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Land Use Land Cover Change Prediction of Tansen Municipality Using Multi-Layer Perceptron-Markov Chain (MLP-MC) Model

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KEYWORDS

Google Earth Engine
Random Forest
LULC
MLP-MC
Prediction

ABSTRACT

LULC is dynamic across all-time series, and precise modelling of LULC dynamics can contribute to more effective planning for a sustainable future. This study aimed to examine the LULC change from 2003 to 2023 and further predict the LULC dynamics of 2033 for Tansen Municipality. Random Forest algorithm in Google Earth Engine (GEE) was used for the supervised image classification for three different years, i.e., 2003, 2013 and 2023. Land Change Modeler (LCM) of TerrSet was used for model development, prediction & its validation. Based on the Cramer's V values, candidate explanatory variables demonstrating a higher association with LULC transitions occurring between 2003 and 2013 were subsequently incorporated into the predictive model's construction. The developed model was then used to predict the LULC map of 2023. After model validation, LULC map for year 2033 was predicted using MLP-MC method. Overall, from 2003 to 2023, forest area continuously decreased, losing a total of 952.38 ha, while agricultural land, barren land and built-up areas steadily increased, by gaining a total of 412.11 ha, 336.18 ha & 206.64 ha respectively. However, the trend of water was unpredictable with a slight decrease of 3.58 ha. Comparing the LULC of 2003 & prediction for 2033, it is predicted that forest area will gradually decline by a total of 25.16%. Interestingly, water area is expected to remain constant with slight increase of 1.57%. But, agricultural land, barren land and built-up areas are projected to increase by 12.53%, 42.15% and 2175% respectively with a boost by the end of 2033. This model is based on the business-as-usual scenario and appropriate interventions can be implemented to reverse undesirable LULC changes and move towards a more sustainable future. This study offers valuable insights into both current & future land use dynamics, aiding policy makers & land use planners in developing better land use management plans.

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INTRODUCTION

The term "land use" relates to how people use the land and its resources, whereas "land cover" refers to the bio-physical cover that can be seen on the earth's surface, such as water bodies, plants, forests, agricultural land, and urban areas (Di Gregorio, 2005). Changes in land use and land cover (LULC) are caused by human activities and they affect the Earth's surface (Roy et al., 2015). These conversions of land surface represent significant changes and, additionally, they contribute significantly to environmental degradation at landscape level (Hamad et al., 2018a).

The rates of LULC dynamics are evolving as a result of the strong correlation between human activity and overuse of natural resources. LULC changes are also a result of natural variability including climate change, soil quality, and topographical features (Serra et al., 2008). As a result, an important global challenge in effective land use is the integration of natural and human variables in LULC dynamics. The current studies by renowned scientists are focused on the assessment of LULC change and the factors that have immediate effects on the environment and human societies (Tiwari et al., 2014). Distance to roads, urban areas and public facilities are crucial LULC change factors as these variables influence how population pressure affects certain land use classes (Regmi et al., 2017). The topography profile of the research region is similarly revealed through elevation and slope. Understanding the LULC change drivers and dynamics is essential for creating sustainable strategies and making educated planning decisions. It was taken into account, in estimating potential future scenarios, that the driving forces LULC change could be either direct or indirect, influencing change over time and across space (Behera et al., 2012).

Since the 1980s, remote sensing image data have been extensively used for LULC data collection, spatial and temporal process representation, model analysis, and simulation (Yuan et al., 2015). It is essential for sustainable development to evaluate how LULC has changed in the past and how it might change going forward. The scientific community is increasingly expanding its use of LULC change modelling. A number of models and software packages are available for the predicting LULC change, including CLUE-S, Markov Chain (MC) model, Cellular Automata (CA), Cellular Automata-Markov chain (CA-MC) model, Artificial Neural Network, Multi-Layer Perception Markov Chain (MLP-MC) model as well as statistical, cellular and hybrid models, System dynamic simulation, Binary Logistic Regression Algorithm, Similarity weighted instance-based machine learning algorithm, mathematical-equation-base, spatiotemporal modelling, cellular & agent-based models. These tools, individually or hybrid forms simulate the complex dynamics of LULC change (Gharaibeh et al., 2020; Kafy et al., 2021). The Artificial Neural Network (ANN)-Markov chain (MC) model is considered one of the most effective approaches for predicting future land change transitions, (Pahlavani et al., 2017). Multi-Layer Perceptron models (MLPs) are one of the ANN applications that are becoming more and more popular, and the MLP-MC hybrid technique has shown to be effective at precisely predicting LULC transitions (Ozturk, 2015).

According to report of (NSO, 2023), the population density of Tansen municipality is 463 people km^2. This indicates that there are significant anthropogenic pressures in the research area that either directly or indirectly result in LULC alterations. The LULC is in a constant state of flux as a result of the several causes outlined above. There is a severe paucity of research on LULC change analysis and the projection of the LULC scenario for the study area. This study will serve as the benchmark for future study of LULC for Tansen Municipality. Natural resource experts, policy makers, and planners will therefore need accurate LULC trajectories for Tansen Municipality in order to create comprehensive development plans and put in place sensible policy decisions. As a result, the findings of this study will be useful in a number of areas, including urban planning, conservation and management of natural resources, and spatial location of the areas that are more susceptible to LULC change. The general objective of this study is to predict the LULC change of Tansen Municipality using MLP Markov model. The specific objectives of this study are: (I) Produce multi-temporal (2003, 2013, 2023) LULC maps of Tansen Municipality, (II) Detect the spatial changes of LULC classes between these periods and (III)Predict the future scenario of LULC for year 2033.

MATERIALS AND METHODS

Description of study area

Tansen is a municipality city of Palpa district, Lumbini Province, Nepal. Tansen is divided into 14 wards, covering an area of 109.89 square kilometres as shown in Figure 1. According to the report of National Statistics Office (2023), Tansen Municipality had a total population of 50,792 with population density of 463/km².

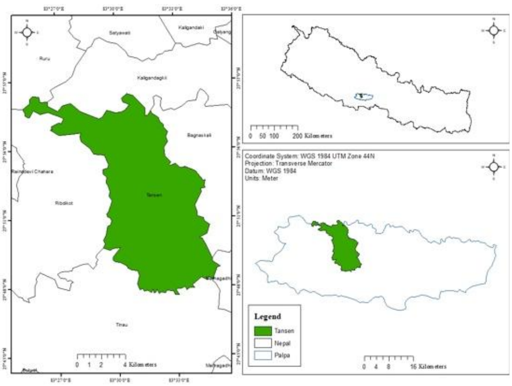

Figure 1: Map of the study area

Data collection

Various types of data as shown in Table 1 were collected for the study. Landsat surface reflectance data of different time period 2003 (ETM+), 2013 (OLI_TIRS), 2023 (OLI_TIRS) with the spatial resolution of 30m × 30 m was assessed from the data provided by USGS (https://earthexplorer.usgs.gov) through the platform of Google Earth Engine. The image from June to February was not used since most of the scenes were cloudy and affected the median value.

The total sample for each land cover class was collected from Google Earth Pro and field data and then split into two portions: 70% for training and 30% validation during accuracy assessment. The samples were collected in the form of points, lines & polygons for different classes. number of samples for each land cover class per year was between 20 to 447. A small number of large polygons is sufficient compared to a large number of points/lines as samples. For this reason, the number of samples varies across different land cover classes. While collecting samples, different geographical aspects and conditions of study area were taken into consideration. The Google Earth Pro was used to collect all the samples for year 2003 and 2013 while both the Google Earth Pro and field samples were collected for year 2023. The samples were collected randomly and then input into the Google Earth Engine (GEE) with the help of JavaScript.

The SRTM Digital Elevation Model was obtained from USGS portal. Likewise, road data were obtained from Open Street Map (OSM) portal. The OSM file was exported as a vector layer from QGIS and further processing was carried out in ArcMap.

Table 1: Data and source

S.N.	Data type	Data source	Remarks
1	Landsat surface reflectance data (2003, 2013, 2023)	https://earthexplorer.usgs.gov/ accessed through GEE	Median image from 1st February to 30th June
2	Ground truth data	Google Earth Pro and field	
3	SRTM Digital Elevation Model	https://earthexplorer.usgs.gov/	
4	Road data	Open Street Map (OSM)	

Methods

Image classification: The Google Earth Engine (GEE) platform was used for image classification. USGS Landsat 7 Collection 2 Tier 1 Level 2 data were used for the year 2003, while USGS Landsat 8 Collection 2 Tier 1 Level 2 data were used for the year 2013. Likewise, Landsat 9 Collection 2 Tier 1 Level 2 data were used for classification for the 2023 image. Median image of Tansen was extracted from the collected images for the time period between February to June. Not all the months were used due to the difficulty of effectively masking the cloud as the median pixel values are affected by the extremes during the cloudy season.

Five LULC classes namely water, forest, agriculture, built up areas and barren land were selected. Out of total collected sampled data, 70% data of each of land cover class were used for training samples. The classification scheme of five classes is mentioned in Table 2. Random Forest classifier using *ee.Classifier.smileRandomForest()* function was selected for supervised classification.

Table 2: Classification scheme

Water	River, streams, ponds, lakes & other water sources
Forest	Forested areas and scattered trees area
Agriculture	Cultivated and vacant cropland
Barren land	River banks, bare ground, landslide zone, grassland
Built-up	Residential, settlements structures and paved roads

Accuracy assessment: Error matrix also named confusion matrix is considered as the most common and reliable method for measuring the accuracy of classified image (Congalton & Green, 2019). 30% of sampled data were used for accuracy assessment in the Google Earth Engine. The error matrix was created on the basis of reference data and classification results in order to obtain producer's accuracy, user's accuracy and overall accuracy. Similarly, Kappa test, a non-parametric test, was calculated using the following formula to determine the extent of the accuracy of the classification:

$$K = \frac{P(A) - P(E)}{1 - P(E)}$$

Where, P(A) is the times the k raters agree and P(E) is the times k raters are expected to agree only by chance (Verma et al., 2020).

Land cover change detection: The images from two-time frame were imported into LCM to quantify changes in LULC occurring between 2003, 2013 and 2023 respectively. Cross tabulate MODULE in TerrSet software environment was used to generate the change matrix on the pixel wise basis. LCM evaluates land use changes between two different periods, identifies and visualizes changes, and presents the results using various maps and graphs.

Change prediction: MLP Markov technique inside the LCM using TerrSet software was used. Ahmed and Ahmed (2012) have described the MLP Markov and concluded the technique to be more accurate than the CA Markov and Stochastic Markov Models. Similarly, Ozturk (2015) compared Cellular Automata-Markov Chain (CA-MC) and Multi-Layer Perceptron-Markov Chain (MLP-MC) models and found that the kappa index of agreement was highest for the MLP-MC method. Therefore, the MLP-MC model was chosen due to its effectiveness in precisely predicting LULC transitions.

Variable preparation: For model building, potential driver variables were identified and analysed based on literature review, expert consultation and data availability. Digital Elevation Model (DEM), distance variables, evidence likelihood change map were considered as the probable driver variables as listed in Table 3.

Table 3: List of potential driver variables

S. N.	Potential Driver Variables	Literatures
1	Elevation (DEM)	(Ansari & Golabi, 2019; Girma et al., 2022; Leta et al., 2021; Mirici et al., 2018; Mishra & Rai, 2016; Nguyen & Doan, 2020)
2	Slope	(Ansari & Golabi, 2019; Girma et al., 2022; Leta et al., 2021; Mirici et al., 2018; Mishra & Rai, 2016; Nguyen & Doan, 2020)
3	Distance from road	(Ansari & Golabi, 2019; Girma et al., 2022; Leta et al., 2021; Mirici et al., 2018; Mishra & Rai, 2016)
4	Distance from river	(Ansari & Golabi, 2019; Girma et al., 2022; Leta et al., 2021; Mirici et al., 2018; Mishra & Rai, 2016; Nguyen & Doan, 2020)
5	Distance from built-up	(Ansari & Golabi, 2019; Girma et al., 2022; Leta et al., 2021; Mirici et al., 2018; Mishra & Rai, 2016)
6	Distance from public facilities	
7	Evidence likelihood	(Girma et al., 2022; Leta et al., 2021; Mirici et al., 2018)
8	Spatial trend of change	

Model building, prediction and validation:
Model building: Transition Potentials tab inside LCM was used to build the model. Inside "Transition Sub-Model Status" panel all the major transitions from one land-cover classes to another from 2003 to 2013 were included. Various kinds of potential driver variables that may contribute to LULC change were considered. Explanatory power of each of the variables that may contribute to land cover change was evaluated. The quantitative measure of association is given in terms of

Cramer's V value, a Chi-square-based measure of nominal association and those with higher explanatory power were selected and added to the model. According to Eastman (2016), variables with a Cramer's V value of 0.4 or higher are good, while those with a value of 0.2 or above are acceptable and have satisfactory explanatory power. The selected and tested driver variables for a specified sub-model were used to create transition potential maps. Transition sum model was run by choosing Multi-Layer Perceptron (MLP) for building future land use land cover model.

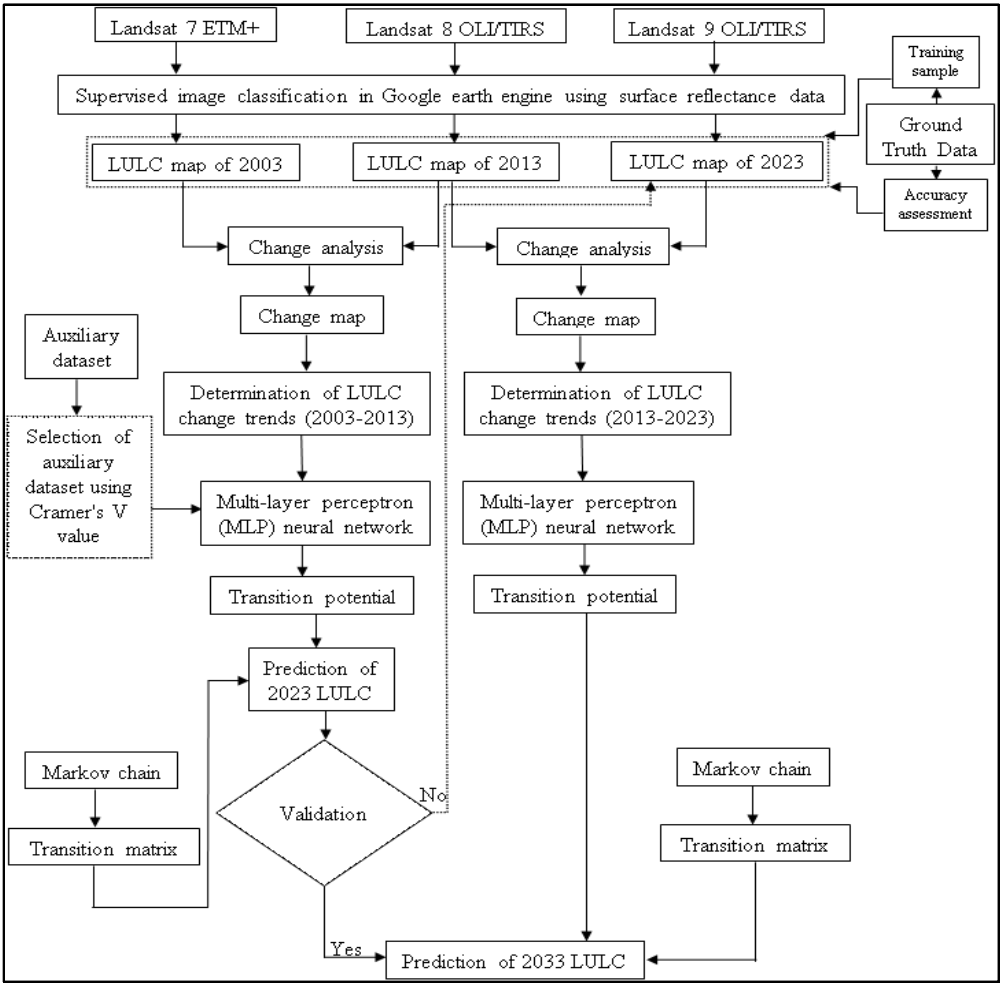

Figure 2: Flow Diagram of Research Design

Model prediction and validation: Markov chain method was used to generate the transition probability matrix for year 2023 using base years of 2003 and 2013. For change prediction, change allocation panel was used to generate predicted map of 2023. Predicted map of 2023 was compared with the actual LULC map of 2023 generated earlier. To assess the validity of the models, validate module inside TerrSet was utilized. Real map of the year 2023 was used as reference image and predicted map was used as comparison image. Various components of kappa index of agreement (KIA) were obtained through cross-tabulate module in TerrSet which helped to assess the strength and weakness of result based on location and quantity (Geri et al., 2011).

Future prediction: After the model had been validated, prediction of LULC for year 2033 was done applying the similar measures as mentioned in model building, prediction and validation.

RESULTS

Land use land cover dynamics

Land use land cover for the year 2003: It was observed that forest was the major land use class in the year 2003 with 49.58% of the total area and it was followed by agriculture, barren land, water bodies and built-up area with 40.22%, 9.68%, 0.37% and 0.15% respectively as given below in the Figure 3.

Land use land cover for the year 2013: It was observed that forest was the major land use class in the year 2013 with 46.02% of the total area and it was followed by agriculture, barren land, built-up area and water bodies with 40.75%, 12.07%, 0.73% and 0.43% respectively as given below in the Figure 4.

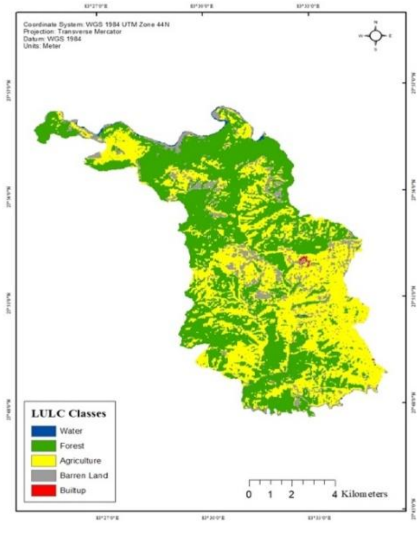

Figure 3: LULC map of Tansen Municipality for year 2003

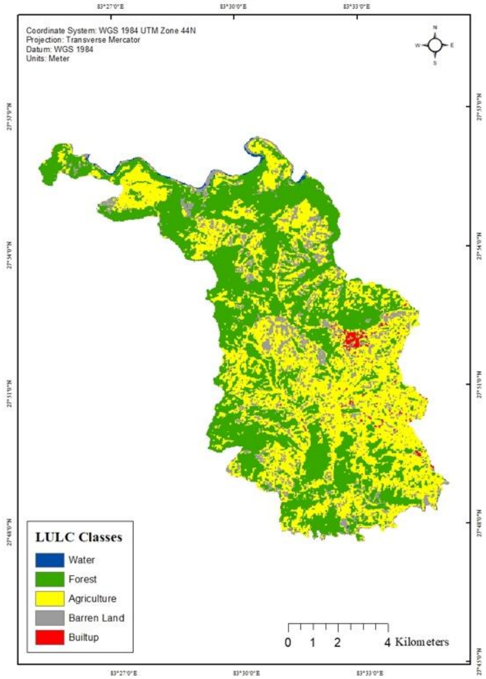

Figure 4: LULC map of Tansen Municipality for year 2013

Land use land cover for the year 2023: It was observed that agriculture was the major land use class in the year 2023 with 43.97% of the total area. It was followed by forest, barren land, built-up area and water bodies with 40.91%, 12.75%, 2.03% and 0.34% respectively as given below in Figure 5.

Accuracy assessment: Accuracy assessment of the LULC map for year 2003, 2013 & 2023 is presented in Table 4. The total accuracy of historical image classification is better than current image classification. One of the reasons behind it might be random collection of samples from different locations within the study area for different study years. Another reason might be that some of the collected samples were used for generating training samples (70%) and for validation during the accuracy assessment (30%).

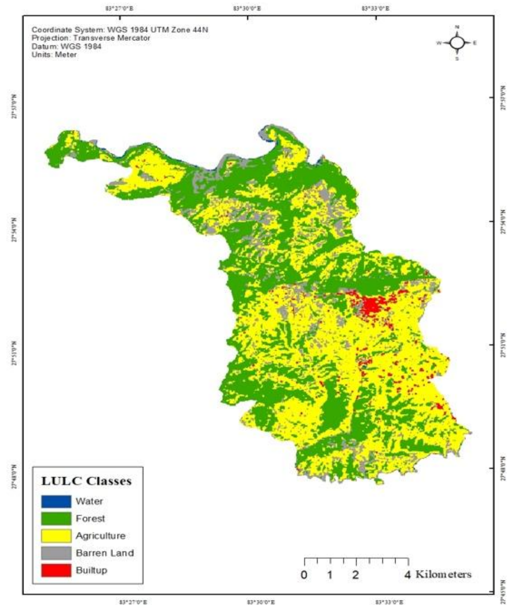

Figure 5: LULC map of Tansen Municipality for year 2023

Table 4: Accuracy assessment of LULC for year 2003, 2013 and 2023

Land Use Class	LULC 2003			LULC 2013			LULC 2023		
	UA	PA	KC	UA	PA	KC	UA	PA	KC
Water	0.86	0.88		0.85	0.91		0.88	0.71	
Forest	0.97	0.96		0.98	0.99		0.95	0.93	
Agriculture	0.83	0.92	0.86	0.79	0.85	0.85	0.86	0.88	0.78
Barren Land	0.89	0.85		0.8	0.81		0.75	0.81	
Built-up	0.59	0.33		0.8	0.43		0.74	0.63	
Total Accuracy	0.9			0.9			0.84		

UA = Users Accuracy, PA = Producers Accuracy, KC = Kappa Coefficient

Change detection
Using Cross Tabulate module in Terrset software, pixel wise change/no change data were obtained which were then further processed to transform the pixel number in area and percentage form using MS-Excel.

Change/no change matrix between year 2003 and 2013: Change/No change confusion matrix between 2003 and 2013 is as shown in Table 5 & Figure 6.

Table 5: Change/no change matrix between year 2003 and 2013

LULC Class 2003-2013		LULC Class 2013 (Area in ha & %)					Total (2003)
		Water	Forest	Agriculture	Barren land	Built-up	
LULC Class 2003 (Area in ha & %)	Water	25.65	6.30	1.89	6.12	0.27	40.23
		0.23	0.06	0.02	0.06	0.00	0.37
	Forest	4.23	4480.47	737.19	225.00	1.35	5448.24
		0.04	40.77	6.71	2.05	0.01	49.58
	Agriculture	1.26	477.90	3215.16	681.48	44.10	4419.90
		0.01	4.35	29.26	6.20	0.40	40.22
	Barren land	15.75	91.98	521.28	413.28	21.60	1063.89
		0.14	0.84	4.74	3.76	0.20	9.68
	Built-up	0.00	0.18	2.97	0.36	13.41	16.92
		0.00	0.00	0.03	0.00	0.12	0.15
Total (2013)		46.89	5056.83	4478.49	1326.24	80.73	10989.18
		0.43	46.02	40.75	12.07	0.73	100.00

Change/no change matrix between year 2013 and 2023: Change/No change confusion matrix between 2013 and 2023 is as shown in Table 6 & Figure 7.

Table 6: Change/no change matrix between year 2013 and 2023

LULC Class 2013-2023		LULC Class 2023 (Area in ha & %)					Total (2013)
		Water	Forest	Agriculture	Barren land	Built-up	
LULC Class 2013 (Area in ha & %)	Water	24.12	6.93	0.45	15.30	0.09	46.89
		0.22	0.06	0.00	0.14	0.00	0.43
	Forest	2.61	4050.45	822.06	178.38	3.33	5056.83
		0.02	36.86	7.48	1.62	0.03	46.02
	Agriculture	4.05	327.96	3320.91	724.14	101.43	4478.49
		0.04	2.98	30.22	6.59	0.92	40.75
	Barren land	6.03	109.26	686.52	480.06	44.37	1326.24
		0.05	0.99	6.25	4.37	0.40	12.07
	Built-up	0.27	1.26	2.07	2.79	74.34	80.73
		0.00	0.01	0.02	0.03	0.68	0.73
Total (2023)		37.08	4495.86	4832.01	1400.67	223.56	10989.18
		0.34	40.91	43.97	12.75	2.03	100.00

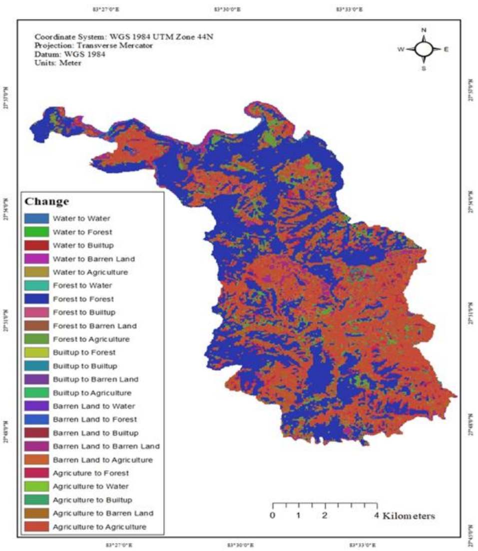

Figure 6: Change map from year 2003 to 2013

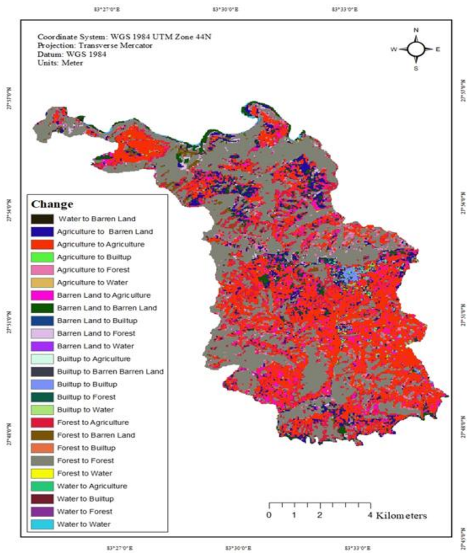

Figure 7: Change map from year 2013 to 2023

LULC change prediction

Model building: LULC images for year 2003 and 2013 from Erdas Imagine were used in Land Change Modeler inside Terrset software environment.

Transition sub-model status: Nine transitions that were incorporated were forest to agriculture, forest to built-up, agriculture to forest, agriculture to barren land, agriculture to built-up, barren land to water, barren land to forest, barren land to agriculture and barren land to built-up. They were grouped into single sub-model so as to evaluate the model.

Test and selection of driver variables: After testing the potentiality of various driver variables, the selected final driver list and their Cramer's V value is listed in Table 7 respectively.

Table 7: Cramer's V value of driver variables (In case: Overall)

S. N.	Driver Variables	Overall
1	DEM	0.2591
2	Euclidean Distance from Built-up (2023)	0.1614
3	Euclidean Distance from Public Facilities	0.1557
4	Euclidean Distance from Road	0.1119
5	Euclidean Distance from Water (2023)	0.1549
6	Evidence Likelihood from All to Agriculture	0.3376
7	Evidence Likelihood from All to Barren Land	0.3494
8	Evidence Likelihood from All to Built-up	0.4255
9	Evidence Likelihood from All to Forest	0.3363
10	Evidence Likelihood from All to Water	0.4255
11	Spatial Trend from Barren to Agriculture (3rd Order Polynomial)	0.1381

Change demand modelling: Markov chain method was used to determine the change of the specific date. The method precisely determines how much land expected to transition from later date to prediction date, based on future estimates of the transition potentials and creates a transition probability file (Eastman, 2016). Table 8 shows the transition probability matrix and transition probability matrix in area (ha) respectively, which was obtained for the prediction year 2023.

Change prediction: It was observed that areas of water, forest, and built-up land were overestimated whereas areas for agriculture and barren land were underestimated. The area statistics of LULC obtained for the predicted year of 2023 versus actual year of 2023 is given in the Table 9.

Table 8: Transition probability matrix for year 2023 (Area in ha)

Land Class		Predicted LULC Class 2023 (Area in ha)					Total 2013
		Water	Forest	Agriculture	Barren Land	Built-up	
LULC Class 2013 (Area in ha)	Water	42.48	0.09	0.07	4.32	0.00	46.96
	Forest	0.27	4560.30	311.04	179.64	5.58	5056.83
	Agriculture	0.54	123.12	3731.60	514.44	108.72	4478.42
	Barren Land	1.89	92.79	513.81	664.83	52.92	1326.24
	Built-up	0.00	0.09	0.36	2.79	77.49	80.73
Total 2023		45.18	4776.39	4556.88	1366.02	244.71	10989.18

Table 9: Actual versus predicted LULC statistics for year 2023

LULC Class	Predicted 2023 (ha)		Real 2023 (ha)		Difference	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Water	45.18	0.41	37.08	0.34	8.10	21.84
Forest	4776.39	43.46	4495.86	40.91	280.53	6.24
Agriculture	4556.88	41.47	4832.01	43.97	-275.13	-5.69
Barren Land	1366.02	12.43	1400.67	12.75	-34.65	-2.47
Built-up	244.71	2.23	223.56	2.03	21.15	9.46
Total	10989.18	100.00	10989.18	100.00	0.00	0.00

Validation of the model: Various kappa statistic parameters are given by the module which is presented in the Table 10. The data presented in the Table 10 show that there is satisfactory agreement between predicted map and actual map of the year 2023 since the kappa parameters were found to be more than 81.50%. The predicted LULC map of Tansen municipality for the year 2023 is as shown in Figure 8 below**.**

Table 10: Kappa statistics

Kappa	Value
Kno (Kappa for no information)	0.8683
Klocation (Kappa for location)	0.8315
KlocationStrata (Kappa for location strata)	0.8315
Kstandard (Kappa standard)	0.8154

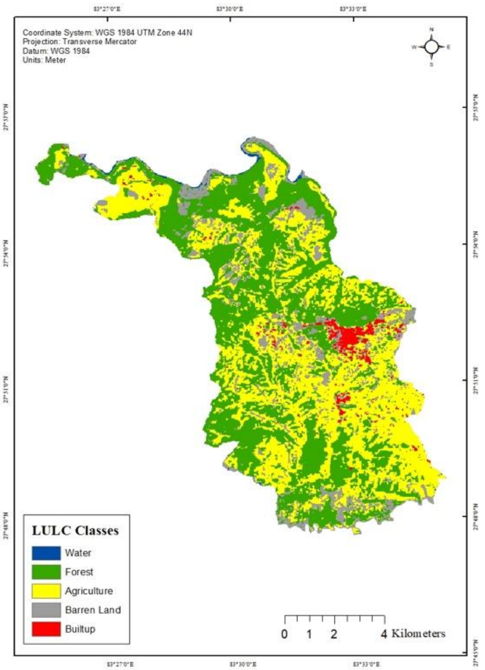

Figure 8: Predicted LULC map of Tansen Municipality for year 2023

Future prediction

Prediction 2033: After the model had been validated, it was used for predicting the LULC map for the year 2033. The base map of the initial model was changed and reference layers were added for the year 2013 and 2023. Driver variable, distance from water was updated along with the evidence likelihood of change. Table 11 shows the transition probability matrix in area (ha), which was obtained for the prediction year 2033.

The predicted LULC map for the year 2033 is shown in Figure 9 below. The area statistics for predicted map for 2033 is given below in the Table 12.

Comparing to LULC of 2023, a slight increase in water area by 3.78 hectares is expected. Meanwhile, agricultural land, barren land and built-up area are projected to increase by 141.57, 111.69 and 161.37 hectares respectively. But Forest land will continue to lose its areas to other land use classes by 418.41 hectares.

From 2003 to 2033, the water area is expected to remain unchanged, maintaining a proportion of 0.37%. Likewise, forest area will decrease from 49.58% to 37.10%. In addition to that, agricultural land will increase from 40.22% to 45.26%. Overall, barren land will continue to increase from 9.68% to 13.76% and built-up area will increase from 0.15% to 3.50%. The highest gains are projected for urban and barren land.

Table 11: Transition probability matrix for year 2033 (Area in ha)

Land Class		Predicted LULC Class 2033 (Area in ha)					Total 2023
		Water	Forest	Agriculture	Barren Land	Built-up	
LULC Class 2023 (Area in ha)	Water	36.54	0.18	0.36	0.00	0.00	37.08
	Forest	0.00	3590.28	740.97	163.44	1.17	4495.86
	Agriculture	0.00	352.98	3532.95	829.71	116.37	4832.01
	Barren Land	2.88	133.83	699.30	519.03	45.63	1400.67
	Built-up	1.44	0.18	0.00	0.18	221.76	223.56
Total 2033		40.86	4077.45	4973.58	1512.36	384.93	10989.18

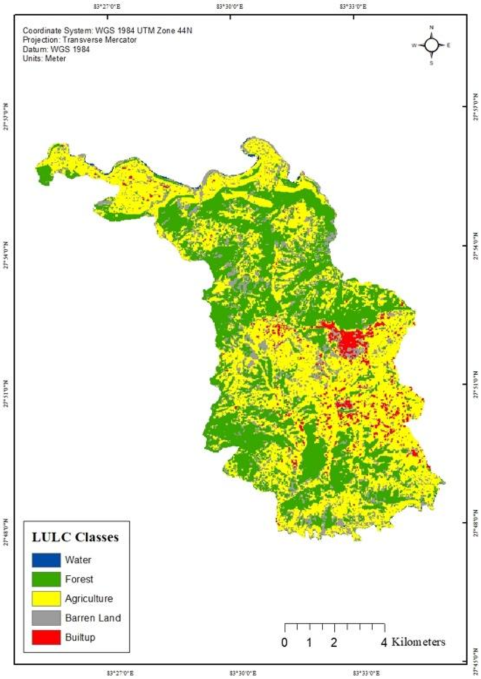

Figure 9: Predicted LULC map of Tansen Municipality for year 2033

Table 12: LULC statistics for year 2033

LULC Class	Area (ha.)	% Occupied
Water	40.86	0.37
Forest	4077.45	37.10
Agriculture	4973.58	45.26
Barren Land	1512.36	13.76
Built-up	384.93	3.50
Total	10989.18	100.00

DISCUSSION

Land use land cover (LULC) prediction modelling

The correlation between the reference and simulated maps is assumed to be stronger when the kappa index of agreement is higher. Similar levels of kappa agreement were discovered by Hamad, et al. (2018b); Nguyen et al. (2020); Rafaai et al. (2020). In this research, we found the predicted LULC for the year 2023 has a standard kappa value of 0.8154, which is almost perfect to real LULC for the year 2023 (Viera and Garrett 2005).

Future prediction

Forest area is predicted to decrease by 418.41 hectares between 2023 and 2033. This decline is based on the model's underlying assumption that the past change may be used to explain the present change using driver variables. According to the Business-as-Usual (BAU) scenario, this loss is anticipated. However, a number of unrelated factors, such as the overregulation of forest laws and policies (Saxena et al., 2022) may have a significant impact on the change in forest cover. Similarly, being the headquarter of Palpa district and a place with good weather conditions, it is always a place of choice to migrate for the people of rural areas of Palpa district and also for the people of neighbouring districts like: Gulmi, Argakhanchi, Syangja, etc. Progressing with this situation will ultimately lead to an increase in urbanization and agricultural activities and a decrease in forest cover. Likewise, agriculture is expected to gain 659.24 hectares whereas built-up land is expected to increase by 63.63 hectares. The loss of forest area is expected to be absorbed by agricultural land, barren land and built-up areas. According to Gartaula & Niehof (2013), the amount of built-up land will depend on how effectively the study area's pull factors (better facilities and opportunities) attract migrants and how effectively the push factors (poverty, a lack of opportunities and facilities) drive people away from other areas, especially rural areas. Contrary to other transitions, which may revert to different land use classes, urban areas rarely transition back to other land use types. Hence the rate of urban area growth is constantly higher. The amount of barren land is predicted to rise by 111.69 hectares as well. The study area's hydrological profile may change as a result of the ever-increasing impacts of climate change (Malinowski & Skoczko, 2018) and natural disasters like floods coupled with upstream impacts (Lovric & Tosic, 2016; Yun et al., 2020). When it comes to water, it is the most unpredictable since waterways constantly change their course (Lovric & Tosic, 2016) with most of the visible water sources lying along Kaligandaki river.

CONCLUSION

The present study was conducted to predict the LULC dynamics of 2033 in Tansen municipality using a combined approach of remote sensing imageries, GIS and predictive modeling methods. Based on the results of accuracy assessment of LULC classification for the years 2003, 2013 and 2023, the overall accuracies were found as 90%, 90% & 84% with Kappa coefficient of 0.86, 0.85 & 0.78 respectively. According to the prediction results for 2033, agriculture, barren land, water and built-up land are expected to increase by 2.93% (141.57 ha), 7.97% (111.69 ha), 10.19% (3.78 ha) and 72.18% (161.37 ha) respectively during the period from 2023 to 2033. Conversely, forest area will decrease by 9.31% (418.41 ha) during the period from 2023 to 2033. Overall, during the period from 2003 to 2033, the trend of water is unpredictable. Forest area is projected to decrease by 25.16% (1370.79 ha), while agriculture & barren lands are expected to increase by 12.53% (553.68 ha) and 42.15% (448.47 ha), respectively. Built-up area is expected to increase significantly by 2175% (368.01 ha). The projected LULC situation for 2033 displays an alarmingly rapid loss of forest area and a sudden increase in the rate of built-up area.

This study predicts the land use land cover dynamics for the year 2033, providing valuable insights to policy makers, planners and stakeholders by indicating the direction of land use change and helping to formulate alternative strategies for achieving a sustainable future. The result achieved through the combined application of Google Earth Engine (GEE) and Multi-Layer Perceptron- Markov Chain (MLP-MC) model is both faster and reliable. For a more detailed analysis, additional relevant drivers of LULC change—such as socio-economic factors, can be incorporated.

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