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Comparative Analysis of Urban Area Extraction Using Different Classification Methods: A Case Study of Ghorahi Sub-Metropolitan City, Nepal

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Abstract

Rapid urban area expansion is taking place Ghorahi Sub-Metropolis City in the last ten years. But there is no detailed analysis carried yet. This study focuses on analyzing the urbanization and LULC changes by adopting different classification techniques in the multispectral remote sensing imagery. For this propose, Landsat OLI data of 2013, 2016 and 2020 have been downloaded from USGS site and analyzed. Four algorithms are compared in this paper to reach the most accurate technique for urban area extraction: namely, supervised maximum-likelihood (SML), Indices-based SML, Support Vector Machine (SVM) classifiers, and Indices-based SVM classifiers. The results shows that the Indices-based SVM classifier had the maximum classification accuracy for LULC maps pertaining to 2013, 2016, and 2020. The accuracy assessments were performed which further established the results and showed notable changes: agricultural land decreased by 13.75%, barren land increased by 297.21%, and the built-up area increased by 82.09% from 2013 to 2020. This rapid growth of urban areas necessitates the adoption of sustainable land-use policies, zoning laws, and measures for preventing the conversion of agricultural land to other land uses. These changes need to be unwrapped for mitigating the environmental and social consequences of growth in Ghorahi Sub-metropolitan City.

Keywords: *Landuse Land Cover, Urban Growth, Satellite Image, RS/GIS, Supervised Maximum Livelihood, Ghorahi*

Introduction

Different technique and algorithm can be used to classify satellite images. It is necessary to select best and appropriate technique for image classification by comparing all results and statistics. So here different types of techniques are compared with its results for selecting appropriate technique to use for extracting urban area in different time series. As we know that number of bands in remote sensing data and different indices plays vital role in increasing accuracy for classified map. If we don't take attention on their results validation, it will be not sufficient and supportive technique to extract feature with high accuracy. Cities experience unprecedented changes in LULC patterns due to urban growth. This research studied urban growth in the Ghorahi Sub-metropolitan. Dynamics of urbanization, spatial configuration and change in the metropolitan areas are the important topics for the analysis of urban studies (Poudel, 2008). LULC change analysis will highlight the best way to indicate the process of urban growth and may prove to be a very effective tool in ascertaining the urbanization prospect in the future. GIS and RS techniques can be very helpful in monitoring and analyzing LULC change. RS techniques will extract built-up areas, urban areas, and other classes of LULC from satellite images. Multispectral and multi-temporal satellite images can be used on account of determination of patterns and processes in the studied area (Thapa & Murayama, 2008). The aim of this research is comparative analysis of urban area extraction using different classification methods of Ghorahi Sub-metropolitan City.

Satellite imagery has been widely used for LULC classification on a local to worldwide scale. Recent developments in sensor technology, public open satellite images, and the availability of user-friendly spatial data processing software may all be factors contributing to user interest in LULC information extraction. As a result, LULC data and maps have become the most widely utilized. The result of such data and classified maps are also widely used for socioeconomics, natural resource conservation and management, the environment, and urban planning. So in order to get more accurate real world information the algorithms have been trained on a sufficient number of selected pixels to classify the correct coverage. Various image classification techniques have been adopted in LULC classification (Jing et al., 2022). In the supervised classification technique, the sample pixels are selected by the user based on knowledge about the area. While choosing representative training pixels, similar other pixels can be identified in the imagery (Kafy et al., 2021). The algorithms have been trained on a sufficient number of selected pixels to classify the correct coverage.

There are numbers of algorithms but Supervised Maximum Likelihood (SML) is a widely used technique for the classification of satellite images. It relies on a normal distribution of data for each class, such as urban or non-urban, and assumes that data points create a fairly predictable pattern (Koranteng et al., 2023). This method calculates the probability of a pixel belonging to a specific class and assigns it to the class with the highest likelihood. This method is straightforward and effective when the different classes are clearly distinct from each other. Indices-Based SML classification method builds on SML by including spectral indices like NDVI (for vegetation), NDBI (for built-up areas), and NDWI (for water bodies) (Indrawati et al., 2020; Raut et al., 2020; Watson et al., 2019). These indices help highlight specific features in the image, such as green spaces or urban areas, before running the SML classification. Using indices gives the classifier more information to work with, making it better at distinguishing between built-up and other uses.

Support Vector Machine (SVM) is a more advanced method that doesn't assume a specific distribution for the data. Instead, it tries to find the best boundary (or "hyperplane") that separates the classes (urban, non-urban, etc.) in the image (Theres et al., 2023). This method can handle more complex boundaries where urban and non-urban areas overlap. SVM is highly effective for difficult classification schemes, especially in urban areas where the land cover types are mixed and not clearly separated. Indices-Based Support Vector Machine (SVM) Classifier method combines the power of SVM with the additional information provided by spectral indices. After calculating indices like NDVI, NDBI, and NDWI, the SVM classifier uses along with the raw data to better separate urban areas from other land cover types (Dinda et al., 2021). By adding indices, this method enhances SVM's ability to differentiate between complex land cover types, making it highly accurate for urban classification.

Materials and Methods

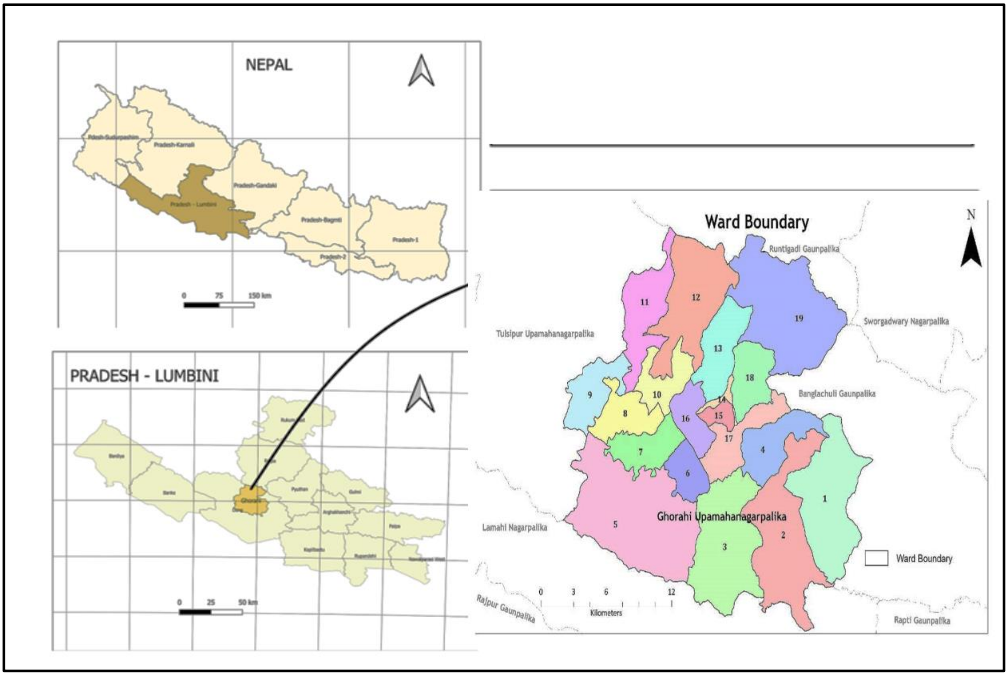
Study Area

Ghorahi Sub-metropolitan City is situated in Lumbini-Province, Mid-Western part of Nepal. Ghorahi is located within Dang Valley in the foothills of the Himalayas, sandwiched between Babai River in the east, south, and in the west which ends with a small river, and North with margin with Rolpa District. Ghorahi Sub-Metropolitan City is a beautiful and natural city with rich potential in the lap of Mahabharata and Chure hills. The city is recognized for its environment and slightly better climate, and serves as a gateway to the neighboring regions of Rolpa, Pyuthan, Salyan, and Rukum. The total population is 200,530 with male 93,806 and female 106,724 (NSO, 2021). Out of 19 wards, ward no. 15 is the densest ward has high service center. The majority of people involved in agriculture, while tourism and hospitality, and other service sectors are also emerging for income source. The district center, Ghorahi, is the largest sub-metropolitan city in Nepal and is ranked as the seventh largest city overall (Ghorahi Profile, 2018). This city is located in $28° 2' 0''$

N82° 29′ 0″ E UTM Zone 44R with coordinate ranges Easting 645809, Northing 3101782. The total area of Ghorahi Sub-metropolitan City is 522.21 Sq.km, with elevation of 701 m (2,300 ft) from msl (Figure 1). Babai is the major river that flows through study area.

Figure 1:

Location Map of Ghorahi Sub-metrpoolitan City, Lumbini Province.



Source of Data

Primary Data

Primary data used for this paper include Land-sat satellite imagery Landsat-8 OLI imagery of Dang Ghorahi (Table 1). The Landsat 8 satellite platform includes two research instruments: the Operational Land Imager and the Thermal Infrared Sensor. These two sensors give seasonal coverage of the global landmass with spatial resolutions of 30 meters (visible, NIR, SWIR), 100 meters thermal, and 15 meters panchromatic.

Table 1

Sources of primary data.

Satellite Images	Sensor	Bands (no.)	Imagery Date	Resolution MSS (m)	Path/ Row	Cloud Cover (%)
Landsat-8	OLI_TIRS	11	Nov-16- 2013	30	143/41	0.07
Landsat-8	OLI_TIRS	11	Nov-08-2016	30	143/41	0.12
Landsat-8	OLI_TIRS	11	Mar.-08-2020	30	143/41	1.19

Source: http//earthexplorer.usgs.gov

Secondary Data

The secondary data using for this research are ground training sample shape file which were collected from Global Positioning System (GPS) and Google Earth imageries (time slide of) which are used as references for classification and accuracy assessment.

Methods

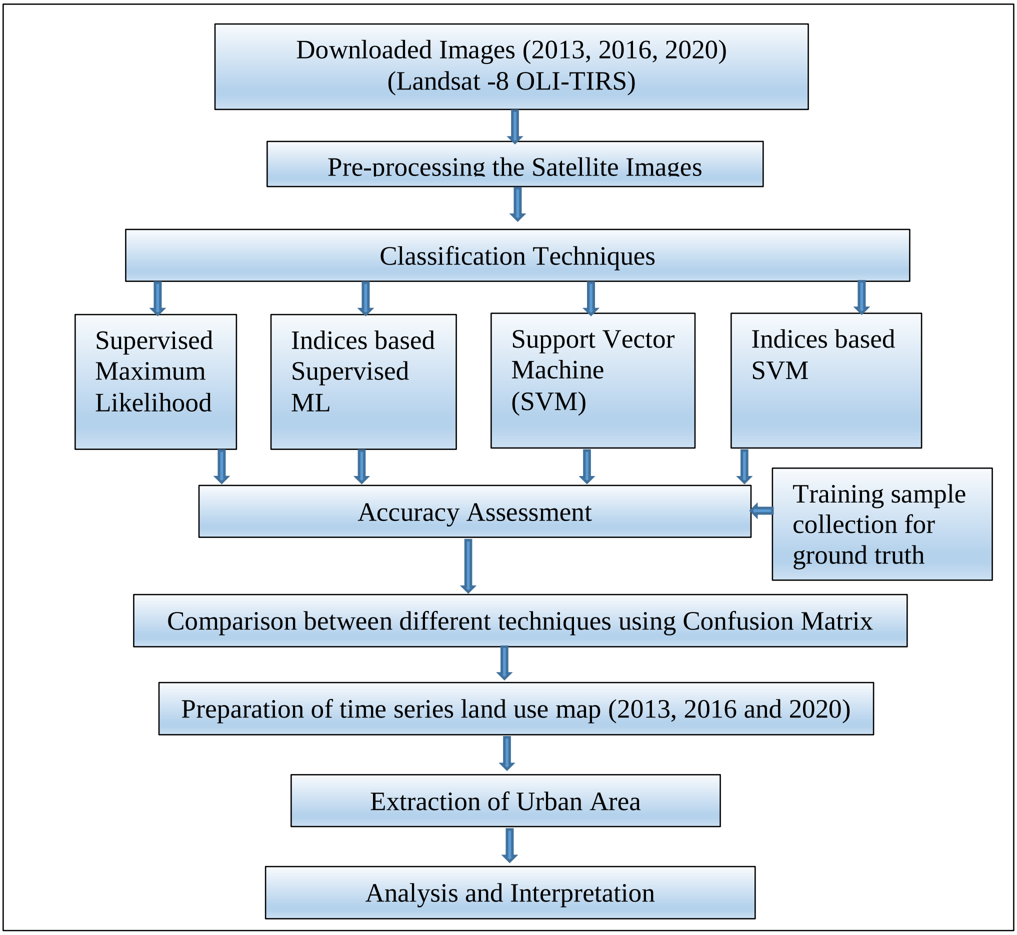
The procedure of extraction of urban growth, comparing the various techniques of classification using remote sensing, is given in (Figure 2): Satellite imageries for Ghorahi using Landsat-8 OLI for 2013, 2016, and 2020 were downloaded from the USGS portal using the UTM projection and WGS84 datum. Performed pan sharpening on optical bands 2-7 and panchromatic band 8 to get a resultant image at 15m resolution, which are used for classification purposes (Figure 2). The pre-processing entails both radiometric and geometric corrections. The ground truth point collection included Google Earth Pro and mobile GPS, 75% of which were used in the classification phase and the remainder for accuracy validation. Supervised classification techniques utilized include the Maximum Likelihood and Support Vector Machine methods (Vapnik, 1995). NDVI, NDBI, and NDWI indices were calculted. The indices-based classification requires layer-stacking with a pan-sharpened image. The process enables the valid and unbiased classification of urban growth in Ghorahi Sub-metropolitan City.

Classification Techniques

Image classification was done by assigning attribute value of the similar feature pixels in different class level, to extract information from image data. The Landsat OLI satellite images with multispectral band (1-7) with 30-m resolution and panchromatic image with 15-m resolution are fused in Gram-Schmidt spectral enhancement method. Comparative analysis of urban area extraction using different classification methods given in Figure 2.

Figure 2

Extraction and Analysis of Urban Growth



Supervised Maximum Likelihood (SML) Classification

The supervised classification was carried out with maximum likelihood estimation. The image has a multispectral information, so the plant and others may be differentiated using near-infrared wavelengths. Training sample's for ground truth were collected from Google Earth Imagery and loaded in view. With the help of ground control point (GCP) from the training sample different class were created. The image's surface characteristics include agricultural land, built-up areas, barren, forests, sand, and lakes and streams were considered. The algorithm Maximum Likelihood was used to calculate appropriate statistics (mean and variance–covariance) and a probability function as all spectral value of training pixels were statistically normally distributed in bell shape. LULC Map of Ghorahi sub-metropolitan area for year 2020 is classified.

- **Indices (NDVI/NDBI/NDWI) based Supervised ML Classification:** Landsat 8 OLI data consists of 11 bands, including the blue, green, red, infrared, thermal, and panchromatic bands. However, for calculating the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Normalized Difference Water Index (NDWI), only four multispectral specific bands are used such as green, red, near-infrared (NIR), and shortwave infrared (SWIR).
  - **The Normalized Difference Vegetation Index (NDVI):-**NDVI is the most commonly used index for identification of greenery, globally. In addition to measuring vegetation greenness, NDVI is helpful for determining changes in plant health and comprehending vegetation density. Chlorophyll contains in a greeneries highly absorbs Blue (0.4 - 0.5 μm) and Red (0.6 - 0.7 μm) spectrum and reflects Green (0.5 – 0.6 μm) spectrum. Therefore, the following equation gives Normalized Difference Vegetation Index (NDVI).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}$$

Where, NIR = Near-Infrared band

Red = Red band

For Land-sat 8 data, $NDVI = \frac{Band\ 5 - Band\ 4}{Band\ 5 + Band\ 4}$

The NDVI value varies from -1 to +1. Higher the value of NDVI reflects high Near Infrared (NIR), means dense greenery.

- **Normalized Difference Built-up Index (NDBI):-**NDBI is most common index for analysis the built-up areas. The built-up areas and bare soil reflects better SWIR than NIR NDVI can be calculated by following formula.

$$\mathrm{NDBI} = \frac{\mathrm{SWIR} - \mathrm{NIR}}{\mathrm{SWIR} + \mathrm{NIR}}$$

Where, SWIR = Shortwave infrared band

NIR = Near-Infrared band

For Landsat 8 data, $NDBI = \frac{Band\ 6 - Band\ 5}{Band\ 6 + Band\ 5}$

NDBI value lies between -1 to +1. Negative value of NDBI represents waterbodies whereas greater value represents build-up areas.

- **Normalized Difference Water Index (NDWI):** The NDWI is utilized for analyzing waterbodies. This index relies on the Green and NIR bands. Since water bodies exhibit low reflectance, they primarily reflect light within the visible range of the electromagnetic spectrum. which generally shows higher reflectance in the blue spectrum (0.4 - 0.5 µm) compared to the green (0.5 - 0.6 µm) and red (0.6 - 0.7 µm) spectra. Xu (2005) proposed an NDWI formula that specifically uses the Green and Shortwave Infrared (SWIR) bands:

$$\mathrm{NDWI} = \frac{\mathrm{Green} - \mathrm{NIR}}{\mathrm{Green} + \mathrm{NIR}}$$ *Where, Green = Green band*

NIR = Near-Infrared ban

For Land-sat 8 data, $NDWI = \frac{Band\ 3 - Band\ 6}{Band\ 3 + Band\ 6}$

Similarly, NDWI value lies between -1 to +1. Normally, waterbodies NDWI value remains is greater than 0.5.

From the above equations, all indices were calculated and finally those 3 bands were layer stacked with 7 bands. Finally layer stacked 10 bands image was taken for further classification with same training sample which was previously used in supervised maximum likelihood classification. The process resulted LULC Map of Ghorahi sub-metropolitan area for year the 2020.

Support Vector Machine Classification

Support Vector Machines (SVM) are grounded in statistical learning theory and are designed to identify decision boundaries that achieve the best possible separation between different classes (Cortes and Vapnik, 1995). It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyper-plane, and the data points closest to the hyper-plane are called support vectors. Different options are available for mathematically representing a kernel function, which gives the weights of nearby data points in estimating target classes. The Radial Basis Function (RBF, default) kernel type works well in most cases so I used this here, RBF chosen is $K(x_i, x_j) = \exp(-g\|x_i - x_j\|^2)$, $g > 0$ (Vapnik, 1995). For classification same training sample was used which was previously used in supervised maximum likelihood classification. LULC Map of Ghorahi Sub-metropolitan area for year 2020.

Indices based Support Vector Machine Classification

Indices-based SVM classification is a method that leverages the strengths of spectral indices to enrich the data input for SVM, improving the classification of land cover types in remote sensing applications (Vapnik 1995). The layer stacked image was taken for further classification with same training sample which were previously used in SVM classification. Based on this process LULC Map of Ghorahi sub-metropolitan area for year 2020 has been prepared.

Accuracy assessment

Accuracy assessment is definitely one important step in the evaluation of the LULC maps derived through classification. The accuracy assessment of the three-time series (year of 2013, 2016, and 2020) LULC maps of Ghorahi Sub-Metropolitan City has been done to find-out consistently high overall accuracy and Kappa statistics.

Result and Discussion

Selecting Appropriate Classification Techniques

Remotely sensed data based classified maps are widely utilized across various disciplines including socioeconomic studies, natural resource protection and management, environmental monitoring, urban development etc. Given the relevance of such data and the effectiveness of classification methods in extracting land use and land cover (LULC) thematic classes for Ghorahi Sub-metropolitan City, their applicability remains significant. This research were used to compare four different classification techniques for extraction urban area - Supervised Maximum-likelihood, Indices based Supervised maximum likelihood, Support Vector Machine Classifier, and Indices based support vector Machine classifier (Figure 2). Atmospheric and radiometric corrected imageries were employed to extract six LULC classes: agriculture, barren land, built-up areas, forests, sand, and water (Table 2). We have taken same training sample for different classification techniques and same ground truth for validating accuracy of results. The comparison of LULC map for year 2020 from Supervised Maximum-likelihood classification have overall accuracy 81.18%, kappa coefficient 0.74, user accuracy 45.16% and producer accuracy 70% for Built-up class (Table 2).

Table 2

Statistical Comparison for Selecting Appropriate Classification Techniques

S. No.	Classification Techniques	Ground Truth Pixel	Overall Accuracy (%)	Kappa coefficient	LULC Class 2020	User Accuracy (%)	Producer Accuracy (%)
1.	Supervised Maximum-likelihood	558	81.1828	0.7390	Agriculture	100	89.11
					Barren	69.47	95.65
					Built-up	45.16	70.00
					Forest	96.94	79.29
					Sand	61.70	90.63
					Water	100.0	25.00

2.	Indices based Supervised maximum likelihood	558	81.8996	0.7460	Agriculture	98.94	92.08
					Barren	75.00	95.65
					Built-up	48.84	70.00
					Forest	93.33	80.00
					Sand	60.87	87.50
					Water	100.0	25.00
3.	Support Vector Machine Classifier	558	89.7849	0.8497	Agriculture	84.11	89.11
					Barren	92.19	85.51
					Built-up	96.43	90.00
					Forest	90.53	92.14
					Sand	83.33	93.75
					Water	100.0	62.50
4.	Indices based support vector Machine classifier	558	90.3226	0.8589	Agriculture	82.05	95.05
					Barren	95.31	88.41
					Built-up	90.32	93.33
					Forest	93.43	91.43
					Sand	81.25	81.25
					Water	100.0	56.25

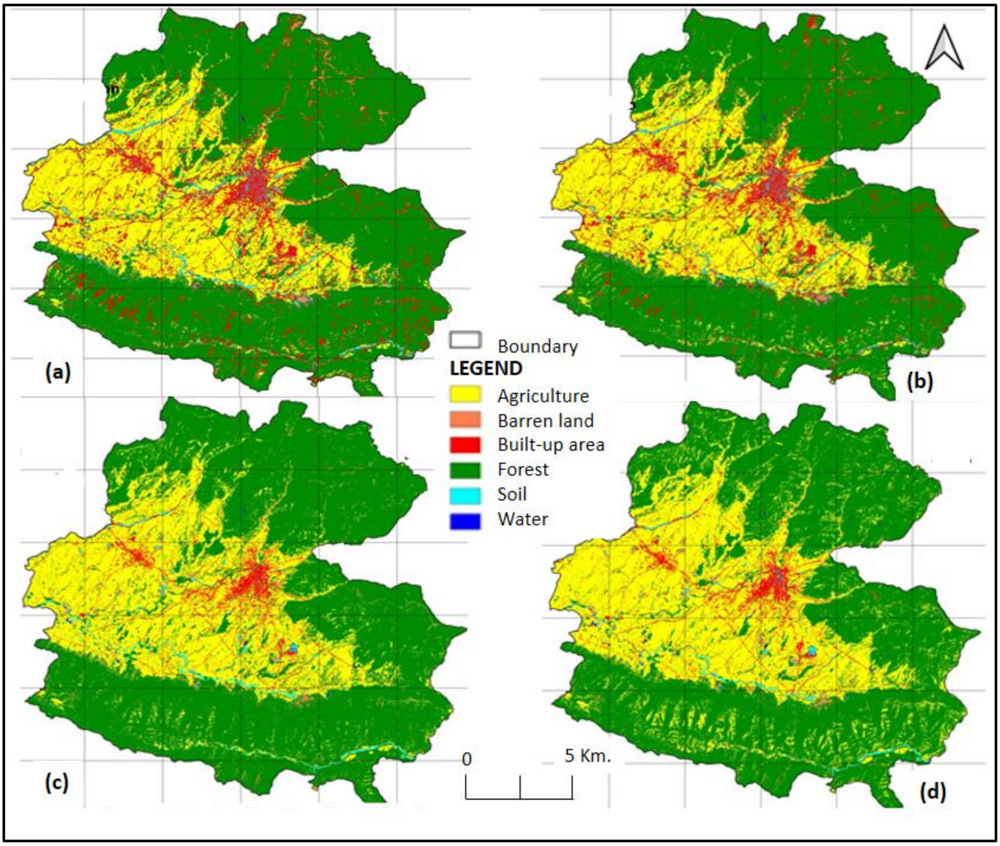
Source: *Source: Four techniques apply on LULC Map derived from Landsat Satellite Image 2020 of Ghorahi Sub-metropolitan City.*

Indices based Supervised Maximum-likelihood classification have overall accuracy 81.90%, kappa coefficient 0.75; user accuracy 48.84% and producer accuracy 70% for built-up class. Support Vector Machine Classifier has overall accuracy 89.78%, kappa coefficient 0.85; user accuracy 96.43% and producer accuracy 90% for built-up class. Indices based Support Vector Machine Classifier has overall accuracy 90.32%, kappa coefficient 0.86; user accuracy 90.32% and producer accuracy 93.33% for built-up class. Analyzing these data LULC map from Indices based Support Vector Machine Classifier has highest magnitude for overall accuracy, kappa coefficient, and producer accuracy. From this result, it can be concluded that this technique is appropriate and best to use for extraction built up area.

Yang and Lunetta (2012) have also suggested using Support Vector Machine Classification Technique. From above comparison on different techniques based on confusion matrix. Indices Based Support Vector Machine Classification Technique to extract urban area is suggested for different Landsat imageries for LULC classifications.

Figure 2

Apply Different Techniques to Derived LULC of Ghorahi Sub-metrpoolitan City.



Source: Classified Landsat Satellite Image 2020 of Ghorahi Sub-metropolitan City. (a) Supervised Maximum Likelihood Classification, (b) Indices Based Supervised Maximum Likelihood, (c) Support Vector Machine Classifier (d) Indices Based Support Vector Machine Classifier.

Spatio-temporal LULC of Ghorahi Sub-metropolitan City through Indices-based SVM Classification Technique

LULC of Ghorahi Sub-Metropolitan City has undergone significant changes in between 2013 and 2020, areas in agriculture is converting to built-up classes. This shows continuous urban expansion and its associated transformation in the landscape of Ghorahi city. It follows that one of the striking trends is the abrupt shrinkage in the agricultural lands (Table 3). While in 2013, agricultural land covered an area of 178.5 km², in 2020, this area went down to 153.9 km². That means a decrease of almost 14%.

The most striking fall happened between 2016 and 2020, during which time agricultural areas contracted by 10%. This decline indeed portrays a clear conversion of farmlands into other uses, probably to meet the increasing urban footprint.

Table 3

Statistical Comparison for Different Years LULC Classes.

S. No.	LULC Class	Year			Change in area Percentage		Total Changes 2013 to 2020 (%)
		2013 Area (km^2)	2016 Area (km^2)	2020 Area (km^2)	From year 2013-2016	From year 2016-2020	
1	Agriculture	178.47	171.02	153.93	- 4.17	-10.0	-13.75
2	Barren	0.78	1.42	3.13	80.10	120.55	297.21
3	Built-up	12.10	16.12	22.05	33.21	36.70	82.09
4	Forest	325.51	329.26	337.13	1.12	2.39	3.57
5	Sand	5.01	4.02	5.47	-19.66	35.85	9.14
6	Water	0.16	0.18	0.34	13.75	88.46	114.37
	Total	522.05	522.05	522.05			

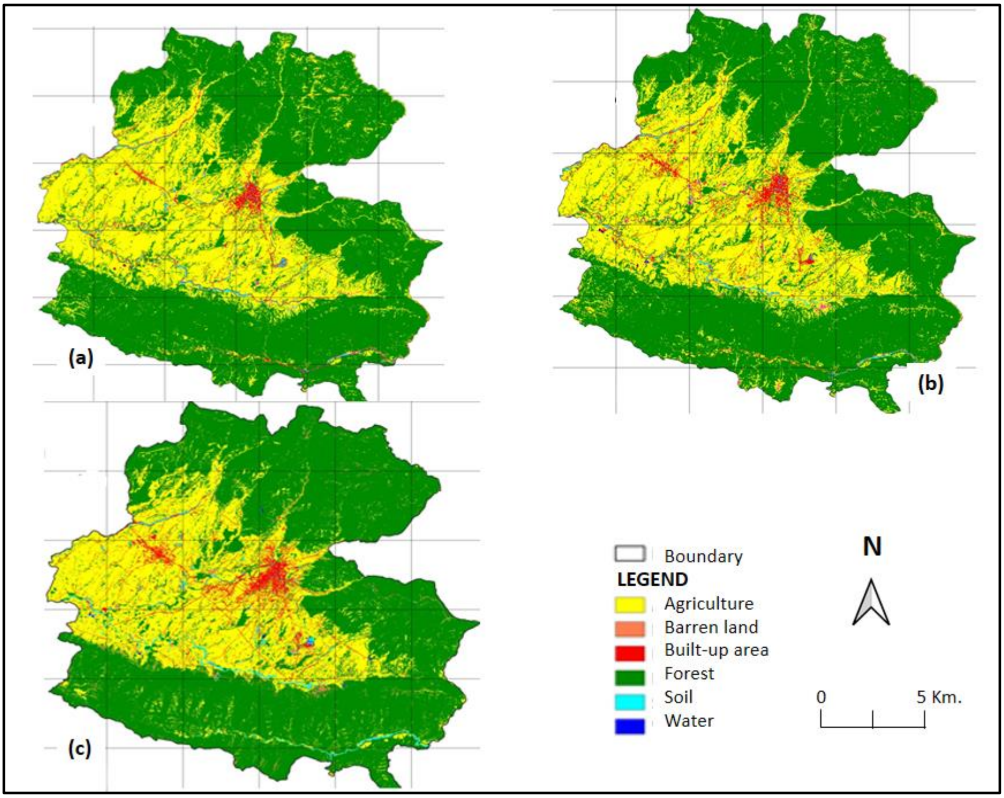
Built-up areas have remarkably increased from 12.1 km² in 2013 and 22.04 km² in 2020 with an overall growth of 82%. Such rapid urbanization is an absolute indicator of population increase through generation of economic growth in the region with the expansion of a city, infrastructure, housing, and commercial areas.

The large rise in barren land, almost a 300% increase, may be due to deforestation, abandonment of land, or preparation for any future development. This rise in land that isn't being put to good use can further denote a transition phase wherein the land is being cleared for future use or is facing utter neglect and degradation. On a positive note, the rise in forest cover is quite small at 3.57%. While this increase is small, it is a good indication that possibly there are efforts being taken to protect or restore the forested areas. On the other hand, this increase is small compared with rapid urban growth.

The sand area first decreased by 20% and then increased by 35% between 2016 and 2020; these changes could be related either to seasonal dynamics of the river or to human activities such as sand extraction. The most noticeable percentage increase was constituted by water bodies, which increased by over 114%. This can be ascribed to new reservoirs or changes in water management, but in a real sense, it is a relatively small change in the overall land cover. Ghorahi Sub-Metropolitan City is indeed undergoing rapid urbanization, as depicted by the increase in the built-up areas and the corresponding loss of agricultural land.

Figure 3

Spatio-temporal LULC of Ghorahi Sub-metropolitan City



Source: Landsat Satellite Images: (a) LULC, 2013, (b) LULC, 2016, and (c) LULC, 2020.

Accuracy Assessment

The accuracy assessment of the three-time series LULC maps of Ghorahi Sub-Metropolitan City in 2013, 2016, and 2020 (Table 4).

Table 4

Accuracy Assessment for three time series LULC map

S.N	Year	Overall Accuracy (%)	Kappa Statistics	Remark
1	2013	89.29	0.85	Accuracy is consistent
2	2016	91.72	0.88	
3	2020	88.95	0.83	

In 2013, overall accuracy was 89.29% with a kappa statistic of 0.85, indicating reliable classification with a minimum of classification errors. In 2016, the accuracy was slightly higher: the overall accuracy stood at 91.72%, with a Kappa statistic of 0.88. Thus, it is indicating even more consistency in the classification of land use. This therefore means that in 2020, the overall accuracy was still better standing at 88.95%, though its Kappa statistic was 0.83, which was slightly lower than that of 2016. But it is high regarding the precision of classification. Relatively high consistency in accuracy among the three periods verifies that the LULC classification was well conducted and reliable across the study.Ttherefore, observed trends in land use change are credible. Slight fluctuations in accuracy, especially in 2020, might relate to increased complexity with regard to distinguishing between some classes of land cover due to rapid urbanization and changes in landscape pattern within the city. However, the high accuracy levels in all three years give confidence to analyze LULC changes.

Built-up Area of 2013, 2016, and 2020

Built-up area map extracted from Decision Tree expression for year 2013, 2016 and 2020 is given in below table 5 and figure 6.

Table 5

Built-up area in 2013, 2016 and 2020

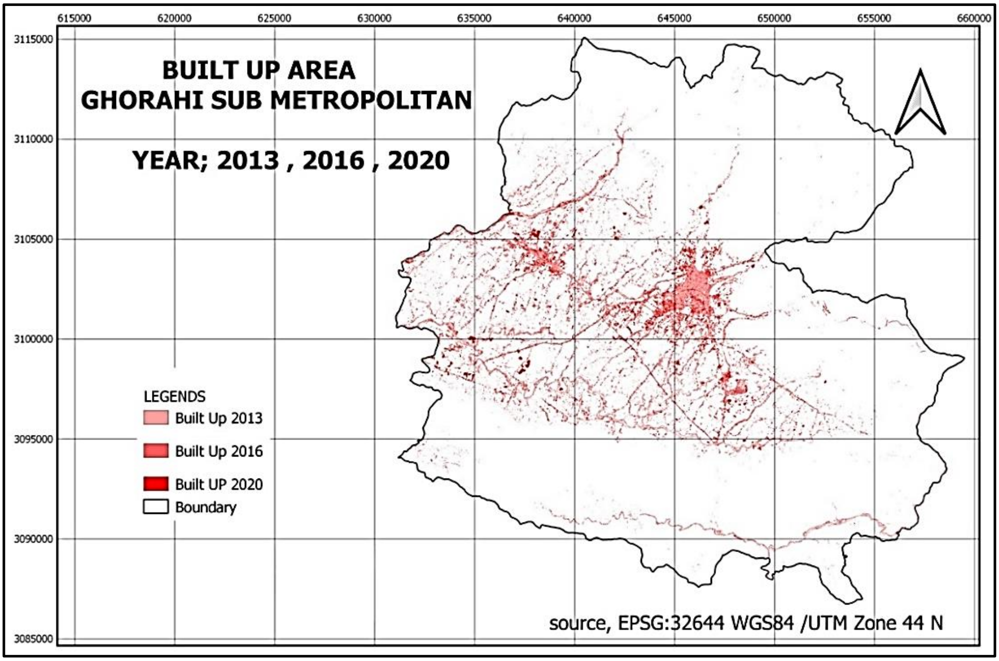
Year			Change in %		Total Changes 2013-2020 %
2013 Area (km^2)	2016 Area (km^2)	2020 Area (km^2)	From year 2013-2016	From year 2016-2020	
12.108	16.129	22.048	33.209	36.70	82.094

Built-up area in 2013 was 12.108 km², showing the urban footprint at the beginning of the study period. During this period, the rate of urbanization was probably just starting to accelerate but it was relatively modest. It increased to 16.129 km² in 2016, which accounted for a 33.209% increase from that of 2013. In this way, the growth of over one-third in only three years marks the rapid urban development brought about by fast population growth, economic development, and infrastructure expansion.

The tendency went on, and within 2016-2020, the built-up area reached 22.048 km², reflecting further increases of 36.7% during the period. That is to say, there has been a continued rise in the urbanization of Ghorahi, and during this period, the development process within the town also increased with increased city growth.

Figure 6

Growth of Built-up Area of Ghorahi Sub-metropolitan City



Source: Classified layer from Landsat satellite images of 2013, 2018, and 2020.

The absolute growth of the built-up area from 2013 to 2020 was +82.094%; it is closer to double within seven years. Such a tremendous increase in this city leads it closer to being an urban center with all that such a city should bear regarding land-use planning, infrastructure, and environmental management.

It is explained that such rapid expansion of built-up areas needs sustainable urban planning-a balance of growth with the limitation of environmental and social burdens from such development.

Conclusion

This study tried to extract urban built-up area from the classification of Landsat OLI Imaganaries of 2013, 2016, and 2020. The methods considered herein in the study adopted a supervised maximum likelihood (SML) classification, indices-based SML classification, the support vector machine (SVM) classifier, and the indices-based SVM classifier algorithm. The findings have revealed that the indices-based SVM classifier using a non-parametric algorithm and a kernel type Radial Basis

Function is more efficient compared to the parametric supervised maximum likelihood classification to extract built-up areas.

Thereafter, the indices-based SVM classifier has been used to extract the built-up areas for three time periods of 2013, 2016, and 2020. For these years, the land use and land cover (LULC) maps of the study area were prepared by categorizing the major land use into agriculture, barren land, built-up areas, forest, sand, and water. This analysis quantified the changes in the urban landscape, showing that agricultural land gradually decreasing while barren and built-up areas are increasing within the period between 2013 and 2020. For this reason, it has been determined that buildings are increasingly taking over productive agricultural and open lands. The future of the city will probably be worse off because of this, so a suitable urban plan is needed to improve.

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