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Land Use and Land Cover Dynamics and Their Driving Factors in the Ritung Khola Watershed, Myagdi District, Nepal

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Abstract

This study examines the Land Use and Land Cover (LULC) changes in the Ritung Khola watershed of Nepal's Myagdi district over a 20-year period (2000–2020) using remote sensing (RS) and geographic information system (GIS) techniques. Landsat satellite images from 2000, 2010, and 2020 were analyzed through supervised classification, categorizing the landscape into five major classes: forest, agricultural land, water bodies, barren ground, and settlement. Field surveys and ground truthing were conducted to validate the classification accuracy and assess the drivers of change. The findings reveal distinct trends in LULC dynamics. From 2000 to 2010, forest cover, water bodies, and settlements decreased, while agricultural and barren lands expanded significantly. In contrast, between 2010 and 2020, forest areas, water bodies, and settlements increased, whereas agricultural and barren lands declined. These shifts were influenced by multiple factors, including population dynamics (growth and migration patterns), economic drivers (agricultural dependence, livelihood opportunities), and natural disasters (frequent floods and landslides altering landforms). The study highlights the complex interplay of human and natural factors shaping LULC changes in the sub-watershed. The findings provide critical insights for policymakers and land managers, emphasizing the need for sustainable land use planning, forest conservation, and disaster risk reduction strategies. Effective watershed management must balance ecological preservation with socio-economic development to ensure long-term sustainability. By integrating these insights into policy frameworks, stakeholders can enhance resilience, protect ecosystem services, and support local livelihoods in the Ritung Khola watershed and similar regions facing comparable challenges.

Keywords: *LULC, Driving factors, GIS, Remote Sensing, Ritung Khola watershed*

Introduction

Land cover denotes the biophysical attributes of the surface (e.g., vegetation, water), whereas land use reflects anthropogenic utilization of these areas (e.g., agriculture, urban development) (FAO, 2000). Continuous LULC modifications emerge from the complex relationship between ecological dynamics and human interventions, carrying major consequences for biodiversity and community resilience (De Bie et al., 1996). Over the past four decades, LULC transformations have profoundly altered biogeochemical cycles, affecting atmospheric exchanges, soil quality, biodiversity, and hydrological systems (Overmars & Verburg, 2005). These changes contribute to watershed degradation, reducing ecosystem services critical for agriculture, water supply, and climate regulation (Lambin et al., 2000).

In developing countries like Nepal, rapid land conversion—particularly deforestation and agricultural expansion—has intensified environmental pressures (FAO, 2005). Population growth, economic demands, and natural disasters further accelerate LULC changes, exacerbating soil erosion, water scarcity, and habitat loss (Zubair, 2006). Watersheds, as integrated hydrological and socio-ecological units, are particularly vulnerable to these shifts, with cascading effects on local communities dependent on natural resources (Wani et al., 2008). Nepal's mountainous terrain, with 690 watersheds spanning 147,181 km² (DFRS, 2017), underscores the urgency of sustainable land management to mitigate environmental degradation.

The integration of satellite remote sensing and GIS has dramatically advanced LULC monitoring by enabling efficient, large-scale analysis of spatial and temporal changes (Rwanga & Ndambuki, 2017). Multisource satellite data (Landsat, MODIS, Sentinel-2) processed via GIS supports high-accuracy mapping, temporal change detection, and future scenario modeling. (Attri et al., 2015). These tools are indispensable for watershed management, providing policymakers with data-driven insights to balance conservation and development needs (Chen et al., 2012).

This study examines LULC dynamics in Nepal's Ritung Khola watershed (Myagdi District) from 2000 to 2020 using RS and GIS techniques. By analyzing Landsat imagery and field data, we classify LULC into five categories—forest, agriculture, water bodies, barren land, and settlements—and assess key drivers of change, including socio-economic factors and natural disasters. The findings aim to inform sustainable land use planning and watershed conservation strategies, ensuring ecological resilience and livelihood security in the region.

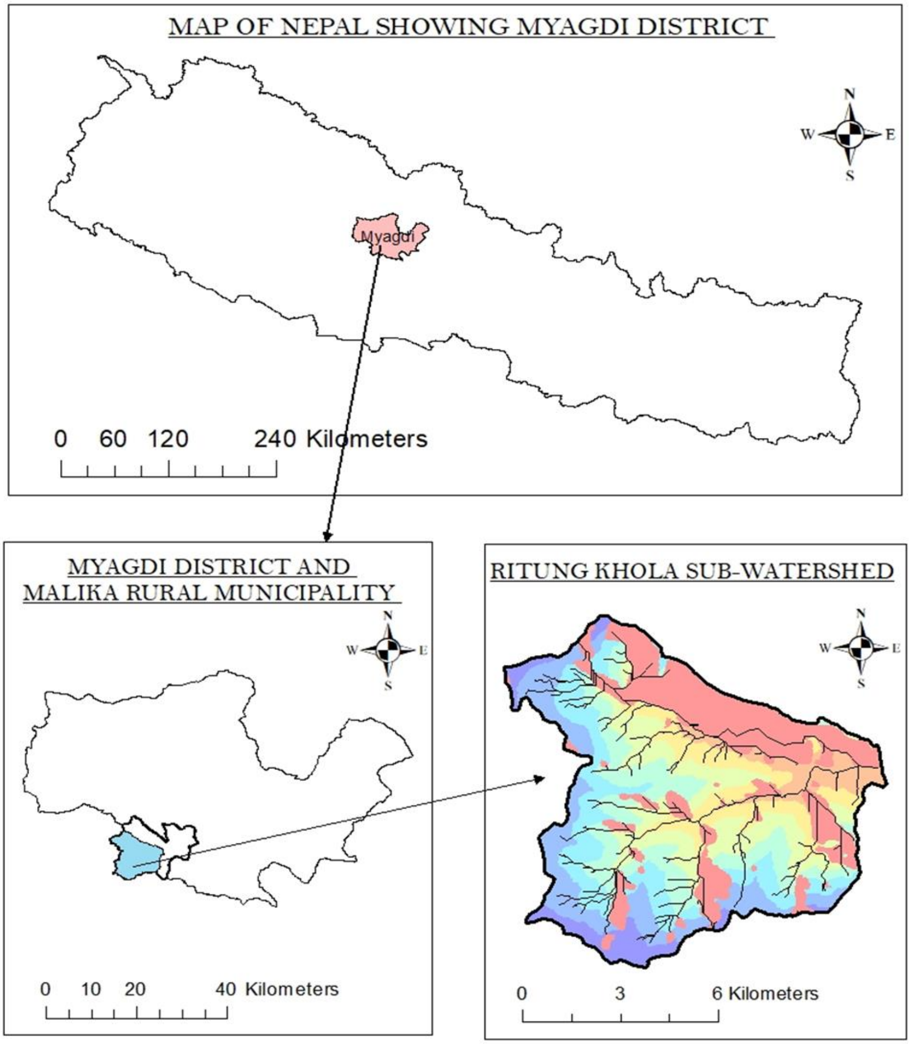
Materials and Methods

Study sites

The watershed of Ritung Khola is situated in the central part of Nepal, specifically in the Malika Rural Municipality of Myagdi district. It spans an area of 69.67 km2 and its outlet flows into the Myagdi Khola through the Ritung Khola which is a significant stream of the Kali Gandaki River. The Ritung Khola has two primary branches, namely the Dajung Khola and Ruma Khola (also known as Khahare Khola), which are mostly seasonal rivulets that experience flooding in rainy season and low water discharge during other seasons. The watershed exhibits three distinct climatic conditions based on altitude: subtropical, temperate, and subalpine. Additionally, the watershed predominantly faces the North-East direction These variations in climate and orientation play crucial role in shaping the environmental characteristics and ecological dynamics of the watershed. The elevation of the watershed ranges from 1,070 m at the junction between the Ritung and Myagdi Khola to 3505 m at Sarbara Danda. The primary settlements within the watershed include Phulbari, Churibot, Okharbot, Chhap, Khapuk, Bhirkharka, Kaban, Ruma, Niskot, Mahabhit, Sisneri, and Adhivara, with a majority of the population belonging to the Magar caste. Settlements cover roughly 30% of the watershed's total area. Dominant arboreal species include Sal (*Shorea robusta*), Pine (*Pinus spp*.), Katus (*Castanopsis tribuloides*), Chilaune (*Schima wallichii*), and Utis (*Alnus nepalensis*).

Figure 1:

Study area map showing Ritung Khola sub-watershed

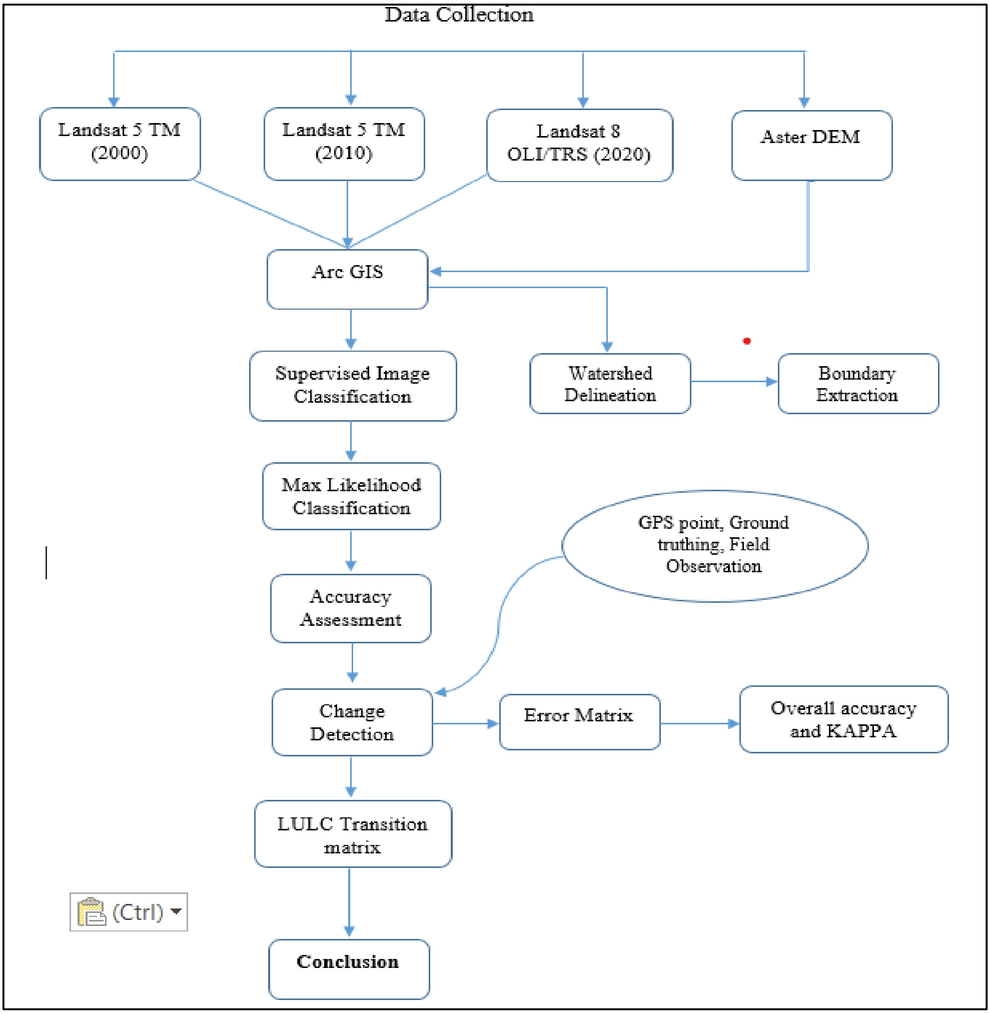


Research frame

This research framework outlines a systematic methodology for assessing LULC changes in the Ritung Khola watershed. The study utilizes multi-temporal Landsat data along with ASTER DEM data for topographic analysis. Key steps include watershed delineation, supervised image classification using maximum likelihood algorithm, and ground validation through GPS points and field observations. Classification reliability was assessed through error matrix analysis (producing overall accuracy and Kappa values), whereas temporal changes were quantified by analyzing transitions between land cover classes via change matrices. The synergistic application of remote sensing and GIS technologies provided a powerful platform for investigating the spatial and temporal dimensions of landscape evolution in the target area over twenty years.

Figure 2:

Research frame



Data collection

Satellite data import

Satellite imageries as well as spatial information were obtained by downloading them from the scientific data-sharing platform of the United States Geological Survey (USGS) at https://earthexplorer.usgs.gov/ To delineate the watershed boundary, the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) data was collected from the USGS SRTM satellite. For detecting LULC and minimizing errors in accuracy assessment, cloud-free satellite images were prioritized. Additionally, Google Earth Pro images served as references for the satellite imagery. The attributes of the satellite data acquired (Table 1).

Table 1:
Characteristics and source of the satellite images used in this study

Satellite	Sensor	Resolution	Acquisition Date
Landsat 5	Thematic Mapper (TM)	30 meters	4/5/2001
Landsat 5	Thematic Mapper (TM)	30 meters	12/10/2010
Landsat 8	Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS)	30 meters	11/19/2020

Field Data

The field data collection process began with a reconnaissance survey, which aimed to gain knowledge on LULC status of the study area. This survey involved gathering ground information to identify various ground covers such as plantation forests, natural forests, agriculture, barren land, settlements and water bodies. Following the reconnaissance survey, field verification points were collected by using GPS devices from different land cover categories. The field data collection involved selecting random locations and obtaining 315 GPS points specifically for image classification. These points covered all the LULC classes and were collected during fieldwork in May 2021. Additionally, participatory mapping techniques and purposive questionnaire surveys were conducted to gather information on the driving factors influencing LULC changes.

Data processing

Watershed delineation

The delineation of a watershed involves defining the boundaries of a drainage area based on a specific point, group of points, or outlet. There are various automated methods available in software programs for watershed delineation. In this particular study, the border of the Ritung Khola watershed was determined using ASTER DEM data with 30meters spatial resolution.

Image pre-processing

Before classification, it is crucial to perform pre-processing on the acquired satellite images. This step is essential as it helps eliminate noise and other unwanted effects, such as cloud cover, from the images. Pre-processing techniques enhance the quality and accuracy of satellite images, making them more suitable for classification purposes.

Enhancements and Corrections

Enhancements and corrections were performed on the Landsat images to ensure their accuracy and improve their quality. The radiometric correction was applied to adjust the brightness and contrast levels, while geometric correction was carried out to rectify any distortions in the image's spatial positioning. Additionally, pan-sharpening techniques were employed to enhance the image resolution and provide a more detailed representation.

Defining Training Sites

The initial stage involves selecting training sites for each land cover class. These sites are identified based on easily distinguishable pixels within the images. The collection of training samples was performed manually by closely examining the area using the satellite imagery provided by the GIS platform. The goal was to gather as many training samples as possible for each class.

Image Classification

ArcGIS 10.4.1 was used in this study for various tasks related to image processing and supervised image classification. The initial step merged the Landsat image bands into a composite layer using image analysis tools. This was done to facilitate further analysis and to extract specific areas of interest, the clip raster tool in ArcGIS was applied. The images were extracted from the shape file created during the watershed delineation process for the watershed. Next, the Landsat imageries were examined using ArcGIS to assign per-pixel fingerprints. Five categories were used to classify the entire watershed area: agriculture land, forest land, barren land, settlement and waterbodies. At least 50 representative sites were selected for each class to ensure minimal confusion in mapping the LULC classes.

Table 2:

Classes defined through supervised classification methods.

Classes	Description
Forest	Areas covered with trees forming closed or nearly closed canopies.
Agriculture	Agricultural lands used for short-term crop rotations including harvest and post-harvest periods.
Waterbodies	Area with the presence of water
Barren Land	Exposed soil, barren area, exposed rocks, and permanently abandoned land.
Settlement	Areas occupied by constructed facilities and man-made infrastructure.

Data analysis

Accuracy assessment

The accuracy assessment is a crucial and final stage in remote sensing data analysis, carried out using ArcGIS to enhance the accuracy of classification. This study employed Google Earth Pro and ground verification points obtained from various locations within the watershed to construct the reference or sample database. To evaluate the accuracy, a set of 315 training samples was utilized. Microsoft Excel 2010 was used to analyze and interpret numerical data on land use/cover transformations. The results were effectively visualized through maps, tables, and pie charts**.** To assess classification accuracy, the ratio of accurately labeled pixels to the total number of pixels was computed. In addition to calculating the overall classification accuracy, individual class accuracy was also determined by considering both producer's accuracy and the user's accuracy. Such a technique facilitates a more comprehensive analysis of the classified data for each specific land cover class (Bharatkar & Patel, 2013). Another commonly used method for accuracy assessment is the Kappa coefficient, which utilizes the error matrix. This agreement metric (0-1 scale) evaluates correspondence between mapped results and validation data. (Congalton, 2001).

$$\text{Overall Accuracy (\%)} = \frac{\text{Total no of accurately labelled pixels}}{\text{Total number of pixel}} * 100 \text{ ……………….. EQ 1}$$

$$\text{User Accuracy} = \frac{\text{Total no of accurately labelled pixel in each category}}{\text{Classified total pixel (Row Total)}} * 100\text{…...........EQ 2}$$

$$\text{Producer Accuracy} = \frac{\text{Total no of accurately labelled pixel in each category}}{\text{classified total pixel (Column Total)}} * 100\text{… EQ 3}$$

The Kappa statistic (K) was computed using the following method:

$$\text{K} = \frac{\text{Po}-\text{Pe}}{1-\text{Pe}}. \quad \text{………………………………. EQ 4}$$

Where,

Po = Proportion of accurately labelled pixels

Pe = Proportion of accurately labelled pixels expected by chance.

Change Detection

The purpose of the LULC mapping was to obtain information regarding the distribution of different land use categories and to detect and estimate land use changes over a span of approximately 20 years. To achieve this, raster images from the years 2000, 2010, and 2020 were overlaid to observe the LULC changes. Using the raster calculator, the changes in LULC were calculated by comparing the "from" and "to" classes. This method calculated change by subtracting earlier land cover class raster values from later period values. This calculation resulted in a table that provided information on the changes that occurred between specific land cover classes. The analysis quantified conversion areas between all land cover classes, revealing important patterns of land use transformation during the study period.

Analysis of driving factor

Once the land use map was generated, further analysis was conducted to investigate the detected transformations and identify the factors driving these changes. This analysis involved field visits to the identified change locations, participatory mapping exercises, and the use of purposive questionnaires during key informant interviews (KII). On-site inspections during fieldwork helped identify and analyze particular changes in the terrain. Participatory mapping exercises involved engaging local stakeholders and community members to actively participate in mapping and identifying the drivers of land use changes. Key informant interviews were conducted with individuals possessing relevant knowledge and expertise in the area. Through these interviews, valuable insights were gathered regarding the factors contributing to the observed land use changes. To derive the trends in land use over the past 20 years, the respective LULC maps from different years were analyzed. This analysis allowed for the examination of changes in land use patterns, particularly in complex terrain and agricultural areas. To facilitate the analysis process, MS Excel was utilized as a tool to organize and process the obtained information. The data collected from field visits, participatory mapping exercises, key informant interviews, and the LULC maps were inputted into Excel for further analysis, visualization, and interpretation.

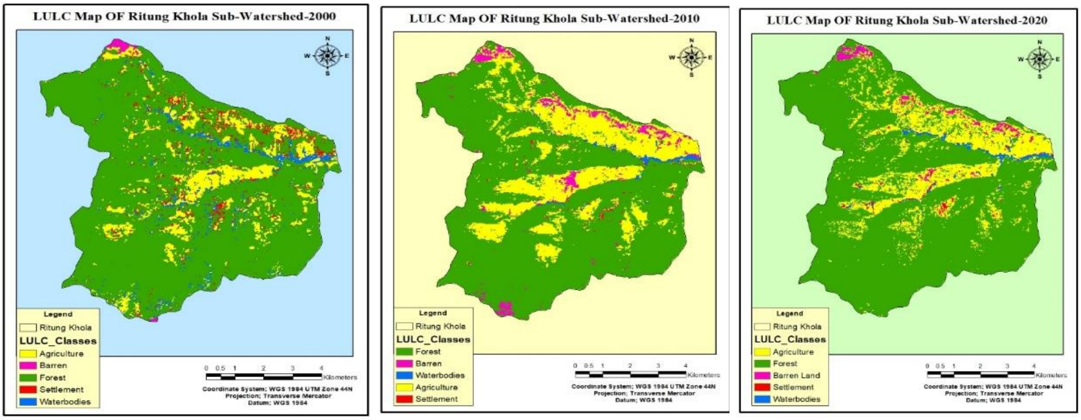
Result and Discussion

LULC of Ritung Khola watershed

LULC maps of 2000, 2010, and 2020 were produced from the Landsat imagery using GIS. For the classification, five land cover classes were used i.e. forest, agriculture, water bodies, barren land, and settlement.

Figure 3:

LULC Map of Ritung Khola Watershed in 2000 and 2010



The LULC analysis from 2000 to 2020 shows dynamic changes in the Ritung Khola watershed. Forest cover initially declined from 84.08% (2000) to 72.93% (2010) but partially recovered to 78.25% by 2020. Agricultural land expanded significantly from 11.32% to 22.41% between 2000-2010, then decreased to 18.19% by 2020. Water bodies experienced a sharp reduction from 3.21% to 0.86% in the first decade, followed by a slight recovery to 1.21% in 2020. Barren land showed dramatic fluctuations, peaking at 3.43% in 2010 before dropping to 1.39% in 2020. Settlements decreased slightly from 0.92% to 0.37% by 2010, then rebounded to near-original levels (0.95%) by 2020. These trends suggest initial ecological stress followed by partial recovery, with agricultural expansion being the most persistent land use change.

Table 3:

Table showing LULC status in 2000, 2010 and 2020

S. N	Land Classes	Area (Ha) 2000	Area (%) 2000	Area (Ha 2010	Area (%) 2010	Area (Ha) 2020	Area (%) 2020
1	Forest	5890.90	84.08	5108.06	72.93	5480.61	78.25
2	Agriculture	793.38	11.32	1569.64	22.41	1274.25	18.19
3	Waterbodies	224.78	3.21	60.20	0.86	84.80	1.21
4	Barren Land	33.00	0.47	240.16	3.43	97.50	1.39
5	Settlement	64.38	0.92	25.90	0.37	66.80	0.95
	Total	7006.44	100	7003.96	100	7003.96	100.0

Assessment of accuracy

The classified LULC map was validated against reference data to evaluate its accuracy. The ground truth points were overlaid on the classified image, allowing for a direct comparison. Furthermore, recently acquired ground reference points were overlaid onto the land use/cover map. To evaluate the classification accuracy, a confusion matrix was created. The matrix was structured such that the classes determined by the supervised classification were represented along the Y-axis, while the classes determined by the ground truth values were represented along the X-axis. This arrangement allows for easy identification of correctly classified values, which align with the main diagonal of the matrix. The confusion matrix provides valuable information on the percentage of correctly and incorrectly identified areas for each land cover class. It serves as a basis for calculating various accuracy metrics such as the kappa coefficient, user accuracy, producer accuracy, and overall accuracy. Examining the confusion matrix helps evaluate the correspondence between the classification results and the actual ground data. This information helps in understanding the performance of the classification method and assessing the reliability of the LULC map generated.

Table 4:

Confusion matrix showing classification accuracy of LULC Map 2000

Year 2000								
Classified Data	Reference Data							
	LULC Classes	Forest	Agri-culture	Water-bodies	Barren Land	Settle-ment	Total	User Accuracy
	Forest	63	6	6	4	4	83	75.9
	Agriculture	5	49	2	2	4	62	79.03
	Waterbodies	3	2	55	3	2	65	84.62
	Barren Land	0	0	0	48	1	49	97.96
	Settlement	0	3	2	2	49	56	87.5
	Total	71	60	65	59	60	**315**	
	Producer Accuracy (%)	88.73	81.67	84.62	81.36	81.67		
	Overall Accuracy: 83.81							
	KAPPA Coefficient (K); 0.80							

Table 5

Confusion matrix showing classification accuracy of LULC Map 2010

Year 2010								
Classified Data	Reference Data							
	LULC Classes	Forest	Agri-culture	Water-bodies	Barren Land	Settle-ment	Total	User Accuracy
	Forest	63	5	8	6	4	86	73.25
	Agriculture	4	50	3	5	3	65	76.92
	Waterbodies	1	1	49	1	1	53	92.45
	Barren Land	1	3	2	45	3	54	83.33
	Settlement	2	2	2	3	46	55	83.64
	Total	71	61	64	60	57	**313**	
	Producer Accuracy(%)	88.73	81.96	76.56	75	80.7		
	Overall Accuracy: 80.83							
	KAPPA Coefficient (K); 0.76							

Table 6

Confusion matrix showing classification accuracy of LULC Map 2020

Year 2020								
Classified Data	Reference Data							
	LULC Classes	Forest	Agri-culture	Water-bodies	Barren Land	Settle-ment	Total	User Accuracy
	Forest	63	4	4	2	3	76	82.89
	Agriculture	4	51	3	4	3	65	78.46
	Waterbodies	3	2	54	2	1	62	87.1
	Barren Land	1	1	2	49	2	55	89.09
	Settlement	0	2	1	3	44	50	88
	Total	71	60	64	60	53	308	
	Producer Accuracy(%)	88.73	85	84.38	81.67	83.02		
	Overall Accuracy: 84.74							
	KAPPA Coefficient (K); 0.81							

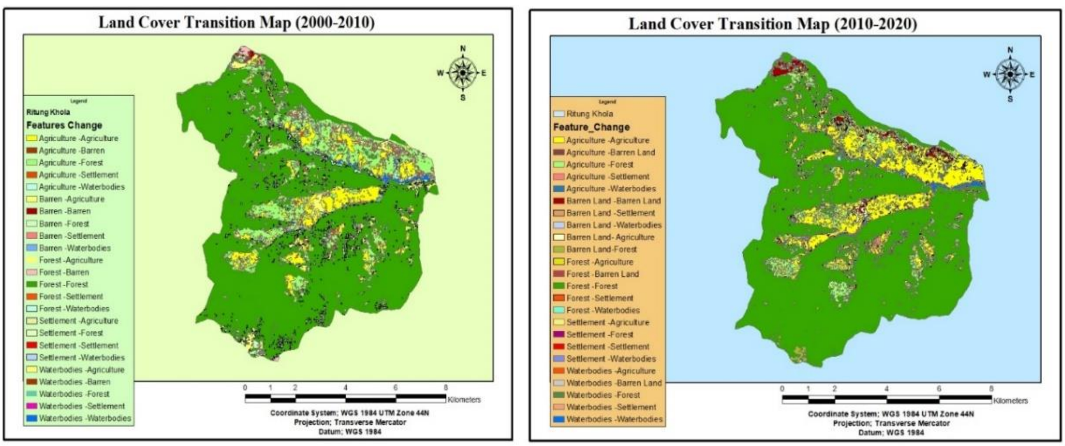
The validation results revealed that the comprehensive accuracy rates for the land use and land cover maps were 83.81% (2000), 80.83% (2010), and 84.74% (2020). The kappa coefficient, which is derived from the confusion matrix table, was found to be 0.80, 0.76, and 0.81 for the respective years. The coefficient is obtained by taking the ratio of correctly classified pixels to the total referenced pixels. These findings suggest that 83.81%, 80.83%, and 85% of the LULC classes were accurately classified for the years 2000, 2010, and 2020, respectively. The user's accuracy, which measures the accuracy of classifying pixels within each class, ranged from 75% to 97% for the 2000 map, 73% to 92% for the 2010 map, and 78% to 89% for the 2020 map. On the contrary, the producer's accuracy, ranged from 81% to 88% for all three maps. In summary, the accuracy assessment results provide insights into the reliability of the LULC maps for different years, highlighting the overall accuracy, kappa coefficient, and the varying accuracies for individual classes as assessed by the user and producer.

LULC change between 2000 to 2010 and 2010 to 2020

The LULC changes in Ritung Khola watershed show distinct patterns between 2000-2010 and 2010-2020. In the first decade, forest cover declined sharply (-13.26%), while agricultural land nearly doubled (+97.87%). Water bodies and settlements decreased significantly (-73.21% and -59.75% respectively), while barren land expanded dramatically (+628.24%).

Figure 4:

LULC change map between 2000-2010 and 2010-2020



The following decade saw partial reversals of these trends: forest cover recovered (+7.29%), agricultural land decreased (-18.82%), and water bodies rebounded (+40.86%). Barren land reduced substantially (-59.4%), and settlements expanded rapidly (+157.92%) from their depleted base. These shifts suggest initial environmental degradation followed by some recovery, with agricultural pressures remaining persistent and settlement growth accelerating in recent years.

Table 7

LULC change expressed in percentage between 2000 -2010 and 2010-2020

LULC Change between 2000 and 2010			LULC Change between 2010 and 2020	
Land Classes	Area Change (Ha)	Percentage Change	Area Change (Ha)	Percentage Change
Forest	-780.73	-13.26	372.55	7.29
Agriculture	776.45	97.87	-295.39	-18.82
Waterbodies	-164.57	-73.21	24.6	40.86
Barren Land	207.32	628.24	-142.66	-59.4
Settlement	-38.47	-59.75	40.9	157.92

Driving factors

For LULC in the Ritung Khola watershed various methods were employed to identify the associated driving factors. We conducted a key informant survey (KII) involving 30 participants(n=30), consisting of officials from Malika Rural Municipality and its associated wards, additionally, we distributed questionnaires to local residents, particularly those who had been living in the Ritung Khola watershed before the year 2000. To analyze the driving factors, we considered infrastructure development, specifically road density additionally, we incorporated terrain-related physical drivers, such as the slope derived from digital elevation models (DEM), to investigate the relationship between topography and cover change. We assessed three different periods: 2000, 2010, and 2020, allowing us to analyze changes in land use dynamics. By examining these periods, we aimed to identify the specific factors that have contributed to variations in forest cover within the Ritung Khola watershed. By employing a combination of surveys, questionnaires, and spatial analysis techniques, we hope to gain insights into the driving forces behind land use and land cover change in the region. This research approach enables us to understand the interplay between human activities, infrastructure development, terrain characteristics, and their impacts on the dynamics of forest cover within the Ritung Khola watershed.

Population dynamics

Population dynamics is a major driving force that influence LULC change in the Ritung Khola watershed. Changes in population size and distribution can directly impact the demand for resources, the growth of inhabited areas and the level of farming practices. Population growth of the Ritung Khola watershed has been steadily increasing over the past 20 years, which has led to increased pressure on land resources. As the population is growing, there is a higher demand for housing, infrastructure, and agricultural land. This could explain the observed decrease in forest areas and water bodies, as well as the increase in agricultural areas during the first decade (2000-2010).

Migration and settlement patterns

During the KII and interaction, the majority of the respondent responded that migration was a major factor for LULC change. The migration of people from the Ritung Khola watershed to the nearby developing market of Darbang during the period of 2000-2010 suggests a movement of population away from the sub-watershed. This out-migration has contributed to the decrease in settlement areas within the Ritung Khola watershed during that time frame. As people relocated to Darbang, the abandoned settlements might have undergone natural vegetation regeneration or eventual conversion to agricultural or barren land. Furthermore, the migration could have resulted in previously farmed land being abandoned or less cultivated, leading to more barren terrain. The migration pattern slowing down during 2010-2020 suggests that fewer people were leaving the Ritung Khola watershed for Darbang during this period. This could indicate a relative stabilization of settlement patterns within the watershed. Consequently, the observed increase in settlement areas during this period might be a result of the return of some migrants or new settlers arriving in the area.

Natural Disasters and Topography

The occurrence of natural disasters, particularly floods, and landslides, can have substantial impacts on land use in the Ritung Khola watershed. The fact that major landslides and river-cutting events were experienced during the period from 2000-2010 suggests that these natural disasters significantly affected the land use dynamics in the study site. Destruction of forest cover and water areas: Floods and landslides have resulted in the destruction of forested areas and water bodies. The force of the water and the movement of debris during these events can lead to the clearing of vegetation and the alteration of watercourses. Therefore, the decrease in forest areas and water bodies observed from 2000-2010 could be attributed to the impact of these natural disasters. Major landslides and river cutting also caused the displacement of settlements and agricultural areas resulting in a barren land or areas left fallow due to the damage caused by the disasters could contribute to the observed increase in barren land during that period. It is worth noting that the decreased occurrence of natural disasters in the period from 2010-2020 could have contributed to the observed changes in land use. With fewer destructive events, the land could have undergone a recovery phase, allowing for the increase in forest area, water bodies, and settlement areas, as well as the decrease in agriculture and barren land.

Economic factors

Economic factors played a crucial role in driving LULC changes in the Ritung Khola watershed. during the period from 2000-2010, people in the Ritung Khola watershed were more dependent on forest resources for their livelihoods during this period, which have resulted in increased deforestation and a decrease in forest area. The increased dependence on agriculture and expansion of agricultural land could be attributed to economic factors as well. People relied heavily on agriculture for income generation and subsistence, they cleared forested areas or converted other land types, such as barren land, into agricultural land. This expansion of agriculture led to the observed increase in agriculture area during the period from 2000-2010. The migration of people to nearby developing markets like Darbang for employment opportunities indicates the influence of economic factors on settlement patterns in the Ritung Khola watershed. Migration out of the area caused a reduction in settlement regions during that time.

Infrastructure

Infrastructure development activities are found to have significant impacts on land use and land cover changes in the Ritung Khola watershed. The construction and expansion of roads can lead to land fragmentation and habitat loss. As roads are built to improve connectivity and accessibility, they often require the clearing of vegetation, including forests and agricultural land. This resulted in a decrease in forest area and agricultural land, and potentially an increase in barren land or settlements due to road construction activities and associated infrastructure development. Infrastructure development resulted in the conversion of agricultural land, forests, or barren land into built-up areas. The increase in settlement areas observed in the Ritung Khola watershed could be attributed to the development of new infrastructure, such as residential houses, buildings, animal sheds.

Conclusion

This study assessed 20 years of land use and land cover (LULC) changes in the Ritung Khola watershed using GIS and remote sensing, revealing significant transformations. Between 2000 and 2010, forest cover, water bodies, and settlements declined by 11.2%, 73.22%, and 87.92%, respectively, while agricultural and barren lands expanded by 97.84% and 627.76%. From 2010 to 2020, partial recovery occurred, with forests increasing by 7.29% and water bodies by 40.86%, though agriculture still grew by 194.22% in some areas. These shifts were driven by population dynamics, economic pressures (e.g., agricultural dependence), and natural disasters (e.g., floods and landslides). The study emphasizes the need for sustainable land management to preserve ecological balance and support local communities. Key recommendations include:

Key recommendations include:

- Expanding forest conservation through afforestation and sustainable management.
- Enhancing water resource management to mitigate degradation in vulnerable sub-watersheds.
- Strengthening policy enforcement by local authorities to regulate land use and promote sustainability.
- Continuing long-term LULC monitoring to inform adaptive planning and conservation strategies.
- By integrating these measures, policymakers can safeguard ecosystem services, enhance resilience, and ensure sustainable development in the Ritung Khola watershed and similar regions.

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