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Application of Remote Sensing and Geographic Information System Technologies to Assess the Impact of Mining: A Case Study at Emalahleni

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Abstract: This article presents an assessment of the impact of mining activities in the Emalahleni municipality, using GIS and RS technologies. The random forest algorithm was used to classify the land use and land cover in the Emalahleni municipality over a three-decade period (1990–2020). The classifications are settlement, water, mining area, vegetation, and bare land. The majority of the study area was found to be rocky ground, accounting for approximately 60% of the total study area. Change detection maps were created for vegetation and mining to assess the extent of land degradation in the study area over the three-decade period. The findings in this study highlight the importance of understanding the changes in land use and vegetation cover in the study area and its impact on the environment, as well as the local community. It is crucial to develop sustainable land management strategies that ensure that a reasonable balance concerning the economic development activities is achieved, such as mining with environmental management for its long-term viability for future generations. The data presented in this study provides a useful baseline for further research and can inform land-use planning and decision-making processes in Emalahleni.

Keywords: geographic information system (GIS); remote sensing (RS); mining; environment; change detection maps; random forest algorithm

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1. Introduction

The mining industry plays a vital role in the economic development of nations, through employment, nation building, and providing trading opportunities with the rest of the world. According to World Bank data, global natural resources contribute 0.8% of gross domestic product (GDP), whereas coal contributes 0.3% of GDP [1]. It becomes a challenge when mining is irresponsibly conducted and affects the environment. Several research works have been conducted to assess the cost associated with the social and environmental impacts of mining, as well as the regulatory frameworks in South Africa [2–5]. This includes almost ZAR 100 million, which is about USD 7.7 million (2017 Unted States dollars), spent by a mining company on a drainage, storage, and treatment system to improve water quantity and quality, plus an additional ZAR 300 million, which is about USD 23 million (2017 United States dollars), to realize a water reclamation plant that decontaminates water from three defunct mines and an active mine in order to adhere to drinking standards [2]. South Africa has recognized itself as a global frontier in mining, with its mines accounting for approximately 53 minerals and accounting for 96% of global reserves of platinum group metals, (PGMs), 74% of chrome, 32% of manganese, 26% of vanadium, and 11% of gold reserves [6]. However, the effects of mining have been recorded as land subsidence [7], severe surface disturbance that changes the land pattern of the mining area [8], deformed upper layer rocks due to the action of gravity [9], and over exploitation that has caused surface collapse and seepage, soil texture damage, water pollution, and waste accumulation [10]. Various authors [11,12] have expressed concerns about land degradation detection and assessment at local and regional scales in Southern Africa. Examples of case studies include land degradation monitoring in Namibia, where indicators such as population pressure, livestock pressure, seasonal rainfall, and erosion hazards were calculated annually from 1971 to 1997. The results revealed a general trend toward increased land degradation risk in the defined period. Another study was conducted in northeastern South Africa, where large areas of former homelands regarded as degraded were measured against non-degraded rangelands [13]. According to Bell et al. [14], the notable primary effects of open mining included the appearance of tension cracks at the surface and crown hole development. Secondary effects included spontaneous combustion of the coal, as air had accessed the mine; the deterioration of groundwater quality, leading to the decimation of vegetation; and the eradication of aquatic flora and fauna [14]. The need to understand land-use patterns is necessary to implement policies and social intervention programs for the sustainable management of natural resources. The modeling of land-use changes keeps policymakers informed of possible future conditions [15,16].

Xue et al. [17] used the residual trend (RESTREND) analysis method to monitor degradation induced by human activity in China and realized a positive residual trend related to shrub encroachment. According to Bielli et al. [18], most of Sub-Saharan Africa's ecological environment and natural resources are depleting due to the dynamics of land degradation.

South Africa like many other countries is endowed with many natural resources of international importance. The income generated by mining, particularly gold mining, has helped to fuel the country's development [19]. Coal mining has been a primary source of energy production in South Africa, which plays a critical role in the country's economic development and energy generation. The coal commodity has significantly impacted the South African economy, by meeting the country's primary energy requirements and bringing foreign direct investment into the country [20]. According to the Minerals Council South Africa [21], the coal industry employed 90,977 people, producing 231 million tons, with total coal sales of ZAR 252.3 billion. A study conducted by Campbell et al. [22] explored how Witbank, a mining city with a rapidly growing economy in mining coal and other metals, had strained the existing infrastructure and natural assets. The abundance of coal in areas like Emalahleni (Witbank) meant that the population and economy experienced large-scale growth resulting in new coal-generated energy plants. [23]. This caused the local government to be affected by the need to meet the demands for service delivery, such as housing or managing the environmental impact of the mining activities. According to Campbell et al. [22], further research is required into mining towns and cities in South Africa to enable foresight planning, to avoid resource curse challenges. For this reason, there is a need to assess the extent to which mining activities have influenced the environment and the livelihoods of the communities where major industrial activities like mining take place. This would enable the knowledge on the land degradation that is occurring, where it is occurring, and the rates at which it is occurring, to be documented. In this study, to understand the spatial changes that have occurred due to mining activities, a case study scenario was conducted in the Emalahleni municipality of Mpumalanga province in South Africa, where the primary mining commodity is coal.

2. Objectives

This study focuses on mine expansion and land-use changes in the Emalahleni municipality over a period of three decades (1990–2020). The objective of this study is to understand the extent to which mining in the Emalahleni municipality has affected the natural resources and the communities over time. A mixed method approach consisting of remote sensing (RS) and geographic information system (GIS)-based analysis was used in this study for change detection; hence, the objectives are listed as follows:

i. To produce land-use–land-cover maps from 1990–2020 of the Emalahleni area;
ii. To evaluate changes in the land cover in the study area;
iii. To assess the extent of land degradation in the study area.

3. Study Area

The research was carried out in the Emalahleni area (Figure 1), Mpumalanga province, South Africa (Figure 1). Emalahleni, formally known as Witbank, is one of South Africa's key mining areas [24]. Emalahleni falls within the grassland biome and is one of six local municipalities in the Nkangala District municipality, with a total area of 331.353 km^2. Like most portions of the country, the study area experiences seasonal weather variations. The temperature ranges from approximately 2.2 °C to 26 °C throughout the year, with temperatures rarely falling below −1 °C or rising over 29 °C. January is the hottest month of the year, while July is the coldest and receives the least amount of rainfall. December has the rainiest days.

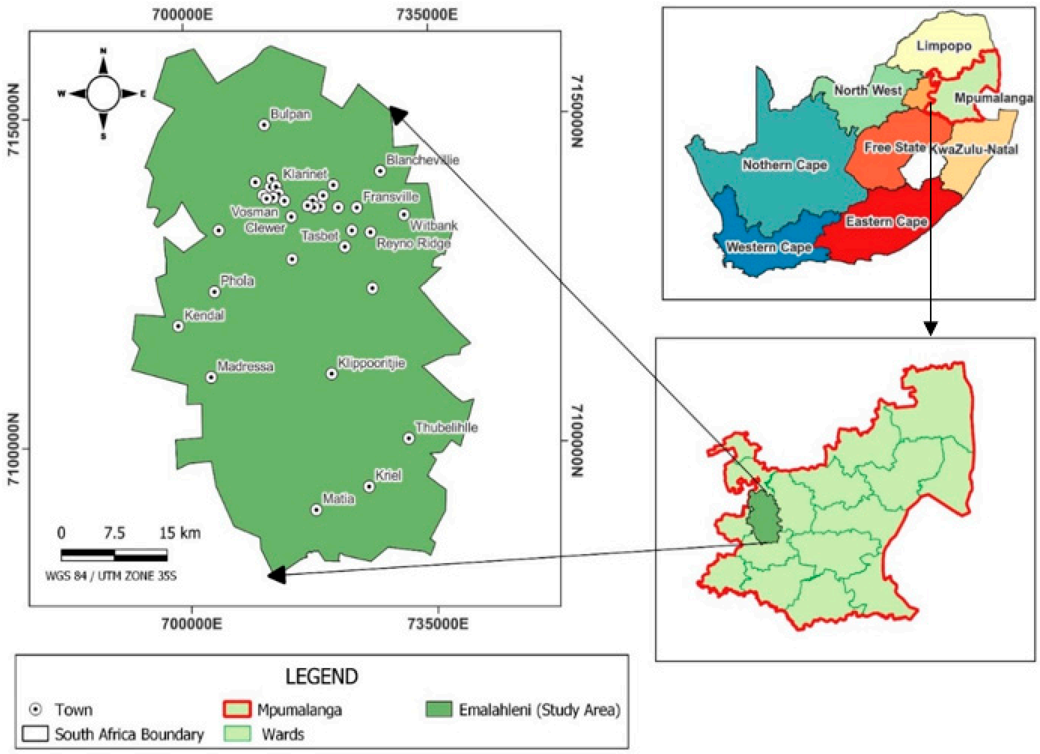

Figure 1. Emalahleni (study area).

4. Methodology

Geometric and atmospheric corrections were performed on the images using the Google Earth Engine. Band combinations known to depict for e.g., vegetation bands (7, 5, 3, and 7, 6, 4), and agriculture bands (5, 4, 1, and 6, 5, 2) were employed during the image classification process. Several classifiers were tested, and the random forest (RF) algorithm was selected as a result of its high performance on our dataset. To examine the accuracy (which refers to how a classified map reflects the reality on the ground), we relied on the internal confusion matrix generated by the RF algorithm. The total number of accurate pixels was further divided by the total number of pixels in the error matrix to yield the overall accuracy.

5. Source of the Data

Quantitative methods, specifically secondary data collection methods, were used to generate the data for this study, in order to fulfill the objectives. The research relied on data from published journals, Landsat scenes with the highest quality data, and shapefiles of the area, as shown in Figure 1.

The mining methods employed in the study area are opencast and underground mining. Some of the minerals produced in the area include aggregate, bituminous coal, clay and shale, vanadium, silicon, and manganese [25].

6. Data Acquisition, Description, and Processing

Land-use maps and satellite images were acquired from the Google Earth Engine for four different timestamps: 1990, 2000, 2010, and 2020. Landsat 7 images, with a spatial resolution of 30 m $\times$ 30 m, were obtained with consideration about the cloud cover limit of less than 10%. These Landsat images were used because their spatial and temporal resolution is appropriate for the data and period of the study. Five land-use classes were set for the classification, based on historical information on the study area. These include:

- Settlement class, which compromises both rural and urban areas;
- Water bodies, including streams, lakes, rivers, plantations, and reservoirs;
- Vegetation class, made up of various kinds of plantations, crops, harvested land, and forests;
- Bare land, constituting stony waste, sheetrock, sand, gullies, ravines, and abandoned mining pits;
- The mining area was also examined for features such as abandoned tailing dams and waste dump sites.

7. Land-Use and Land-Cover Classification

The land-cover classes were determined using unsupervised classification to obtain an initial knowledge of the land cover in the study area, to guide the collection of the training samples. The training samples for the supervised image classification were collected via the Google Earth Engine platform. Four land-use and land-cover classes were considered, including vegetation, bare ground, settlement, and waterbodies. The random forest and gradient tree boosting algorithms were tested and the best-performing algorithm was used for the classification process. The dataset was split 70–30% for the training and validation, respectively.

8. Random Forest Technique

RF, developed by Breiman [26], is an ensemble learning method for classification and regression. The method combines the bagging sampling approach by Breiman [27] and the random selection of features, introduced independently by Amit and Geman [28] and Ho [29,30], to enable the construction of decision trees with controlled variation. Whilst using the bagging approach, each decision tree in the ensemble is constructed using a sample with a replacement from the training data. Each tree in the ensemble acts as a base classifier to determine the class label of an unlabeled instance. Based on majority voting, where each classifier casts one vote for its predicted class label, the class label with the most votes is used to classify the instance.

RF applications have been developed over the past few years in almost all disciplines. In the field of ecology, Cutler et al. [31] compared the accuracy of RF and four other commonly used statistical classifiers using various species data taken from multiple locations in the United States of America. The results indicated that RF was superior to the other techniques. In the field of astronomy, Gao et al. [32] conducted some experiments on multi-wavelength data classification. The results showed that RF proved effective for astronomical object classification. Boulesteix et al. [33], in the field of bioinformatics, successfully implemented the use of RF and SVM classifiers to improve crop classification accuracy and to provide spatial information on map uncertainty. With the advancement of remote sensing (RS) and deep learning techniques, many methods for revealing land-use changes are accessible [34–37]. In the field of geological modeling, Abert and Ammar [38] applied RF classification and RS in geological mapping in the Jebel Meloussi area. According to Breiman [26], some of the advantages of RF are:

- The accuracy is good and most often better;
- It is faster than bagging or boosting;
- It provides useful internal estimates of error, strength, correlation, and variable importance;
- It is simple and easily parallelized.

9. Classification of Land Use and Land Cover in Emalahleni

The output of the classified images is shown in Figure 2. The random forest algorithm had an overall accuracy of 94.39%, as shown in Table 1, and, therefore, was effective in classifying the land use and land cover in the study area.

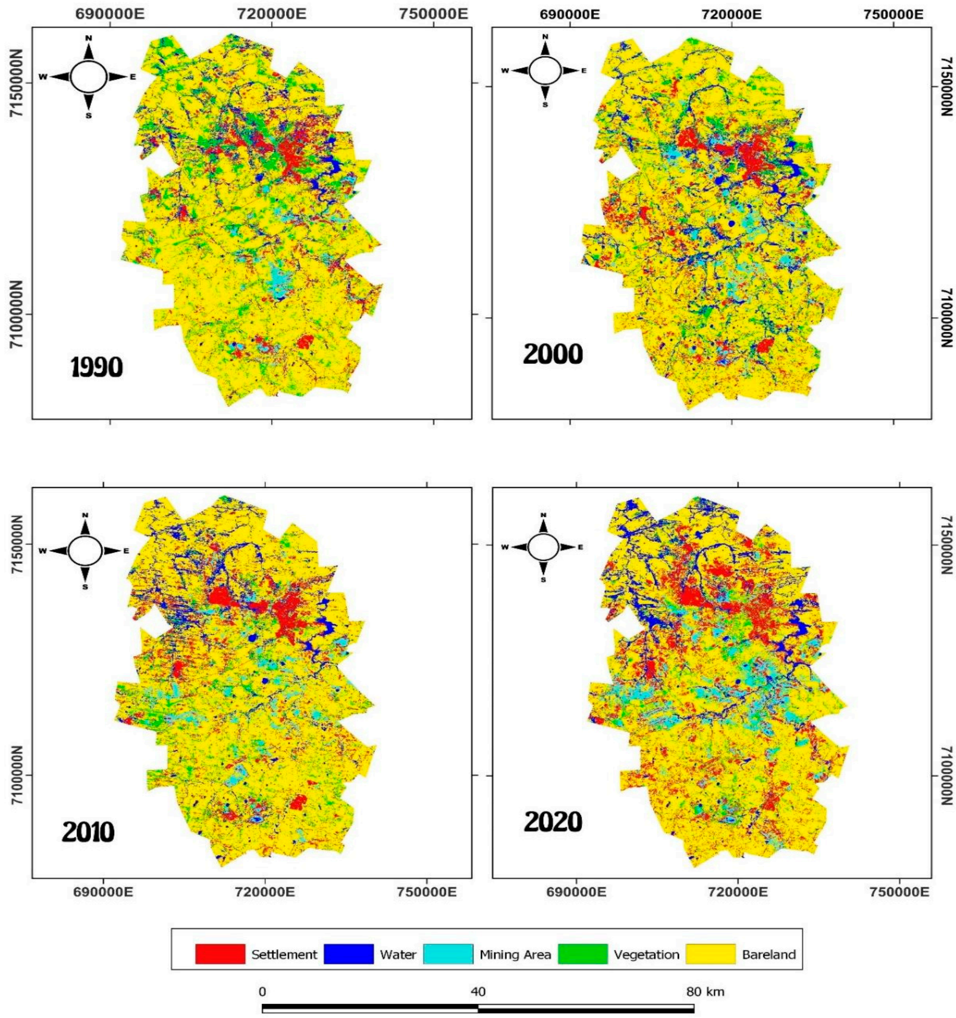

Figure 2. LULC map of Emalahleni from 1920–2020.

The land cover per year (i.e., 1990, 2000, 2010, and 2020) was computed, as shown in Figure 3. A major part of the region is made up of rocky or bare ground, accounting for more than 60% of the total area. There has been an increase in the settlement amount since 1990, with an average percentage growth of 8.4%, and a drastic increase of 15% between 2010 and 2020. On the other hand, the mean proportion of vegetation in the area revealed a gradual decrease from 14.30% to 6.30% as of 2020. The mining activity in the region indicated exponential growth over time, according to the following percentages: 2.7%, 3.6%, 4.0%, and 7.9%, respectively, in 1990, 2000, 2010, and 2020, as shown in Figure 3.

Table 1. Confusion matrix showing classification accuracy.

Confusion Matrix							
	Settlement	**Water**	**Mining Area**	**Vegetation**	**Bareland**	**Total**	**User Accuracy**
Settlement	173	8	1	0	1	183	95.05%
Water	8	166	4	0	5	183	91.21%
Mining Area	1	4	89	1	0	95	90.82%
Vegetation	0	3	0	171	0	174	99.41%
Bareland	0	1	4	0	91	96	93.81%
Total	182	182	98	172	97	731	
Producer Accuracy	94.50%	90.71%	93.68%	98.27%	94.79%		94.39%

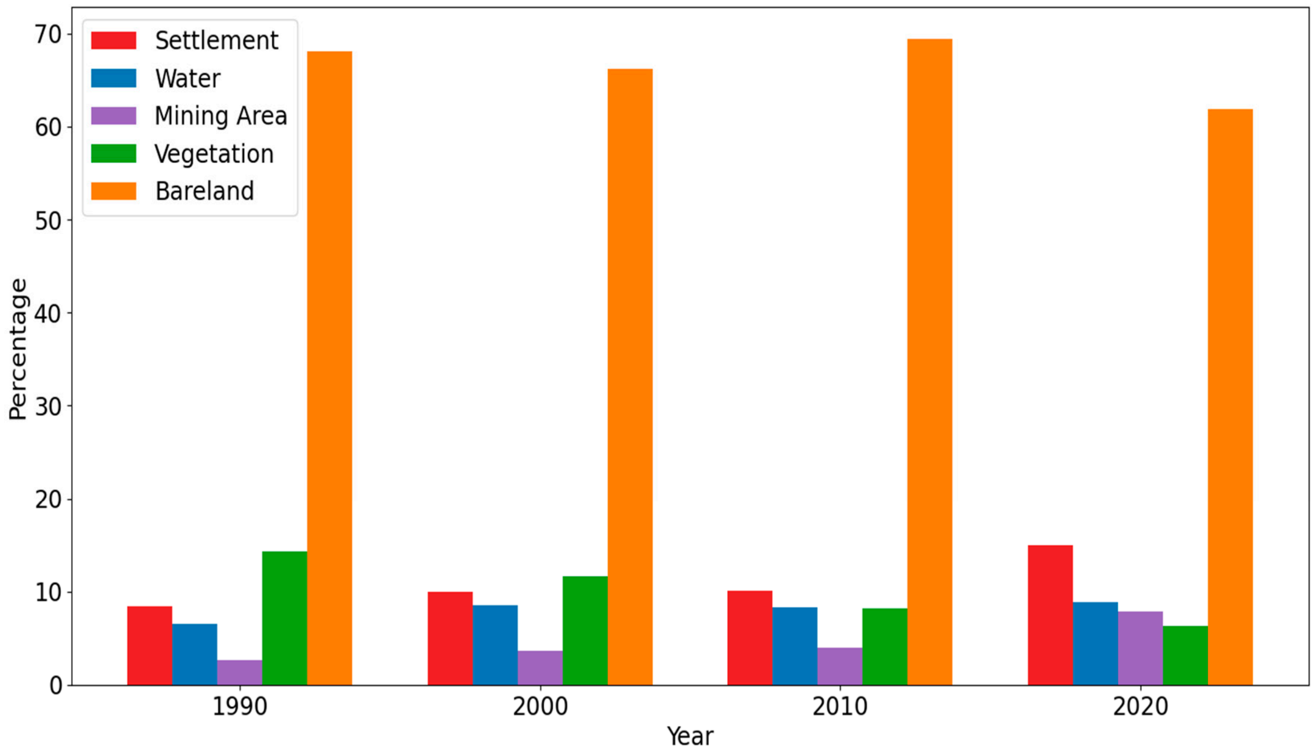

Figure 3. LULC percentage area change in the classified areas from 1990 to 2020.

To determine the percentage area covered by each of the classified lands covered over the study period, the total size of the study area was computed to be 2,678,646,673 m^2. Figure 4 highlights the total area covered by each type of land cover in m^2, from 1990 to 2020. Although there was a steady increase in the total land area covered by settlement, mining, and water over the years, the vegetation areas experienced a decrease in the total area cover. Bareland also revealed a decrease from 1990 to 2000, then appeared to increase slightly until 2010. From 2010 to 2020, the area that was bare decreased sharply.

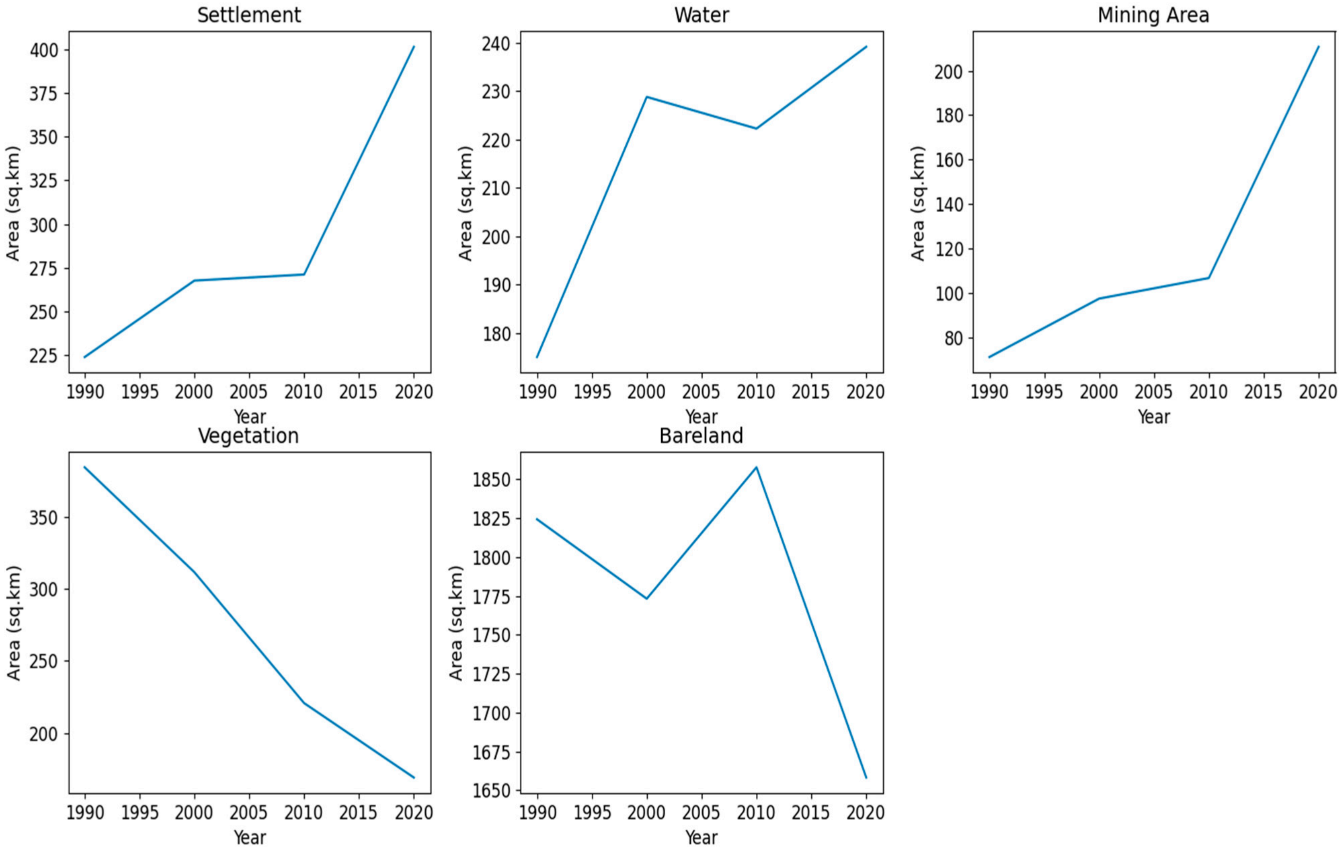

Figure 4. Area performance for each class over three decades.

10. Change Detection

To determine land-cover change that may be attributed to mining over the years, land classification over three decades was performed. A classified image of 1990 served as the baseline image for the change analysis throughout the various study years. In this study, the method of image differencing was adopted, where the baseline image was deducted from the subsequent years. Figure 5 represents the changes in land cover between the years 1990 and 2020.

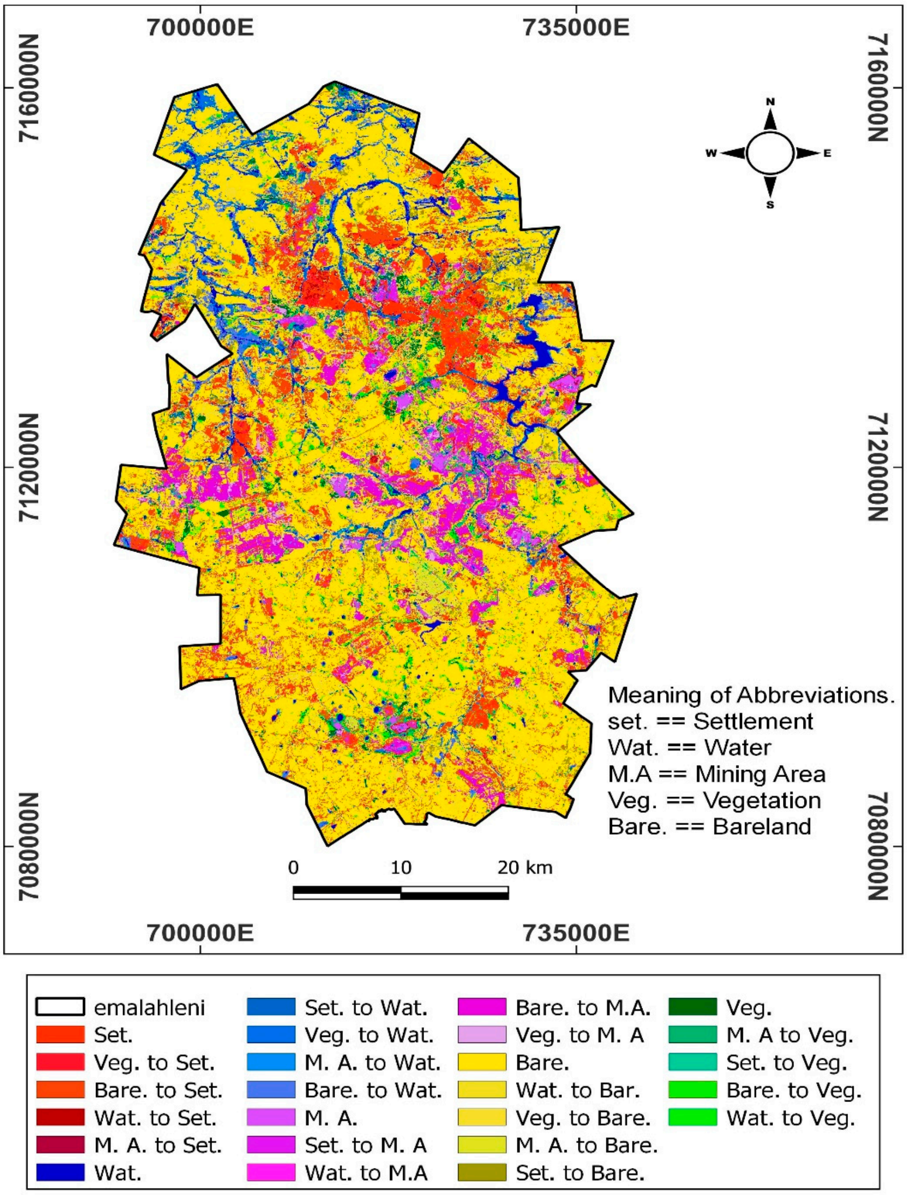

Figure 5. Three decades of LULC change detection.

11. Changes in Mining Activities over Time

The mining activities on the land were examined based on gain, loss, persistence, and not applicable. The categorization of gains and losses was additionally organized according to whether they were positive or negative. Positive gains are any improvements that exclusively serve to make the land greener, such as those involving settlement, water, mining, or the conversion of bare ground for vegetation. Negative loss areas have a significant impact on the local landscape, such as vegetation, settlement, water, or bare terrain being turned into a mining area. Positive losses are those that have a minor impact on the land component, such as vegetation, settlement, or water that becomes bare land. Changes like mining into water, vegetation into settlement, settlement into water, and mining into bare land, all contribute to the improvement of the most vegetated parts of the land, as well as urbanization in the area; these areas were classified as negative gains. Areas that remain constant over time are classified as the persistent category. Classes that are not relevant in terms of mining activities are marked as “not applicable”.

Figure 6 shows that 64.56% of the study area is made up of changes that are not attributable to changes in mining and vegetation land cover or land use. Moreover, 7.66% of the area has been changed from other land uses to vegetation, while 13.40% has been used for mining. In addition, 11.82% of the existing mining areas have been revegetated. Regarding the region's changes, there has been a 13.40% negative gain representing a change from mining to any other land cover type aside from vegetation, 11.82% being a positive loss, representing a 7.65% positive gain, and a 2.56% negative loss, respectively.

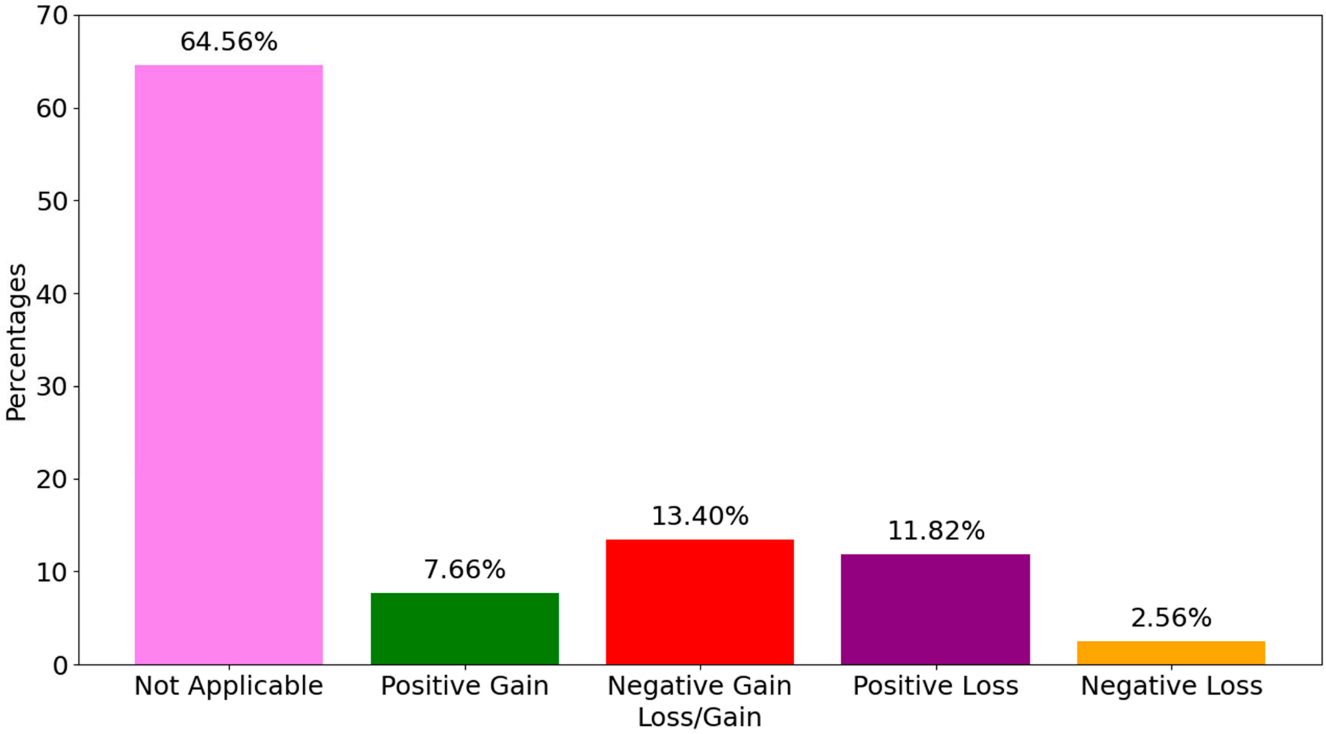

Figure 6. Changes in the study region over three decades.

12. Vegetation Change

From Figures 7 and 8, it can be deduced that approximately 2.4% of the vegetated areas have not changed in the study area over the three decades. A gain of 4.03 to 5% in vegetation was observed, representing areas that have changed from other land cover types to vegetation. However, between 6 to 12% of the original vegetated lands have been lost to other land uses. Figure 8 shows that there has been vegetation loss in each of the investigated decades, with percentages of 12.05%, 8.87%, and 6.06% in 1990–2000, 2000–2010, and 2010–2020, respectively.

Figure 9 shows the vegetation changes over the three-decade period. The vegetation decreased by 10.38% over that time, while increasing by 7.66%, and 3.96% of the vegetation has persisted during these alterations.

From Figure 10, we observed the highest gain in mining activities from 1990 to 2000, while the lowest gain in mining activities occurred from 2000 to 2010, then a sharp increase of 5.65% was experienced from 2010 to 2020. Additionally, the percentage of persistent mining activities in the years 1990–2000, 2000–2010, and 2010–2020 are 0.91%, 1.33%, and 2.21%, respectively (Figure 11). This demonstrates that the mining activities have grown over time.

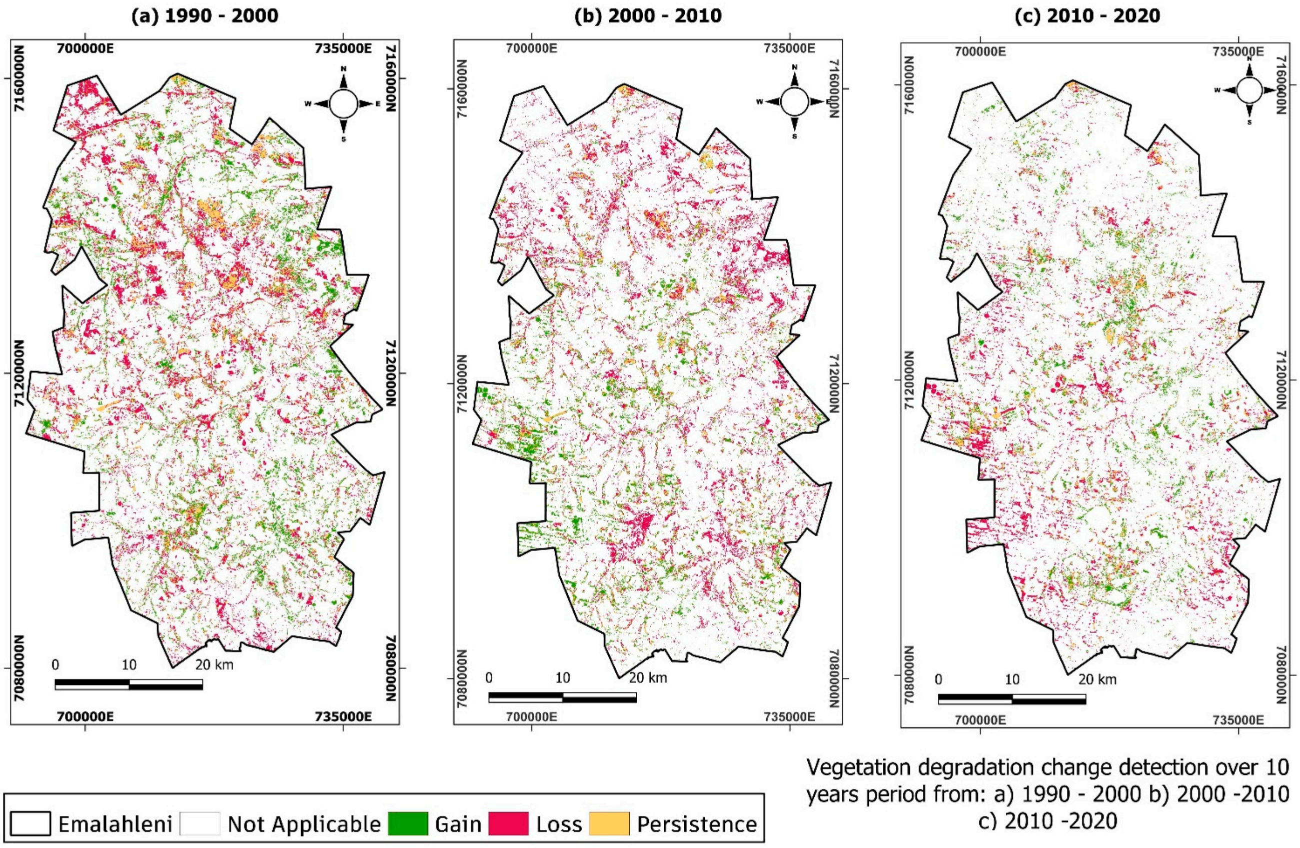

Figure 7. Vegetation change detection in each of the three decades.

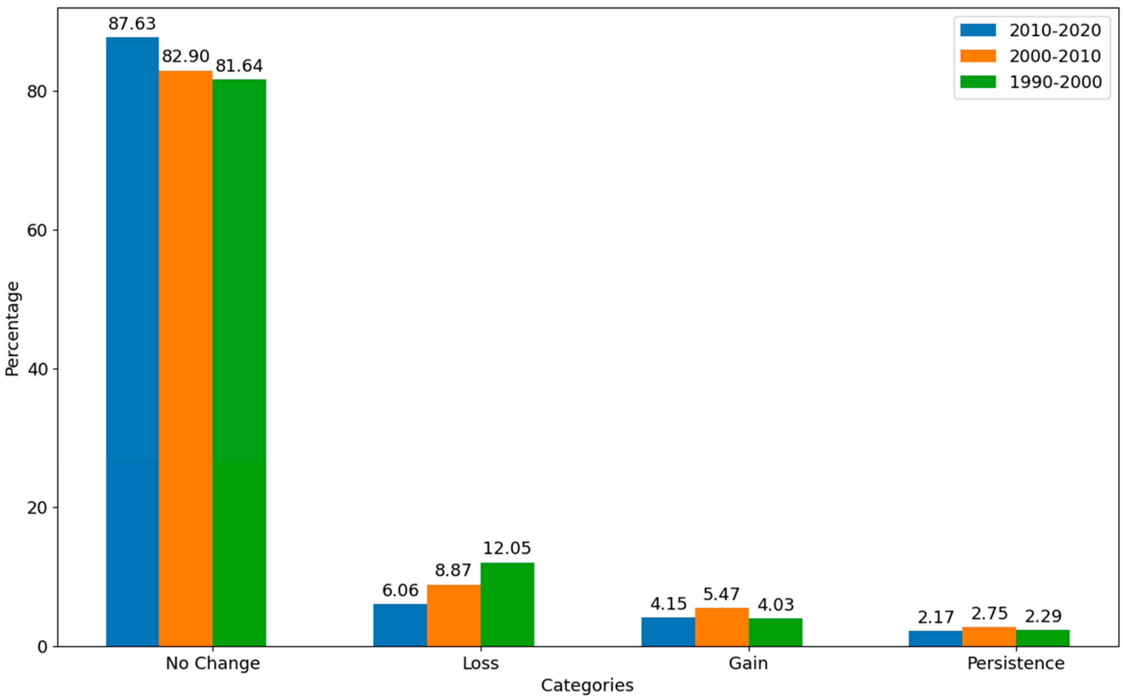

Figure 8. Percentage vegetation change in the decades from 1990 to 2020.

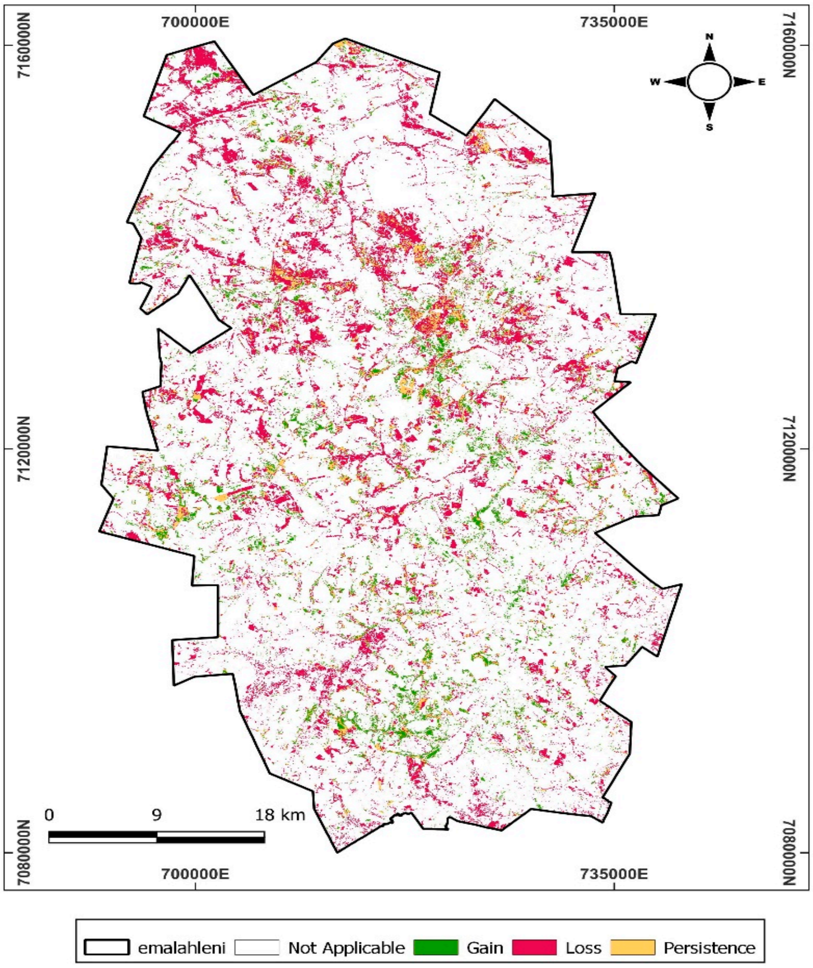

Figure 9. Vegetation changes in the area between 1990–2020.

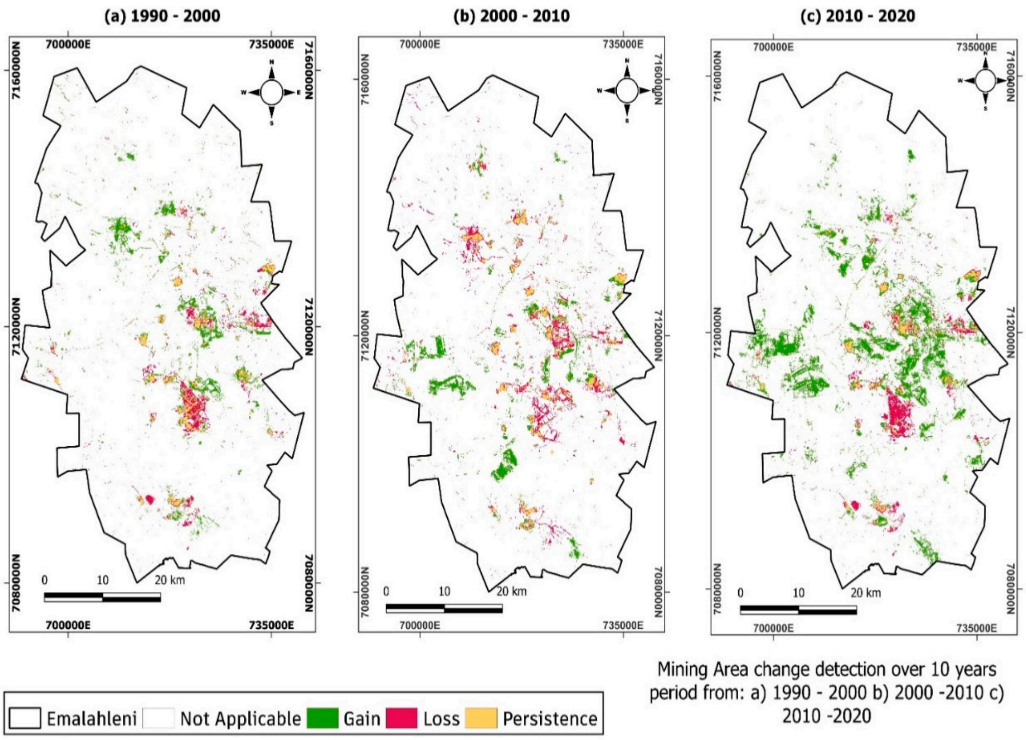

Figure 10. Mining activities change detection in the three decades.

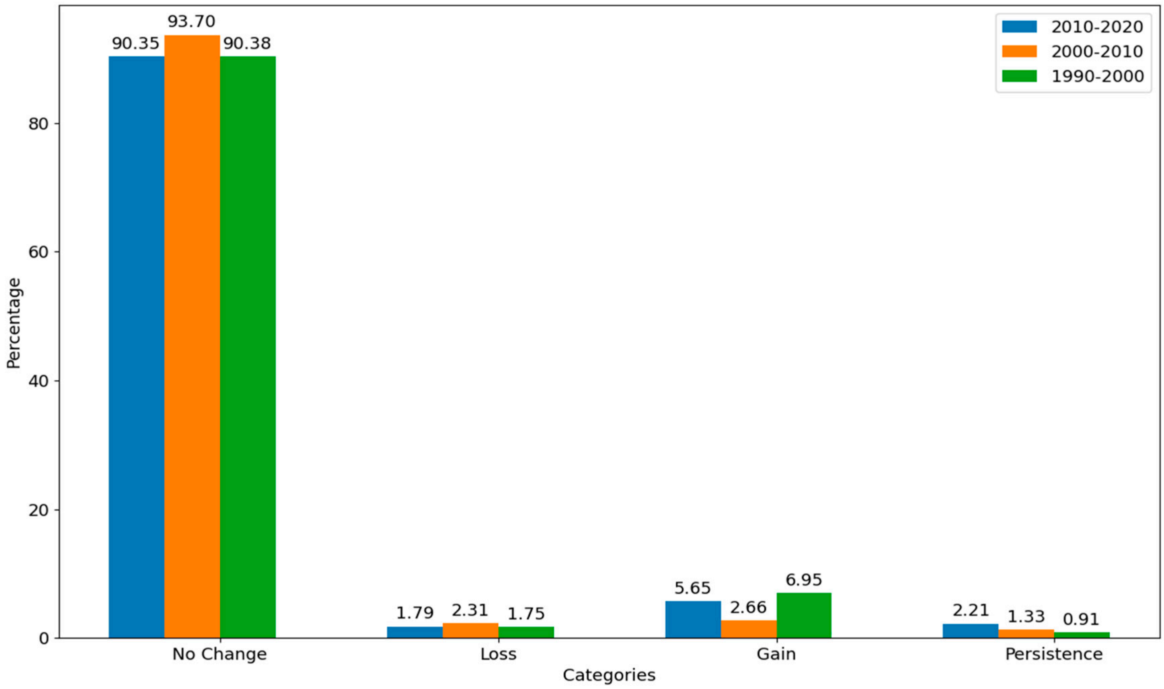

Figure 11. Percentage change in mining activities in each decade from 1990 to 2020.

13. Discussion

The impact of mining on land cover and vegetation dynamics has been of significant concern in South Africa; although mining contributes significantly to the country's gross domestic product (GDP). During mining operations, significant land-use–land-cover change (LULC) occurs as a result of infrastructure that is needed to support the mining operations, such as buildings, tailing dams, and ponds, etc. [39]. To investigate land-use change over the years, this study used Landsat data to examine land-cover patterns and processes over three decades in Emalahleni, South Africa. Using time series data to assess the changes from 1990 to 2020, the results revealed significant alterations to the land cover and vegetation dynamics.

The extent of the change that has occurred in the study area included changes from vegetation land cover to settlement, water, bare terrain, and mining areas. The majority of the study area was found to be rocky or bare ground, accounting for approximately 60% of the total area. In Figure 6, it was also deduced that 64.56% of the study area experienced changes that are not attributed to mining and vegetation land use types (Figure 6).

However, 13.40% of the total area has been used for mining, with the highest gain observed from 1990 to 2000, and the least gain from 2000 to 2010. This supports the findings of previous studies, indicating a continuous increase in mining activities in South Africa and the subsequent impact on the environment. A study conducted by Ochieng et al. [40], indicates that an increase in mining activities in South Africa has resulted in high acid rain drainage into streams/rivers, which threatens the country's scarce water resources.

In contrast, positive gains serve to make the land greener and contribute to urbanization. Figure 5 provides a picture of some gains in vegetation over the years. Additionally, 11.82% of the existing mining areas have been revegetated, while 7.66% of the area has seen changes from other land use types to vegetation, possibly due to reclamation practices. Although this is good, serious challenges remain as rehabilitated lands are not always returned to capabilities equivalent to their pre-mining state [41].

14. Conclusions

This article used the RF algorithm to classify the land use and land cover in the Emalahleni municipality over three decades (1990–2020). The classifications are settlement, water, mining area, vegetation, and bare land. It was deduced that approximately 60% of the study area is made up of bare land. The study further revealed an increase in the settlement from 1990, at a growth of 8.4%, and an increase of 15.0% from 2010 to 2020. Vegetation decreased from 14.3% to 6.3%, also from 2010 to 2020. The mining activities showed a steady increase from 2.7% in 1990, 3.6% in 2000, 4.0% in 2010, and 7.90% in 2020. Change detection maps were created to assess the land-cover changes in the study area over the three decades and the results are depicted in Figures 9 and 11, respectively.

In the author's opinion, the findings in this study highlight the importance of understanding the changes in land use and vegetation cover in the study area and its impact on the environment, as well as the local community. It is crucial to develop sustainable land management strategies that balance economic development with environmental conservation to ensure the long-term viability of the area. The data presented in this study provides a useful baseline for further research and can inform land-use planning and decision-making processes in Emalahleni.

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Conflicts of Interest: The authors have no conflict of interest to declare.

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