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

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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 suburb-urban areas demands more land and promotes rural areas' transformation to the urban area (Farooq and Ahmad 2008; Mohan et al. 2011; Xiaqing 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 classification 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., Vikas Nagar 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 km²; and its elevation range varies from 362m to 2320m. The Lowest elevation was found in Vikas Nagar C.D block, and the highest elevational point was found in Mussoorie range.

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 .tifff 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 was 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 Earth’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 effectiveness 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)

\[
O_{vAc} = \frac{\sum_{i=1}^{n} e_{\text{ras}}}{Q} \times 100\%
\]  

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% | Use% | Producer% |
|---------------------|-------|-----------|------|-----------|
| Agricultural Land   | 75.96 | 75.24     | 87.4 | 88.59     |
| Built-Up Areas      | 64.39 | 87.63     | 92.0 | 89.50     |
| Open/Scrub Area     | 83.82 | 71.25     | 96.1 | 72.22     |
| Vegetation/Forest   | 92.16 | 87.85     | 84.6 | 97.10     |
| Water Bodies        | 85.00 | 80.00     | 8    | 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 (Jeness 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).

\[
K = \frac{n\sum_{i=1}^{n} x_{ii} - \sum_{i=1}^{n} (x_{i+} \times x_{+i})}{n^2 - \sum_{i=1}^{n} (x_{i+} \times x_{+i})}
\]  

Where, \(\sum_{i=1}^{n} x_{ij}\) = Total number elements of the error matrix; \(\sum_{x_{i+}} = \sum \) 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 Zaplewski 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).

\[
MC (km^2) = A_i - A_f
\]

\[
PC (%) = \frac{A_i - A_f}{A_i} \times 100
\]

\[
ARC (km^2\cdot year^{-1}) = \frac{A_i - A_f}{n}
\]

\[
ARC (%) = \frac{A_i - A_f}{A_i \times n} \times 100
\]

Where, \(A_i\) is the class area in km2 at the final time and \(A_i\) is the class area in km2 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 2020; 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 38.9 km$^2$ 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% or 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

| LULC | Year 1989 | Year 2020 |
|------|-----------|-----------|
| AL   | 256.8     | 248.7     |
| BUAs | 44.4      | 154.4     |
| O&SL | 72.9      | 9.8       |
| V&FC | 526.9     | 511.3     |
| WB   | 30.3      | 7.1       |

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

| LULC Class | 1989 Area in km$^2$ | 2020 Area in km$^2$ | 1989-2020 Area in km$^2$ |
|------------|---------------------|---------------------|--------------------------|
| AL         | 256.8               | 248.7               | -8.1                     |
| BUAs       | 44.4                | 154.4               | 100.0                    |
| O&SL       | 72.9                | 9.8                 | -63.1                    |
| V&FC       | 526.9               | 511.3               | -15.6                    |
| WB         | 30.3                | 7.1                 | -23.2                    |
Table 4.3. Statistical description of area and amount of change in different LULC change categories in the study area during 1989-2020

| LU/LC Cover Categories | 1989 Area Km² | 2020 Area Km² | Rate of Change | Annual rate of Change |
|------------------------|---------------|---------------|----------------|----------------------|
|                        | 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 69.9 km² or 27.22% agricultural land area was converted into built-up areas.

On the other hand, 53.36% or 38.9 km² 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/scrubland 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

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