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Mapping Major Land Use And Land Cover Dynamics In Growing Urban Areas Based On Landsat Imagery Using Google Earth Engine

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Abstract: *In the present context of rapid change which is occurring either due to the natural or artificial phenomenon, tracking environmental changes with the aid of remote sensing applications has been an important tool for multidisciplinary sectors. One of these applications is the construction of land use and land cover maps through the image classification process. The Google Earth Engine is becoming a crucial tool in remote sensing data analysis as it provides cloud-based platform with huge amount of multiple source satellite data and excellent computation services. The present study aims to know the extent of land cover in Tokha Municipality of Kathmandu of the year 2001, 2009 & 2019 along with the dynamics between the year and the rate of change. In this study, Landsat image of Tokha Municipality of the year 2001, 2009 &2019 were used for LULC supervised classification in Google Earth Engine platform. Five LULC classes were decided and classified using random forest classification, and the output map was obtained with an overall accuracy of 94.8%, 88.40% & 86.95% for the year 2000, 2009 & 2109 respectively. It was found that most of the landcover was dominated by agricultural land and very few were covered by waterbody. From the analysis section, it was clear that major LULC change between 2000 and 2009 was seen in otherland with the total decrease of 354.84 ha. whereas settlement area of 61.5 ha. significantly increased between 2009 and 2019. For the whole study period annual rate of change was found to be in increasing for the categories settlement (1.558%) and forest (1.072%) and decreasing for Agriculture (0.846, waterbody (0.001%) and otherland (1.786%).*

***Keywords**: Remote Sensing, Land Use, Land Cover, image Classification, Google earth engine*

Introduction

Land cover is commonly considered as coverage on the ground surface which is utilized in multi-disciplines as a geographical reference (e.g. for land-use, climatic or ecological studies) (FAO, 2016). Land use refers to the specific activities carried out in and for economic purpose, intended use, and/or management strategy placed on the land cover type(s) by human agents or land managers (European Communities, 2001). The land is one of the natural resources living beings depends upon either directly or indirectly which in association with natural phenomenon's are subjected to different changes.

Information on land use and land cover's geographical distribution over a large coverage is essentially important for many environmental monitoring tasks, including climate change, ecosystem dynamics analysis, etc. (Gallego et al., 2010). Land-cover mapping and monitoring are one of the major applications of satellite data (Rodriguez-Galian, 2012) as it provides an overall good understanding of ecosystem monitoring and functioning along with responses to these environmental factors. Application of remote sensing techniques has been considered as a powerful means to acquire information on Earth's surface features at different spatial and temporal scales (Liang, 2015; Satyanarayana, 2001). Availability of fine-grained long-term satellite data record going dating back to 1972 images from the Landsat satellite series are an important data source for studying land use and land class data (Gerard, 2010; Zhu, 2014). In recent years a fine resolution (30m) land cover outputs have been generated using images from Landsat TM with a supervised classification scheme (Chen, 2015; Gong, 2013). More recently, several researchers carried out focuses on evaluating the potential of satellite data on land use classification and hence to quantify, monitor, and analyze land use and hence evaluating its changes (Baumann, 2014).

Change in land cover is a dynamic and continuous process (Mondal, 2016). Land cover patterns across the world are constantly being changed by different human activities, thereby influencing biophysical processes (Li & Shao, 2014). The land resource is depleting and land use is raising phenomenon over a long generation of human existence causing serious problems which are mostly driven by anthropogenic activities and, on many occasions, these changes directly impact both humans and the natural environment (Ruiz-Luna & Berlanga-Robles, 2003). Land-use and land-cover modification have important environmental consequences through their impacts on soil and water quality, biodiversity, microclimate, methane emission, and reduced CO2 absorption and, hence, contribute to watershed degradation (Lambin et al., 2000; Schneider & Pontius, 2001).

Continuous observation of those changes is very essential in overall environmental and ecosystem services monitoring (Lal & Anouncia, 2015). Earlier attempts to get continental-scale LULC products were limited to a coarse spatial scale (250m-1km) which lacked sufficient spatial details (Arino et. al, 2008; Friedl et. al, 2010; Hansen et. al, 2000; Loveland et al., 2000). Nowadays various platforms like United States Geological Survey (USGS), Amazon Web Service (AWS), etc. provides access to the Landsat data archive and hence enabling analysis of this dataset on the cloud but these data are of high storage and takes more time to download. However, the increasing volume and sort of remote sensing data, dubbed as a "Big Data" problem, creates new challenges in handling datasets that need new approaches for extracting relevant information from remote sensing (RS) considering knowledge science perspective (Kussul, 2015).

Landsat observations are however affected by cloud coverage, and also Landsat 7 data has issues of Sensor line error (SLE) which eventually occurred due to sensor failure issues. Generally, there are two multi-temporal Landsat classification methods which are widely used to eliminate the effects of missing observations caused by cloud cover or sensor failure were used. The first method being extraction of metrics (such as the percentiles, Minimum, etc.) for time-series of Landsat annual reflectance observations and finally classifying the metrics (Zhang, 2017). For the time-series of cloud-free composites, the change in reflectance with time is retained between temporal composites. by calculating medoids (observed value closest to the median) and percentiles (to capture variability within the year). Also, another method is making cloud-free composites of time-series Landsat images(Griffiths et al., 2013). The two compositing methods are physically different in the sense that for metric composites, the pixel values of the same feature image have different acquisition times during the year, and information regarding how the reflectance observations change with time is missing between metric features

The Google Earth Engine (GEE) is a cloud platform that provides full access to a complete catalogue of freely available satellite data along with the opportunity to process these products quickly online through massive parallelization (Mutanga & Kumar, 2019). It is accessed and controlled through an Internet-accessible application programming interface (API) and an associated web-based interactive development environment (IDE) that enables rapid prototyping and visualization of results based on JavaScript and Python (Gorelick et al., 2017). Various data from Landsat 4, 5, 7, and 8 processed by the United States Geological Survey (USGS), several MODIS products, including global composites, recent imagery from Sentinel 1, 2, and 3 satellites, and many more can be found in GEE data catalogue. Also, user data in raster or vector formats can be uploaded (ingested using GEE terminology) and processed in the GEE (U.S. Geological Survey, 2010). Various satellite imagery from different sources and time can be easily processed using this platform without paying much attention to mosaicking, registration, projection conversion, etc. The GEE does not need to require remote sensing image archives to be downloaded but has its base for users to work on making it a convenient platform. Further, GEE has 10 classifiers: CART, Random Forest, Minimum Distance, GMO MaxEnt, Naïve Bayes, SVM, Perceptron, IKPamir, and Winnow, for image classification. Each of these classifiers uses a different algorithm to assign pixels to classes and perform land cover classification in a pixel-based manner (Lee, 2016). The advantages of this platform make it convenient and flexible for use in land-cover classification, especially when a large number of features are used as input data.

Till the data, most of the LULC research has been limited to the national level with very small in regional level (Paudel et al., 2016). This has restricted specific results regarding the situation at the micro-level. According to UNDESA (2015), Nepal is recorded as the top ten fastest urbanizing countries. The rate of increase in population in the Kathmandu Valley is more than two times more than that the national population growth rate (CBS, 2012). Peri-urban areas of the KV also have a high population density of 4445 people/sq.km in an average, which is expected to increase rapidly shortly. The study area here is one of the major rapid urbanizing Municipalities where the population is increasing with urbanization trends at a swift pace which can be visualized with daily site changes. The majority of the agricultural land has been converted into residential buildings. However, changes incurring in the whole of the Municipality are still unknown. Also, no proper details regarding land use can be found in the records. Lack of land cover data in the municipal records restricts it from carrying out activities related to proper land resource management. The study aims to fulfil theses gaps by carrying out an automatic 30 m land cover classification using Landsat data based on the GEE platform for years 2001,2009 & 2019 along with change detection and the rate of changes between these years. The study further aims to provide insight into the general land use and land cover condition of Tokha Municipality helping for better planning and proper management of land resources.

Materials and methods

Study area: Tokha is an ancient city of Kathmandu Valley, Nepal. This municipality was formed in Mangsir 21st, 2071 B.S. by merging five existing VDCs: Dhapasi, Jhor Mahankal, Gonggabu, Tokha Chandeshwori, and Tokha Saraswoti (The_Kathmandu_Post, 2017) with a geographical area, 17.1 km^2. Geographically Tokha Municipality lies in the Latitude of 27.770075° and Longitude of 85.329129° at an Elevation of 1330 m.

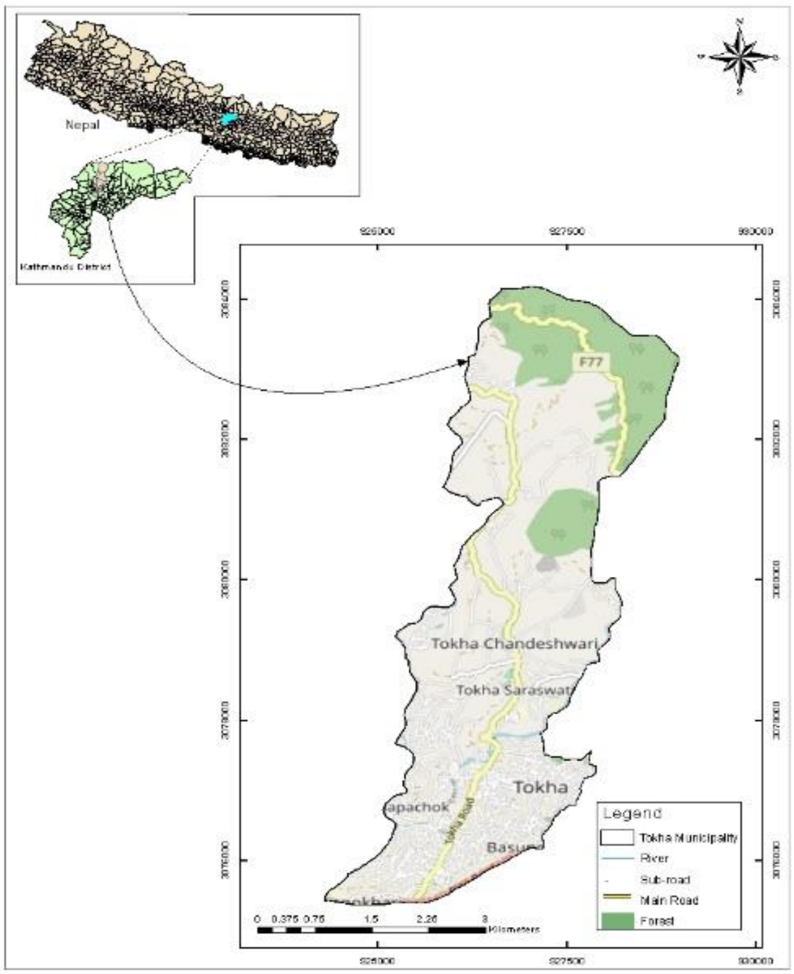

Fig1: Location and map of Tokha Municipality

Sub-tropical climate with an average annual temperature for Tokha is 21° degrees and 1377 mm of annual rainfall can be seen in Tokha. As per the vegetation, Sub-tropical vegetation proceeds towards temperate vegetation as altitude increases towards the Northern side. A total of 1,00,780 people resides in Tokha Municipality (CBS, 2012). Furthermore, this municipality is situated at the base of Shivapuri National wildlife reserve conservation area.

Data collection: For LULC classification of Tokha Municipality available Landsat images of the

Year	Satellite	Launch date	Sensor	Spatial Resolution	Date of Acquisition
2019	Landsat 8	February 11, 2013	OLI/TIRS	30 m	Jan- Dec, 2019
2000 & 2009	Landsat 7	April 15, 1999	ETM+	30 m	Jan- Dec, 2000 Jan- Dec, 2009

year 2001, 2009 and 2019 were directly imported from GEE catalogue. The satellite data for each year were obtained for year long.

Table 1: Characteristics of acquired satellite data

Data processing: Landsat images are known to have distortions; hence, for pre-processing four major corrections were applied as Cloud Masking(to address cloud-free pixels), Cloud Shadow Masking (the address darker pixels), BRDF Correction (also called Bidirectional Reflectance Distribution Function, addresses illumination between images with relation to the angle of sun and sensor) and Topographic Correction (radiometric correction to account for illumination effects from the slope, aspect, and elevation with different terrain positions). All the pre-processed images were thereafter subjected to the composite of respective years. The overall methodological flow in the research is provided in the following figure 2.

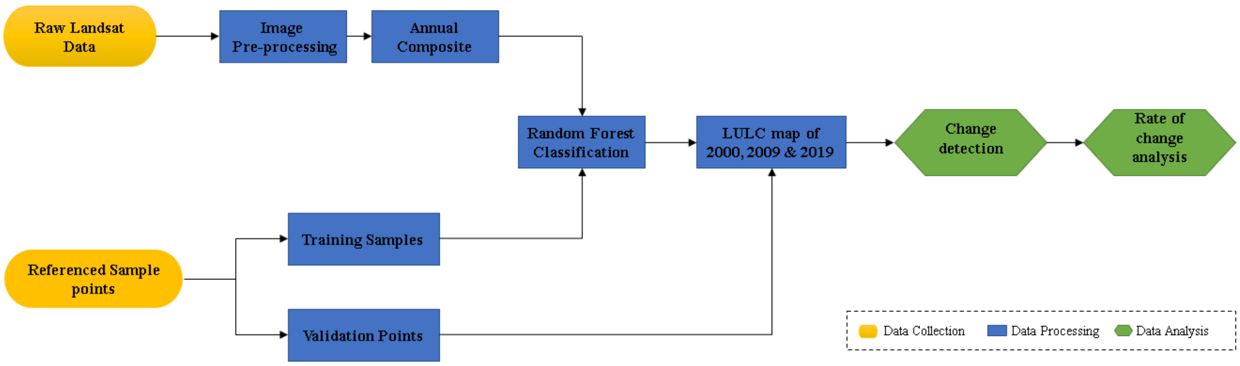

Fig : 2 Flowchart of the image processing and analysis

In the study, five land cover classes which represented the total land cover of the study area were determined as shown in Table 2. Grasslands were kept under otherland as it covered a very negligible area of the total study area. Generally, Grasslands are the most confusing land covers to identify in imageries (Zhao et al., 2017) which is also a reason for not selecting grassland as a separate land class. A total of 269 training points were obtained. The acquired training points were sampled to append all the Landsat matrix and covariates (data used to perform classification) in a single form.

Table 2: Landcover classification scheme.

Land cover	Description
Agriculture (Cropland)	Lands covered with temporary crops followed by harvest period & crop field.
Settlement (Built-up area)	Land covered by buildings or other man-made structures. Residential, commercial services, industrial area, mixed urban, or built uplands.
Forest	Areas covered with trees forming closed or nearly closed canopies, mostly dominated by tree species

Waterbody	The area with the presence of water.
Otherland	Includes all the excluded lands like bare land, bare soil, grassland, etc.

Random Forest (RF) classifier was used for the process of classification. As a sample is entered into the RF model, each decision tree works under separate assessment to determine the category that the sample should fall under, and the category that is most frequently selected is ultimately considered the sample category (Hu, 2019). The use of RF was selected over the others since it overcomes the major problem of the Decision tree (DT) classifier of overfitting by constructing an ensemble of DTs (Breiman, 2001). More specifically, RF operates by constructing a multitude of DT at training time and outputting the class that is the mode of the classes (classification) of the individual trees along with correcting the DT habit of overfitting to their training set (Shelestov et al., 2017). The RF classifier has been effective in the classification accuracy even when applied to analyze data with stronger noise (Breiman, 2001; Tian et al., 2016). Thus, obtained classification was then sampled and finally assembled to obtain a landcover map.

The accuracy assessment of the image classification is a very crucial part. For accuracy assessment, validation points were collected with the aid field visit using a handheld Garmin Global Positioning System (GPS) and high resolution google earth images. Producer's accuracy, user's accuracy, overall accuracy, and kappa coefficient were computed for the final land cover maps produced. The acquired land cover map had overall accuracy ranged from 86-95% and kappa coefficient value ranged from 0.79-0.96 indication almost accurate classification according to (Mango,2010) and (Congalton, 1999).

Table 3: Accuracy assessment of output landcover maps

LULC categories	Year 2000				Year 2009				Year 2019			
	PA (%)	UA (%)	OA (%)	KC (%)	PA (%)	UA (%)	OA (%)	KC (%)	PA (%)	UA (%)	OA (%)	KC (%)
Agricultural land	31.66	81.48	86.95	0.810	100	77.77	88.40	0.790	100	92.59	95.65	0.963
Settlement	85.16	100			82.14	100			85.83	100		
Forest	88.23	93.75			93.75	93.75			100	100		
Waterbody	0	0			50	66.66			50	66.66		

For the change detection process, post-classification comparison (PCC) was used. This approach is supportive in determining "from-to" changes to identify the transformations among the land cover classes (Yuan et al., 2005). PCC works on the principle of identifying changes by independently comparing classified multi-date imagery on a pixel-by-pixel basis under a change detection matrix (Yuan & Elvidge, 1998).

The annual rate of change of land use land cover was calculated using the following formula adopted from (Shiferaw, 2011):

$$\Delta R = \frac{A - B}{C}$$

Where ΔR is the annual rate of change, A is a recent area of land use land cover type in ha, B is the previous area of land use land cover type in ha and C is the time interval between A and B in years.

Also, the percentage rate of annual change was determined by the following formula.

$$\Delta \mathrm{R(in\%)} = \frac{\text{(change in between two study years/total change in these years)}}{\text{Total time interval}} * 100$$

Results

Status of land cover in a different period: In the year 2000, agricultural land dominated the landscape with 756.59 ha. (44.22%) of total land cover share. Otherland was the next dominant land cover class covering 517.65 ha. (30.25%) of study area followed by 295.39 ha. (17.26%) of forest. Settlement area and waterbody covered only 140.83 ha. (8.23%) and 0.04 ha. (0.04%) of total areas respectively.

Proceeding to the year 2009, the greatest share of land use/land cover from all classes remains for agricultural land, which covered an area of 627.15 ha. (36.65 %). Forest area covered the second majority with an area of 508.49 ha. (29.71%). Settlement area covered 389.28 ha. (22.75%) area followed by 185.88 ha. (10.86%) of Otherland. The least aerial coverage remains for waterbody with 0.24 ha. (0.014%) area.

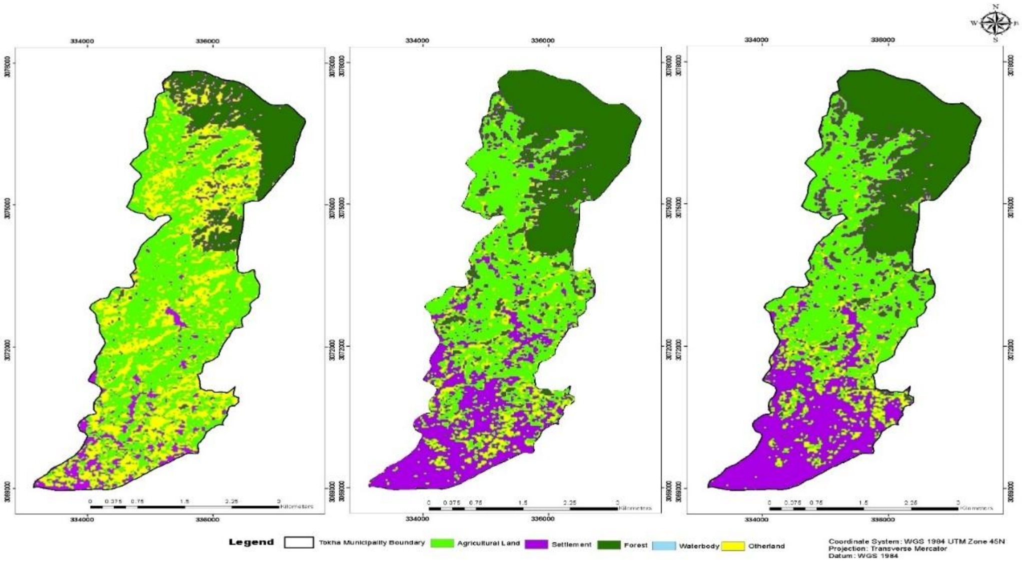

Fig 3: LULC maps for a)2000 b)2009 and c)2019

For the year 2019, the same sequence of landuse/land cover follows as with 588.31 ha. (34.38%) Agricultural land, 509.12 ha. (29.75%) Forest area, 450.78(26.34%) settlement area, 162.37(9.48%) otherland and 0.475 ha. (0.03%) waterbody.

Table: Status of LULC in different time period

Year 2000				**Year 2009**			**Year 2019**		
Features	**Area (km^2)**	**Area (ha.)**	**Coverage (%)**	**Area (km^2)**	**Area (ha.)**	**Coverage (%)**	**Area (km^2)**	**Area (ha.)**	**Coverage (%)**
Agriculture	7.5659	756.59	44.22	6.2715	627.15	36.65	5.8831	588.31	34.38
Forest	2.9539	295.39	17.26	5.0849	508.49	29.71	5.0913	509.12	29.75
Waterbody	0.0060	0.60	0.04	0.0024	0.24	0.014	0.0048	0.475	0.03
Settlement	1.4083	140.83	8.23	3.8928	389.28	22.75	4.5079	450.78	26.34
Otherlands	5.1765	517.65	30.25	1.8588	185.88	10.86	1.6234	162.37	9.48

Ever since the beginning of the study period, agricultural land dominated the landscape representing the major occupation and heavy dependency in Agriculture. Agricultural lands are mostly found in between the forest area and core urban area, indicating its dependence on forest for natural inputs such as manure, pasture, etc, and people of the urban area using the land for food output. Forest area can be seen confined mostly on the Northern parts of higher elevation. Settlement areas are mostly confined in the southern part of the municipality. A very small area was occupied by waterbody with no surprise as Bishnumati river is the only river as a waterbody in the Municipality. Such low coverage by and waterbody is an indication of low levels of ecological diversity. Otherlands are fairly distributed all over the study area.

LULC change in Tokha Municipality: Major changes in landcover were seen between the year 2000 and 2009. Agriculture was seen to be significantly decreasing with a total of 168.28 ha. (9.84%) loss in the whole study period. Forest area can be seen gradually increased from the year 2000 to 2009 of 213 ha. (12.45%) then after seems to be relatively stable. Initially, very few settlement areas were seen due to low population and mostly the local inhabitants residing during that period which gradually increased in the consecutive years with a total of 309.95 ha. additional area. Waterbody covering a very small portion of the total area can be seen in a state of very less decreasing change of 0.13 ha. (0.01%). Otherlands is one of the most affected with a gradual decrease of 331.77 ha. (19.39%) until the year 2009 and further by23.54 ha. (1.37%).

Table 5: LULC change between the different time interval

		Total change (2000-2009)			Total change (2009-2019)			Total change (2000-2019)		
S.No.	Land cover classes	Area (km^2)	Area (ha.)	Coverage (%)	Area (km^2)	Area (ha.)	Coverage (%)	Area (km^2)	Area (ha.)	Coverage (%)
1	Agriculture	-1.29	-129.44	-7.57	-0.388	-38.84	-2.27	-1.68	-168.28	-9.84
2	Forest	2.13	213.10	12.45	0.0063	0.63	0.03	2.14	213.73	12.49
3	Waterbody	0.003	-0.36	-0.02	0.0024	0.24	0.014	0.00	-0.13	-0.01
4	Settlement	2.48	248.45	14.52	0.6151	61.51	3.59	3.10	309.95	18.11
5	Otherland	-3.32	-331.77	-19.39	-0.235	-23.54	-1.37	-3.55	-355.28	-20.77

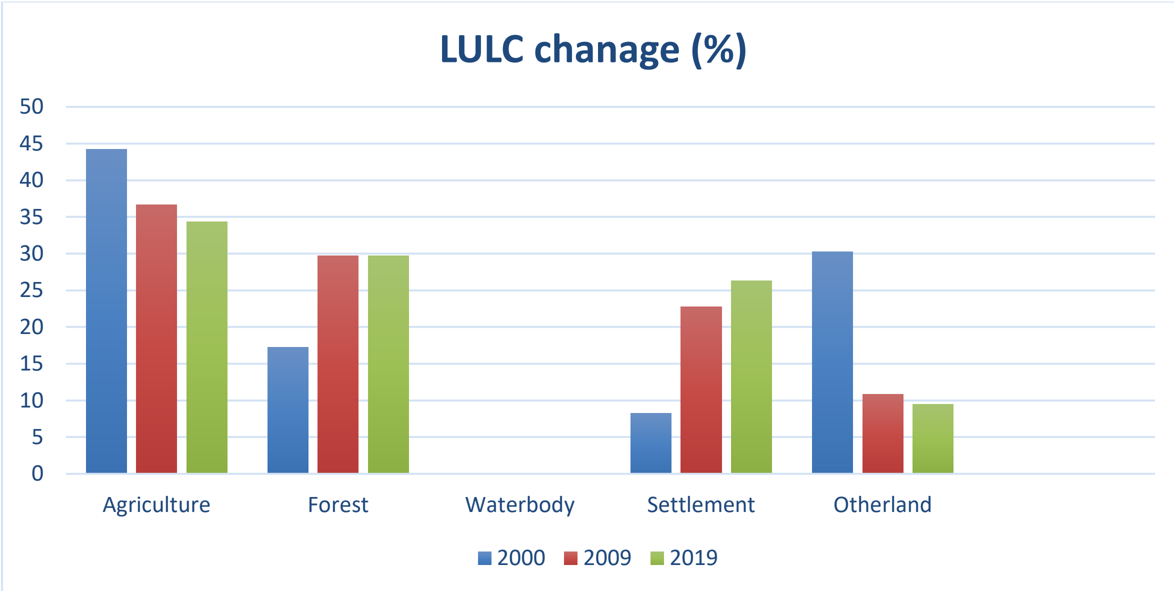

Fig 4: LULC trend of year 2000, 2009 and 2019

LULC dynamics: Agricultural land gradually decreased with a major portion(139.39 ha.) being replaced by settlement area. This period i.e 2000-2009 coincides with the flourishing period of the real estate market in Kathmandu Valley largely characterized by the influx of migrants from the countryside displaced by political turmoil and/or by stagnant growth in the agricultural sector. Forest area almost accelerated its area with nearly double growth. Most of the Northern area previously covered by otherland classes were managed as NP was established in 2002. Bishnumati river slowly being encroached by Agriculture and settlement area leading to a decrease in the area of the waterbody. Very fewer changes in the previous area of settlement observed which has rather increased. Otherland is gradually replaced by Forest, Agriculture and Settlement area with 443.48 ha. total decrease.

During the time interval of 2009-2019, major changes can be seen in the class of Agriculture (126.94 ha.) converted to other land cover classes subjecting to an overall decrease of this land cover class. A similar trend of a good range of conversion from agricultural land to forest and settlement was also recorded by National level forest and land cover analysis between the period 2008 and 2017 (FRTC, 2019). Similarly, the settlement area still found to be in increasing order obtaining net gain of 61.4 ha. additional area which doesn't seem to have an overall increase due to conversion to other landcover classes (112 ha.). Otherlands are gradually decreasing (116 ha.) with the major portion replaced by Agriculture (75.04 ha.) and settlement (30.85 ha.). The least change was observed on Waterbody as 0.11 ha. waterbody converted to Agriculture (0.03 ha.) and settlement (0.16 ha).

About 23% of the agricultural land decrease in the 19 years interval with major conversion to Settlement. Forest area increased about 72% to that of the year 2000. Waterbody mostly encroached and converted to agriculture and otherlands. Settlement area increased more than 200% to that of the year 2000 with very less conversion to other land cover classes. Otherland decreased by about 67% to that of 2000. Major conversion to Settlement followed by Forest and settlement. Bare lands conversion depends on the ownership and location and of these lands. The bare grounds proximate to hilly areas are replaced mostly for agriculture, whereas, the bare grounds located at the outskirts of the city are mostly cleared up to expand the built-up area.

Table 6: LULC transition matrix between year a)2000 and 2009 b)2009 and 2019 & c) 2000 and 2019

Land use land cover classes		**Year 2009**					
		Agricultural land	Forest	Waterbody	Settlement	Otherland	**Total (2000)**
Year 2000	Agricultural land	**474.427**	62.46	0	139.39	80.31	756.59
	Forest	0.822	**282.24**	0	0.47	11.86	295.39
	Waterbody	0.12	0	**0.24**	0.20	0.04	0.60
	Settlement	6.89	0.56	0	**106.97**	26.41	140.83
	Otherland	144.89	163.24	0	142.26	**67.25**	517.65
	Total (2009)	627.149	508.50	0.24	389.29	185.87	**1711.04**

Land use land cover classes		**Year 2019**					
		Agricultural land	Forest	Waterbody	Settlement	Otherland	**Total (2009)**
Year 2009	Agricultural land	**500.19**	38.93	0	42.05	45.96	627.15
	Forest	25.287	**459.162**	0	0.523	23.509	508.49
	Waterbody	0.029943	0	**0.1**	0.16	0.11	0.24
	Settlement	55.77	2.45	0.03	**277.29**	53.75	389.28
	Otherland	75.04	10.89	0.05	30.85	**69.05**	185.88
	Total (2019)	588.314	509.127	0.476	450.787	162.337	1711.040

Land use land cover classes		**Year 2019**					
		Agricultural land	Forest	Waterbody	Settlement	Otherland	**Total (2000)**
Year 2000	Agricultural land	**454.444**	63.75	0	162.47	75.93	756.59
	Forest	2.904	**290.27**	0	0.87	1.88	295.93
	Waterbody	0.035	0	**0.40**	0.05	0.04	0.60
	Settlement	3.92	0.85	0.03	**125.28**	10.79	140.83
	Otherland	127.05	154.26	0.05	162.17	**73.74**	517.22
	Total (2019)	588.349	509.13	0.48	450.84	173.12	**1711.04**

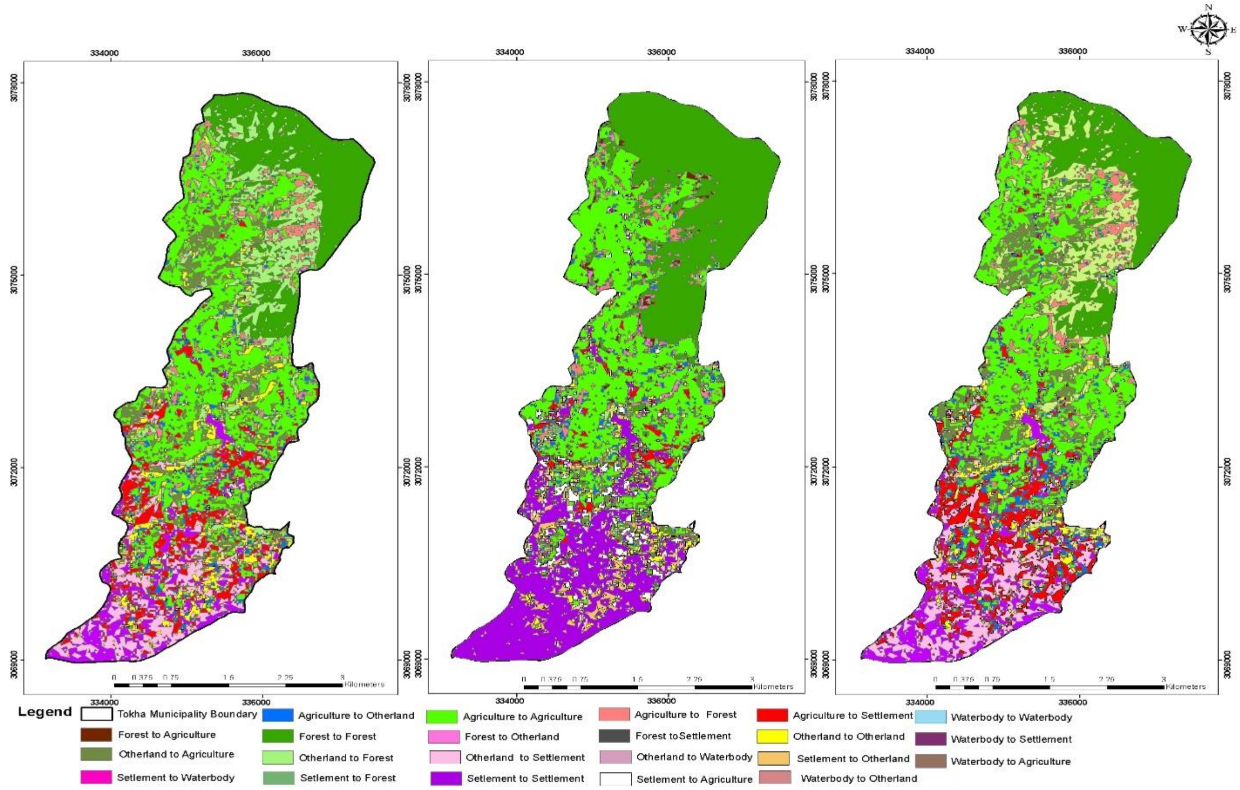

Fig 5: Transition of all LULC classes between the year a)2000 and 2009 b)2009 and 2019 & c) 2000 and 2019

Rate of change:

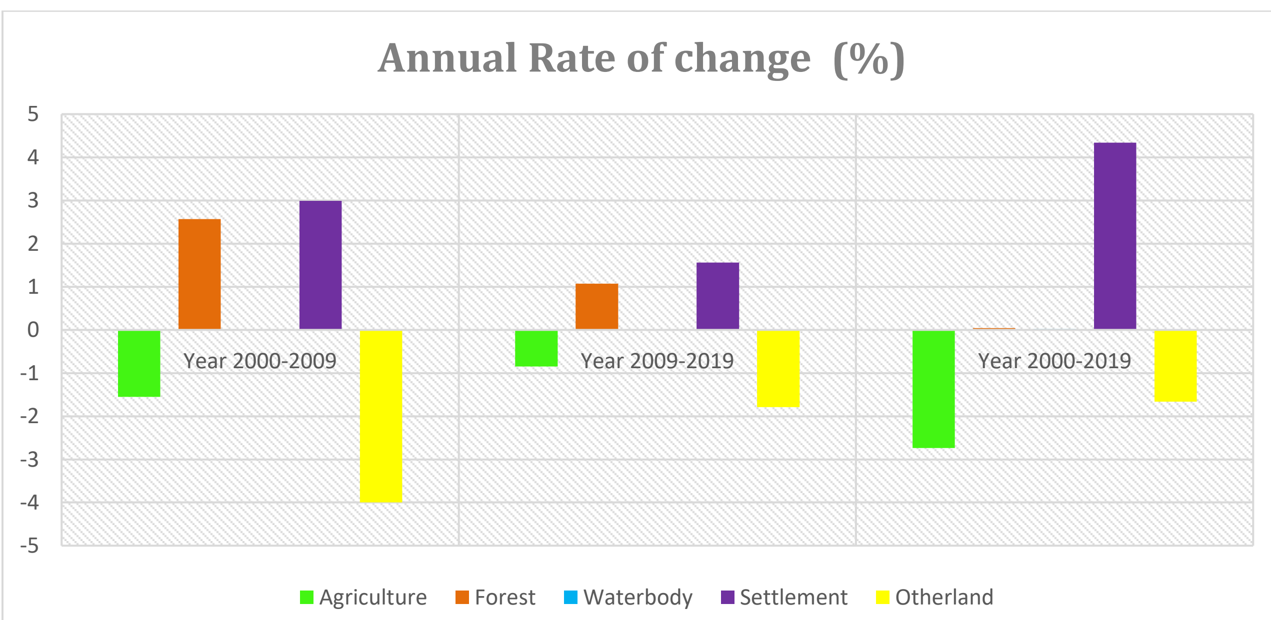

Fig 6: Rate of change of different LULC classes in different time interval.

Table 7: Rate of change in different LULC classes of Tokha Municipality

It can be seen that each land cover classes were subjected to specific changes. The maximum annual rate of change in all the transition was seen for settlement area which increased from annual 2.991% in period 2000-2009 to 4.34% in 2009. Agricultural land is in continuous decreasing phase form 1.558% each year from 2000-2009 to 2.47% annual decrease in the period of 2009-2019. Forest area initially paced up its increasing rate with 2.565% gain per annum in the time range of 2000-2009 then after became more or less stable with a very slight increase in the next transition period. Otherland suffered a gradual decrease of 3.994% per annum in the first transition period thereafter with slight less decrement of 1.66% per annum in the next transition period. Waterbody having a very small area coverage was subjected to a slight decrease in the initial transition but increased in the next transition period.

		2000-2009		2009-2019		2000-2019	
S.No.	Land cover classes	Annual rate of change (ha. /yr.)	Annual rate of change (%)	Annual rate of change (ha. /yr.)	Annual rate of change (%)	Annual rate of change (ha. /yr.)	Annual rate of change (%)
1	Agriculture	-14.382	-1.558	-3.884	-2.74	-8.857	-0.846
2	Forest	23.678	2.565	0.063	0.045	11.221	1.072
3	Waterbody	-0.040	-0.004	0.024	0.017	-0.007	-0.001
4	Settlement	27.606	2.991	6.151	4.34	16.314	1.558
5	Otherland	-36.863	-3.994	-2.354	-1.66	-18.701	-1.786

Discussion

By using the Landsat images in the GEE platform land use land cover map of Tokha Municipality was prepared for three different years 2000,2009 and 2019 which included five major classes as

Agriculture, Forest, Settlement, Waterbody and otherland to access the spatial and temporal changes over time. The majority of land cover has been used for agricultural purposes and the least land cover can be seen for the waterbody. Till the 1980s, the urban areas (interchangeably used as built-up areas) of Kathmandu Valley were limited within the confines of the historic settlements of the five municipalities. The outward expansion of the urban area began in the early 1990s establishment of democracy in 1990, Kathmandu became the centre of political power and hub of business activities (Thapa et al., 2008) and accelerated at the turn of the 20th century. There is no sign that it is going to stop anytime shortly. Most agricultural lands that once were considered to be the most fertile and productive are replaced by newly expended built-up. Agricultural land decreased to a great extent and waterbody was subjected to a very slight change from 1999 to 2016. (Thapa & Murayama, 2011) also supported the growth of settlement area at expense of mostly settlement area in Kathmandu valley. This also supported their stimulated model to predict the land cover pattern and state of Kathmandu Valley in 2020 were built-up area will dominate the land cover at a swift increasing rate where agricultural land will be in a decreasing phase.

The land use land cover dynamics reveals that Tokha Municipality has been experiencing a rapid land use land cover change. The change map also showed the transition of different land cover classes over the study period. Settlement area was to have the maximum rate of increase among all land cover classes with an increase of 16.314 ha. per year. This indicates the trend of urbanization in the Municipality area. It is well obvious of an increase in the settlement area with an increase in population. The population status of the Tokha Municipality increased from 42,308 in 2001 to 1,00,780 in 2011 (CBS, 2012; CBS, 2001) with 9% per year. Past studies reporting similar findings for Kathmandu valley (Ishtiaque et al., 2017; Paudel et al., 2016; Potapov et al., 2015; Wang et al., 2020) reasoned that the rate of urbanization and its sprawl outwards from the urban core increased sharply after the civil war ended in 2006, which was followed by reinvigorated development. Agricultural lands are being converted mostly into settlement areas with a decrease of 8.857 ha. per year but this rate hasn't decreased rapidly in the sense that otherlands are slowly being used for agricultural purposes. Past studies by (Ishtiaque et al., 2017; Khanal et al., 2019; Paudel et al., 2016) reported causes of the reduction of agricultural land to rapid urbanization and lack of strengthing policies governing land conversions. Poor management in recent years has led to the conversion of agricultural land to highly built-up areas in Nepal (Paudel et al., 2018). Waterbody favours slight overall increase which may be due to artificial pond creation for irrigation and clearing of bushes on the banks of Bishnumati River. Unlike the present scenario and recent studies, forest areas seemed initially increasing and later towards stability. The reason for the vast increase in the forest area from year 2000 to 2009 goes to the establishment of Shivapuri NP on 2002. In the later transition of 2009 to 2019 slight increase in forest area is obserbved which may be due to canopy expansion in the previously unaltered forest area. A study by (Ishtiaque, Shrestha, & Chhetri, 2017) for land cover change analysis for Kathmandu Valley from year 1989 and 2016 represented similar trends of Forest area gradually in increasing phase. The reasons for no decrease in the forest area in the context of rapid change is the fact that deforestation rate is very low due to the presence of forest with religious importance (e.g. Bhootkhel, forest area adjoining Chandeshwori Temple, etc.), presence of forest area in sloppy land maintaining land stability, and a majority of forest area lying under Shivapuri N.P and its base areas.

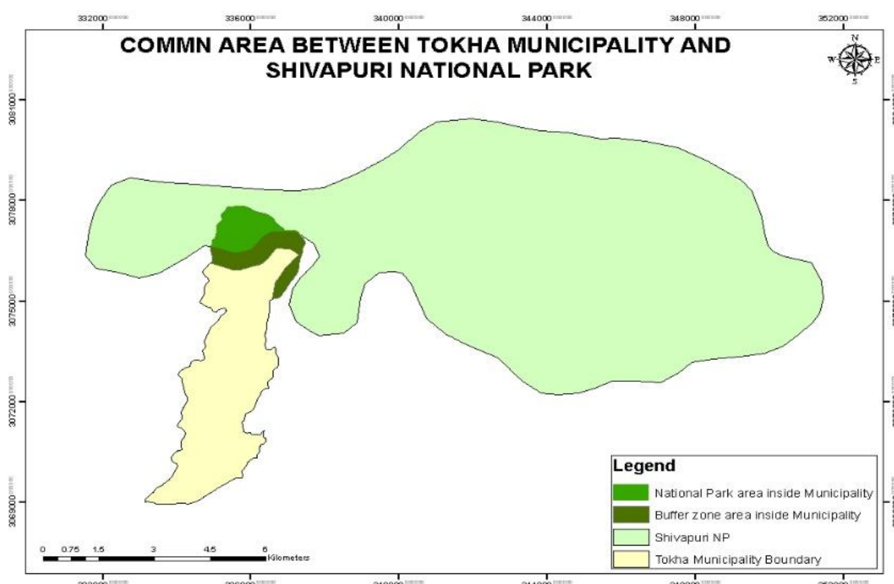

Fig 7: Common area between Tokha Municipality and Shivapuri NP

Otherlands are decreasing at an annual rate of 1.786% which has both positive and negative aspects. The positive aspect lies in the fact that barren lands are slowly being used for agricultural purposes. The negative side is because grasslands inside the municipality have started disappearing and now the record of the existence of grasslands only remains in the memory. The reason for less settlement area in higher altitude is obvious as people prefer to migrate toward urban setting in search of various facilities including employment. Population density data supported Gonggabu and Dhapasi areas as the populated part in Tokha Municipality. Various studies have shown rapid high rural to urban migration as one of the major demographic problem prevailing in Nepal from a long time which in our study also implies for higher altitude to lower altitude migration (Pradhanang, 1983; Timalsina, 2007; Gurung, 2011).

Conclusion

Hence, it can be seen that land use and land cover statistics obtained and processed using satellite images from Google Earth Engine platform were found effective and well convincing with the overall accuracy of 86.85% (kappa coefficient: 0.810), 88.40% (kappa coefficient: 0.831) & 94.11% (kappa coefficient: 0.963) for the year 2000, 2009 & 2019 respectively. The obtained land cover was almost comparable to that of the Municipality area with defendable reasons. Use of temporal satellite data sets are very useful, time-saving and cost-effective for the preparation of LULC maps and change analysis.

From the result and analysis section, it can be seen that Tokha Municipality is urbanizing at the annual rate of 1.558%. Forest area in Tokha Municipality is in a safe status. The major change occurred in Otherland and Agricultural land which had been subjected to conversion into other land classes. The result from land use land cover dynamics map showed that there was no conversion observed in three transitions i.e. Waterbody to Forest, Agriculture to Waterbody & Forest to Waterbody in all three-transition period. However, the transition of Settlement to Waterbody and Otherbody to waterbody remained absent for dynamics between the year 2000-2009.

Thus, it is evident that user-friendly geospatial information systems like Google Earth Engine and GIS are much effective high-resolution tools over other such platforms in monitoring and controlling the land use and land cover changes from time to time to maintain good ecological balance.

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Conflicts of Interest

There are no conflicts to declare.