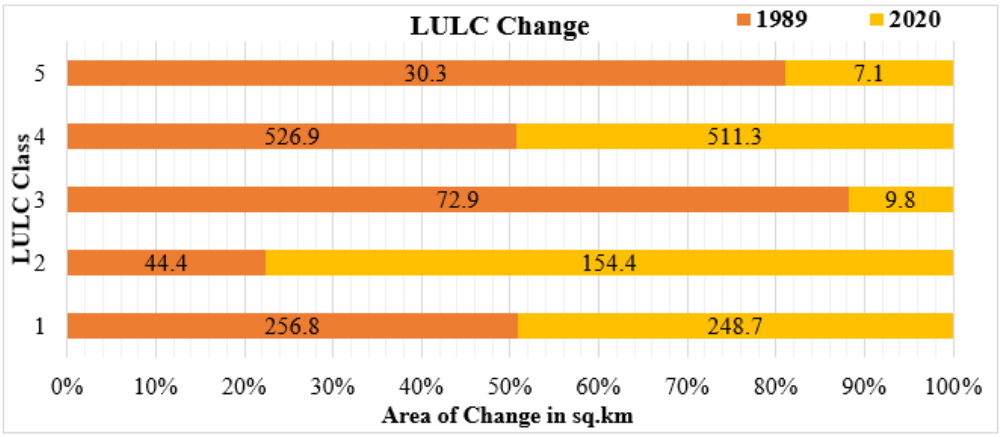

Figure 4.1. LULC change in the Pachhua Dun between 1989-2020. (1) AL (2) BUAs (3) O/SL (4) V/FC (5) WB

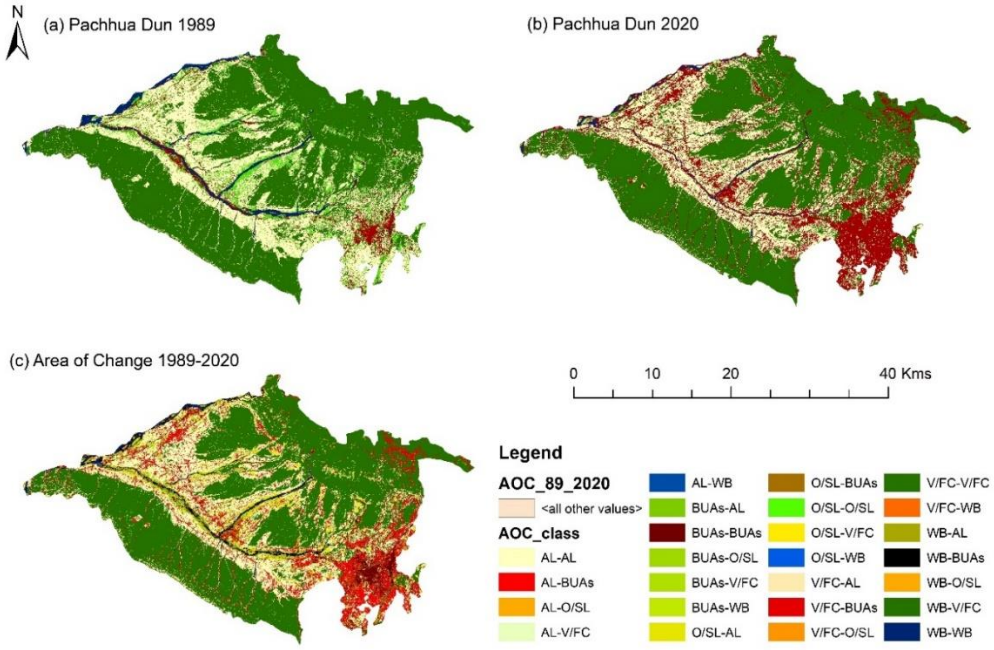

Figure 4.2. Illustration of LULC change in the study area between (1989-2020) : Where (a) Landsat 5 image of year 1989; (b) Landsat image of year 2020 (c) represents the overall area of change map

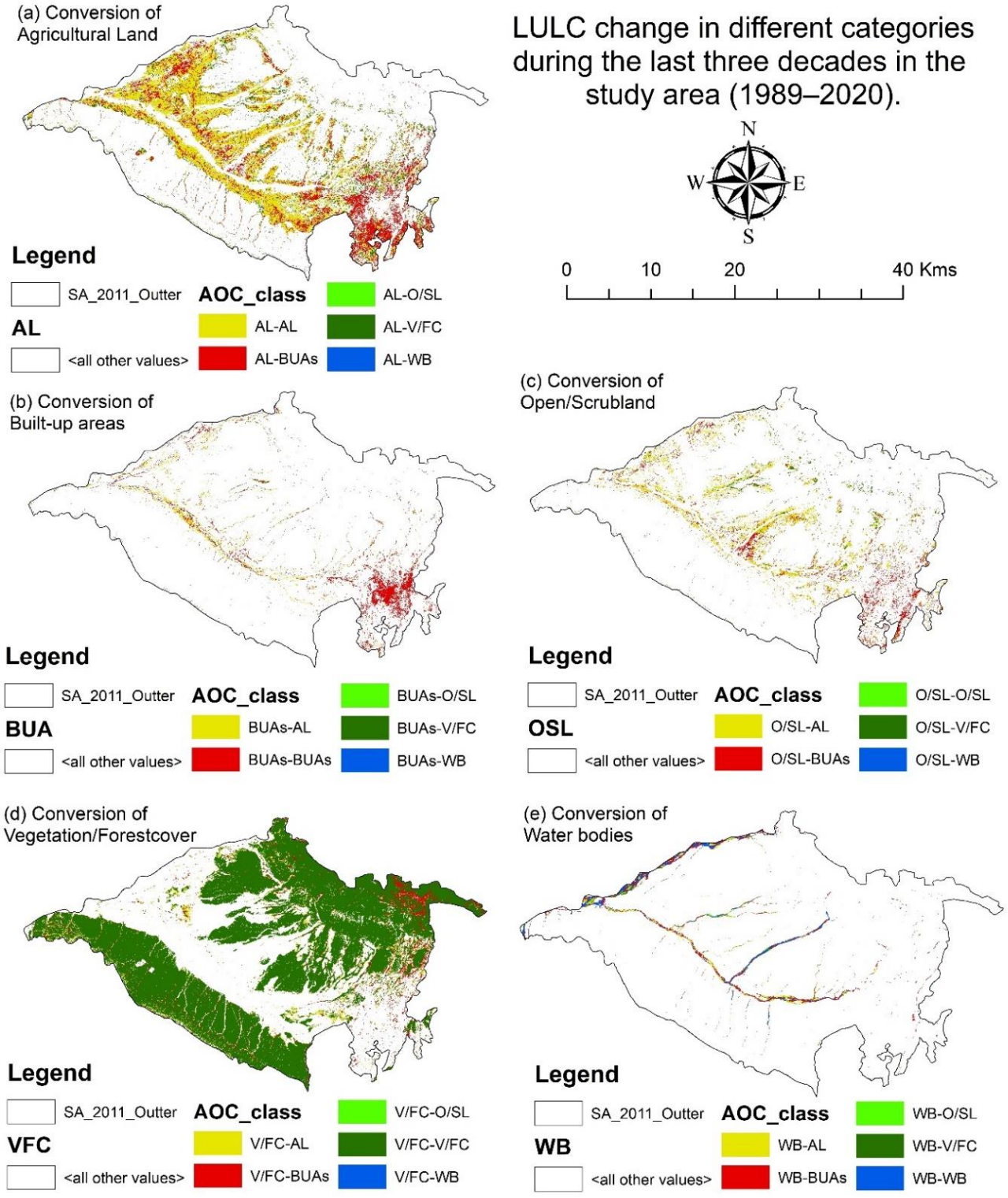

Figure 4.3. Illustration of LULC change in the study area between (1989-2020) : Where (a) Landsat 5 image of year 1989; (b) Landsat image of year 2020 (c) represents the overall area of change map.

4.3. The calculated rate of change and the annual rate of change of Landsat image 1989 and 2020

Table 4.2 and 4.3 help to understand the LULC change of each LULC class during the last three decades in detail. The table showed that.

(i) Agricultural land and vegetation/forest cover both have registered a negative growth rate of **-3.15%** and **-2.96%**, respectively, whereas its annual rate of change was **-0.10%** for both classes. On the other hand, a significant portion of open/scrub land and vegetation/forest cover have replaced by agricultural land, as highlighted in Table 4.2. Thereby highlighted the anthropogenic land cover conversion and decline of natural vegetation in the study area.

(ii) Built-up areas have registered the highest growth rate of **+247.75%** or **110.00 km²**. At the same time, having an annual rate of change of ARC= +**7.99%** or +**3.55 km²**. Notably, the built-up areas have primarily replaced the areas previously covered by agricultural land and open/scrubland. Such newly built-up explicitly appeared mainly in the plain areas and at the proximity to the nearby urban centres and significant road junction points.

(iii) Open/scrubland and water bodies have registered the lowest negative growth of **-86.56%** and **-76.57%**. Both were highly subjected to anthropogenic influences, thereby primarily converted into built-up areas and agricultural land. The ARC for each class was negative, and the result found the ARC= **-2.79%** and -**2.47%**, respectively.

5. Conclusion

The present research has assessed the LULC change in the Pachhua dun, including Dehradun and Mussoorie urban agglomerations, over 31 years using the Landsat data of 1989, 2020. The result reveals that the Pachhua dun region (Sahaspur and Vikasnagar C.D. Blocks) has consistently bear the brunt of the exponential growth of the BUAs and urban expansions; the built-up areas have registered a consistent increase. The change detection analysis results further supported the evidence of the expansion of BUAs; the result showed the growth of BUAs with +247.75% or (110 km²), but primarily at the expense of agricultural land use, open/scrubland and vegetation/forest cover. The calculated annual rate of change of the built-up regions was highest among all LULC class; and it is the only LULC class that has registered a highest positive annual rate of change of 3.55 km² per year or 7.99% per year. Both agricultural land and vegetation/forest cover have reported a negative growth rate of -3.15% and -2.96%, respectively and exhibited an annual rate of -0.10% for both classes. The result also found that among all LULC class, agricultural land was the prime contributor to built-up areas growth followed by open/scrubland and vegetation/forest cover. During the analysis period, approximately 69.9km² or 27.22% agricultural land area was converted into built-up areas.

On the other hand, 53.36% or 38.9km² of open/scrubland area has been converted into agricultural land and 24.8 km² or 34% into built-up areas. However, a significant portion of open/scrub land and vegetation/forest cover have been simultaneously converted into agricultural land. During the overall agricultural land assessment, the change rate and annual rate of change value were less. The result showed that anthropogenic activities have significantly caused changes in LULC; thus, it highlights the problem of unsustainable land-use practices in the study area, which is a significant environmental challenge. The massive expansion of BUAs is driven by urbanization, and rural-urban migrations lead to haphazard and fragmented development of the settlement deep into fertile agricultural land.

As a recommendation, the land use conversion of agricultural land and open/scrub land of the Pachhua Dun, primarily into uses like residential, commercial and industrial purposes needs to be sustainably managed.

In conclusion, the outcome of the result has provided the long-term, accurate and updated information required for the optimum decision-making process and sustainable land-use planning in the Pachhua Dun.

6. Conflict of Interest

The authors declare no competing interest.

7. References

Agarwal, Apeksha, K. K. Soni, and M. S. S. Rawat. 2019. "Monitoring Land Use Land Cover Change for Dehradun District of Uttarakhand from 2009-2019." *Cloud Publications* 8(1):3106–13. doi: 10.23953/cloud.ijarsg.431.

Arveti, Nagaraju, Balaji Etikala, and Padmanava Dash. 2016. "Land Use/Land Cover Analysis Based on Various Comprehensive Geospatial Data Sets: A Case Study from Tirupati Area, South India." *Scientific Research Publishing Inc* 5:73–82. doi: 10.4236/ars.2016.52006.

Birhane, Emiru, Haregeweini Ashfare, Ayele Almaw Fenta, Hadgu Hishe, M. A. Gebremedhin, Hailemariam G. Wahed, and Negasi Solomon. 2019. "Land Use Land Cover Changes along Topographic Gradients in Hugumburda National Forest Priority Area, Northern Ethiopia." *Remote Sensing Applications: Society and Environment* 13:61–68. doi: 10.1016/j.rsase.2018.10.017.

Clevers, J. G. P. W. 2009. "Russell G. Congalton, Kass Green, Assessing the Accuracy of Remotely Sensed Data - Principles and Practices Second Edition (2009) CRC Press, Taylor & Francis Group, Boca Raton, FL 978-1-4200-5512-2 183 Pp., Price: $99.95." *Int. J. Applied Earth Observation and Geoinformation* 11:448–49. doi: 10.1016/j.jag.2009.07.002.

Deep, S., and S. P. S. Kushwaha. 2020. "Urbanization, Urban Sprawl and Environment in Dehradun." Pp. 175–84 in *Energy, Environment and Globalization: Recent Trends, Opportunities and Challenges in India*, edited by A. Gupta and N. N. Dalei. Singapore: Springer.

Donnay, Jean-Paul, Mike J. Barnsley, and Paul A. Longley. 2000. *Remote Sensing and Urban Analysis: GISDATA 9*. CRC Press.

Farooq, S., and S. Ahmad. 2008. "Urban Sprawl Development around Aligarh City: A Study Aided by Satellite Remote Sensing and GIS." *Journal of the Indian Society of Remote Sensing* 36(1):77–88. doi: 10.1007/s12524-008-0008-0.

Gašparović, Mateo, Mladen Zrinjski, and Marina Gudelj. 2019. "Automatic Cost-Effective Method for Land Cover Classification (ALCC)." *Computers, Environment and Urban Systems* 76:1–10. doi: 10.1016/j.compenvurbsys.2019.03.001.

Giri, C., Z. Zhu, and B. Reed. 2005. "A Comparative Analysis of the Global Land Cover 2000 and MODIS Land Cover Data Sets." *Remote Sensing of Environment* 94(1):10.

Hassan, Zahra, Rabia Shabbir, Sheikh Saeed Ahmad, Amir Haider Malik, Neelam Aziz, Amna Butt, and Summra Erum. 2016. "Dynamics of Land Use and Land Cover Change (LULCC) Using Geospatial Techniques: A Case Study of Islamabad Pakistan." *SpringerPlus* 5(1):812. doi: 10.1186/s40064-016-2414-z.

Huang, C., L. S. Davis, and J. R. G. Townshend. 2002. "An Assessment of Support Vector Machines for Land Cover Classification." *International Journal of Remote Sensing* 23(4):725–49. doi: 10.1080/01431160110040323.

Iortyom, Enoch Terlumun, John Terwase Semaka, and Jonathan Ityofa Abawua. 2020. "Spatial Expansion of Urban Activities and Agricultural Lands Encroachment in Makurdi Metropolis." *European Journal of Environment and Earth Sciences* 1(6). doi: 10.24018/ejgeo.2020.1.6.89.

Jenness, Jeff, and J. Judson Wynne. 2005. "Cohen's Kappa and Classification Table Metrics 2.0: An ArcView 3.x Extension for Accuracy Assessment of Spatially Explicit Models." *Open-File Report OF 2005-1363. Flagstaff, AZ: U.S. Geological Survey, Southwest Biological Science Center. 86 p*.

Jin, Suming, Limin Yang, Patrick Danielson, Collin G. Homer, Joyce Fry, and George Xian. 2013. "A Comprehensive Change Detection Method for Updating the National Land Cover Database to circa 2011." *Remote Sensing of Environment* 132:159175.

Jin, Suming, Limin Yang, Zhe Zhu, and Collin Homer. 2017. "A Land Cover Change Detection and Classification Protocol for Updating Alaska NLCD 2001 to 2011." *Remote Sensing of Environment* 195:44–55. doi: 10.1016/j.rse.2017.04.021.

Kafi, K. M., H. Z. M. Shafri, and A. B. M. Shariff. 2014. "An Analysis of LULC Change Detection Using Remotely Sensed Data$\mathsemicolon$ A Case Study of Bauchi City." *IOP Conference Series: Earth and Environmental Science* 20:012056. doi: 10.1088/1755-1315/20/1/012056.

Kun, Jia, Xiangqin Wei, Xingfa Gu, Yunjun Yao, Xianhong Xie, and Bin Li. n.d. "Land Cover Classification Using Landsat 8 Operational Land Imager Data in Beijing, China: Geocarto International: Vol 29, No 8." Retrieved December 29, 2020 (https://www.tandfonline.com/doi/abs/10.1080/10106049.2014.894586).

Lillesand, Thomas, Ralph W. Kiefer, and Jonathan Chipman. 2015. *Remote Sensing and Image Interpretation*. John Wiley & Sons.

Liu, Canran, Paul Frazier, and Lalit Kumar. 2007. "Comparative Assessment of the Measures of Thematic Classification Accuracy." *Remote Sensing of Environment* 107(4):606–16. doi: 10.1016/j.rse.2006.10.010.

Lu, D., P. Mausel, E. Brondizio, and E. Moran. 2004. "Change Detection Techniques." *Taylor & Francis Online* 25(12). doi: 10.1080/0143116031000139863.

Lv, Zhiyong, Tongfei Liu, Yiliang Wan, Jón Atli Benediktsson, and Xiaokang Zhang. 2018. "Post-Processing Approach for Refining Raw Land Cover Change Detection of Very High-Resolution Remote Sensing Images." *Remote Sensing* 10(3):472. doi: 10.3390/rs10030472.

Maithani, Sandeep. 2020. "A Quantitative Spatial Model of Urban Sprawl and Its Application to Dehradun Urban Agglomeration, India." *Journal of the Indian Society of Remote Sensing* 48(11):1583–92. doi: 10.1007/s12524-020-01182-9.

Mallupattu, Praveen Kumar, and Jayarama Reddy Sreenivasula Reddy. 2013. "Analysis of Land Use/Land Cover Changes Using Remote Sensing Data and GIS at an Urban Area, Tirupati, India." *The Scientific World Journal* 2013:e268623. Retrieved February 27, 2021 (https://www.hindawi.com/journals/tswj/2013/268623/).

Mamun, Abdullah Al, and Asif Mahmood. 2013. "Identification and Monitoring the Change of Land Use Pattern Using Remote Sensing and GIS: A Case Study of Dhaka City." *IOSR Journal of Mechanical and Civil Engineering* 6:20–28. doi: 10.9790/1684-0622028.

Mishra, Nitin, Sanjeev Kumar, and Bhaskar R. Nikam. 2019. "Land Use/Land Cover Change Analysis of Doon Valley Using ArcGIS Tools." Pp. 175–84 in *Smart Technologies for Energy, Environment and*

Sustainable Development, *Lecture Notes on Multidisciplinary Industrial Engineering*, edited by M. L. Kolhe, P. K. Labhasetwar, and H. M. Suryawanshi. Singapore: Springer.

Mishra, Prabuddh Kumar, Aman Rai, and Suresh Chand Rai. 2020. "Land Use and Land Cover Change Detection Using Geospatial Techniques in the Sikkim Himalaya, India." *The Egyptian Journal of Remote Sensing and Space Science* 23(2):133–43. doi: 10.1016/j.ejrs.2019.02.001.

Mohan, Manju, Subhan K. Pathan, Kolli Narendrareddy, Anurag Kandya, and Sucheta Pandey. 2011. "Dynamics of Urbanization and Its Impact on Land-Use/Land-Cover: A Case Study of Megacity Delhi." *Journal of Environmental Protection* 2(9):1274–83. doi: 10.4236/jep.2011.29147.

Nijagunappa, R., Sulochana Shekhar, B. Gurugnanam, P. L. N. Raju, and Prabir De. 2007. "Road Network Analysis of Dehradun City Using High Resolution Satellite Data and Gis." *Journal of the Indian Society of Remote Sensing* 35(3):267–74. doi: 10.1007 /BF03013494.

Phiri, Darius, and Justin Morgenroth. n.d. "Remote Sensing | Free Full-Text | Developments in Landsat Land Cover Classification Methods: A Review." Retrieved December 29, 2020 (https://www.mdpi. com/2072-4292/9/9/967).

Rawat, J. S., and Manish Kumar. 2015. "Monitoring Land Use/Cover Change Using Remote Sensing and GIS Techniques: A Case Study of Hawalbagh Block, District Almora, Uttarakhand, India." *The Egyptian Journal of Remote Sensing and Space Science* 18(1):77–84. doi: 10.1016/j.ejrs.2015.02.002.

Richards, John A. n.d. "Remote Sensing Digital Image Analysis | SpringerLink." Retrieved December 29, 2020 (https://link.springer.com/book/10.1007%2F978-3-642-30062-2).

Rwanga, Sophia S., and J. M. Ndambuki. 2017. "Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS." *International Journal of Geosciences* 08(04):611–22. doi: 10.4236/ijg.2017.84033.

Santosa, P. B. 2016. "Evaluation of satellite image correction methods caused by differential terrain illumination". *Jurnal Forum Geografi*. Vol. 30, No. 1 (2016). https://doi.org/10.23917/forgeo.v30i1.1768

Sawant, Kunal, Rishi Prakash, and Nitin Mishra. 2021. "Effect of Urban Land Use on Agriculture, Forest, and River Beds: A Case Study of Dehradun City, Uttarakhand, India." Pp. 187–96 in *Advances in Civil Engineering and Infrastructural Development*, *Lecture Notes in Civil Engineering*, edited by L. M. Gupta, M. R. Ray, and P. K. Labhasetwar. Singapore: Springer.

Sharma, Ankita, and Dhirendra Singh Bagri. 2020. "Monitoring Of Urban Sprawl And Spatio-Temporal Variability Of Landuse/ Landcover Change In Asan Watershed, Doon Valley, Uttarakhand, India." *Earth and Space Science Open Archive*. Retrieved April 2, 2021 (http://www.essoar.org/doi/10.1002/essoar.10505204.1).

Singh, A., S. Singh, P. K. Garg, and K. Khanduri. 2013. "Land Use and Land Cover Change Detection: A Comparative Approach Using Post Classification Change Matrix and Discriminate Function Change Detection Methodology of Allahabad City." *Undefined*.

Srivastava, Prashant K., Dawei Han, Miguel A. Rico-Ramirez, Michaela Bray, and Tanvir Islam. 2012a. "Selection of Classification Techniques for Land Use/Land Cover Change Investigation." *Advances in Space Research* 50(9):1250–65. doi: 10.1016/j.asr.2012.06.032.

Srivastava, Prashant K., Dawei Han, Miguel A. Rico-Ramirez, Michaela Bray, and Tanvir Islam. 2012b. "Selection of Classification Techniques for Land Use/Land Cover Change Investigation." *Advances in Space Research* 50(9):1250–65. doi: 10.1016/j.asr.2012. 06.032.

Stehman, Stephen V., and Raymond L. Czaplewski. 1998. "Design and Analysis for Thematic Map Accuracy Assessment: Fundamental Principles." *Remote Sensing of Environment* 64(3):331–44. doi: 10.1016/S0034-4257(98)00010-8.

Tiwari, Kuldeep, and Kamlesh Khanduri. 2011. "Land Use/Land Cover Change Detection in Doon Valley (Dehradun Tehsil), Uttarakhand: Using GIS& Remote Sensing Technique-Indian Journals." *International Journal of Geomatics and Geosciences* 2(1):34–41.

Tripathi, R., S. M. Pingale, and D. Khare. 2019. "Assessment of LULC Changes and Urban Water Demand for Sustainable Water Management: A Case Study of Dehradun City." Pp. 1–6 in *2019 IEEE International Conference on Smart Cities Model (ICSCM)*.

Verma, Pramit, Aditya Raghubanshi, Prashant K. Srivastava, and A. S. Raghubanshi. 2020. "Appraisal of Kappa-Based Metrics and Disagreement Indices of Accuracy Assessment for Parametric and Nonparametric Techniques Used in LULC Classification and Change Detection." *Modeling Earth Systems and Environment* 6(2):1045–59. doi: 10.1007/s40808-020-00740-x.

Vivekananda, G. N., R. Swathi, and AVLN Sujith. 2020. "Multi-Temporal Image Analysis for LULC Classification and Change Detection." *European Journal of Remote Sensing* 0(0):1–11. doi: 10.1080/22797254.2020.1771215.

Wu, T., J. Luo, J. Fang, J. Ma, and X. Song. 2018. "Unsupervised Object-Based Change Detection via a Weibull Mixture Model-Based Binarization for High-Resolution Remote Sensing Images." *IEEE Geoscience and Remote Sensing Letters* 15(1):63–67. doi: 10.1109/LGRS.2017.2773118.

Xiaoqing, Zhang, and Ren Jianlan. 2007. "Study on Dynamic Mechanism of Urban Expansion: A Case Study of Shandong Province." *Chinese Journal of Population Resources and Environment* 5(3):37–42. doi: 10.1080/10042857.2007.10677516.

Zhang, Penglin, Zhiyong Lv, and Wenzhong Shi. n.d. "Local Spectrum-Trend Similarity Approach for Detecting Land-Cover Change by Using SPOT-5 Satellite Images - IEEE Journals & Magazine." Retrieved December 29, 2020 (https://ieeexplore.ieee.org/abstract/document/6605510/).

Zhu, Zhe, and Curtis E. Woodcock. 2014. "Continuous Change Detection and Classification of Land Cover Using All Available Landsat Data." *Remote Sensing of Environment* 144:152–71. doi: 10.1016/j.rse.2014.01.011.