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Spatio-Temporal Analysis of Land Use Change and Prediction in an Artisanal Mining Hotspot: A Multi-Decadal Study of the Kampene Mining Area, DRC

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Abstract

Artisanal and small-scale (ASM) gold mining activities contribute to the livelihoods of about 200,000 miners and their dependents in the eastern provinces of the Democratic Republic of the Congo (DRC). Despite their socio-economic importance, mining activities cause significant alterations to the environment, especially due to their impact on forest cover. Deforestation at mining sites, timber consumption, and pollution are among the observed direct impacts of mining activities. Land use and land cover (LULC) changes have been assessed for the period between 1984 and 2020 and predicted for the period between 2020 and 2040 using Landsat images in the Pangi Territory in general, and the Kampene mining area in particular, in the Maniema Province, known as an important mining province in the eastern part of the DRC. In this study, the Support Vector Machine algorithm, Post Classification Change Detection, and Markov Chain Analysis were used to classify, detect, and predict LULC changes, respectively. The results indicate a significant decrease in forest cover from 1984 to 2020, mainly due to the conversion of these areas into agricultural lands, while a significant loss is predicted for the period between 2020 and 2040 as the need for more croplands will increase mainly because of population growth. A transition probability of 0.25 is found for the conversion of primary forest to bare soils and mines, which is comparable with the greatest transition probability of 0.28 obtained in this study for the conversion of primary forest into agricultural lands. This shows the harmful effects of mining activities on the destruction of forest cover. The implementation of land protection and restoration policies and strong control of mining activities are required to reduce the impacts on the environment and forests.

Keywords

Land Use and Land Cover, Environmental Change, Artisanal and Small-Scale Mining, Gold, Environment, Kampene, Pangi, Maniema

1. Introduction

The pressure on natural resources is particularly strong in developing countries where demographic factors, including extreme poverty, push people to focus on short-term survival goals. Although there is a large consensus that tropical Africa is the region most affected by environmental problems [1] [2], the situation in the eastern part of the Democratic Republic of the Congo (DRC) is by far the worst. In this part of the globe, an endless series of political turmoils has led the population to rely on natural ecosystems for their living.

Although at the global scale, agriculture can be considered the main driver of deforestation, forest degradation, and even habitat fragmentation [3]-[6]; the situation in eastern DRC is exacerbated by other phenomena including mining activities, largely dominated in recent years by international mining companies. However, there is a clear contrast between the financial returns made by the direct beneficiaries of these activities and the real environmental challenges. Even the protected areas have been severely affected by mining and other extractive activities over the last decades [7]-[9].

Mineral exploitation contributes significantly to economic growth and development in most world economies [10]. The current contribution of mining activities to the GDP of many African countries and the rising demand and recent spikes in mineral prices indicate that both social and ecological effects of the industry are likely to grow in the forthcoming years [11]-[13]. Despite their important contribution to GDP in the DRC (nearly 25%), mining activities cause significant land alterations [14]. The expansion of mining concessions threatens the DRC's forests, even though nearly 12% of the forests are under some form of protection [14]. In the eastern provinces of the DRC (where most of the Congolese gold is mined), artisanal and small-scale (ASM) gold mining contributes to the livelihood of about 200,000 miners and their dependents. In this region where mining activities started in the twentieth century, the environmental consequences of artisanal mining exploitation are largely negative, including chemical pollution of water tables, deforestation, diversion of rivers, leveling of hills and reduction of arable land, as well as intensive poaching in adjoining national parks [15]. In gold and base metal mining areas, sulfide oxidation resulting from chemical and biogeochemical processes leads to the production of low pH groundwater that induces the dissolution of trace metals into the groundwater system in very high concentrations. The groundwater, thus, becomes dangerous for human consumption [16]. Mining activities, especially illegal small-scale mining, deplete environmental resources such as water, soil, landscape, vegetation and ecosystems, among others [10].

Although environmental degradation is persistent in most of the DRC's mining areas for each mining activity and its phases, the law has provided corresponding environmental plans, including the Mitigation and Rehabilitation Plan (PAR, Plan d'Atténuation et Remediation) during the research phase and the Project Environmental Management Plan (PGEP, Plan de Gestion Environnementale du Projet), which are included in the Mining Code [17]. The PGEP is associated with the Environmental Impact Study (EIE, Etude d'Impact Environnemental) required during the feasibility study phase before the start of mining activities. The principle of environmental protection is enshrined in the constitution of the DRC (articles 53, 54 and 55). Articles 203 and 204 of the Mining Code specify the environmental protection measures during the two major phases of a given mining project, namely the research phase and the exploitation phase. All environmental plans follow the same procedural regime for obtaining environmental permits. The practical modalities are fixed by the Mining Regulations [18], especially in articles from 430 to 436 and from 454 to 456. However, these studies are expensive; thus, most artisanal miners do not have the means to conduct them.

2. Land Use and Land Cover

Understanding the distribution and dynamics of land cover is challenging, but it is critical for better understanding the Earth's fundamental characteristics and processes, including the productivity of the land, the diversity of plant and animal species, and biogeochemical and hydrological cycles [19] [20]. Land use and land cover (LULC) is one of the most important domains of human-induced environmental transformation [21]. Land use and land cover change (LULCC) is the conversion of different land use types as a result of complex interactions between humans and the physical environment [22].

The mapping of LULCC is an important activity of land management and monitoring [23]. Recent advancements in remote sensing, GIS, and computer technology allow the assessment and monitoring of LULCC at multiple spatial and temporal scales [20] [22] [24]. Although fine-resolution data have been used to examine changes in surface mining extent, many studies are based on Landsat imagery due to its global coverage, medium resolution (30 m), and data acquisition at regular intervals [25]. The monitoring of LULCC and the building of spatio-temporal patterns of change can be done using change detection methods. This use of multi-date images allows for a better understanding of the causes and consequences of the change [26]. Principal component analysis and post-classification comparison are common methods used for change detection for image differentiation in remote sensing change detection [27] [28].

The prediction of future disturbances can be based on different scenarios during the modeling of LULC. The commonly used models for the estimation of future land cover changes include analytical equation-based models, statistical models, evolutionary models, cellular models, Markov models, hybrid models, expert system models, and multi-agent models [22]. Markov chains harness the advantages of long-term predictions, the simplicity of the logic, and efficiency in computation [22] [29] [30]. The assemblage of Landsat spatial, spectral, and temporal resolutions, over a reasonably-sized image extent, results in imagery that can be processed to represent land cover over large areas with an amount of spatial detail that is absolutely unique and indispensable for monitoring, management, and scientific activities [31].

The main objective of the present study is to assess the dynamics of LULCC, in time and space, in Kampene mining areas using Landsat images. Specifically, this study focuses on: 1) the determination of the LULCC over the last 40 years, 2) the prediction of future LULC dynamics from 2020 to 2040 using historical records, 3) the investigation of the relationship between the LULCC and the mining activities.

3. The Study Area

Kampene is located in the Maniema Province in the centre-eastern part of the DRC (**Figure 1**). The climate in the province is predominantly equatorial, characterised by continuous precipitation throughout the year (mean annual rainfall of 1600 mm), but the southern area is affected by a humid tropical climate with alternating dry and wet seasons. The vegetation also displays features as per climatic patterns, with dense forests in the north and savannahs to the south. The hydrographic network is dense and three-quarters of the rivers belong to the Congo River basin.

This study was undertaken within the chiefdom of Babene, in Pangi Territory, and focused on the Kampene mining area located in the southern portion of the Babene chiefdom, at approximately 110 km southeast of the city of Kindu (capital city of Maniema Province, **Figure 1**). In this study, Pangi Territory provides the territorial context, while the Kampene mining area is analyzed as a focused hotspot of artisanal mining. Territory-wide LULC assessments were conducted first, followed by a site-scale analysis of Kampene to quantify LULC change within the mining area.

This study region is a forested area known for its cassiterite, diamond, and gold mineralisation hosted in the Kivu Supergroup formations [32]. These resources have been mined since the early 20th century by different companies (including SYMETAIN and COBELMINES Mining Companies) for industrial extraction [15]. Since 1974, the Société Minière et Industrielle du Kivu (SOMINKI, now Société Aurifère du Kivu et du Maniema, SAKIMA since 1997), a privately held

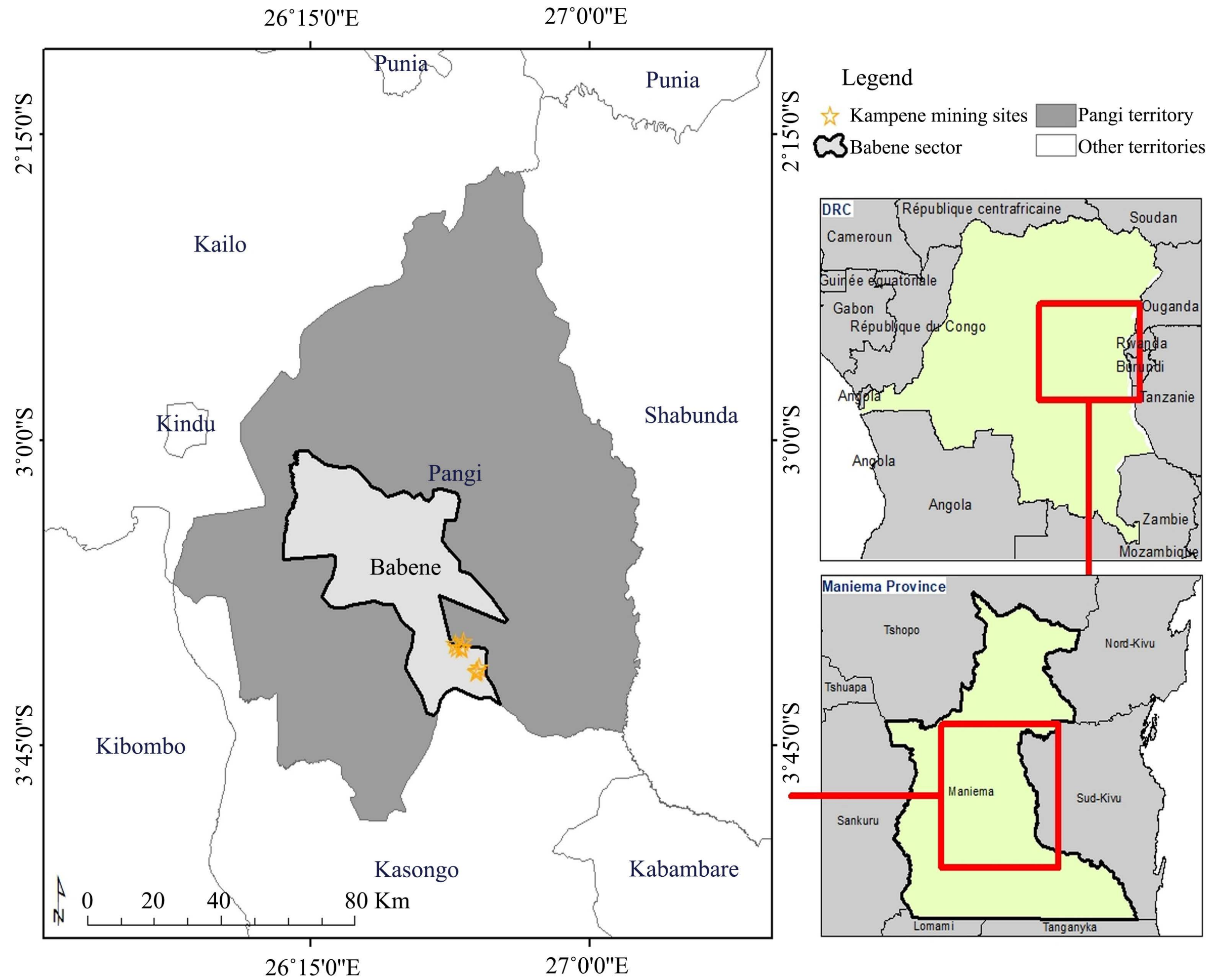


Figure 1. Study area location.

mining company of former Zaire, took over the exploitation of gold and tin mines. Since SAKIMA does not have the means to develop these mines, gold extraction in the area is mainly performed by artisanal miners. The common methodology used to extract gold is panning and amalgamation using chemicals, especially mercury, which is not health-nor environment-friendly.

4. Methodology

4.1. Data Acquisition

Landsat (30-m resolution) level-1 images were downloaded from the United States Geological Survey (USGS) Earth Explorer website (https://earthexplorer.usgs.gov/). The details of the images used in this study are presented in Table 1. The selection of the years' interval used a quasi-decadal approach. Three sets of ortho-rectified satellite images, namely Landsat Thematic Mapper (TM) image of 1984, Landsat Enhanced Thematic Mapper (ETM) image of 2000, and Landsat OLI-TIRS of 2020, were analyzed to determine the past and current LULCC in the whole Pangi Territory.

Table 1. Details of the acquired Landsat satellite images.

N˚	Date of collection (YY/MM/DD)	Satellite and Sensor	Path - Row
1	1984/6/2	Landsat Thematic Mapper (TM) image	174 - 62
2	1984/6/2		174 - 63
3	1984/9/13		175 - 62
4	1984/6/9		175 - 62
5	1984/11/6		175 - 63
6	2000/5/5	Landsat Enhanced Thematic Mapper (ETM) image	174 - 62
7	2000/7/24		174 - 63
8	2000/5/12		175 - 62
9	2000/4/10		175 - 62
10	2000/5/18		175 - 63
11	2020/4/2	Landsat OLI-TIRS	174 - 62
12	2020/5/4		174 - 63
13	2020/2/21		175 - 62
14	2020/5/27		175 - 63

Scene selection was based on two criteria: the acquisition date and the cloud cover. Data from the same season give uniform spectral and radiometric characteristics and minimise the seasonal variation in spectral reflectance of land cover types [26]. Images captured between May and August (dry season) were chosen to best distinguish the spectral signatures of the different types of land cover, especially the uncovered areas [24]. The acceptable cloud cover threshold was less than 10%. Some images were downloaded and mosaicked with other images of the same scene and year to reduce their cloud cover. A total of 4 to 5 different images per year were required to cover the entire study area.

The projection of images into the GIS platform uses the WGS-1984 and UTM 35S-Zone Coordinate System. The digital elevation model (DEM, 30-m resolution) was downloaded from the USGS Earth Explorer website, while all administrative shapefiles and road networks were downloaded from the "Référentiel Géographique Commun" (RGC) website (http://www.rgc.cd).

4.2. Image Pre-Processing

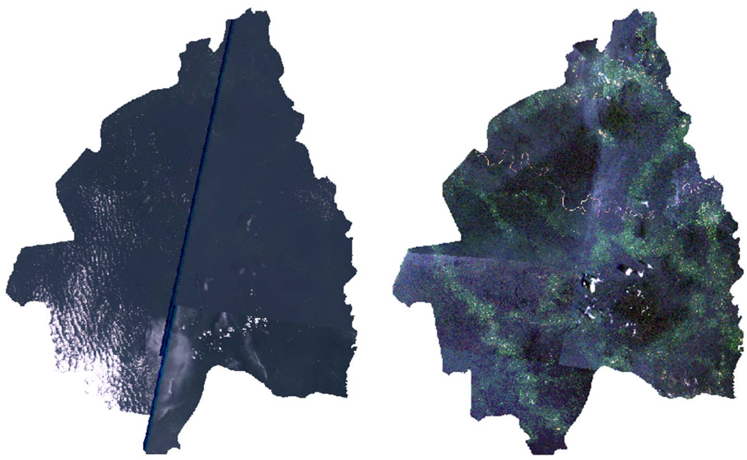
The following steps were adopted, as per [33]:

- Radiometric calibration: image data calibration from digital number values to top-of-atmosphere (TOA) reflectance values (ranging from 0 to 1). The gains, offsets, solar irradiance, sun elevation, and acquisition time information were used, and they are presented in the satellite image metadata.
- QUick Atmospheric Correction (QUAC): an automated atmospheric correction method for multispectral and hyperspectral imagery that works with the visible

and near-infrared through shortwave infrared (VNIR-SWIR) wavelength ranges. The QUAC determines the atmospheric correction parameters directly from the observed spectra pixels in a scene, without ancillary information [34].

- Dark Subtraction: removal of residual atmospheric scattering effects from an image by subtracting a pixel value that represents a background signature from each band.
- Image pan sharpening: an image fusion method in which high-resolution panchromatic data is fused with lower resolution multispectral data to create a colourised high-resolution fused dataset. The principal component pan sharpening method was used to increase the image resolution from 30 m to 15 m [35].
- Mosaicking: the Seamless Mosaic workflow was used to merge georeferenced images into one image. This workflow applies color balancing and edge feathering to create high-quality mosaics.

The pre-processed image after these steps (**Figure 2(b)**) looks better than the raw image (**Figure 2(a)**).



(a) (b)

Figure 2. Images before preprocessing (a) and after preprocessing (b).

4.3. Image Processing

4.3.1. Reference Data Collection

The reference data were collected using the Collect Earth Online (CEO) tool, which is a free, open-source, and user-friendly tool for land monitoring. It uses a Google Earth interface in conjunction with an HTML-based data entry form and facilitates land use assessment through a sampling approach rather than wall-to-wall mapping. However, land use data (point vector files) generated with CEO can be used as training sites for wall-to-wall image classification [36].

A total of 100 ground control points were collected as reference data for the year 2020, and 80 points per year for each of the 1984 and 2000 classifications, using a stratified approach of 20 points per class.

4.3.2. DRC Land Use and Land Cover Type Requirements

The operational guide on the forest classification standards of DRC was used for the definition of different classes. There are 3 major subdivisions: non-forest land (land for mining, areas of human occupation, agricultural plantations, and other lands), productive forest land (secondary forests, primary forests on dry land, gallery forests, forest on hydromorphic soil) and non-productive forest land (barren land and savannahs) [37].

Thus, for this study, primary forests on dry land are considered as primary forests, agricultural plantations as croplands or agroforestry, zones of human occupation as settlements, humid denuded lands as wetlands, and bare soils and mining sites as bare soils and mines.

4.3.3. Supervised Classification

Generally, a good classifier should be able to discriminate pixels into desirable land covers. The factors taken into consideration when selecting a classification method include accuracy, processing speed, and practicality [38]. The maximum likelihood classification (MLC) and artificial neural network (ANN) are among the frequently used methods in the classification of land covers. However, ANN has been associated with overfitting and local minima problems [39], while MLC needs a large training area and the assumption that data are normally distributed. The support vector machine (SVM) is one of the more reliable classification methods developed recently [38] [40].

The SVM is a supervised classification method derived from statistical learning theory that often yields good classification results from complex and noisy data. It separates the classes with a decision surface called a hyperplane that maximizes the margins between the classes. The data points closest to the hyperplane are called support vectors, which are the critical elements of the training set [41] [42].

The SVM can be transformed into a non-linear classifier using non-linear kernels. While SVM is a binary classifier in its simplest form, it can function as a multi-class classifier by combining several binary SVM classifiers (creating a binary classifier for each possible pair of classes) [41]-[43]. The pairwise classification strategy for multi-class classification was used in this study. The basic idea for understanding the SVM classification is presented in **Figure 3**.

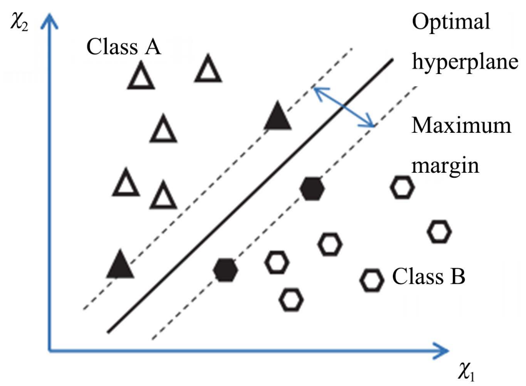


Figure 3. Basic idea of SVM [44], showing the support vectors in bold.

The use of CEO with Google Earth has led to five main LULC classes in Pangi Territory: the Primary Forest, the Croplands/Agroforestry, the Settlements, the Wetlands and the Bare Soils/Mines. Mines have been detected by searching for features that look similar to the ones shown in **Figure 4** on Google Earth based on a contextual knowledge of the study area.

(a) (b)

Figure 4. View of mines as detected on Google Earth: (a) small scale and (b) large scale.

4.3.4. Land Use and Land Cover Change Detection

The timely and accurate change detection of Earth's surface features is extremely important for understanding the relationships and interactions between human and natural phenomena in order to promote better decision making [27].

In this study, the Change Analysis tool [44] was used for LULCC detection. This tool is a component of the Land Change Modeler embedded in the software. It uses a post-classification change detection method and requires two (earlier and later) land cover images. The LULCC has been assessed for two different periods: from 1984 to 2000 and from 2000 to 2020.

In post-classification change detection, the images from each time period were classified using the same classification scheme into a number of discrete categories (e.g., land cover types). The two (or more) classifications are compared, and the area that is classified the same or different is tallied [45].

4.3.5. Land Use and Land Cover Change Prediction

The land cover change modeling means a time interpolation or extrapolation when the modeling exceeds the known period. The Markov Chain model treats the LULCC as a stochastic process; the later state (land cover type) of a pixel is only related to its immediately preceding state, but not to any other previous states. A transition probability is the direct outcome of the Markov Chain model. LULCC being a very complex process, the model includes social, economic, historical, and biophysical factors as change drivers to prevent its success [29].

In this study, the LULCC has been predicted up to the year 2040, using the Markov Chain Analysis (MCA). The LULC prediction has been assessed in two main steps:

1) Creation of Transition Potentials

First, the different land cover changes have been grouped into Transition Sub-Models, each of which includes all the changes from different classes to the same class (e.g., all the changes transitioning from different classes to the Settlement class were grouped into the Settlement Sub-Model). Then, five change drivers are added, including slope, elevation, distance from roads, distance from settlements, and distance from bare soils/mines. Roads were considered one of the main factors influencing LULCC because, after different years' classifications, obvious changes were observed along the roads. These drivers were selected because they are widely used in existing literature on tropical regions, where they have demonstrated a strong influence on LULC changes [46] [47].

Finally, the Transition Potential is created for each Transition Sub-Model.

2) Change prediction

The Markov Chain model simulation process produces mainly a land use area transfer matrix and a probability transfer matrix to predict land use change trends. The Markov Chain model can be described as a set of states, $S = \{S_0, S_1, S_2, \ldots, S_n\}$, assuming that the current state is S_t, and then, it changes to state S_j at the next step with a probability denoted by transition probabilities P_{ij}. Thus, state S_{t+1} in the system could be determined from the former stage S_t in the Markov Chain using the formula in **Figure 5** [22]. The transition probability matrix from 1984 to 2020 and the predicted LULC map for 2040 were obtained using MCA in TerrSet software [44].

$$P_{ij} = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \vdots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix}$$

$$\left(0 \le P_{ij} < 1 \quad and \quad \sum_{j=1}^{n} P_{ij} = 1, i, j = 1, 2, \cdots, n \right)$$

$$S_{t+1} = P_{ij} \times S_t$$

Figure 5. Matrix for state transition probability (P_{ij}) calculation. S is land use status, t and $t + 1$ are the time points.

4.3.6. Classification Validation and Accuracy (Kappa Coefficient)

The error or confusion matrix is the standard method used to assess the classification accuracy and measure the quality of the classification system of an image [48] [49]. It is typical to extract several statistics from the error matrix, including overall accuracy, Kappa coefficient, producer's accuracy, and user's accuracy [49]. In this study, the overall accuracy and the Kappa coefficient were used to assess the accuracy of the different years' classifications, and the omission and commission errors were used to evaluate the class-specific classification errors.

A total of 50 ground control points were collected to assess the accuracy of the 2020 LULC classification, while 40 points were collected for the 2001 classification and 40 other points for the 1984 classification. Thus, 10 points were collected per class for accuracy assessment. Figure 6 summarizes all the methodological steps.

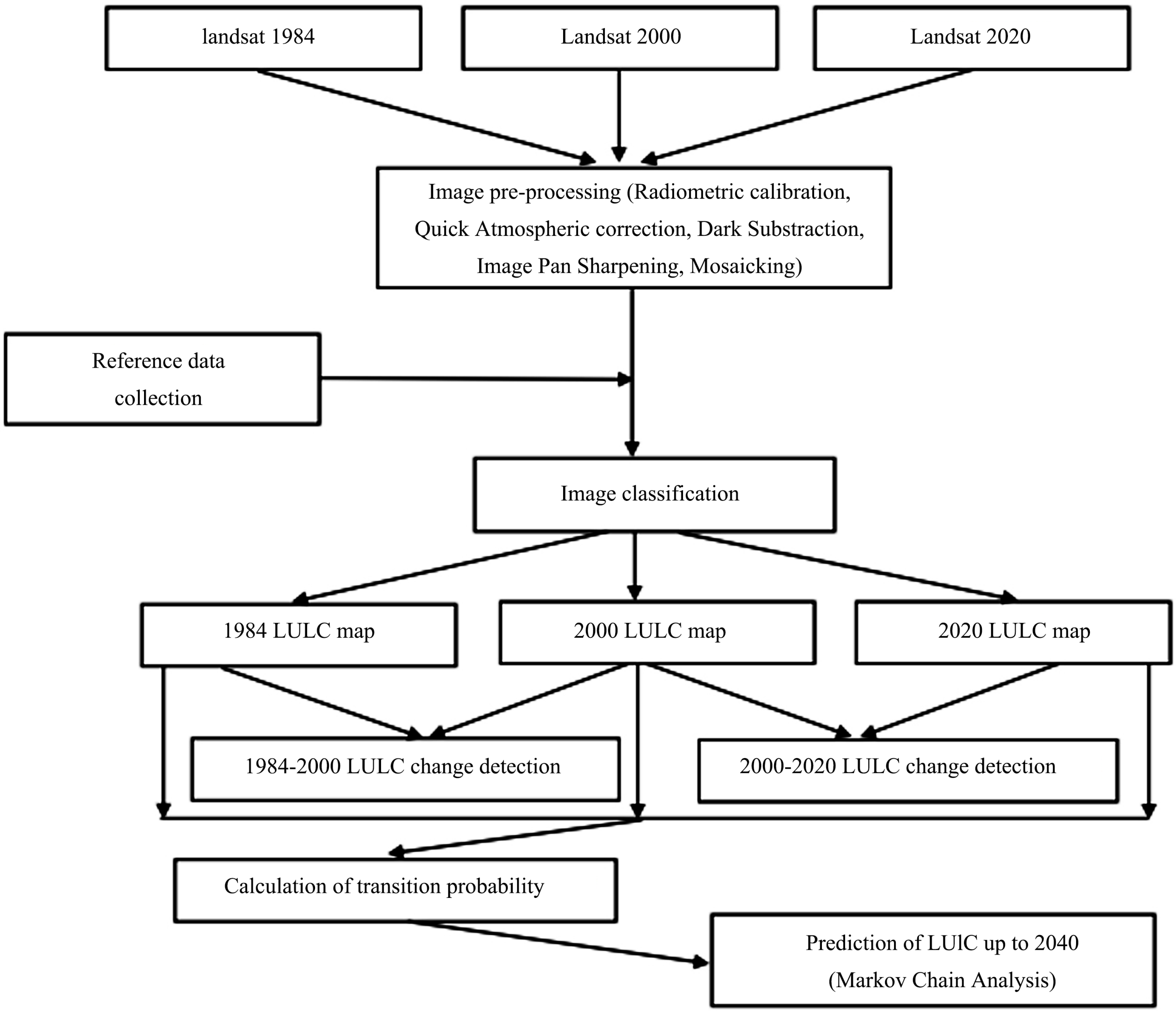


Figure 6. Methodology workflow flowchart.

5. Results and Discussions

5.1. Land Use and Land Cover Change in Pangi Territory from 1984 to 2020

5.1.1. Land Use and Land Cover Mapping

The results indicate a decrease in forest cover and an increase in other LULC classes such as settlements, croplands and agroforestry, bare soils, mines, and wetlands between 1984 and 2020 (Table 2). The observed considerable decrease in forest cover from 13338.02 km^2 (in 1984) to 11080.26 km^2 (in 2020) (Table 2) is mostly due to human activities such as agriculture, building, and mining (Figure 7). Mining activities increased significantly from 1984 (10.15 km^2) to 2020 (50.94 km^2), as well as agricultural activities (from 871.95 km^2 in 1984 to 2885.24 km^2 in

2020) and settlements (from 81.49 km² in 1984 to 208.21 km² in 2020) (**Figure 7**). This is mainly due to the increase in human population in Maniema Province from 1984 to 2020. This province has registered around 148,000 internally displaced people (IDPs), including 90% due to clashes and armed attacks in the neighbouring Sud-Kivu Province. The territory of Pangi has registered 32,755 IDPs from 2009 to June 2016 [50].

Table 2. Summary of the area covered by different land use and land cover classes from 1984 to 2020.

Class	1984		2000		2020	
	Area (km²)	%	Area (km²)	%	Area (km²)	%
Bare soils/Mines	10.15	0.07	66.36	0.46	50.94	0.36
Wetlands	0	0	0	0	119.96	0.84
Croplands/Agroforestry	871.95	6.1	2179.41	15.24	2885.24	20.17
Primary Forest	13338.02	93.26	12008.15	83.96	11080.26	77.48
Settlements	81.49	0.57	47.69	0.33	165.23	1.16
Total	**14301.62**	**100**	**14301.62**	**100**	**14301.62**	**100**

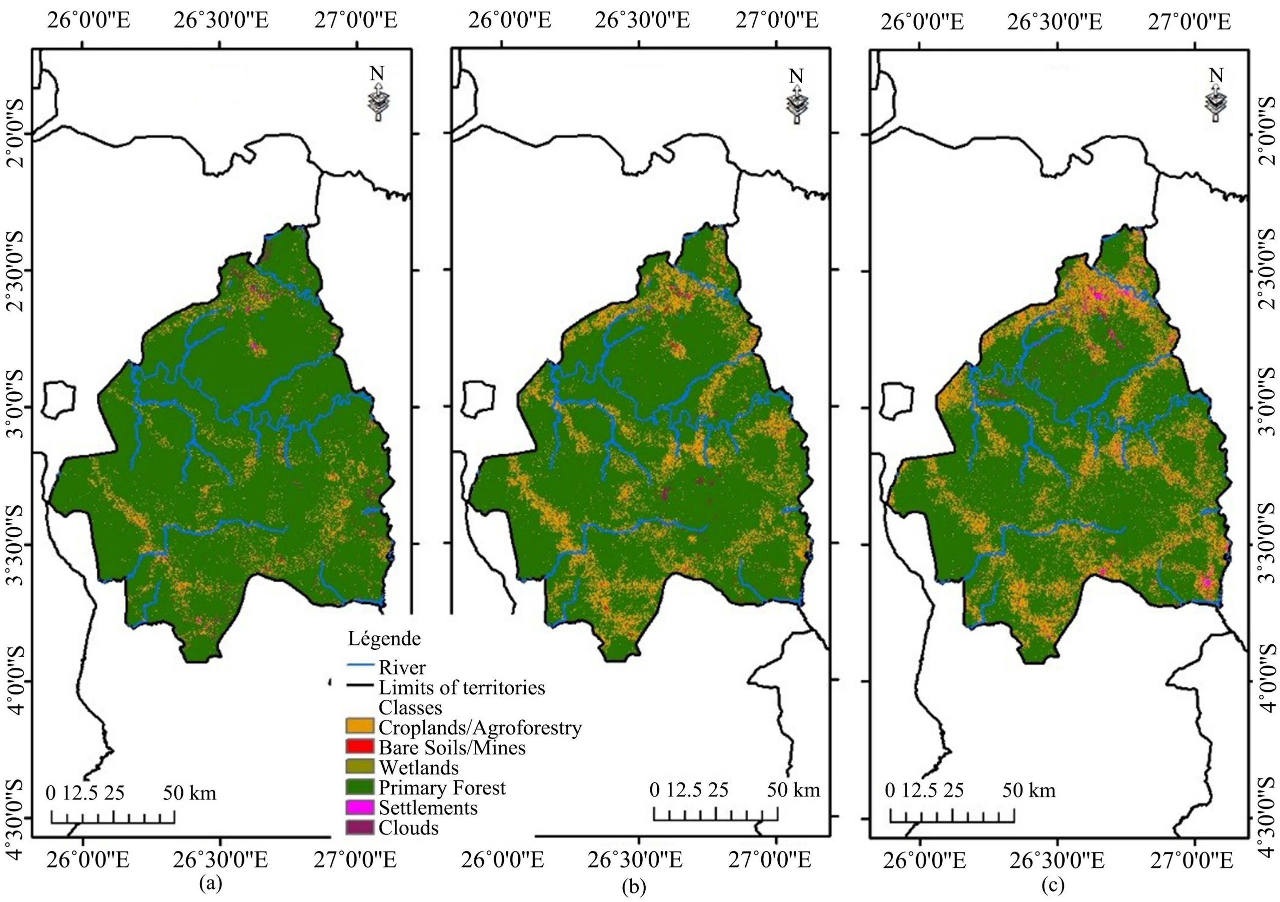


Figure 7. Illustration of land use and land cover changes from 1984 to 2020: (a) 1984, (b) 2000, and (c) 2020.

The supervised classification of Landsat images using the Support Vector Machine algorithm produced the LULC maps with overall high accuracy (83.3%, 86.8%, and 87.7% for 1984, 2000, and 2020, respectively). The Kappa coefficients were 0.77, 0.82, and 0.84 for 1984, 2000, and 2020, respectively (**Table 3**). The Bare Soils and Mines classes, which cover smaller areas mainly inside the forests, could be easily confused with other classes in general and with forests in particular, so they had higher omission and commission errors for all the years' classifications (**Figure 8**). According to [51], heterogeneous classes that occupy smaller areas can easily be confused with other LULC classes.

Table 3. Accuracy assessment for land use and land cover classification for the years 1984, 2000, and 2020.

Year	Overall accuracy (%)	Kappa	Mean omission/class (%)	Mean commission/class (%)
1984	83.3	0.77	10.25 ± 14.58	13.24 ± 15.83
2000	86.8	0.82	8.25 ± 13.56	11.35 ± 14.35
2020	87.7	0.84	11 ± 10.24	11.41 ± 6.70

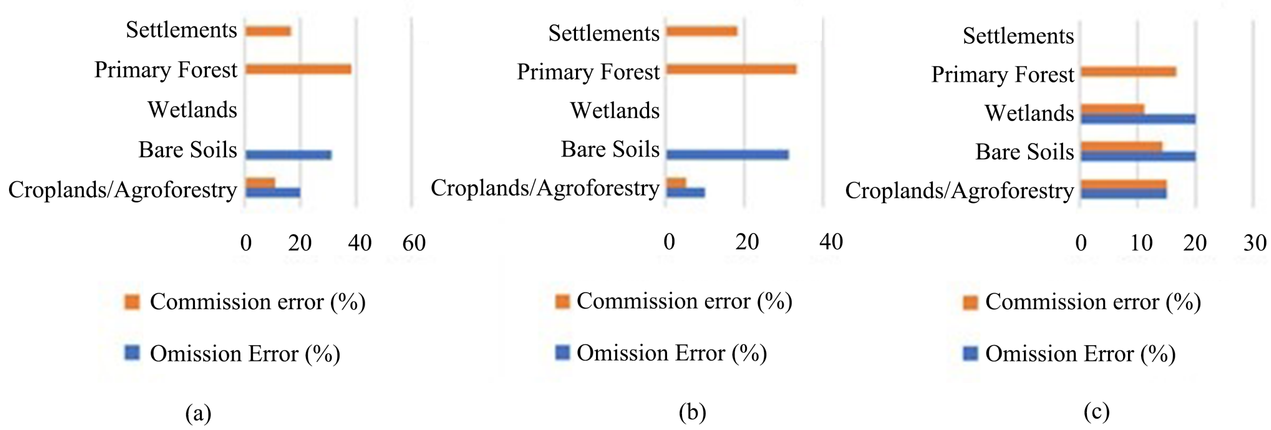
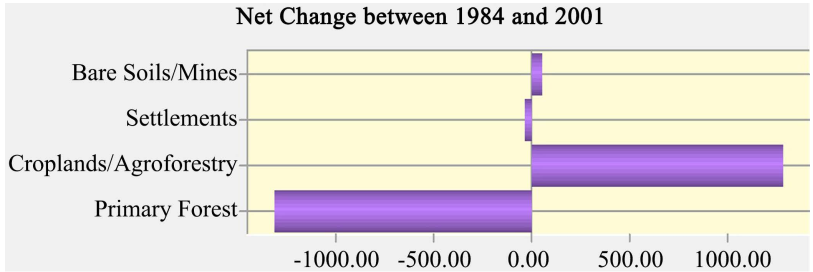


Figure 8. Commission and omission errors per class for each year's classification: (a) 1984; (b) 2000; and (c) 2020.

5.1.2. Land Use and Land Cover Change

The Primary Forest lost up to 1350 km^2 between 1984 and 2000, and 900 km^2 from 2000 to 2020 (**Figure 9**). During the 1984-2000 period, agricultural lands gained up to 1300 km^2 and more than 700 km^2 from 2000 to 2020.

More than 1200 km^2 of Primary Forest lost from 1984 to 2000 were converted into agricultural areas (croplands and agroforestry), and 42 km^2 were converted into Bare Soils and Mines (**Figure 10**). The loss of Primary Forest from 2000 to 2020 was up to 913 km^2, including 720 km^2 converted into Agricultural lands, 80 km^2 converted into Settlements, 100 km^2 gained by Wetlands, and 13 km^2 gained by Bare Soils and Mines (**Figure 11**). From 1984 to 2020, forest cover lost more than 2250 km^2 that were converted into other LULC classes, with the larger area converted into agricultural lands.



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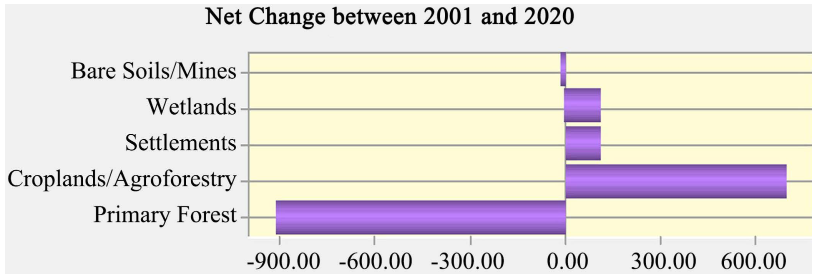
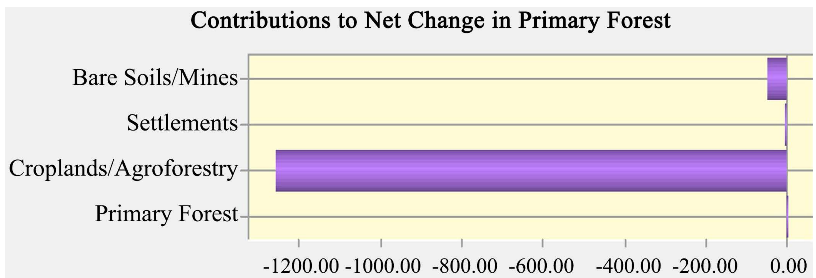


(b)

Figure 9. Total area (km^2) gained or lost by each LULC class from: (a) 1984 to 2000 and (b) 2000 to 2020.



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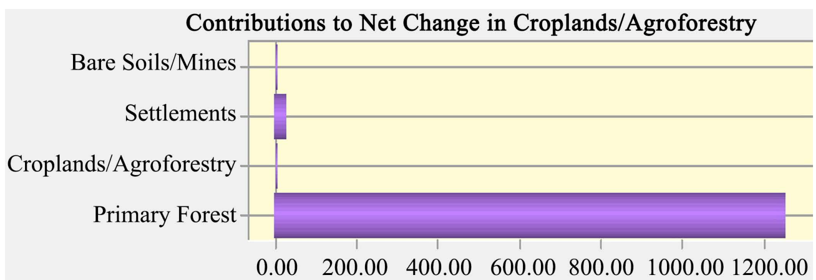

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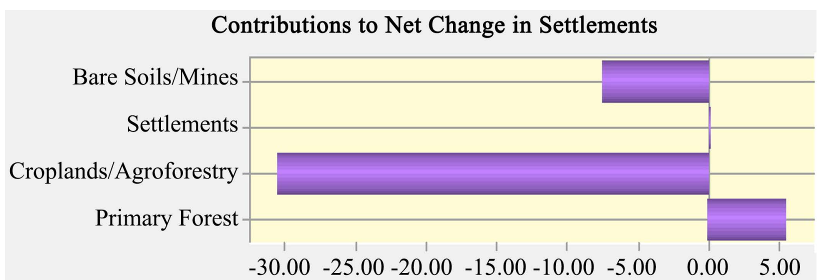

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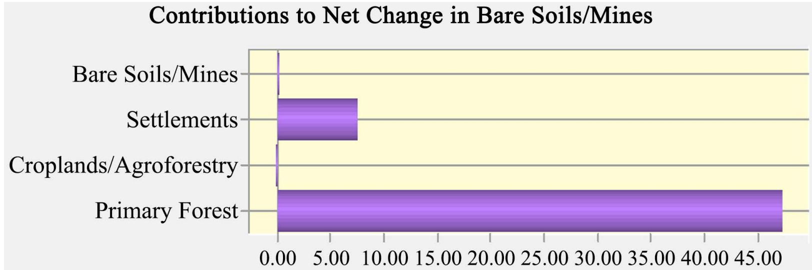
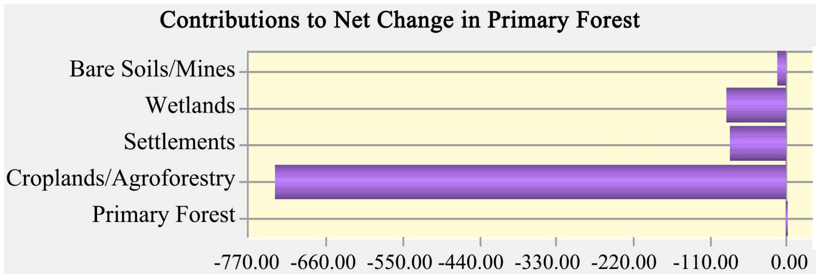
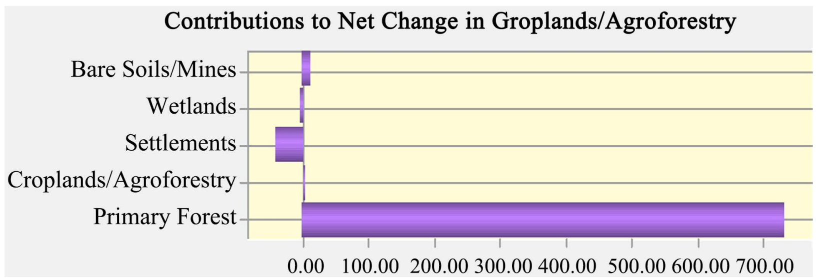


(d)

Figure 10. Contribution to net change in each class: (a) Primary Forest, (b) Croplands/Agroforestry, (c) Settlements, and (d) Bare Soils/Mines from 1984 to 2000.



(a)



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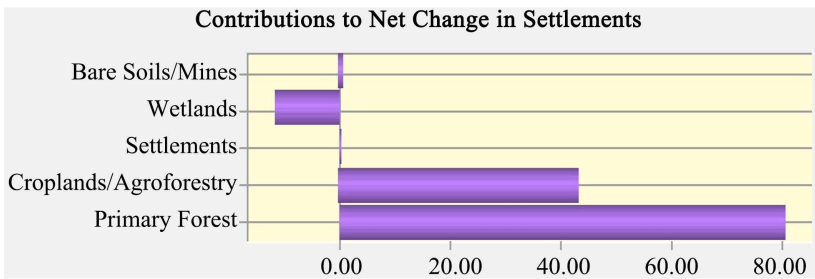

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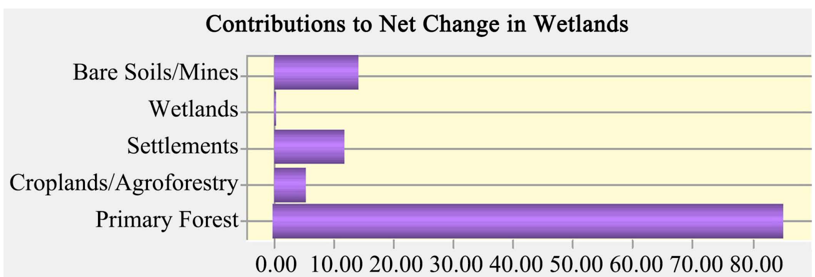

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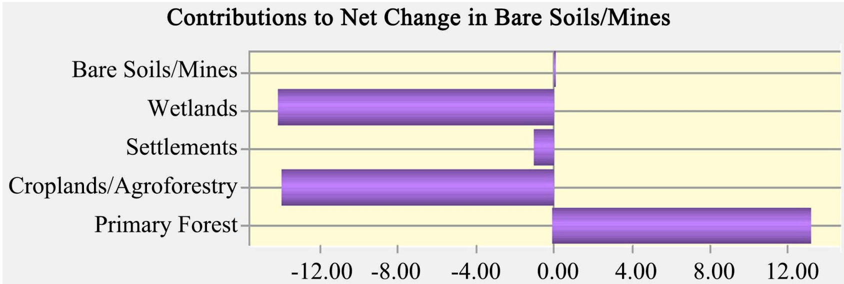


(e)

Figure 11. Contribution to net change in each class: (a) Primary Forest, (b) Croplands/Agroforestry, (c) Settlements, (d) Wetlands, and (e) Bare Soils/Mines from 2000 to 2020.

Similar results were observed in the Lwiro area (Sud-Kivu) [21] where the trees were cut as timber for more lucrative benefits, and some parts of the forest were converted into agricultural lands. Furthermore, it has been observed that changes that occurred in and around mining areas were very significant, leading to significant deforestation. This is in line with [11], who observed many conflicts for land use in the DRC, particularly between mining activities and forests. The observed direct impacts of mining activities on forests include deforestation at mining sites, timber consumption, and pollution.

5.1.3. Prediction of Land Use and Land Cover

The LULC prediction for 2040 indicates that forest areas will cover 9601.90 km^2, while agricultural lands will cover 4213.32 km^2, and there will be a total area of 59.99 km^2 for Bare Soils and Mines, 218.20 km^2 for Wetlands and 208.21 km^2 for Settlements (Figure 12, Table 4). This will represent a total deforestation of 28% from 1984 to 2040, while a deforestation of 16.93% is observed from 1984 to 2020. This indicates a deforestation rate of 83.12 km^2 per year from 1984 to 2000, 46 km^2 per year from 2000 to 2020, and 73.92 km^2 per year from 2020 to 2040.

Table 4. Surface area of different land use and land cover classes by year.

Class	1984		2000		2020		2040	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Bare soils/Mines	10.15	0.07	66.36	0.46	50.94	0.36	59.99	0.42
Wetlands	0	0	0	0	119.96	0.84	218.2	1.53
Croplands/ Agroforestry	871.95	6.1	2179.41	15.24	2885.24	20.17	4213.32	29.46
Primary Forest	13338.02	93.26	12008.15	83.96	11080.26	77.48	9601.90	67.14
Settlements	81.49	0.57	47.69	0.33	165.23	1.16	208.21	1.46
Total	**14301.62**	**100**	**14301.62**	**100**	**14301.62**	**100**	**14301.62**	100

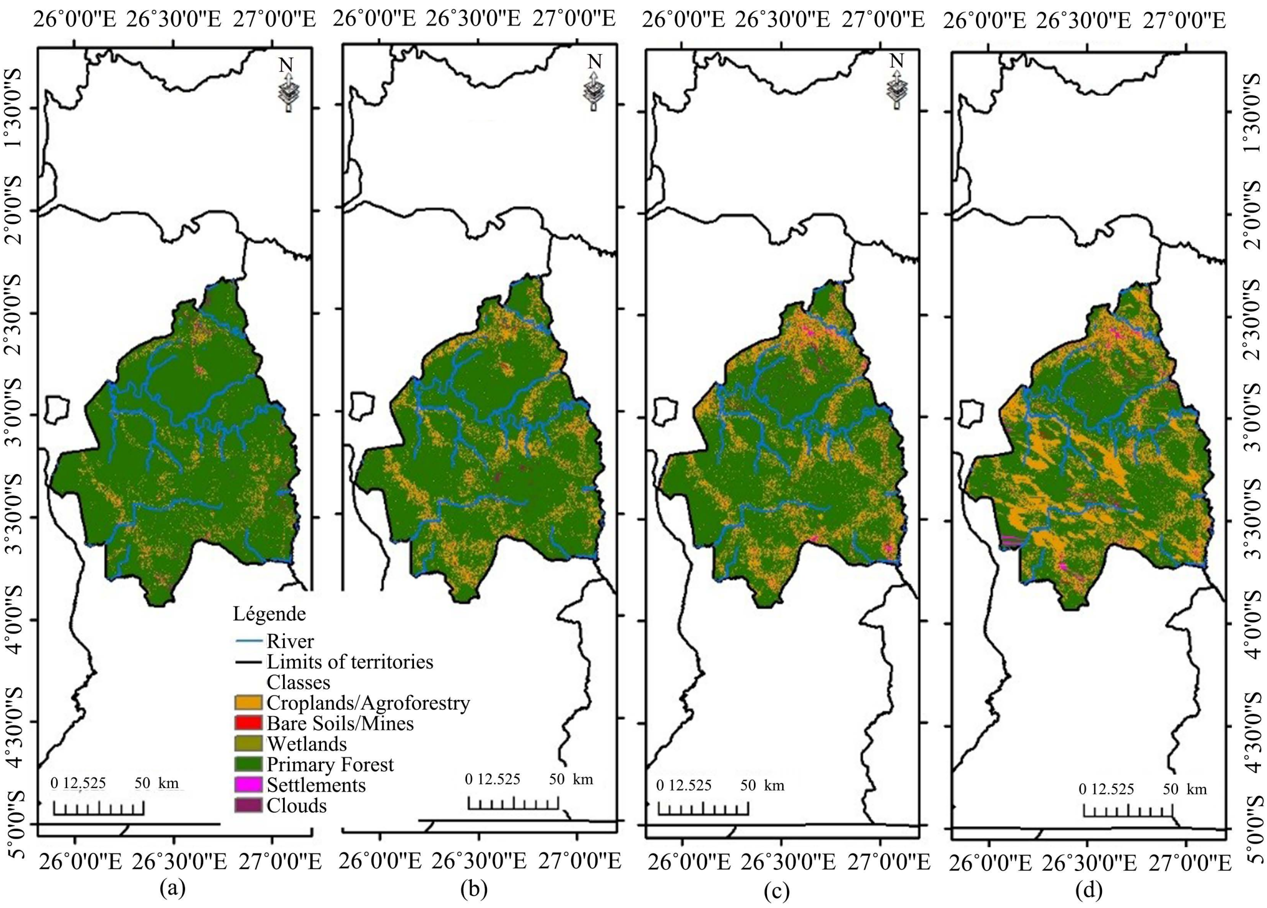


Figure 12. Change detection maps: (a) 1984, (b) 2000, (c) 2020 and (d) 2040.

The Markov transition matrices present the transition trends or transition probabilities from 1984 to 2020 (**Table 5**). In the transition matrices, the diagonal values represent the probability that each LULC class remains persistent from time 0 to time 1, while the other values represent the probability that a given LULC class undergoes transition to another LULC class. Over the whole period from 1984 to 2020, only Primary Forest attains the highest probability of persistence, with a transition probability exceeding 0.75 [51].

Table 5. Markov chain matrix of LULC transition probabilities from 1984 to 2020.

	Primary Forest	Croplands/ Agroforestry	Settlements	Wetlands	Bare Soils/Mines
Primary Forest	0.86	0.12	0.01	0.01	0.00
Croplands/ Agroforestry	0.28	0.70	0.02	0.00	0.00
Settlements	0.14	0.37	0.45	0.01	0.03
Wetlands	0.25	0.25	0.25	0.00	0.25
Bare Soils/Mines	0.25	0.42	0.14	0.06	0.13

The Primary Forest in the Pangi Territory that covered 13338.02 km^2 (93.26% of the total area) in 1984 was reduced to only 11080.26 km^2 (77.48%) in 2020 (Table 4), representing a loss of 2256.8 km^2 (15.78% of the total area). Croplands/Agroforestry, which covered 871.95 km^2 (6.10% of the total area) in 1984, accounted for 2885.24 km^2 (20.17% of the total area) in 2020, representing an increase of 2012.24 km^2 (14.07% of the total area). This means that 89% of the total loss of the forest area was transformed into Croplands/Agroforestry. Agriculture was identified by [52]-[55] as being by far the main cause of deforestation in the tropical world. The expansion of infrastructure, the development of the mining sector, and the extraction of timber represent the other observed causes.

The probability of transition from Primary Forest to Croplands/Agroforestry was the greatest change probability (0.28) compared with the transition probability from Primary Forest to Bare Soils/Mines (0.25), which is similar to that from Primary Forest to Wetlands (Table 5). This effectively proves that mining activities are among the most important causes of forest cover decrease in the study area.

5.2. Relationship between Land Use and Land Cover Change and Mining Activities in the Kampene Area

5.2.1. Land Use and Land Cover Mapping

The extension of some LULC classes such as Bare Soils/Mines, Wetlands, Croplands/Agroforestry and Settlements, and their impacts on the destruction of Primary Forest cover, which decreased significantly from 1984 to 2020 in the Kampene mining area and surroundings, are presented in Figure 13. Furthermore, it is predicted that, in 2040, a significant loss will be observed in Primary Forest (up to 349.45 km^2), which will mainly be converted into Croplands/Agroforestry. The increase in Bare Soils/Mines ranges from 0.36 km^2 in 1984 to 5.28 km^2 in 2020 (Table 6), representing up to 1466.66%. This exceptional increase in mining activities is one of the drivers of deforestation and several other changes observed in the local landscapes. In the eastern DRC, the environmental consequences of artisanal mining exploitation are all highly negative, including chemical pollution of water tables, deforestation, diversion of rivers, levelling of hills and disappearance of arable land as well as intensive poaching (to feed the miners) [15].

Table 6. Surface of different land use and land cover classes in the Kampene mining area and its surroundings.

Class	1984		2000		2020		2040	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Bare soils/Mines	0.36	0.02	4.45	0.21	5.28	0.25	13.39	0.64
Wetlands	0	0	0	0	7.43	0.36	13.43	0.65
Croplands/ Agroforestry	146.38	7.04	302.79	14.56	384.69	18.49	714.82	34.37

Continued

Primary Forest	1926.42	92.61	1769.99	85.09	1670.6	80.32	1321.15	63.52
Settlements	6.87	0.33	2.8	0.13	12.04	0.58	17.25	0.83
Total	**2080.03**	**100**	**2080.03**	**100**	**2080.03**	**100**	**2080.03**	**100**

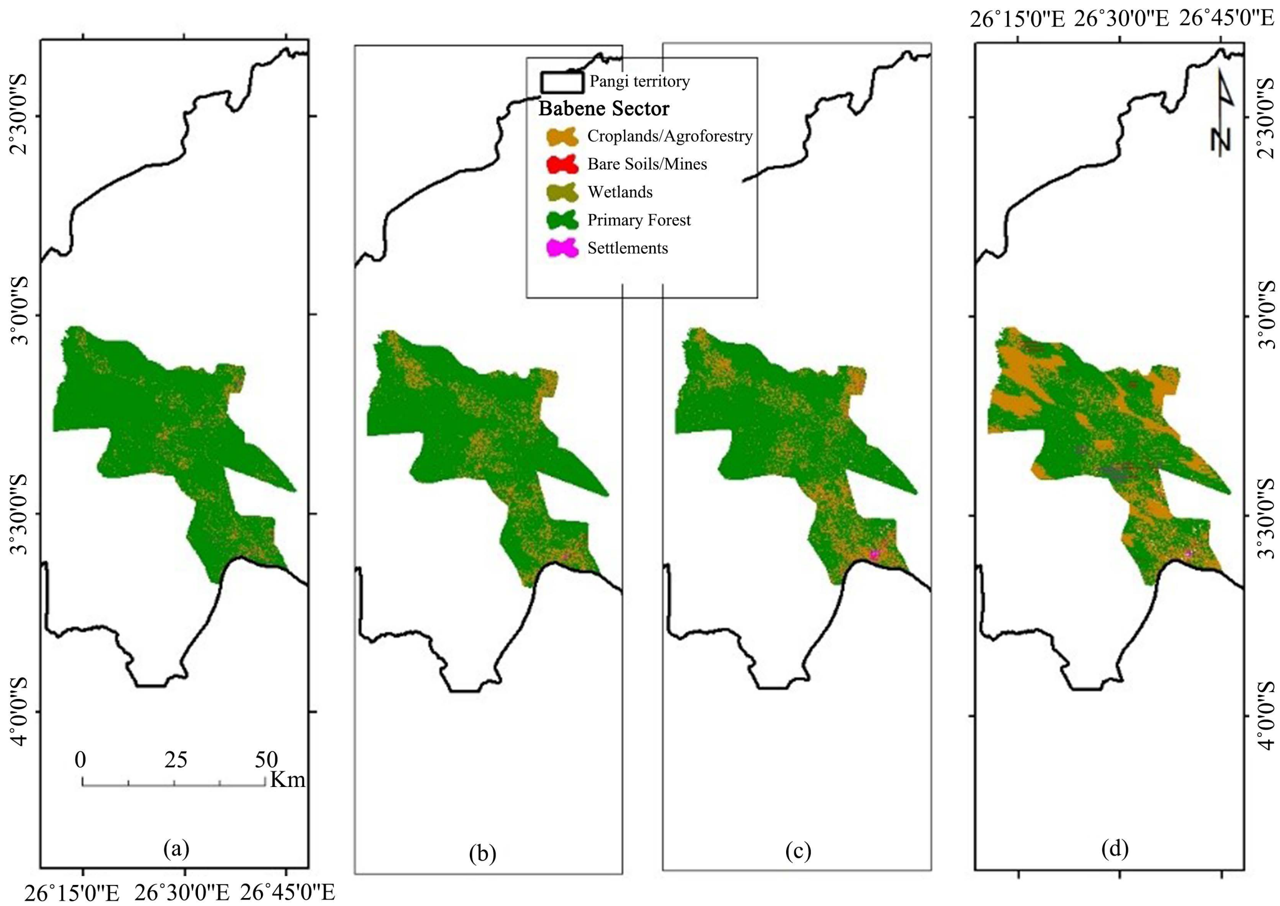
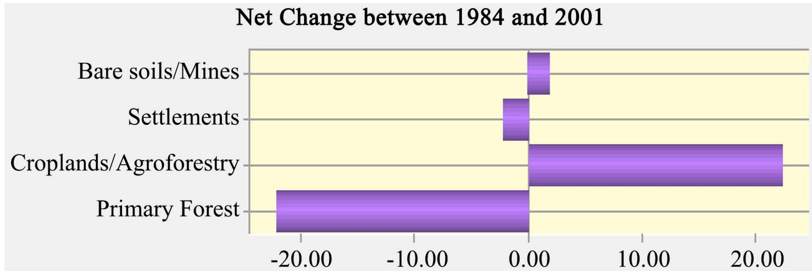


Figure 13. LULC distribution of the Pangi Territory at three different times: (a) 1984, (b) 2000, and (c) 2020; and Markov model prediction for 2040 (d).

5.2.2. Land Use and Land Cover Change

Primary Forest lost up to 22.4 km^2 from 1984 to 2000, gained by Agricultural lands and Bare Soils/Mines, with the majority transformed into Agricultural lands (21 km^2, **Figure 14**). The loss was greater between 2000 and 2020 (33 km^2) and mainly gained by Agricultural lands and Settlements.

Settlements gained 1.30 km^2 from Agricultural lands. The Primary Forest lost 28 km^2 to Agricultural lands between 2000 and 2020, while Agricultural lands lost 3.50 km^2, which were converted into Settlements (**Figure 15**). Settlements also gained 3.10 km^2 from Primary Forest and 0.50 km^2 from Bare Soils/Mines. Wetlands gained 1.85 km^2 from Primary Forest, 0.20 km^2 from Agricultural lands, and 0.15 km^2 from Bare Soils/Mines (**Figure 16**). **Figure 17** presents the change detection map from 1984 to 2000 and the map of LULC change detection from 2000 to 2020.



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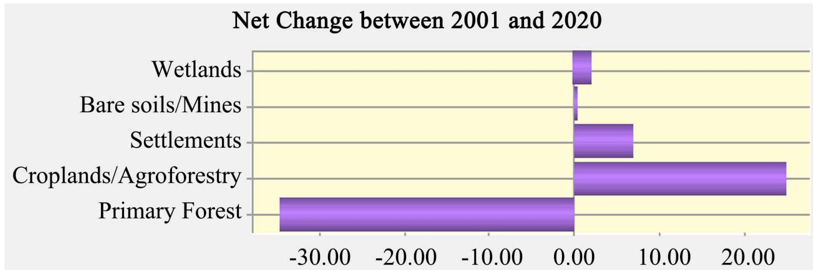

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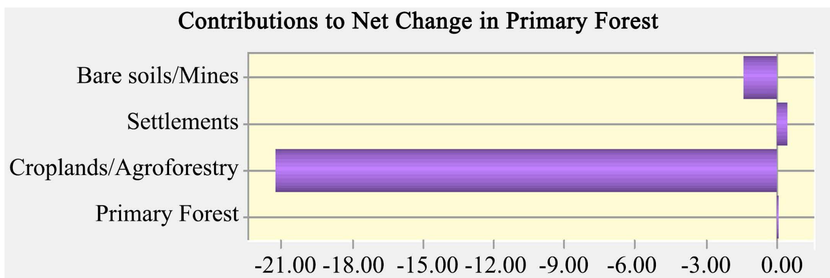
Figure 14. Land use and land cover distribution in the Kampene mining area and the surroundings at: (a) 1984; (b) 2000.



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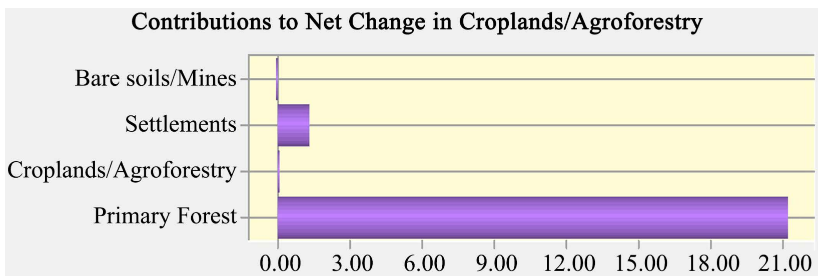

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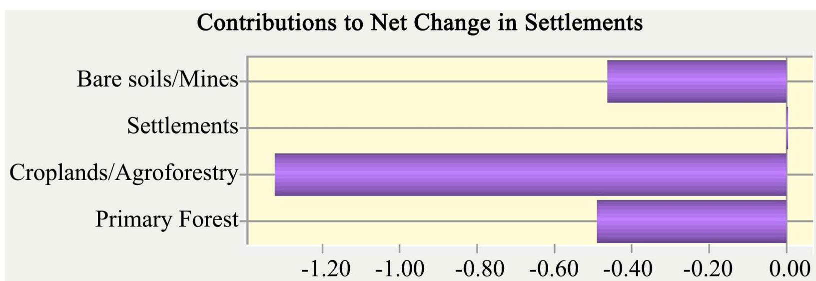

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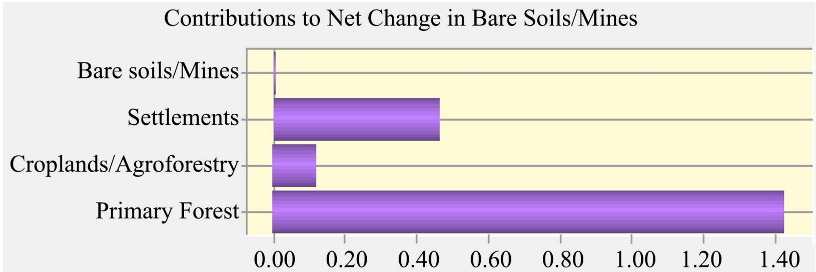
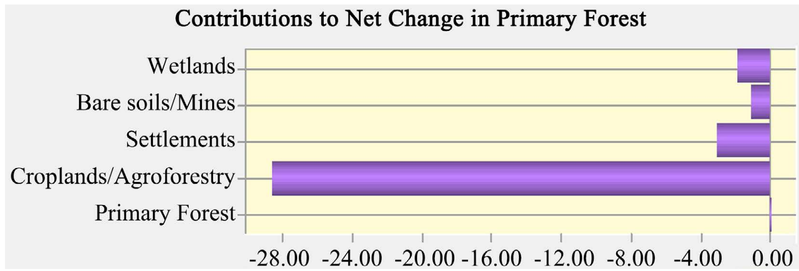


(d)

Figure 15. Contribution to net change in each land use and land cover class: (a) Primary Forest; (b) Croplands/Agroforestry; (c) Settlements; (d) Bare Soils/Mines) in the Kampene mining areas from 1984 to 2000.



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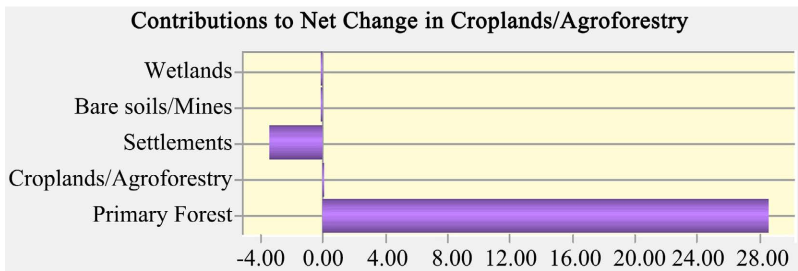

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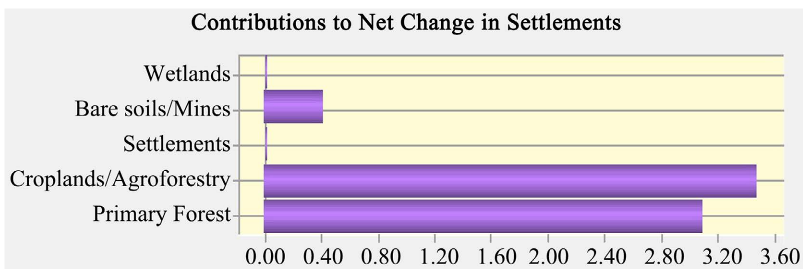

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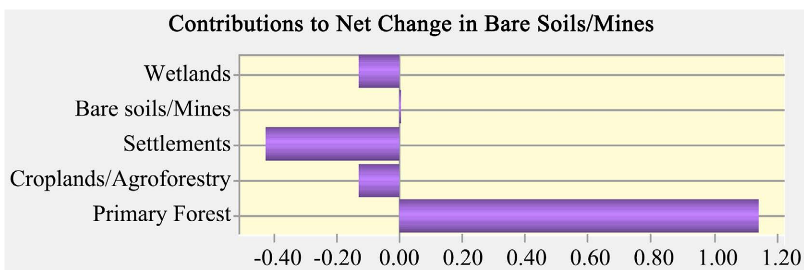

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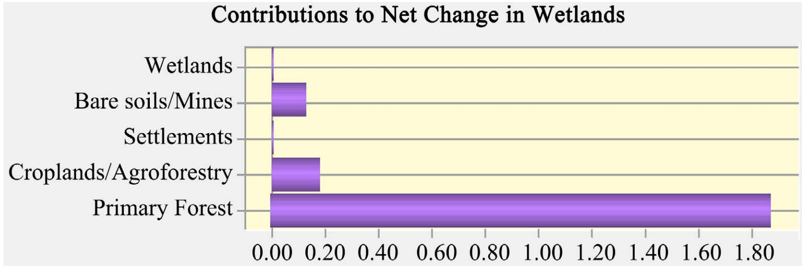

(e)

Figure 16. Contribution to net change in each land use and land cover class (a) Primary Forest; (b) Croplands/Agroforestry; (c) Settlements; (d) Bare Soils/Mines; (e) Wetlands in the Kampene mining areas from 2000 to 2020.

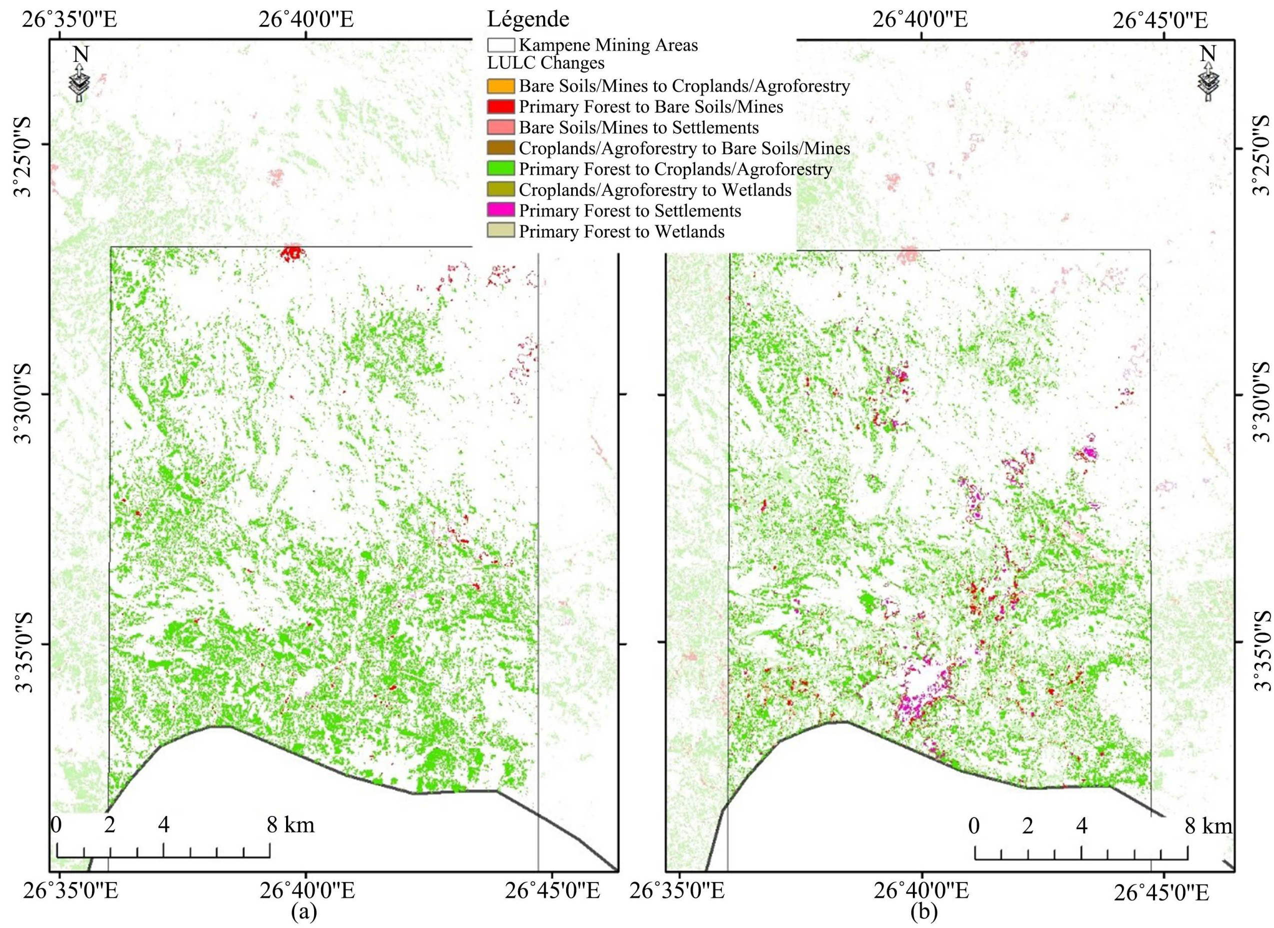

Figure 17. Change detection maps (a) from 1984 to 2000 and (b) from 2000 to 2020.

5.2.3. Forest Cover, Forest Loss, and Mining Activities

Several authors have identified agriculture as being by far the main cause of deforestation in the tropical world (e.g., [51] [53]-[55]). The Congo basin is not an exception to the rule as agriculture is the most important direct cause of deforestation. This same trend is observed in the Kampene mining area (**Table 6**), where the Primary Forest was reduced by 255.82 km² (12.3% of the total area) from 1984 to 2020. During the same period, the area covered by the Croplands/Agroforestry class increased by 238.31 km^2 (11.46% of the total area). This means that 93.16% of the lost forest area has been turned into Croplands/Agroforestry. An increase of 4.92 km^2 (0.24% of the total area and 1.92% of the lost forest area) for Bare Soils/Mines, 7.43 km^2 (0.36%) for the Wetlands and 5.17 km^2 (0.25%) for Settlements was observed during this period.

The same trend was observed in the littoral region of Cameroon, where the area of high-value forest landscapes decreased by 12% from 1975 to 2017, but conversely, disturbed vegetation, cleared areas, and urban areas all expanded by 32%, 5.6%, and 6.6%, respectively [56]. In the Sangha Trinational Park region of Cameroon, the Central African Republic, and the Republic of Congo, the amount of deforestation induced by small-scale mining is lower compared with the impact of other activities such as logging, subsistence farming, or charcoal production [57] [58].

This pattern shows that the direct impacts of mining on deforestation are modest compared with their indirect impacts in Kampene. Only a small portion of forest cover was converted to bare land/mines (1.8 km^2), corresponding to the land cleared for pits and infrastructure, whereas a much larger area was converted to agricultural lands and settlements (33 km^2 and 0.8 km^2, respectively), both supporting mining activity. These constitute indirect impacts, essential for daily life but outside the immediate extraction footprint. Moreover, despite relatively low direct conversion to mines and settlements, the creation of new infrastructure (e.g., roads) further exacerbates LULC change by improving access, a key driver of landscape conversion. Areas closest to roads are more affected by land-cover change [59].

In the copperbelt region (SE DRC, Haut Katanga and Lualaba provinces), another mining region of DRC, slash and burn agriculture represents the main cause of deforestation, followed by brick making, firewood collection, charcoal production, logging, and mining [60]. This indicates that mining, although representing one of the causes of deforestation, is not the principal one.

The results of [56] [57] [60] are consistent with [61]'s research on deforestation due to mining activities in the DRC. This study shows that mining could have a smaller footprint than the effects of other major commodity production processes such as agriculture or charcoal production. **Figure 15** illustrates the replacement of forests by settlements and tree cutting for the installation of mines.

6. Environmental Impact of Mining Activities

The Pangi Territory is generally well known as a forest-covered area, but mining activities have induced the cutting of trees. Whether it is from artisanal miners or industrial companies, the extraction of minerals leads ipso facto to the conversion of natural habitats, with many ecological consequences both at the local and landscape scales. In a recent assessment of global primary forest landscapes, [62] highlighted the scale of land cover change worldwide. In the DRC, while the general trend reflects a relative stability in the forested areas of the central part of the

Congo basin, the eastern regions of the country (e.g., Sud Kivu, Nord Kivu, and Maniema) are known to be alarmingly losing their forests [63] [64]. Following an analysis of Landsat images, from the data published by CARPE during the period between 2000 and 2010, [63] indicated that a significant proportion of Congolese primary forest cover was lost, mainly in the Kivu provinces.

If the loss of vegetation cover (deforestation) is a phenomenon directly associated with mining and other extractive activities, expansion of agriculture and other anthropogenic pressures; natural forests also lose their original quality through degradation, resulting in intense ecosystem imbalances. Such landscape conversion undeniably affects the migration of a large number of animal species (mammals, birds, etc.) and contributes to increasing landscape fragmentation with immense ecological consequences. Similar to habitat destruction, fragmentation is also a cause of declining biodiversity. It is known to severely impact animal and plant communities by altering natural processes in ecosystems [6] [65]-[71].

Due to poor conservation measures and the absence of updated inventory data, the risk of large-scale biological erosion is high, especially in the absence of research studies and a thorough environmental impact assessment of extractive activities. At a time when the whole world is focusing on the preservation of forest ecosystems in the process of fighting climate change and conserving biodiversity, an analytical study of the consequences of anthropogenic pressures on natural ecosystems in eastern DRC becomes indispensable. Moreover, it is common knowledge that the loss or reduction of vegetation cover inevitably affects the hydrological cycle of the concerned region, inducing the disruption of biogeochemical cycles and the physiological phenomena specific to plant organisms. All of this can, in turn, affect the supply systems of local people and their well-being in general.

Land conversion and intense deforestation in the watersheds significantly increase the risk of erosion, resulting in a positive feedback loop. Erosion accelerates the sedimentation of aquatic ecosystems. Sedimentation and its subsequent turbidity (lack of clarity in water) are known to reduce the biological productivity of aquatic systems through the decrease of ecosystem primary productivity, thus disrupting the whole trophic levels in water bodies. The resulting species reduction affects the overall biodiversity and impacts human communities that depend on fishing for their livelihood.

Pollution is another threat to the water bodies in eastern DRC because of soil erosion, due to mining and other extractive activities. The immediate consequence for aquatic ecosystems is eutrophication through mineral and nutrient enrichment, all this resulting in decreased biodiversity and reduced water quality. Pollution of aquatic ecosystems may also result in serious health issues for human populations, among which, in the case of eastern DRC, are water-borne diseases such as cholera, enteritis, dysentery, typhoid fever, etc. that plague vast regions in the developing countries, due to difficult access to clean drinking water. The various problems affecting natural ecosystems in this part of the globe, if not addressed properly, can result in unprecedented consequences for global biodiversity and the lives of millions of people who depend on the various services offered by those natural ecosystems.

Furthermore, the use of chemicals in ASM results in a massive release of liquid elemental mercury into the environment, with serious environmental consequences. The tailings produced from mining activity generally have high levels of mercury and uranium, and they are considered or classified as hazardous waste. Small-scale miners dump them directly into rivers and lakes. In these tailings, the concentrations of toxic heavy metals such as cadmium, zinc, and lead are generally 2 to 10 times higher than international standards. For example, in the Amazon basin, approximately 63% of measured mercury concentrations in the atmosphere were attributable to gold mining [72].

Finally, from a single biodiversity point of view, it appears very important to assess the affected areas and determine conservation priorities following international criteria, such as the IUCN Red List of species. Figure 18 and Figure 19 illustrate the degradation of the environment due to mining activities in the Kampene mining area. The degradation mainly affects soil, water, and forest cover.

Figure 18. Illustration of deforestation in the Kampene area by ((a) and (b)) settlements and ((c) and (d)) mining activities.

(a) (b)

(c) (d) (e)

Figure 19. Environmental degradation due to mining activities in the Kampene area in active artisanal mines ((a)-(d)) and abandoned mines becoming a lake (e).

7. Study Limitations

A potential limitation of this study is its reliance on medium-resolution (30 m) Landsat imagery for the land use and land cover analysis. While the Landsat archive is invaluable for its long-term temporal coverage, enabling a multi-decadal analysis, its spatial resolution may not fully capture the extent of certain fine-scale land cover changes. For instance, small-scale artisanal mining operations, which can be characterized by small, isolated pits and localized clearings, may be smaller than a single pixel. This can lead to them being missed or misclassified, an issue reflected in the higher omission and commission errors observed for the "Bare Soils and Mines" class, which covers smaller and heterogeneous areas. Similarly, highly fragmented agricultural plots, which are common in subsistence farming systems, may be challenging to distinguish accurately from the surrounding forest matrix, potentially leading to an underestimation of their total footprint. Future research could benefit from integrating higher-resolution satellite data or targeted analyses with unmanned aerial vehicles (UAVs) to conduct more granular assessments and validate the changes driven by these small-scale activities.

8. Conclusions

The Maniema Province is characterized by its forestry and mining activities, which have represented for decades one of the main activities in the Kivu region. The pressure on natural resources is high because of the extreme poverty of the population living around the mines and the lack of employment. People are obliged to look for ways of obtaining or increasing their financial income.

In this study, an evaluation of the artisanal mining impact on the land cover and land use change dynamics in the Pangi Territory in general and in the Kampene mining area in particular was conducted using the Support Vector Machine algorithm for LULC classification and post-classification change detection, and the Markov Chain Analysis for LULC prediction.

The results of this study indicate that:

1) The Primary Forest is the predominant LULC class in Pangi Territory.

2) There is a consistent decrease in forest cover from 1984 to 2020, with a deforestation rate of 83.12 km^2 per year from 1984 to 2000 and 46 km^2 per year from 2000 to 2020.

3) A deforestation of 73.92 km^2 per year is predicted for the period from 2020 to 2040.

4) A total of 1920 km^2 of forest cover was converted into agricultural land, which is equivalent to 82.7% of the total forest cover lost from 1984 to 2020.

Despite the considerable share of artisanal mining in forest loss, the study shows that the conversion of forests into agricultural areas is the primary driver of forest loss in Pangi Territory.

The techniques of sustainable agriculture should be advertised and enforced, and artisanal miners should work together in cooperatives to allow proper supervision and training on sustainable mining techniques. This will enable a change in this trend in the next 20 years; otherwise, the environment will suffer a loss of 1478 km^2 as predicted for the Primary Forest.

Given the strong influence of proximity to roads on LULC change, land-use controls should prioritize road corridors. Establishing zoning buffers along new and upgraded roads could improve environmental protection and reduce the probability of LULC transitions.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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