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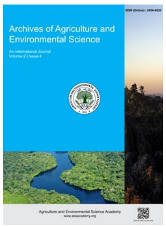

ORIGINAL RESEARCH ARTICLE

CrossMark

Machine learning approach to detect Land Use Land Cover (LULC) change in Chure region of Sarlahi district, Nepal

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ABSTRACT

Land Use and Land Cover (LULC) changes are major global environmental issues, affecting ecological systems, climate change, and biodiversity. The Chure region of the Sarlahi district in Nepal is a critical ecological zone that has experienced significant LULC changes in recent years. In this study, our aim was to apply a machine learning approach to detect LULC changes in the Chure region using Google Earth Engine (GEE) and the Random Forest classifier. We utilized Landsat imagery of 2007 and 2022 to generate land cover maps for each year, which were then compared to identify changes over time. The major findings of this study indicate that the forest cover in the region has increased by approximately 16% over the past 15 years, while the agriculture and built-up areas have also shown a significant increase. Conversely, the barren land and water areas have decreased. The classifier obtained an overall accuracy of 85.7% and a kappa coefficient of 81.2% for the year 2022, and an overall accuracy of 82.2% and a kappa coefficient of 76.8% for the year 2007, which demonstrates the high accuracy of the proposed approach. The use of GEE and random forest classifiers provided a cost-effective and efficient method for analysing large datasets and producing accurate LULC maps. Our findings can inform policymakers and conservationists about the need for sustainable land management practices to preserve the ecological integrity of the Chure region. The approach can be applied to other regions to monitor and manage LULC changes and support effective conservation efforts.

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INTRODUCTION

In Nepal, the Chure or Chure range is the youngest mountain range located in between low plains in the South and the mid-hills in the North. Geographically, it is referred to as the "Sub-Himalaya" or the "Siwalik". It spans 37 districts in Nepal which extends continuously from east to west (Bashyal, 2020). The Churia hills are fragile and highly susceptible to erosion and other natural disasters. This fragility presents a significant issue not only for individuals who live in the Churia, but also for those who live downstream in lowland areas of the Terai (DFRS, 2014). In 2014, the Government of Nepal designated this landscape as an "Environmental Protection Area (EPA)" and established the "President Chure-Terai Madhesh Conservation Development Committee"(referred to as the "Chure Board"), an umbrella organization that manages the Chure landscape, particularly its forest (Bishwokarma *et al*., 2019).
Due to the significant changes brought on by anthropogenic and natural forces, Land Use and Land Cover (LULC) have been continuously changing in Nepal over the past few decades (Paudel *et al*., 2016). A change in land cover can significantly impact an area's potential characteristics, ultimately resulting in soil degradation and decreased productivity (Zewdu *et al*., 2016). For effective spatial planning and management of land and its best use, knowledge of the various types of land use, as well as its spatial distribution in the form of maps and statistical data is

essential (Tomar *et al*., 2013). The study of LULC provides data on the condition of natural resources and aids in monitoring, modelling, and recognizing environmental change (Budhathoki, 2022).

Currently, cloud computing systems are being used to monitor changes in LULC through the development of remote sensing technology. In order to make computationally intensive processes more accessible, Google Earth Engine (GEE) was introduced as a platform that can process and analyse a variety of satellite images and geospatial information. This cloud-based spatial analytics platform is hosted by Google and is available to all users for research purposes, providing access to a high-performance, organically parallel computing system that distributes calculations throughout Google's computational infrastructure (Crego *et al*., 2022; Gorelick *et al*., 2017). Land Use and Land Cover (LULC) changes in the Chure region of Sarlahi district are crucial for understanding the region's environmental and ecological status. However, there is a limited understanding of the dynamics of LULC change in this region, particularly during the period between 2007 and 2022 A.D. This study aims to fill this research gap by providing an analysis of LULC changes using the Random Forest classifier implemented on GEE. The novelty of this study lies in its use of this advanced technology to analyse LULC changes, which offers a more efficient and accurate method of data analysis. The study's findings can be used for more thorough research, informed decision-making, and improved land use planning in the Chure region. Overall, this study provides preliminary information on LULC change in the region, which is critical for addressing the challenges of sustainable land use and environmental conservation in Nepal.

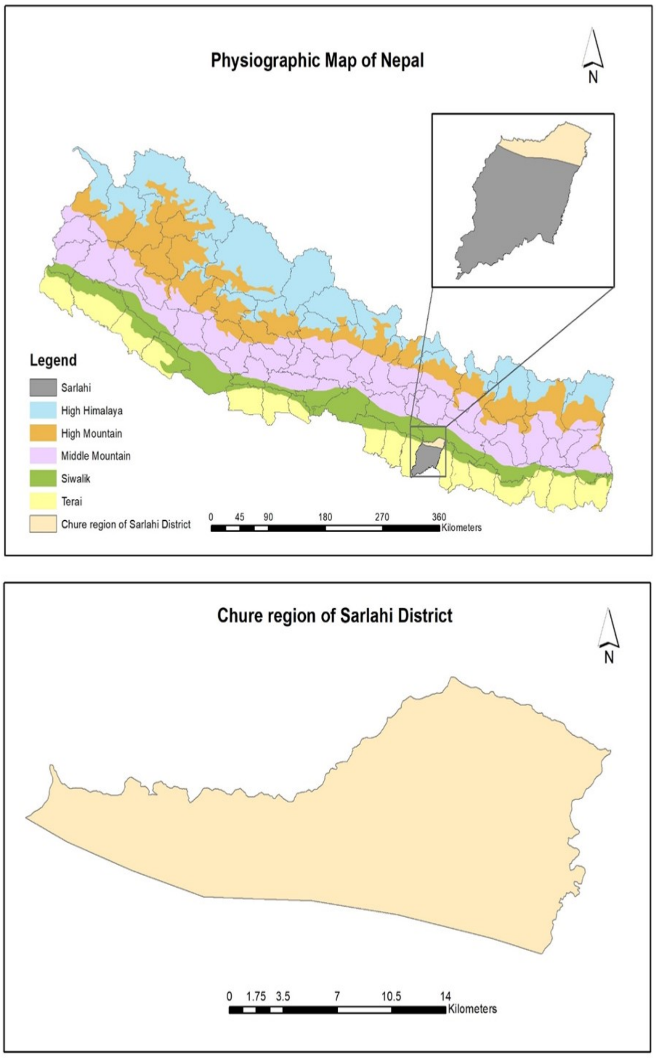

Figure 1. *Study area: Chure region of Sarlahi district.*

MATERIALS AND METHODS

Study area

The study was conducted in the Chure region of the Sarlahi district, as shown in Figure 1. The Chure region comprises an area of 234.98 km^2, including four municipalities out of the twenty in the district. The northern portion of the upper Siwalik is interspersed with sandstone, conglomerates, and pebbles, while the southern Terai area features eutric, flurosols, dystric regosols, and poorly developed acidic soils with thin surface layers. The middle Siwalik is composed of thick beds of coarse-grained sandstone with interactions with mudstone, and its colour is mainly gray and hard (Pokhrel, 2013). The climate of the study area ranges from tropical to subtropical with an average annual rainfall of 1732.94mm (Adhikari *et al*., 2022).

Dataset

Satellite data

For the development of the Land Use Land Cover map for the year 2022 AD, Landsat 9 Level 2, Collection 2, Tier 1 dataset was used, since it incorporates atmospherically adjusted surface reflectance and land surface temperature obtained from the data provided by Landsat 9 OLI/TIRS sensors courtesy of the U.S. Geological Survey. Similar to this, Landsat 5 Level 2, Collection 2, Tier 1 was used for the development LULC map of 2007, which also includes atmospherically adjusted surface reflectance and land surface temperature provided by the Landsat TM sensor courtesy of the U.S. Geological Survey. Similarly, to derive slope and elevation, NASA SRTM (Shuttle Radar Topographic Mission) digital elevation data with 30m spatial resolution was accessed (Farr *et al*., 2007). To prepare the input data for classification, we performed cloud masking using qa.bitwiseAnd function in GEE. We then created 1-year median composite of Landsat image which, along with SRTM data was exported as asset in GEE.

Sample point data

In this study, high-resolution satellite imagery from Google Earth Engine and Google Earth Pro were utilized to collect a total of 944 training points for 2007 A.D. and 942 training points for 2022 A.D. The training points were selected to represent various land use types, including agriculture, barren land, built-up areas, forest, and water bodies. This approach ensured a diverse and representative sample, enhancing the accuracy and reliability of the Random Forest classifier.

Construction of various indices

Building efficient feature datasets is crucial for LULC classification (Feng *et al*., 2022; Vizzari, 2022). Various Landsat indices were constructed and merged into a cloud free composite of both Landsat 5 and Landsat 9 bands. We calculated Normalized Difference Vegetation Index (NDVI), which characterizes different features of vegetation (Gandhi *et al*., 2015); Normalized Difference Built-up Index (NDBI), which is capable to map built-up areas effectively (Zha *et al*., 2003); Modified Normalized Difference Water Index (MNDWI) and Normalized Difference Water Index (NDWI), which enhances the water features (Singh *et al*., 2015); Dry Bare Soil Index (DBSI), Bare Soil Index (BSI), Index-based Built-up Index (IBI), and Dry Built-up Index (DBI), for characterizing bare soil and built-up (Rasul *et al*., 2018; Xu, 2008); Soil Adjusted Vegetation Index (SAVI) , which characterizes health and density of vegetation cover and Enhanced Vegetation Index (EVI), which enhances the sensitivity to changes in vegetation and reduces soil background noise (Huete, 1988; Tomar *et al*., 2013). We used GEE to calculate these indices and applied them for LULC classification. This approach is expected to improve the accuracy of classification. The spectral indices and their respective specification are listed in Table 1.

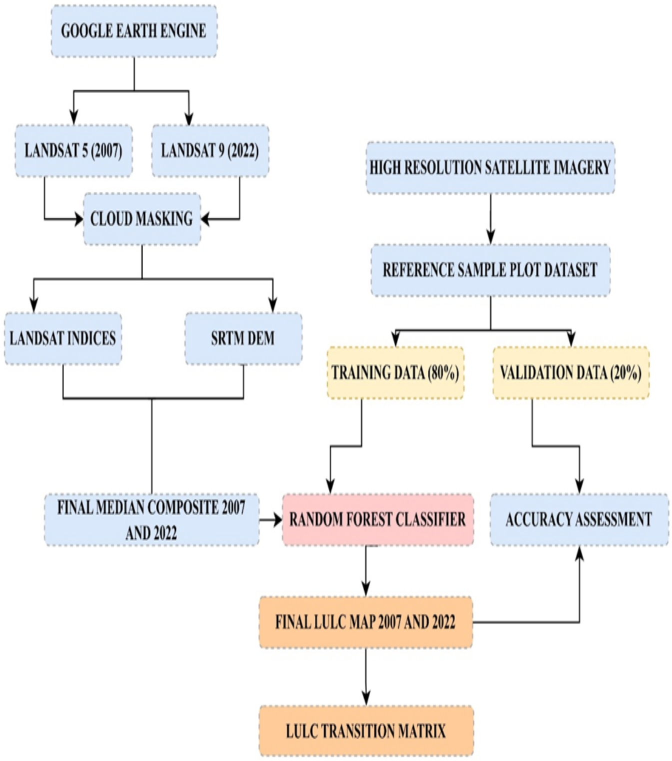

Figure 2. *Methodological framework of land classification.*

Table 1. Spectral indices and their specifications.

Spectral Index	Formula	
NDVI	$\frac{\text{NIR-RED}}{\text{NIR+RED}}$	(1)
NDBI	$\frac{\text{SWIR1-RED}}{\text{SWIR1+RED}}$	(2)
MNDWI	$\frac{\text{GREEN-SWIR1}}{\text{GREEN+SWIR1}}$	(3)
BSI	$\frac{\text{(RED+SWIR1)-(NIR+BLUE)}}{\text{(RED+SWIR1)+(NIR+BLUE)}}$	(4)
NDWI	$\frac{\text{GREEN-NIR}}{\text{GREEN+NIR}}$	(5)
SAVI	$\frac{\text{(NIR-RED)*(1+0.5)}}{\text{(NIR+RED+1)}}$	(6)
EVI	$\frac{\text{2.5*(NIR-RED)}}{\text{(NIR+6*RED-7.5*B2+1)}}$	(7)
IBI	$\frac{\text{NDBI-}\frac{\text{SAVI+MNDWI}}{2}}{\text{NDBI+}\frac{\text{SAVI+MNDWI}}{2}}$	(8)
DBSI	$\frac{\text{SWIR1-GREEN}}{\text{SWIR1+GREEN}}\text{-NDVI}$	(9)
DBI	$\frac{\text{BLUE-TIRS1}}{\text{BLUE+TIRS1}}\text{-NDVI}$	(10)

NIR= Near Infrared; SWIR1= Shortwave Infrared 1; TIRS1= Thermal Infrared Sensor 1

Table 2. Classification scheme of land use land cover map.

Class	Descriptions
Forest	Includes all land with woody vegetation in accordance with the national GHG inventory's criteria for defining forest land, subdivided into managed areas and by ecosystem type in accordance with the IPCC Guidelines.
Agriculture	Includes single, mixed, multiple and seasonal cropping systems in arable and tillage land. Also, Agroforest land where vegetation falls below the threshold of forest category.
Built-up	Includes all developed lands, buildings, roads, transportation infrastructure and other built-structures.
Barren land	Includes natural and semi-natural lands comprised of exposed soil, sand and rocks.eg Riverbed
Water body	Includes open water sources such as rivers, ponds.

Classification scheme

We have classified the map into five classes as shown in Table 2.

Methodological framework for classification

The description of the framework for land classification in the Chure region of Sarlahi district for the years 2007 and 2022, as presented in Figure 2, highlights the use Random Forest(RF) classifier, which is widely used machine learning algorithm known for its robustness and high accuracy in landcover classification tasks (Gislason *et al*., 2006; Liaw and Wiener, 2002; Rodriguez-Galiano *et al*., 2012). The framework relies on the use of the GEE platform, which allows for the processing and analysis of large-scale geospatial data in a cloud-based environment. The framework begins with the import of sample plot data and the study area into GEE assets for classification. This is followed by importing Landsat 5 surface reflectance data for the year 2007 and Landsat 9 surface reflectance data for the year 2022, both of which were exported as asset previously. Next, we split the imported sample plot data into 80% for training and 20% for accuracy assessment, enabling the use of a pixel based random forest classifier, for classification. RF classifier was trained with training data set with 1500 decision trees. This approach allowed for the creation of a reliable and accurate land cover classification model.

The final classified image, which was exported from GEE, serves as the input for the transition matrix analysis in ArcMap version 10.8. By subtracting the two raster images of both the years, the change in land use land cover was calculated and visualized. This allows for the identification of areas that have undergone a change in land cover, as well as the magnitude and direction of the change. The transition matrix provides a quantitative representation of the changes in land cover over time. It shows the proportion of each land cover class that has remained the same, transitioned to another class, or newly emerged in a given period.

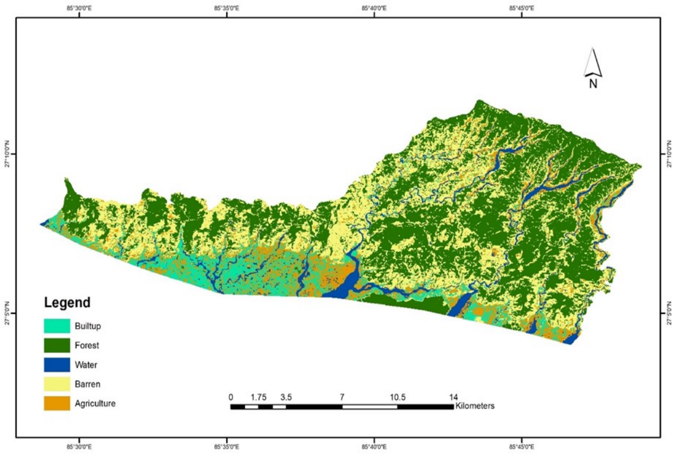

Figure 3. *Land use land cover map of 2007 AD.*

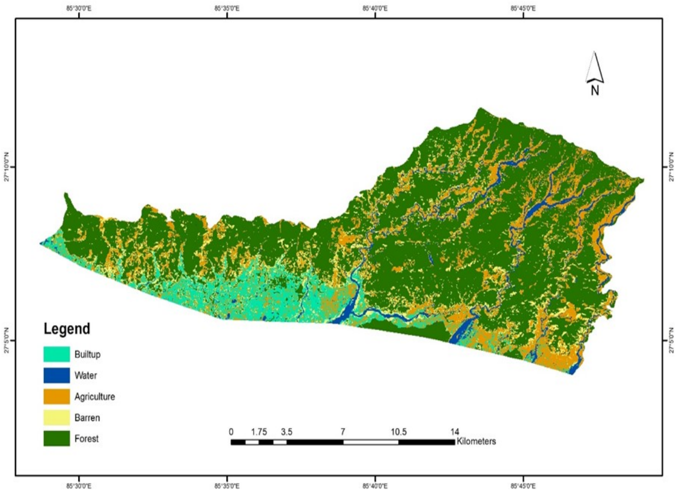

Figure 4. *Land use land cover map of 2022 AD.*

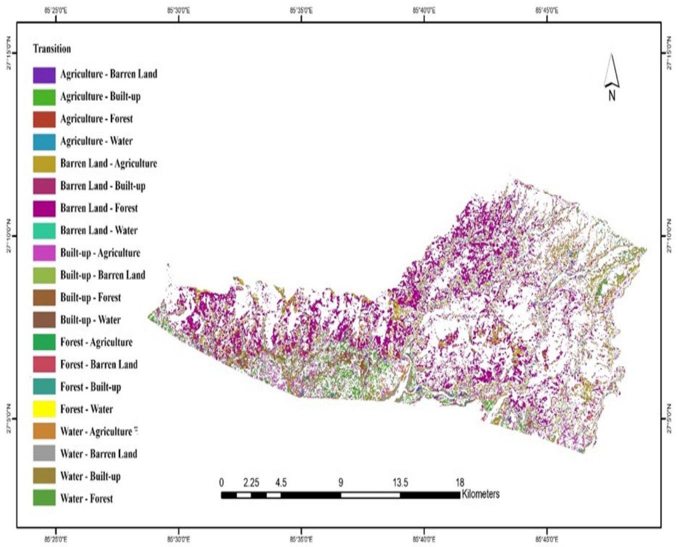

Figure 5. *Land use Land cover transition from one class to another from 2007 to 2022.*

RESULTS AND DISCUSSION

Accuracy assessment

Accurately categorizing, detecting, and predicting changes in land use and land cover is critical in research. The Kappa statistic is a commonly used metric for assessing the classification accuracy of both the model and the user. The Kappa coefficient values range from +1 to -1, representing the agreement between the land use and land cover values in the categorized image and the reference data. A kappa value of less than 0 indicates no agreement, 0-0.2 indicates slight agreement, 0.2-0.41 indicates fair agreement, 0.41-0.60 indicates moderate agreement, 0.60-0.80 indicates significant agreement, and 0.80-1.0 indicates practically perfect agreement (Maingi *et al*., 2002; Prabaharan *et al*., 2010; Wang *et al*., 2020). We utilized the Classify function within Google Earth Engine to generate a confusion matrix based on a 20% sample plot data that was split for accuracy assessment purposes. The confusion matrix enabled us to evaluate the accuracy of the classification model and compare the classified land use and land cover values against the reference data. We calculated both the kappa coefficient and overall accuracy values using GEE, which provided us with reliable metrics for assessing the classification model's performance. In this study, we found that the corresponding Kappa values for the years 2007 and 2022 were 76.8% and 81.2%, respectively, indicating moderate to significant agreement. Additionally, the overall accuracies for 2007 and 2022 were found to be 82.2% and 85.7%, respectively. This level of agreement is suitable for the classification, detection, and prediction of changes in land use and land cover.

Analysis of land use and land cover types

Figure 3 and Figure 4 illustrate the classification outcomes for the 2007 and 2022 pre-processed satellite pictures respectively. Table 3 includes the areas and percentage of land classified in various land cover categories as determined by the classification outcomes.

Analysis of land use and land cover classes for 2007 and 2022

Based on their respective initial years as a point of reference, the land use and landcover class change trend analysis shows the direction of land class changes (Appiah *et al*., 2015; Wang *et al*., 2020). In 2007, the largest LULC class was forest, covering 10,037.06 hectares, which accounted for 42.70% of the total area. Agriculture and barren land were the next most extensive classes, covering 2,795.88 hectares (11.89%) and 7,255.07 hectares (30.86%), respectively. The built-up and water classes had smaller areas, accounting for 2,047.45 hectares (8.71%) and 1,371.66 hectares (5.84%), respectively. In 2022, there were significant changes in the LULC classes. The forest class remained the largest LULC class, covering 13,793.343 hectares, which accounted for 58.68% of the total area. Agriculture was the second most extensive class, covering 4,469.592 hectares (19.01%), an increase from 2007. The built-up and water classes also increased in the area, covering 2,094.784 hectares (8.91%) and 1,070.622 hectares (4.55%), respectively. The barren land class decreased in area, covering only 2,078.78 hectares (8.84%), a substantial decrease from 2007. These changes in LULC classes reflect the dynamics of land use and land cover change in the study area over the past years. The increase in agriculture and built-up areas indicates the impact of human activities on land use, while the decrease in barren land suggests that some of it have been converted to other land use types. The substantial increase in forest cover could be attributed to reforestation efforts or natural regeneration.

Land use land cover change transition matrix

Important patterns in the shift of land use from one class to another were revealed by the land use and land cover transition matrix from 2007 to 2022. Figure 5 shows the distribution of transitions between land use classes, while Table 4 provides a thorough breakdown of the areas affected by the transition between each class. A considerable amount of land, i.e 9476ha (40%) has undergone changes in land cover between 2007 and 2022. The highest percentage of land transition was observed from barren land to forest (53%), which is a positive change as it indicates a possible increase in forest cover and ecosystem services. This transition could be attributed to conservation and afforestation efforts in the area. Another significant transition was observed from barren land to agriculture (28%), indicating an increase in agricultural land in the study area. This indicates the expansion of farming activities and increasing demand for agricultural products.

Table 3. LULC Distribution in Chure region of Sarlahi district.

LULC Class	2007		2022		Change (%)
	Area (ha)	Area (%)	Area(ha)	Area (%)	
Built-up	2,047.45	8.71	2094.784	8.91	0.2
Water	1,371.66	5.84	1070.622	4.55	-1.29
Agriculture	2,795.88	11.89	4469.592	19.01	7.12
Barren land	7,255.07	30.86	2078.78	8.84	-22.02
Forest	10,037.06	42.7	13793.34	58.68	15.98
	23,507.12	100	23507.12	100	

Table 4. Land Cover Transition Matrix.

	Landcover Class	2022 (Area in ha)				
		Builtup	Forest	Water	Barren	Agriculture
2007 (area in ha)	Built-up	1063.7	185.73	35.88	214.19	539.08
	Forest	19	9646.94	46.75	121.75	256.19
	Water	240.88	24.24	740.84	165.08	199.85
	Barren	54.59	3850.17	128.62	1172.87	2050.14
	Agriculture	747.42	224.44	109.25	262.84	1376.67

The conversion of forest land to agriculture (256.19 ha) and barren land (121.75 ha) is a worrying trend as it indicates deforestation and loss of ecosystem services. The conversion of agricultural land to built-up areas (747.42 ha) is also a concerning trend, as it signifies urbanization and encroachment of agricultural land, which may impact food security and livelihoods in the area. The evidences show that this region experienced significant deforestation between 1988 and 2001, with an annual loss of forest cover of 0.60% (Aulestia, 2019). This period coincided with the implementation of the Community Forestry (CF) program in 1993, which aimed to promote sustainable forest management practices and engage local communities in forest conservation. However, the CF program may not have been fully effective in the early years, and deforestation continued to occur.

One of the notable conservation programs is the Chure Terai Madesh Conservation Program, which was initiated in 2010. The program aims to restore and conserve the degraded Chure region and improve the livelihoods of the local communities through sustainable management practices. It includes activities such as reforestation, afforestation, soil conservation, and community forestry. The program has been successful in increasing forest cover and enhancing the region's biodiversity. Additionally, the Chure region was designated as an Environmentally Protected Area (EPA) under the Environment Protection Act (1997) on July 14, 2014. The EPA designation provides legal protection and management measures for the region's natural resources, including forests, rivers, and wildlife. It aims to ensure the sustainable use and management of these resources while promoting conservation and restoration efforts (MoEF, 2019).

Moreover, the Forest Policy (2015) of Nepal provides a framework for sustainable forest management and conservation. The policy emphasizes the protection, restoration, and sustainable use of forests and promotes the participation of local communities in forest management. It also aims to increase forest cover to 45% of the country's total land area by 2025 (GoN, 2015). All these policies and programs have contributed to the increase in forest cover in the Chure region from 2007 to 2022. The results of our study are consistent with the findings of FRTC (2022) National Landcover Monitoring System of Nepal (NLCMS), which reported an increase in forest cover in the Chure region. The decreasing trend of the water bodies in the research area from our finding is similar to a study by Sawtee (2016). This is a major concern in many areas of Chure region as the blame is on the increasing urbanization and haphazard river substance extraction. The evidence of such activities was visible during the field visits.

A study by Singh (2017) highlighted that land tenure is a critical issue in the Chure region, with many settlers lacking official land titles despite utilizing their land for an extended period. This lack of formal recognition of land rights has resulted in unsustainable land-use practices such as encroachment on forest areas for agriculture and new communities, which contribute to migration. The absence of formal land titles also facilitates deforestation and conversion of forest land to agricultural use. Notably, the UNDP agroforestry program, in collaboration with Hariwon municipality and Grameen Swayam Sewak Samaj, is addressing this issue by converting barren land into productive agricultural land. Our study aligns with this finding, showing an increase in agricultural land cover in the Chure region from 2007 to 2022.

The reasons behind the migration of people from the hills to the Terai region can be attributed to the desire for better access to facilities such as infrastructure, markets, and economic opportunities. However, the challenging terrain in the hills, characterized by steep slopes, harsh climate, landslides, and soil erosion, can impede the development of cities in those areas, thereby exacerbating migration patterns (Portnov *et al*., 2007). Additionally, the alarming impacts of natural hazards such as landslides, widening rivers, and siltation in the Chure region can result in the loss of land and property for households, leading to an increase in landless owners (Singh, 2010 and 2017). This trend may also explain the limited increase in the built-up area which was observed in our study.

Conclusion

In conclusion, our study on land use and land cover change detection in the Chure region of the Sarlahi district has revealed promising trends, such as a significant increase in forest area and agricultural land, as well as a low increase in built-up areas. These findings indicate that reforestation efforts and sustainable agriculture practices are gaining ground in the region, which is critical for promoting ecological and economic sustainability. However, our study also highlights some areas of concern, including the conversion of barren land to agricultural use, which can have unintended consequences if not managed sustainably, and a slight decrease in water bodies, which can significantly impact the region's ecological health. Therefore, our study underscores the need for sustainable land use and management practices in the Chure region, such as continued promotion of reforestation efforts and sustainable agriculture practices, and monitoring of water resources to ensure long-term ecological and economic sustainability. The use of Google Earth Engine has allowed for an efficient and accurate analysis of land use and land cover changes in the Chure region, providing valuable insights for future land use planning and management. Our study highlights the importance of utilizing advanced tools and techniques for timely monitoring and management of land resources to achieve sustainable development goals. Overall, our study provides valuable insights into land use and land cover changes in the Chure region and emphasizes the need for continued efforts to promote sustainable land use practices and monitor land resources to ensure a more sustainable future for the region.

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Disclosure statement

The authors declare no conflicts of interest in the conduct of this research. The authors have no financial or personal relationships with individuals or organizations that could potentially bias the results of this study or its interpretation. All authors have read and approved the final version of the manuscript.

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