Evaluating Land Use and Land Cover Dynamics Using GIS and Remote Sensing: A Case Study of Ngweshe Sub-location, Eastern DR Congo

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Abstract

The Earth's surface is undergoing rapid changes in land use and land cover (LULC) due to various socioeconomic activities and natural phenomena. This study aimed to quantitatively assess the LULC changes in Ngweshe Chiefdom, located in eastern DR Congo, from 1994 to 2022. The research used a supervised classification method with a maximum likelihood algorithm in ArcMap 10.8.2 to identify LULC changes, utilizing multispectral satellite imagery from Landsat for 1994, 2008, and 2022. The study area was divided into five primary LULC classes: forestland, cropland, grassland, woodlot, and bare land. Change detection analysis was conducted to compare the extent of land cover conversions between different time intervals. The findings indicated increases and decreases in various LULC classes from 1994 to 2022, with significant transitions observed. A combination of climatic factors, such as variations in rainfall occurrences of drought and socioeconomic influences, drove the observed changes. Ongoing LULC mapping is crucial to identifying and characterizing these changes, helping to establish trends and enabling resource managers to project realistic change scenarios that are valuable for effective natural resource management.

Keywords: Land use; Land cover change; Change detection; Supervised classification; Ngweshe Chiefdom

Introduction

Throughout history, humans have relied on land for food production and economic development, leading to significant changes in the global landscape. The growing population and increasing demand for development have put immense pressure on Earth's land, leading to environmental degradation. Human activities and their impact on land use and land cover (LULC) have become a major concern, accentuating the risks of environmental degradation worldwide (Foley et al., 2011; Weinzettel et al., 2013; Paiboonvorachat, 2008; Stabile, 2012).

The rapid growth and expansion of urban centres, along with rapid population growth, land scarcity, increased production needs, and evolving technologies, are some of the primary factors driving LULCC worldwide (Barros, 2004). According to Masek et al. (2000) LULCCs are influenced by socioeconomic, political, cultural, demographic, and environmental conditions, largely shaped by dense human populations.

Many researchers argue that Land Use and Land Cover Change (LULCC) has become a major focus in the global change debate. They believe this change is driven by human impacts on the environment and their implications for climate change (Ginblett, 2006). The signs of these changes are evident in pressing global issues such as rising levels of carbon dioxide (CO_2) in the atmosphere, loss of biodiversity, conversion and fragmentation of natural vegetation areas, and increased emission of greenhouse gases (Steffen & Tyson, 2001).

LULC dynamics are widespread, accelerating, and significant processes primarily driven by human actions, resulting in changes that impact human livelihood (Agarwal et al., 2002). These dynamics alter the availability of important resources such as vegetation, soil, and water (Bruijnzeel, 2004).

Due to the increasing population over the years, there has been considerable pressure on the land resources in Eastern DR Congo, where approximately 75% of the population engages in agriculture, yet only 20% of the land is arable. Consequently, the scarcity of arable land has led to the expansion of cultivation into the wetter margins of rangelands, deforestation, and the decline of grassland due to overgrazing, charcoal burning, and other unsustainable land uses. These actions have significant implications for the country's integrity of natural resources and ecosystems. In recent years, land use and land cover changes (LULCC) have occurred in the Walunugu territory. The land has experienced significant pressure due to over-reliance on its resources, and as far as we know, no researchers have focused on analyzing the extent and measurement of land use change in Ngweshe Chiefdom. This study aims to assess the dynamic changes in land use and land cover over time in the Ngweshe sub-location.

Materials and Methods

Study area

The research was conducted in the Ngweshe chiefdom, which covers an area of 97 km^2 and is situated within the Walungu territory of South Kivu province in the eastern DR Congo. The study focused on an agroecological zone with coordinates ranging from 2°38' South latitude to 28°34' East longitude, at elevations of 1445 and 2371 meters above sea level meters (see Figure 1) (IPAPEL-SK, 2022). The region's primary economic activities, such as agriculture and livestock farming, serve as central livelihood sectors for the local inhabitants (Bisimwa et al., 2018).

The Ngweshe chiefdom depends mainly on agriculture as its primary land-use practice, containing cropping, livestock rearing, subsistence, and commercial farming (Heri-Kazi & Bielders, 2020). The vegetative cover in the area is dominated by tea and Eucalyptus plantations, which play a significant role in ground cover (Chuma et al., 2021).

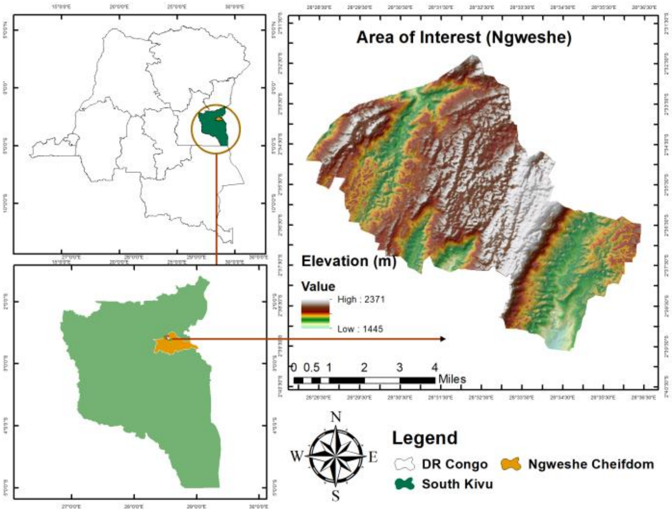


Figure 1: Location of the study area

Data collection

The Landsat imagery required for this study was obtained on the United States Geological Survey (USGS) website for 1994, 2008, and 2022 (USGS, 2022). More specifically, the focus was on two scenes that covered the Ngweshe region, namely Path 173 and Row 062, situated in the southern part at approximately 35S latitude. To acquire the imagery data, we utilized the following Landsat sensors: Landsat 5 Thematic Mapper (TM), Landsat 9 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). To ensure the quality and suitability of the data for the analysis, factors such as image availability, the extent of cloud cover, and the seasonality (dry season) were considered. These considerations were vital in selecting the appropriate timeframe for the study and the years for analysis. Only images with 10% or less cloud cover were included in the study to minimize any possible impact of cloud cover on the analysis results.

Image preprocessing and classification

All tasks were performed using standard, widely applied tools and modules in ArcGIS 10.8.2 software.

Substantial procedures were performed on the scenes to prepare them for the analysis, including correcting colour differences, performing geometric correction, and clipping the final image to fit within the study area boundaries. The atmospheric correction ensured accurate analysis using the optimal method recommended in previous studies (Nguyen et al., 2015). The ENVI 5.7 software implemented specific steps for the chosen three-year dataset. These steps involved radiometric calibration to determine top-of-atmosphere reflectance and the application of Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH), ultimately obtaining surface reflectance. Furthermore, for all years of analysis, the Minimum Noise Fraction (MNF) linear transformation process, a widely employed technique in remote sensing, was applied using the ENVI 5.7 software (Liu et al., 2016). This process effectively reduced spectral dimensionality and minimized data noise.

The study utilized the maximum likelihood supervised classification method. Classification iterations for each classification year were performed on the images with minor noise. The maximum likelihood classification tool was repeatedly run, adjusting the number of training samples until consistent classification results were obtained. Post-classification tasks included merging classes, rectifying misclassifications, and assigning codes to land-use classes. A detailed field survey was carried out throughout the study zone using a Global Positioning System (GPS) instrument before the preprocessing and classification of satellite imagery. This survey was performed to obtain accurate locational point data for each LULC class in the classification scheme and to create training sites and signature generation.

Based on ground truth and image analysis activities, five major LULC classes were identified: Forestland, cropland, grassland, woodlot and bare land, which were used to map the entire study area. In supervised classification, spectral signatures are developed from specified locations in the image. Generally, a vector layer is digitized over the raster scene. The vector layer consists of various polygons overlaying different land use types. The training sites were used to develop spectral signatures for the outlined areas, as described by Mallupattu and Sreenivasula (2013).

Accuracy assessment

Accuracy assessment or validation is essential in processing remote sensing data as it provides valuable information to users and evaluates data quality (Rwanga et al., 2017; Tilahun et al., 2015). Typically, classification accuracy is evaluated by comparing the classification results with ground truth data or using imagery data from Google Earth in limited fieldwork cases. The minimum acceptable level for overall accuracy in identifying land-use/cover categories from remote sensing data is generally set at 85%, as specified by Anderson et al. (1996). Furthermore, according to Congalton (1991), a kappa value greater than 0.8 indicates strong agreement, a value between 0.4 and 0.8 denotes moderate agreement, and a value below 0.4 represents poor agreement.

Accuracy assessments consider four types of accuracy: overall accuracy, producer's accuracy, user's accuracy, and the overall kappa coefficient accuracy. The user's accuracy measures the likelihood of a given pixel being correctly identified on the Earth's surface as depicted in the classified image. On the other hand, the producer's accuracy represents the percentage of a specified class that is accurately identified on the map. Overall accuracy is computed by dividing the total number of correctly classified pixels by the total number of reference pixels (Congalton, 2001).

The Kappa coefficient expresses the proportionate reduction in error made by a classification process compared with the error of an utterly random classification (Coppin & Bauer, 1996). Kappa will be computed as follows:

$$\text{KHAT}=\frac{N\sum_{i=1}^{r} x_{ii}-\sum_{i=1}^{r}(x_{i+}\times x_{+i})}{N^2-\sum_{i=1}^{r}(x_{i+}\times x_{+i})}$$

Where:

r = number of rows in the error matrix

x_{ii}= number of observations in row I and column I (I The diagonal element)

x_{i+} = marginal totals of row I

x_{+i}= marginal totals of column I

N = Total number of observations

KHAT = Kappa Coefficient

The accuracy of LUCC classifications was evaluated using an error matrix and descriptive statistics.

Change Detection Analysis

Land-use/cover change detection was conducted by utilizing the images of (1994/2008) and (2008/2022) through a confusion matrix analysis, enabling the comparison of two thematic images or vector files of different years in GIS. By comparing two classified datasets, the matrix operation could show all the changes from one class to another. A method of change detection using post-classification comparison was applied to interpret images. Over time, the cross-operation process of mapping LUCC began with mapping the present 2022 satellite imagery and then looking back to the past 1994 imagery. Post-classification is among the most widely applied techniques for change detection purposes (Coppin & Bauer, 1996; Lunetta & Elvidge, 1999). The shift in LUCC percentage was computed as Lambin (2001) applied his methodology.

$$\text{Percentage change} = \frac{\text{Observed Change}}{\text{Sum of area}} * 100$$

Results and Discussion

Analysis of Land-use/Cover Change Dynamics from 1994 to 2022

The LULC types in the study area were classified into five classes: Forestland, cropland, grassland, woodlot and bare land. The classification results are presented in Table 1 for the 1994 Landsat 5 TM image, 2008 Landsat 5 TM image, and 2022 Landsat 9 OLI/TIR image. Detailed statistical data for each of these classes and the LULC map of the study period are shown in Table 2.

LULC Type	1994 (km²)		2008 (km²)		2022 (km²)	
	Area (Km²)	Area (%)	Area (km²)	Area (%)	Area (km²)	Area (%)
Forestland	59.57	61.39	47.25	48.69	32.54	33.53
Cropland	18.89	19.47	20.94	21.58	21.47	22.12
Grassland	7.47	7.70	14.04	14.47	23.05	23.75
Woodlot	5.55	5.72	9.55	9.84	11.96	12.32
Bare land	5.56	5.73	5.27	5.43	8.04	8.28
Total	97.04	100	97.05	100	97.06	100

Source: Author, 2024

Table 1: Land area by land cover type in Ngweshe Sub-location, 1994, 2008 and 2022

In 1994, land use/land cover classification data in Table 1 showed that over 61.39% of the area was forestland, 19.47% was cropland, 7.7% was grassland, 7.72% was woodlot, and 5.73% was bare land. According to Figure 1, in the Ngweshe sub-location, forestland and cropland were the dominant LULC types, followed by grassland. Woodlot had the smallest coverage area. Analysis of the 2008 image also indicates that forestland constitutes the most significant proportion of land in the study area, with a value of 48.69%, followed by cropland, which accounted for 20.94%. The other LULC classes, such as grassland and woodland, accounted for 23.59% of the total area. Bare land (5.27%) has the most negligible area coverage of all other classes in the 2008 image classification, as shown in Figure 2.

The LULC classification results for the 2022 image show that the main categories were forestland and grassland, making up 55.65% of the total area. Forestland covered 33.53%, and grassland covered 23.75% of the total area, indicating that they comprise half of the study area. The remaining LULC classes, including cropland, woodlot, and bare land, accounted for 42.22% of the total area. Figure 2 illustrates the change in LULC proportions over time in Ngweshe Sub-location.

Accuracy Assessment of the LULC Classification

The accuracy assessment of the final classified image was validated against earth surface features using randomly distributed ground truth points. These points were considered references for examining the accuracy of the LULC map of the study area and the change detection results. The confusion error matrix and Kappa statistics used for the classification accuracy of 1994, 2008, and 2022 LULC maps are presented in **Error! Reference source not found.**. The overall accuracy for the 1994, 2008, and 2022 maps was 92%, 96%, and 90%, respectively. The Kappa statistics were 0.89, 0.94, and 0.86 for the 1994, 2008, and 2022 maps. The Kappa statistics showed a firm agreement for the three study years, implying that the results are acceptable.

LULC Class	Landsat TM 1994		Landsat TM 2008		Landsat OLI 2022	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Forestland	99	90	98	95	96	91
Cropland	90	96	96	98	88	94
Grassland	85	94	94	92	85	92
Woodlot	76	97	81	100	89	86
Bare land	100	90	100	95	88	65
Overall accuracy	**92%**		**96%**		**90%**	
Kappa statistics	**0.89**		**0.94**		**0.86**	

UA=user accuracy; PA=producer accuracy; Source: Author, 2024

Table 2: Accuracy assessment of classified images for 1994, 2008 and 2022

The user's accuracy results indicate that in 1994, the highest-class accuracy was for woodlot (97%), while the lowest was for forestland and bare land (90%). In 2008, the user's accuracy varied from the lowest (92%, grassland) to the relatively highest-class accuracy (100%, woodlot). In 2022, the range was from 65% for bare land to 94% for cropland.

The producer's accuracy indicates the percentage of correctly classified pixels in each category divided by the total number of pixels in the reference dataset for that category. The results revealed that woodlots were mostly misclassified, with an accuracy of 76% in 1994 and 81% in 2008. The highest accuracy was achieved for bare land, with 100% accuracy in 1994 and 2008, and for cropland in 2022.

a. Change detection analysis

Land use and land-cover patterns in the study area have changed significantly between 1994 and 2022. The changes were calculated using satellite image classification for 1994-2008, 2008-2022, and 1994-2022. The predominant LULC types in the study area during 1994, 2008, and 2022 were forestland, cropland, and grassland, while woodlot and bare land were present in smaller areas. Table 3 compares the different LULC changes during these years. Figure 2 illustrates the spatial changes in land use and land cover across the study area over 28 years. The map uses different colours to represent various transitions between land cover categories.

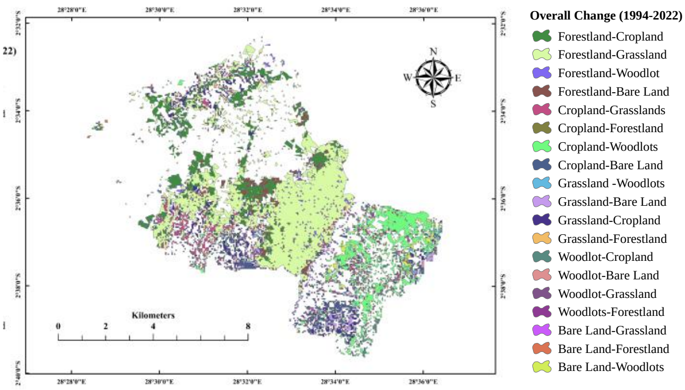
As presented in Table 3, the spatial extent increasing from 1994 to 2022 was for the grassland, woodlot, bare land and cropland, with an increasing land percentage of 207.89%, 115.48%, 44.6% and 13.65% respectively. The spatial extent of forestland decreased the most between 1994 and 2022 by 45.37%, which is -20.68 km² from 1994 to 2008 and -31.13 km² from 2008 to 2022 for a total change of -59.57km²—the study period between 2008 and 2022 experienced the most significant reduction in forestland cover, with a loss of 31.13 km² compared to 20.68 km² lost between 1994 and 2008.

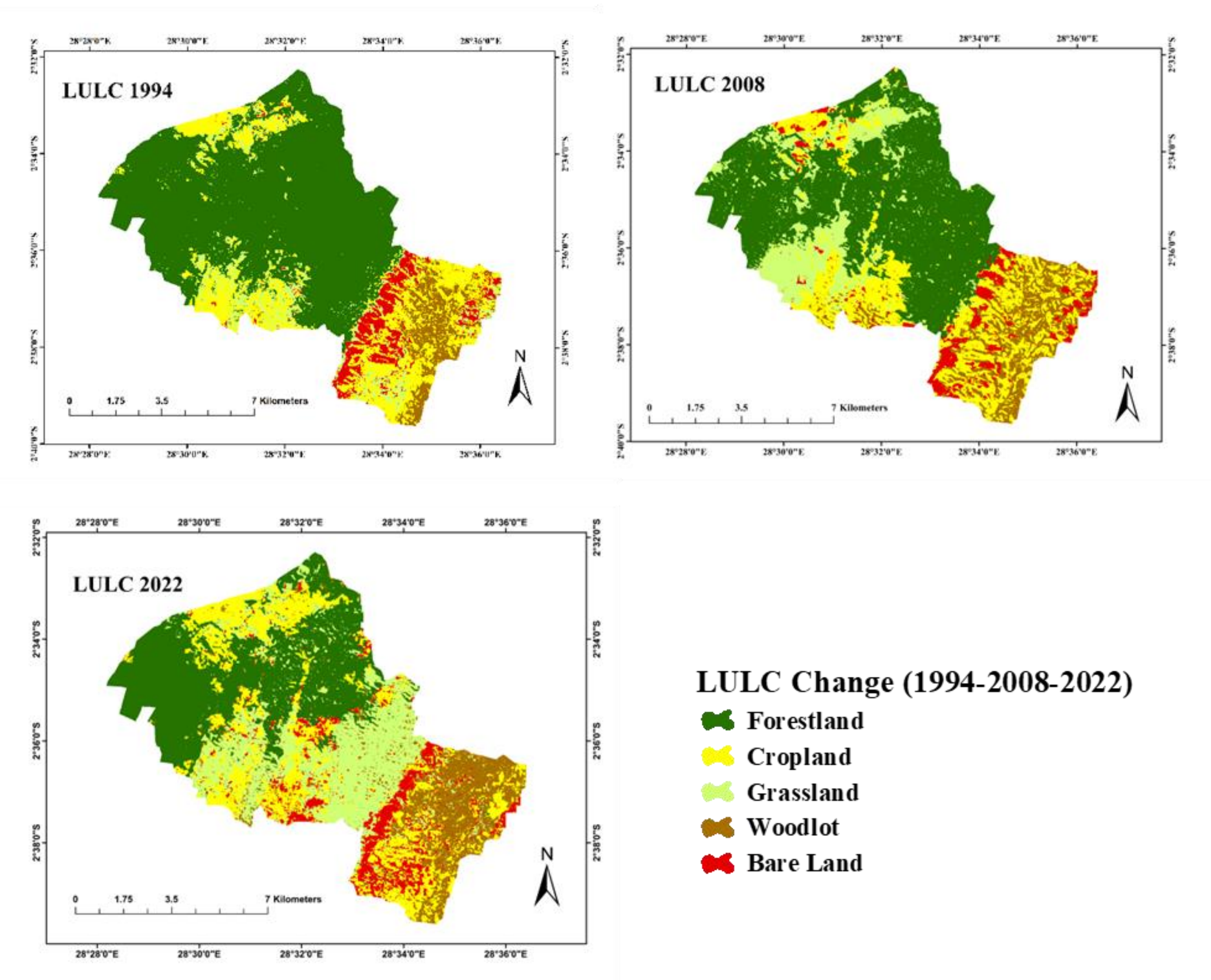
LULC category	Area (Km^2)			Change (%)		Overall change (%)
	1994	**2008**	**2022**	**1994-2008**	**2008-2022**	**1994-2022**
Forestland	59.57	47.25	32.54	-20.68	-31.13	-45.37
Cropland	18.89	20.94	21.47	10.85	2.53	13.65
Grassland	7.47	14.04	23.05	87.95	64.17	207.89
Woodlot	5.55	9.55	11.96	72.07	25.23	115.49
Bare land	5.56	5.27	8.04	-5.21	52.56	44.6
Total	97.04	97.04	97.04			

Source: Author, 2024

Table 3: Land use and land cover changes in Ngweshe sub-location between 1994 and 2022

Figure 2: Spatial distribution of land use and land cover changes (1994-2022)





Discussion

The study's results show changes in Ngweshe's LULC from 1994 to 2022 (see Table 1). In 1994, forestland comprised 61.39% of the total area, but by 2022, this had decreased significantly to 33.53%. This drop represents a loss of about 45.37% of forestland during the study period. The decline in forestland indicates a substantial conversion of forest areas to other land uses, primarily due to agricultural expansion and other human activities (Ibrahim, 2022). The research findings align with Mugumaarhahama et al. (2021) studies that noted comparable LULC change patterns in Ngweshe, showing the significant degradation of forestland and its conversion to cropland and other purposes. This consistency emphasizes the ongoing trend of decreasing forestland and expanding regional agricultural activities. The portion of cropland has increased from 19.47% in 1994 to 23.75% in 2022, indicating a growing demand for agricultural land due to population growth and the need to boost food production, as stated by Miladinov (2023). The grassland area showed the most significant increase, from 7.7% in 1994 to 23.75% in 2022, indicating a 207.89% increase. The woodlot areas increased by 115.48%, and bare land increased by 44.6%.

These findings correspond with earlier research on the LULC changes in the area. Tiando et al. (2021), Li et al. (2017) and Andrew et al. (2014) have highlighted the impact of LULC changes on ecosystem services and biodiversity in influencing greenhouse gas emissions and climate regulation. The decrease in forest land and the increase in agricultural and grassland areas observed in this study support the idea that LULC changes can cause significant ecological disruptions. Mucova et al. (2018) and Padonou et al. (2017) found that population growth and human activities are the main reasons for changes in LULC, which aligns with the observed increase in cropland and grassland in the study area. These results indicate that the growing population in Ngweshe is putting pressure on land resources, leading to the conversion of natural landscapes for agricultural purposes. For instance, Chuma and colleagues' (2021) studies in the neighbouring areas showed dynamic changes in LULC, such as transforming forestland into agriculture and other purposes. The trends observed in this study support their findings, suggesting a larger regional trend of land change influenced by socioeconomic factors.

However, certain studies, such as the one by Shapiro et al. (2021), have reported more considerable increases in bare land. This inconsistency implies that there may be regional variations in LULC dynamics, potentially influenced by local socioeconomic conditions, land management practices, and environmental policies.

Conclusion

This study demonstrates significant changes in LULC in the study area from 1994 to 2022, showing substantial landscape transformation over nearly three decades. In 1994, forestland covered over 61% of the area, but by 2022, it had decreased sharply to 33.53%, marking a total reduction of 45.37%. On the other hand, grassland increased by 207.89%, and other LULC types, such as cropland, woodlot, and bare land, also experienced notable growth. These changes indicate increasing human-induced pressures and land-use changes driven by agricultural expansion and development activities, posing more challenges to local ecosystems and biodiversity.

The study relied on Geographic Information Systems (GIS) and remote sensing to accurately map, analyze, and monitor LULC changes. The classified images had high accuracy rates of 92%, 96%, and 90% for 1994, 2008, and 2022, with robust Kappa statistics of 0.89, 0.94, and 0.86, respectively, highlighting the reliability of these tools in capturing dynamic landscape patterns. These technologies offer a comprehensive and systematic approach to detecting and quantifying land cover changes, facilitating a better understanding of environmental impacts and guiding policy-making and land management practices.

The findings underline the pressing requirement for sustainable land management strategies to reduce further forest loss and environmental degradation. Using GIS and remote sensing in environmental monitoring is crucial for guiding conservation efforts and creating effective policies that balance economic development and ecological sustainability. These tools improve the ability to evaluate past changes and enable proactive planning and management to safeguard natural resources and guarantee sustainable land use in the future.

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