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Spatial and Temporal Analysis of the Land Use and Land Cover Changes in Gatumba Mining Landscape, Rwanda

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Abstract

Mining activities are one of the main driving forces of land use and land cover changes. While opencast mining is continuously carried out, land cover change assessment is of paramount importance for sustainable land resource management and use as a tool for policymakers to understand the mining-induced changes and their response to water flow, forest, and soil in a mining landscape. In Gatumba Region of the Western part of Rwanda, mining activities are still inadequately undertaken and the surrounding environment is affected by artisanal and small scale mining practices. Soil erosion, barren waste rock dumps, and polluted rivers reflect the lack of implementation of proper environmental protection measures. This study aims to spatially and temporally analyse the land use and cover changes induced by the mining activities in Gatumba mining landscape for optimization of land use planning and management of the mined and restoring the degraded mining landscapes in Rwanda. Landsat images were used to generate the land use/cover maps for the periods of 1999, 2008 and 2015 by using maximum likelihood pixel-based classification method. The comparison of land use/land cover maps during those periods derived from toposheet and multispectral satellite imagery interpretation indicates that there is a significant increase in bare soil, built-up areas at the rate of 0.63% and 45.43% respectively. Over a period of 16 years, mining areas has increased progressively from 2.85 Km^2 to 5.55 Km^2 representing 3.95% of the total land coverage. The expansion has taken place especially in central and southern part of Gatumba. It is also noted that substantial amount of the agriculture land and forest area vanished during the period of study which may be due to rapid population growth and the development of rural centers. The information obtained from change detection of land use/land cover helps in providing optimal solutions for land management, planning for the mining sites, monitoring of the related environmental effects and restoration of the degraded mining landscapes in Rwanda.

Key words: land use/land cover, Gatumba, Mining, spatio-temporal assessment,

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1. Introduction

In developing countries, mining activities are currently practiced in poor and inadequate manners but they are productive indeed. There is no doubt that mining sector is crucial for those living, working and investing in developing countries (Amponsah-Tawiah and Dartey-Baah 2011). Mining tends to make a notable impact on the environment which may vary in severity depending on whether the mine under exploitation or abandoned, the mining methods used, and the geological condition of the mining areas (Mondal, Chakravarty and Bandayopadhyay 2013, Mondal, Chakravatry and Bandayopadhyay 2014). In Rwanda, mining activities are mainly competing with agricultural land uses and often results in significant and irreversible impacts on the environment (Haidula, Ellmies and Kayumba 2011). The discovery of mining deposits or small mineralized veins in an agricultural land and in forests lead to the abandonment of cultivation practices for artisanal mining to develop. It may pose critical questions on the survival of farmers or forest owners surrounding the mining who mainly rely on agriculture, cattle farming and small services. The legacy of bad mining practices from colonial and immediate post-independence era in Rwanda has left behind waste dumps and degraded landscapes adjacent to or near current mining operations. This explains why the environmental impacts from mining in Gatumba region remains a sensitive topic as mining practices are still inadequately developed and the environment suffers from the artisanal and small scale mining activities (Haidula *et al.* 2011).

Some of the impacts of mining on land surfaces in Gatumba region include the destruction of natural ecosystems through the removal of soils and vegetation (Byizigiro 2016, Byizigiro, Raab and Maurer 2015). These impacts also include among other haphazard excavations with no land reclamation plan, loss of vegetation, landforms alteration, accelerated soil erosion, interrupts ecosystem fluxes, loss of valuable farmland rendering the sites dangerous to use for other purposes (Byizigiro, Biryabarema and Rwanyiziri 2020). Near Mukura and Gishwati Forests, mining activities exerted a negative effect on landscape through destruction of vegetation cover, creation of rills, gullies, and scars that accelerate erosion and landslides. In some points, eroded materials contribute to the disruption of the drainage system. Mining also resulted into degradation of soil physicochemical properties and contamination by metals and metalloids, and the loss of agricultural land by accumulation of sandy overburden and mine tailings that are prone to erosion. Such a soil will hardly retain soil nutrients and water

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necessary for the plant growth, hence reduced vegetation cover and increased downstream erosion, modification of physico-chemical properties of water, siltation and sedimentation of streams and flooding risks (Nsanganwimana, Muhire and Manirakiza 2018).

The development of gullies following the excavation sometimes create sinkholes (Byizigiro *et al.* 2015). On the other hand, Macháček and Dušková (2016) illustrated how the mining of tin, tantalum and tungsten (3Ts) minerals provides positive business opportunities for the local population, while causing negative impacts on the environment. Problems with erosion that deflect the flow of rivers and increase the levels of suspension and sedimentation in river basins are the biggest environmental problems connected with artisanal and small-scale mining as observed in Rutsiro mining area in Rwanda. Despite these problems, artisanal and small-scale mining provides a possibility of increasing economic growth and securing the basic needs of local inhabitants (Macháček and Dušková 2016). A digest of environmental impacts of alluvial artisanal and small-scale mining with a focus on anthropogenic influences on topography with regard to the methods used in raw material mining was provided by Macháček (2020) and Muhire *et al.* (2021). The authors draw on a case study from the mining site of Rutsiro district in Rwanda where alluvial artisanal mining in a riverscape lead to the changes in landscape structure, deforestation, intensification of geomorphological processes, new relief shapes (such as erosion depressions, check dams, gravel benches, anthropogenic channels) and hydrological river regime, chemical pollution of soil and watercourses (Macháček 2020).

If not permanent, the negative impacts of mining can last for many years. This necessitates the management of mining sites in an exemplary manner, during and after mining in conformity with existing mining regulations. The change of existing land use or securing access to land to allow mining activities can be controversial for communities who may be affected (AGA 2009). For instance, open cast mining encroaches on arable lands which are zoned for farming. Many trees and forests are cut down making the place more susceptible to soil erosion thereby reducing the soil fertility. Minerals extraction leads to sub-optimal and much reduced farming activities and agricultural production due to land clearance, soil erosion and landscape degradation. Mine sites in Rwanda are mostly located close to farms with some agricultural activities taking place directly in the proximity of mine waste deposits (Haidula *et al.* 2011). These conflicts between mining and agriculture end up with some households being relocated and land users being expropriated. The lack of proper rehabilitation of sites formally exploited by some companies has exacerbated the problem of top soil losses because heavy rains continue to wash away top soil on unprotected mining sites (Byizigiro *et al.*, 2015).

In Gatumba region there are no sufficient monitoring practices of mining activities as remarked by the author above in 2014. Such harmful habits lead to a messed up and damaged environment. A large amount of waste has been generated in the form of soil and rock debris during mining, tailings from the processing plant and waste water from several operations. Some of this waste is easily washed into the rivers, compounding the already critical erosion on the steep of highly cultivated slopes (Biryabarema, Rukazambuga and Pohl 2008a, Biryabarema, Rukazambuga and Pohl 2008b). The overburden of rare-metal mines when dumped in unmined areas creates mine spoils which ultimately affects the surrounding vegetation (Singh, Singh and Singh 2010, Byizigiro *et al.* 2020). Limited attention has been attributed to such practices as no study has been undertaken to assess the spatial temporal evolution of mining activities on land use/land cover change in the study area. A comprehensive method to assess spatial temporal land use/land cover changes is the aim of this research in Gatumba region. In this regard, by classifying and interpreting Landsat Images of 1999, 2008 and 2015 land use/land cover (LULC) changes were noticed. The information obtained from change detection of land use/land cover helps to optimize land management options, planning for mine sites, monitoring environmental effect of mining and restoring the degraded mining landscapes in Rwanda. The results of this research highlight the significance and implication of future mining expansion and associated land use/land cover changes in order to bridge the knowledge gap in terms of artisanal and small-scale local mining activities and the status of environmental protection practices.

2. Methods

2.1. Study area

The study area covers the former Gatumba mining concession, one of the largest formerly Rwandan Government owned concession with a surface area of 26,000 hectares extending in Ngororero and Muhanga Districts. The minerals exploration in Gatumba mining site has been done between 1926 and 1954 in Western of Rwanda. Gatumba region is characterized by pegmatites that are variably mineralized in columbite-tantalite and/or cassiterite. Beryl, amblygonite, spodumene, apatite and Li-phosphates seem to form the most important

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accessory minerals (Dewaele *et al.* 2010). According to Lehmann *et al*. (2013), the pegmatites of Gatumba concession has been exploited by Belgians private companies untill the time of SOMIRWA creation in 1973. Mineral deposits of Gatumba region has been studied and described by many authors:Polinard (1950), Thoreau and Delhal (1950), Varlamoff (1955), Bertosa (1961), J. Gérards (1965), Dewaele *et al*. (2011) and Pohl (1994). Gatumba pegmatites field has an 80-years history of artisanal and semi-industrial coltan and tin mining (Lehmann *et al.* 2013). Mine sites that have been mined out by large mining interests may still hold value for small-scale operators (ICMM 2011). Figure 1 shows the location of the study area in Rwanda.

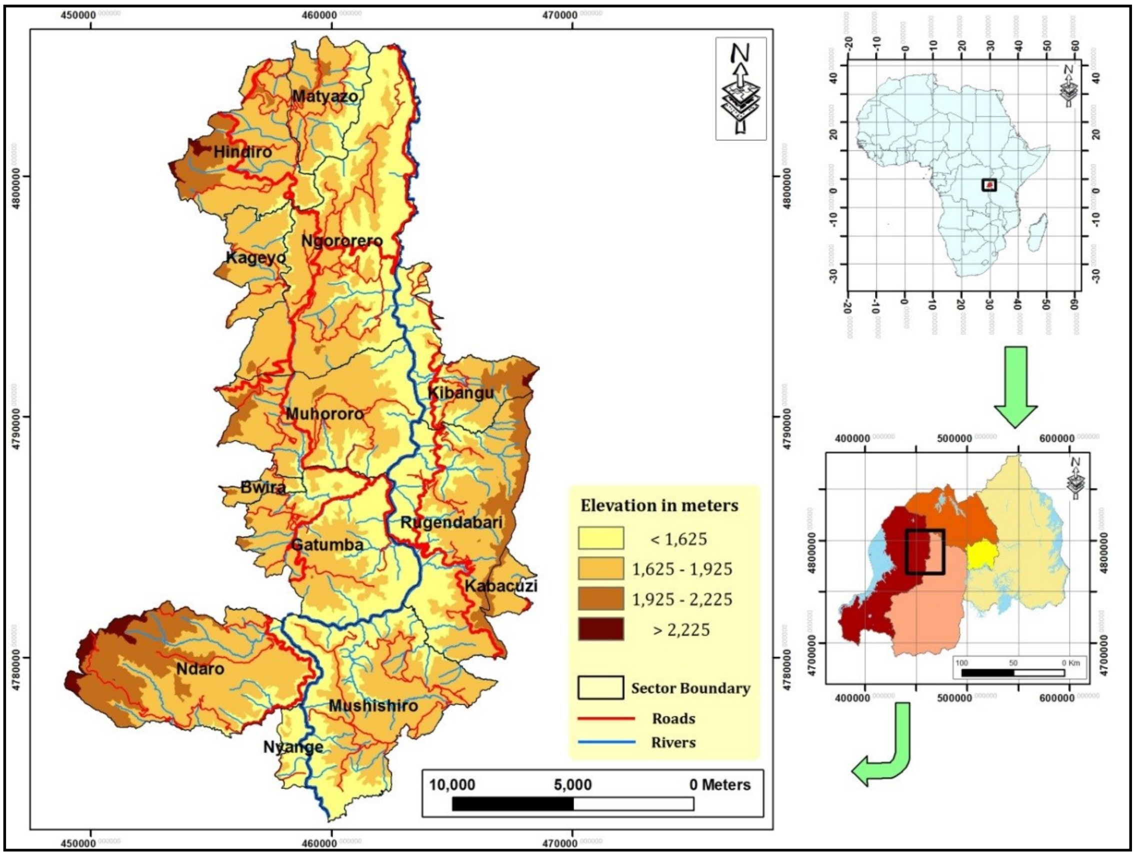

Figure 1: Location of the study area in Rwanda
Source: Rwanda Natural Resource Authority, 2005

Before the privatization of mining concessions in 2007, Gatumba concession was developed in artisanal way by subcontractors as well as independent mining companies which operated from outside of the concession. From 2008 until 2014, Gatumba concession has been managed by a Private Company with a joint venture with the Government of Rwanda to form "Gatumba Mining Concession" (GMC). In 2014, the joint venture failed untill the concession was split into medium to big perimeters granted to Private Mining Companies. Concerning mining sites,

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mining activities are practiced in many corners of Gatumba region. The pegmatites of Gatumba region have historically been mined for their columbite-tantalite and cassiterite mineralization (Dewaele *et al.* 2011). This indicates that mining activities have been key for local employment and development and the region offers a good case for the evaluation of long term impact of mining activities.

2.2. Primary data acquisition

Primary data collection focused on collecting Ground Truth data and verifying the extent of abandoned and current mine sites. It also consisted in vectorization of mine sites from topographic maps (1988), aerial photographs taken in 2008 and 2014 Google earth maps. Handheld GPS, digital camera, sampling segment maps (showing current land use/land cover), drawing kit, field work tablet with GPS built-in, geological hammer, compass and field template to get details of the ground truth data were used. For the analysis of land use/land cover classification, field observation, identification and description of the current land use/ land cover patterns were conducted using prepared template. The sampling frame approach was applied to cover the whole study area. The sampling took into account the area of Gatumba and the population (Delince 2003). Figure shows the area frame, sampling segments and sampling points.

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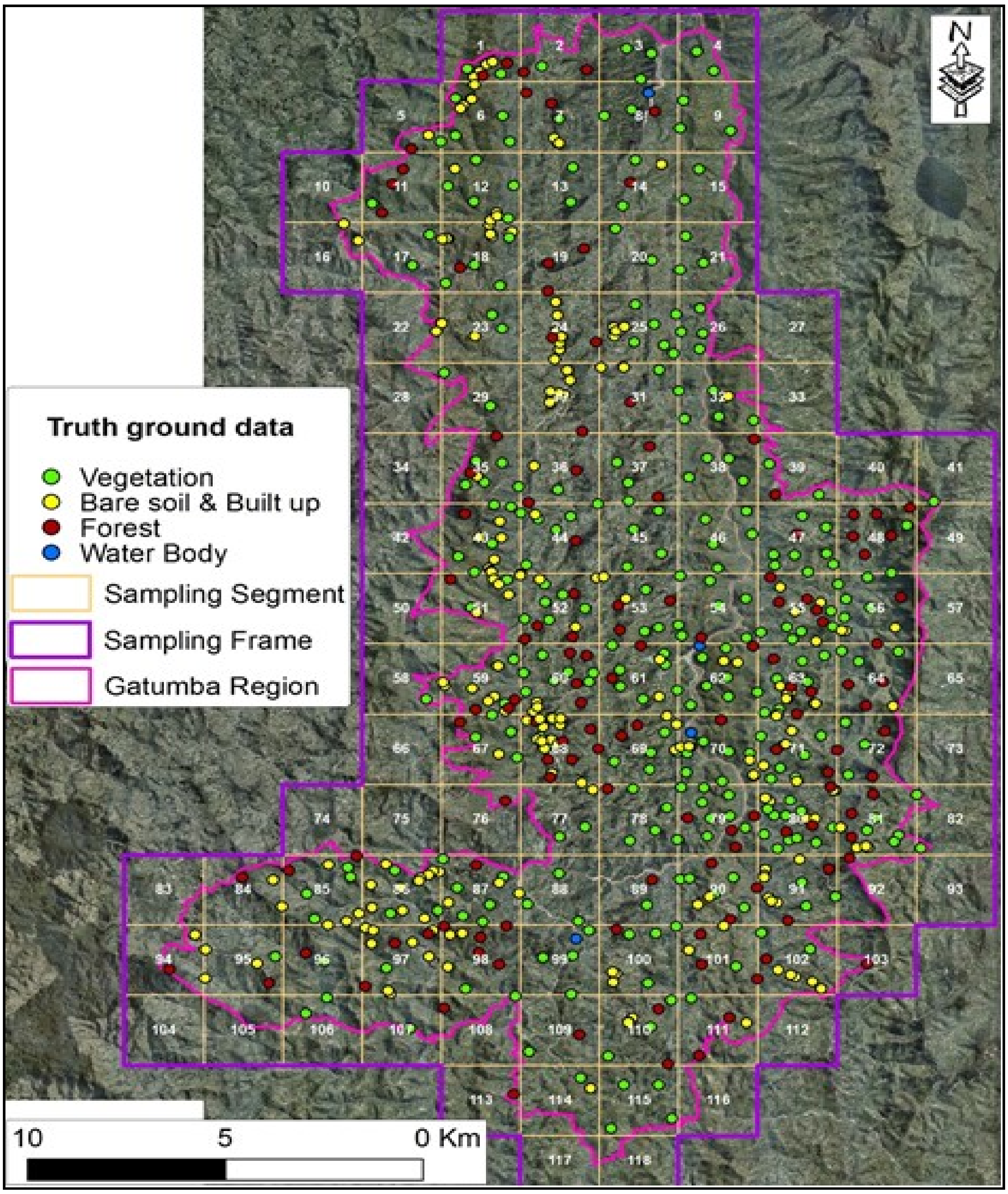

Figure 2: Sampling segments and related points
Source: Rwanda Natural Resource Authority, 2008

The used approach of sampling segment consists of dividing the region into pieces or segments with regular or irregular shape (Gallego 1995). Some mine sites were delineated in the office but as long as mining activities were still dynamic, new entries have been found and added on printed maps for further updates. Common sample grids of 2 km x 2 km were used and 109 sample segments were produced and covered. For the purpose of adequacy in sampling, about 82% of the total areas have been checked and covered. Figure 2 shows the area frame, sampling segments and sampling points. A total 631 ground truth data was collected, including roughly 70% for training and 30 % for validation per each land cover type; 212 built up, 282 vegetation,

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133 forest cover and 4 for water bodies.

2.3. Secondary data acquisition

The satellite images from Landsat 4-5 TM, Landsat 7 ETM+ and Landsat 8 OLI/TIRS recorded within the periods of 1999 until 2015 are the main source of information. They have been downloaded from geo-information portal of USGS (United States Geological Survey). The accessed Landsat images were all recorded on “path” 173, “row” 61. The first image used was recorded in December 1999 with clouds less than 10%. The second image was recorded in September 2008 with clouds less than 50%. The third image taken was recorded in October 2015 with clouds less than 10%. These images are in false color composite from 4-3-2 band combination for Gatumba region. High resolution image covering the zone of interest was recorded in 2008 by the Swedish Survey and another image recorded in 2014 by Geoimage (Data type: Pleiades imagery) covering the western part of Rwanda where Gatumba region is located were used. Other spatial data included administrative boundaries and mining license cadastral data. Mineral map was used to highlight the occurrences of mineable resources. The use of various datasets in this study enriched the analysis of mining challenges in Gatumba.

The selection of time spans used was linked to significant episode of mining activities in Rwanda and the quality of available Landsat images. The year 1999 has been selected to evaluate the status of mining activities after the 1994 Genocide. Secondarily, the period of 1999 is one year before the so called “*coltan boom*” in Rwanda between 2000 and 2002. During this period, local minors have been involved in artisanal and informal mining after panning sands from rivers and digging in mountains to get minerals. The year 2008 has been preferred to evaluate the mining activities after the privatization of Gatumba mine concession in 2007. Since then, local operators started to create mining companies and cooperatives in order to formalize the business of minerals. In 2014, the mining sector yielded 52% of the export compared to share of coffee and tea and it turns 26% of the total value of export while incorporating all products including tourism. The year 2015 has been selected to evaluate the current status of mining activities considering that from 2009 the number of private companies started to increase. Technically, the selection of Landsat images was based on the availability of corresponding high-resolution images for validation, images without strips or uncovered lines and images without clouds and hazes. Table 1 shows the summary of the characteristics of the spatial data sets and satellite images that have been used in this study.

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Table 1: Spatial datasets and satellite images that have been used

Dataset	Time recorded	Resolution	Source	Particularity	Target
Landsat 7 ETM+	06-December-1999	30 m	USGS	Pan-sharpening to 15 m Resolution	To create land use/land cover maps
Landsat 5 TM	17-September-2008	30 m	USGS	*Not Pan-sharpenable*	
Landsat 8 OLI/TIRS	07-October-2015	30 m	USGS	Pan-sharpening to 15 m resolution	
Aerial Photography	1974	2 m	RNRA		Verification and validation of processing results, Field survey preparation
Aerial Photography	2008	0.25 m	RNRA		
Aerial Photography	2014	0.50 m	RNRA		
Topographic map	1988	1/50,000 Scale	RNRA		Gather mines, mineral information
Mineral map	1982	1/250,000 Scale	RNRA		

The figure 6 shows the geo-processing steps of Landsat images to produce accurate land use/land cover map. It highlights the inputs data, the processing and classification methods and the results after classifying the satellite images.

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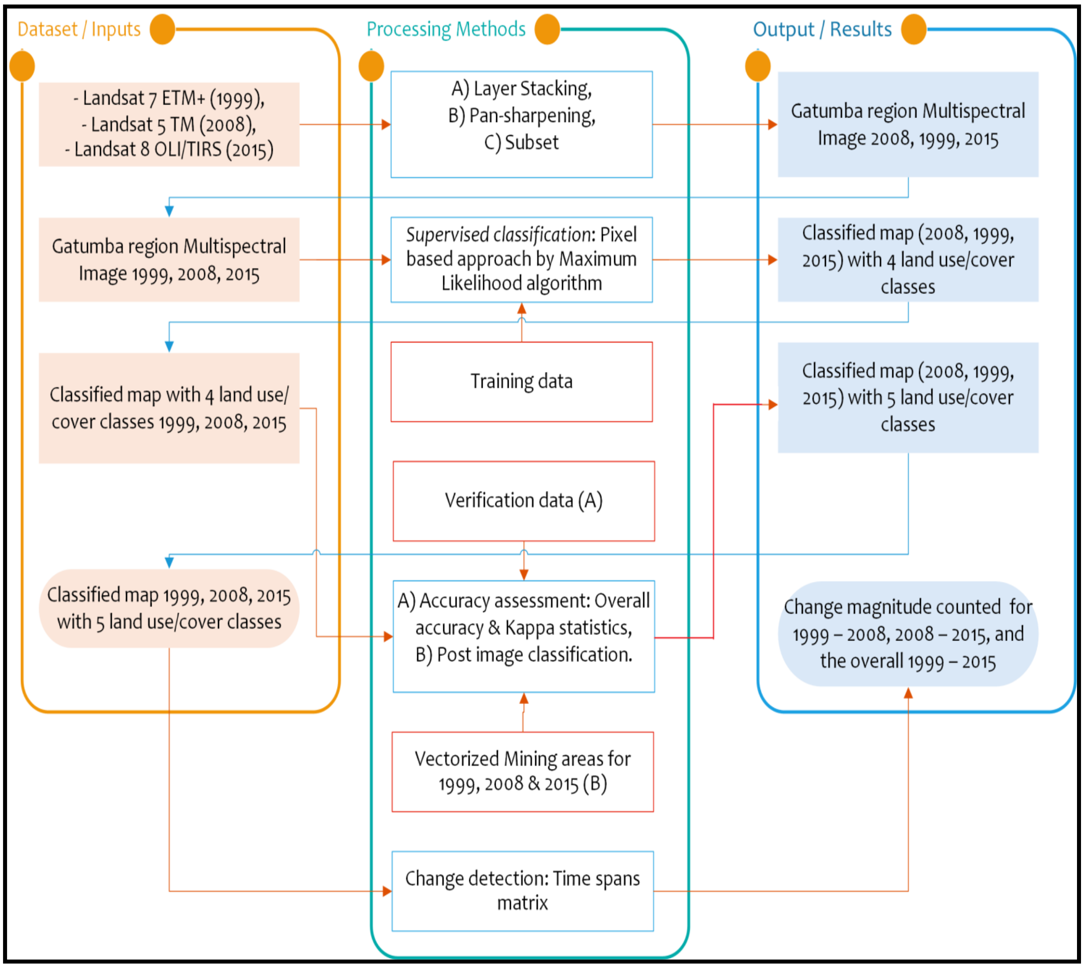

Figure 3: Flowchart for land use/land cover mapping

2.4. Integrating Multispectral Satellite Images

Pixel-based image classification is commonly applied to obtain thematic classes from multi-band Satellite images (Lillesand and Kiefer 2000). Pixel-based classification employs digital spectral data values (Digital Numbers) laid in the images and categorizes those according to spectral similarity with predefined land cover classes (Rafieemajoomard *et al.* 2019). It generates spectral classes where each pixel is assigned only to one class. The supervised classification uses the selected pixels that represent land cover features that the analyst well recognizes. The training samples of objects of interest can be identified from image or from aerial photographs, ground truth data, topographic or cadastral maps. The result of training is a set of signatures that defines the training samples. Parametric signatures include statistical parameters in each band for each sample such as the number of bands in the input image, minimum and maximum data file value (minimum vector and maximum vector), mean data file value (mean vector), covariance matrix and the number of pixels (ERDAS, 1999). Non-parametric signatures are based on discrete objects (polygons or rectangles) in a feature space

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image. These feature space objects are used for defining boundaries of classes. When both types of signatures are used during image classification process, class definitions are more analysed and visualized compared the results when type of signature are used independently (Sanchez and Canton, 1998). There are several classification algorithms, but the commonly used parametric decision rules are Minimum Distance and Maximum Likelihood (Bakx *et al.* 2013, Lillesand and Kiefer 2000).

A plenty of land cover change detection techniques have been developed such as algebra, classification based, visual analysis as well as GIS. Algebra technique includes algorithms that are based on combining values of a pixel in subsequent images (Kishor and Singh 2014). Algebra category includes image differencing, image rationing, vegetation index differencing, image regression and change vector analysis. This method is often used in detecting a very specific change, such as detection of forest fires, deforestation mapping as well as detecting vegetation change. However, applying algebra methods, except vector analysis, a complete identification of the nature of the changes is absent, meaning that a complete matrix change is impossible. Classification-based change detection involves some kind of classification of separate or combined images. The most commonly used technique in this category include post-classification comparison approach.

2.4.1. From pre-processing to post-classification

2.4.1.1. Image pre-processing

High resolution images of 2008 and 2014, Landsat data: Landsat 5 TM (2008), Landsat 7 ETM+ (1999) and Landsat 8 OLI/TIRS (2015) were used. The Landsat images were downloaded in format of TIFF as separated band by single color composite. Since Landsat image of 1999 and 2008 were covered by few clouds in the eastern part of the study area, the field check was an appropriate way to identify what is under the cloud on the image. The separated bands of the same period have been combined in order to get a multispectral image of Gatumba mining area. For Landsat 5 TM and Landsat 7 ETM+, the layer combination process included band 1, 2,3,4,5 & 7. For Landsat 8 OLI/TIRS, layer stacking process involved band 2, 3,4,5,6 and band 7 depending on the study of land use/land cover patterns. Before the subset of Landsat images of 1999 and 2015, the spatial resolution was increased from 30 m to 15 m by the process of pan-sharpening using the remaining band 8 contained by each time

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span. After that, the subset process involved the pan-sharped images for all time spans with the boundary of the Gatumba region.

2.4.1.2. Image classification

Generating land use/land cover maps was done using the pixel-based approach via supervised classification. Truth ground data were used to delineate training areas on the multispectral images by visualizing the false color composite result of 4-3-2 as RGB order combination. By using ERDAS Imagine 2011 software, each pixel was classified according to the assigned value of spatial spectral. The similar pixels have been grouped to define the pretended land use/land cover class that are easily recognizable. Therefore 4 important classes were identified based on common physical character and spectral values: *bare soil & built up class* incorporated mining areas, barren land, roads, non-cultivated farm and built up land. *Water body class* combined rivers, streams, reservoirs and ponds. *Forest class* englobed dense forest, open forest, scrub forest and forest plantation, and *Vegetation class* fused mining areas, cultivated farms, small scrubs, pastures and green covered grounds. It was particularly difficult to precisely distinguish the non- cultivated farm, bare land and mining sites cover types based on colour tones and texture information from Landsat images. To overcome the issue, mining sites were manually digitized to distinguish it from non-cultivated and bare land by a visual image interpretation and field work.

2.4.1.3. Accuracy assessment

Since the classified image is based on samples of few classes, the quality of the classification result needs to be assessed by comparing the output classified image with true real world data (Lillesand and Kiefer 2000). The most commonly cited measure of mapping and classification accuracy is the overall accuracy, or proportion of correctly classified (PCC) derived from an error matrix. Overall accuracy is the number of the correct classified pixels divided by the total number of pixels checked. Another widely used indicator of accuracy assessment obtained from error matrix is the Kappa or k coefficient. The following equation is used to compute the kappa coefficient (Bakx *et al.* 2013).:

$$k = \frac{N \sum_{i=1}^{r} Xii - \sum_{i=1}^{r} Xi + X + i}{N^2 - \sum_{i=1}^{r} Xi + X + i} \qquad [1]$$

where: r: The number of rows and columns in error matrix; Xii: The number of observations in row i and column i; Xi+: The marginal total of row i; X+i: The marginal total of column i;Xij: The number *of observations in row i and column j; Xj+: The marginal total of row j; N: The total number of observations.*

Kappa coefficient indicates the proportionate reduction in error produced during the classification process compared with the error of a completely random classification. For instance, a value of 0.91 means that the classification process is avoiding 91 percent of the errors that a completely random classification produces.

2.4.1.4. Post classification

The classified images often manifest a mixture of misclassified pixels due to the inherent spectral variability. Therefore, it is valuable to enhance the classification by filtering the classified output to show only the dominant classified pixels (Ruchika Chandel 2013). To achieve this, the most commonly used method is majority filtering, which involves a moving window pixel kernel. Lillesand and Kieffer (2000) showed that smoothing image using major filtering is effective for removing misclassified pixels and eliminating noise in the post-classification of image output. Fuzzy classification algorithm is one method that is more sensitive to the imprecise nature of that case (Brandt and Mather 2016). Fuzzy algorithm operation creates a single classification layer by calculating the total weighted inverse distance of all the classes in a 3*3, 5*5 and 7*7 moving window of pixels. In this process, a class with a very small distance value remain unchanged while classes with higher distance values change in the neighbouring values. This is completed if there are a sufficient number of neighbouring pixels with class values and small corresponding distance values. The following equation is used in the process (ERDAS, 1999):

$$T[k] = \sum_{i=o}^{s} \sum_{j=o}^{s} \sum_{l=o}^{n} \frac{w_{ij}}{D_{ijl}[k]} \quad [2]$$

where: i = row index of window; j = column index of window; s =size of window (3, 5, or 7); l = layer index of fuzzy set; n = number of fussy layer used; w=weight table for window; k = class value; $D[k]$ = distance file value for class k; $T[k]$ = total weighted distance of window for class k The centre pixel is assigned the class with the maximum $T[k]$.

After checking the accuracy, the post classification 3*3 moving window smoothing filter was applied to remove unneeded pixels to improve the classification accuracy. A fuzzy algorithm of 3*3 window size (eight surrounding neighbourhood) followed by vector overlay rectification (using forest and wetlands datasets) were applied for Landsat classified images. Features such as mines and roads were hard to detect automatically on Landsat images given the lack of spectral information variability. It was particularly difficult to reliably distinguish bare land and mining areas based on colour tones and texture information. For post-processing a visual interpretation via vector overlay rectification was applied to identify the mining areas between bare land and mines). Historical mining sites consisting of quarries, overburden dumps and abandoned sites were digitized based on the historical aerial photographs, topographic and geological maps from 1974 to 2008 where mining sites were marked. For 2009 and 2015, mining areas were identified based on the corresponding Google earth image and own field observations. Finally, each classified map among the distinct time spans had 5 classes after the consideration of mining areas class.

2.4.1.5. Assessing environmental impact of mining activities

To ascertain the environmental impact caused by mining activities in the region, the questionnaire and focus group discussion were used. Focus Group Discussions (FGDs) were held with selected people involved in mining activity including miners and their leaders selected from each mining site. Interviews with Key informant were conducted targeting mainly experts with deep understanding of mining activities in Rwanda and specifically in Gatumba concessions.

2.4.1.6. Land cover change detection

In this study, the post-classification comparison was used to compare the images that are classified separately and classification outputs images at different dates. This is the most applied method as it provides a complete change matrix (Lillesand and Kiefer 2000). The change matrix was performed by map-to-map operations. Two times spans among three were compared between each other. Pixel algorithms were made for 1999-2008, 2008-2015 and the overall comparison for 1999-2015. The changes and trends of mining activities as well as land use/land cover patterns were compared, analyzed, counted, displayed and explained.

3. Results and discussions

3.1. Land use/land cover patterns

The study area covers the total counted area (after classification) reaching 316.24 Km^2. It reveals that mining areas occupied 0.91% of the total area of Gatumba region. Water bodies reached 0.92% while bare soil and built-up areas engaged 9.35% of the total area. Forests and vegetation occupied the biggest areas, a very common aspect in rural areas. In 1999, agriculture

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practices were dominant more than any other sector. The proportionality from the lower occupier to the highest occupier indicated that mining activities occupied small areas, followed respectively by water body and the bare soil and built-up class. The 1999 distribution of land use/land cover patterns shows that, mostly the forest is seen in the south-eastern part of the study area. The forested areas extend in Rugendabari, Kibangu and Mushishiro Sectors and in the mountains of Ndiza. Ndaro, Kageyo and Matyazo Sectors. Vegetation namely cropland was almost everywhere in Gatumba region. The concentration of mining activities lies mainly in Gatumba, Muhororo, Rugendabari and Ndaro Sectors. Other sectors are represented in minority though there were no mining activities in Hindiro, Kageyo and Matyazo Sector.

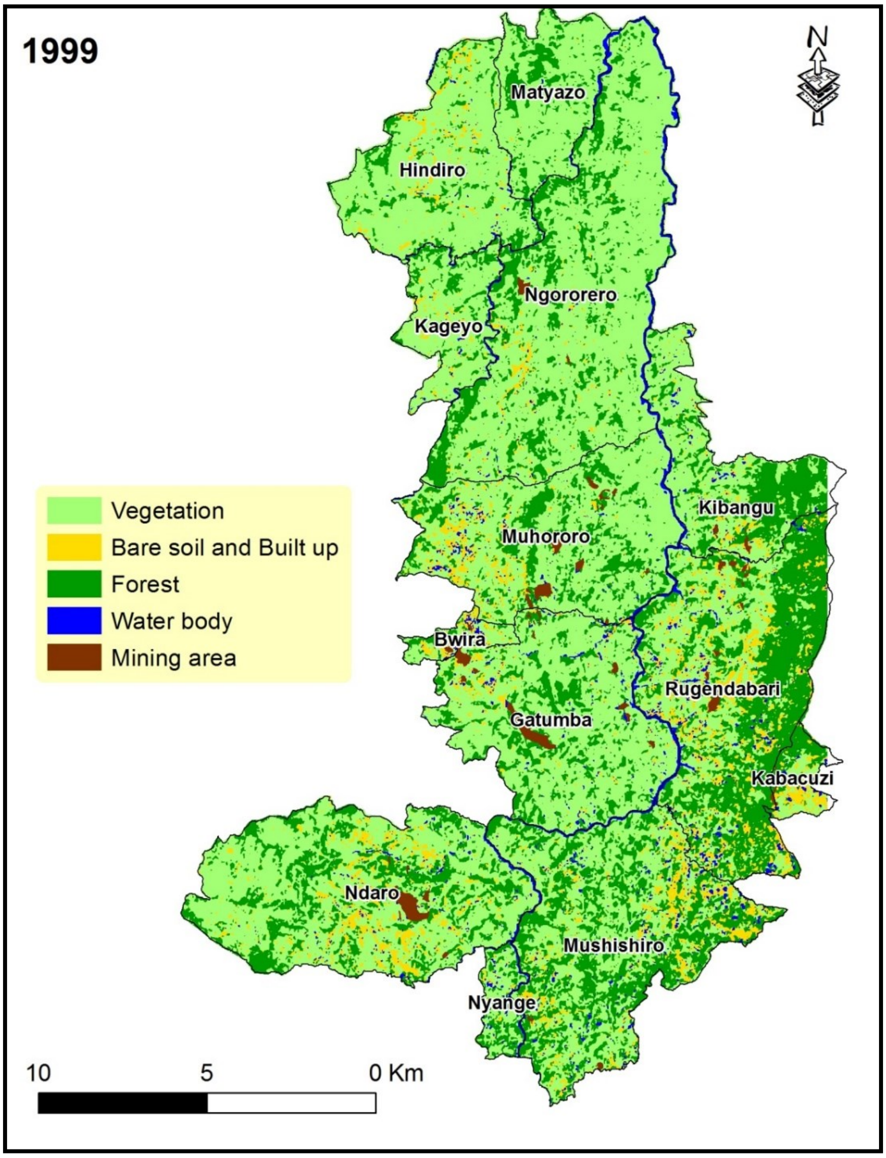

Figure 4: Land use/land cover pattern and extent in Gatumba region in 1999

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The results of classified image of 2008 clear-up that mining areas were increasing compared to the counted area of 1999. After 9 years it occupied 1.04% of the total area of Gatumba region. Meantime, the water body decreased by occupying the lowest value of 0.68%. The next value was 23.78% corresponding to the occupancy of the forest compared to the total size of Gatumba region. Bare soil combined with built up areas has a value of 29.83% and the last but the biggest tenure still the vegetation class representing 44.67%. Forest and vegetation recorded a decrease compared to the situation in 1999.

The 2008 land use/ land cover patterns have kept their original aspects even though changes occurred. The forested area reduced in the southern parts in Mushishiro and Nyange Sectors, but increased in Ndaro and Ngororero sectors in addition to the existing Rugendabari, Kabacuzi and Kibangu sectors which are predominated by forest cover. New mine sites have been mapped in Bwira, Mushishiro, Kabacuzi and Kibangu sector in additional to the existing mine sites in Rugendabari, Ndaro, Muhororo and Gatumba Sectors. Bare soil & built up areas have significantly increased in the whole parts of the study area.

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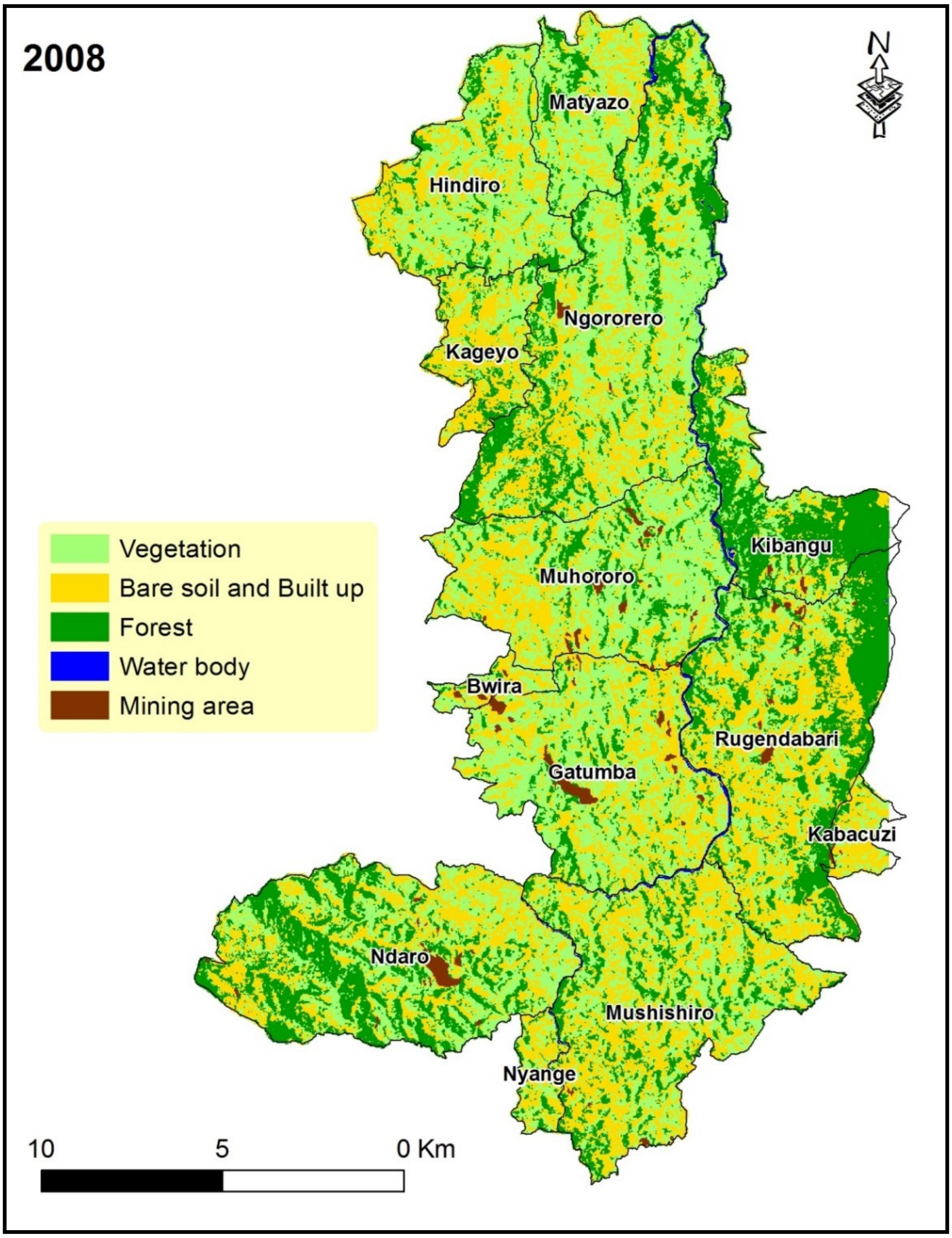

Figure 5: Land use/land cover pattern and extent in Gatumba region in 2008

The situation resulting from the classified image of 2015 revealed that mining activities have increased effectively. In the said period, mining areas counted 1.76% of the total area. The progress of mining activities for 16 years doubled the initial occupancy. This means that in 1999 it occupied 2.85 Km^2 and then counted 5.55 km^2 in 2015. This is the impressive image of mining activities evolution while the environment was still suffering. During that period, the water body was covering 1.06% of the total area, which reflect an increase compared to the previous situation. On the other hand, bare soil and built-up counted 19.18% indicating the

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decrease. Forest represented 16.08% of the total area which indicated the progressive loss of cover while the vegetation counted 61.92% to imply the increase in Gatumba region. New patterns of water body clarify the concentration of water in the southern part compared to the other parts of the river bed. New mine sites growth was noticed as well as new discoveries in Ndaro, Mushishiro, Kabacuzi, Rugendabari, Muhororo, Ngororero, Kibangu and Gatumba sectors. Forests were preserved mainly in Ndiza Mountains (South-East) whereas other parts of the study area hold moderate identical rates of Land use/Land cover change detection from 1999 to 2015.

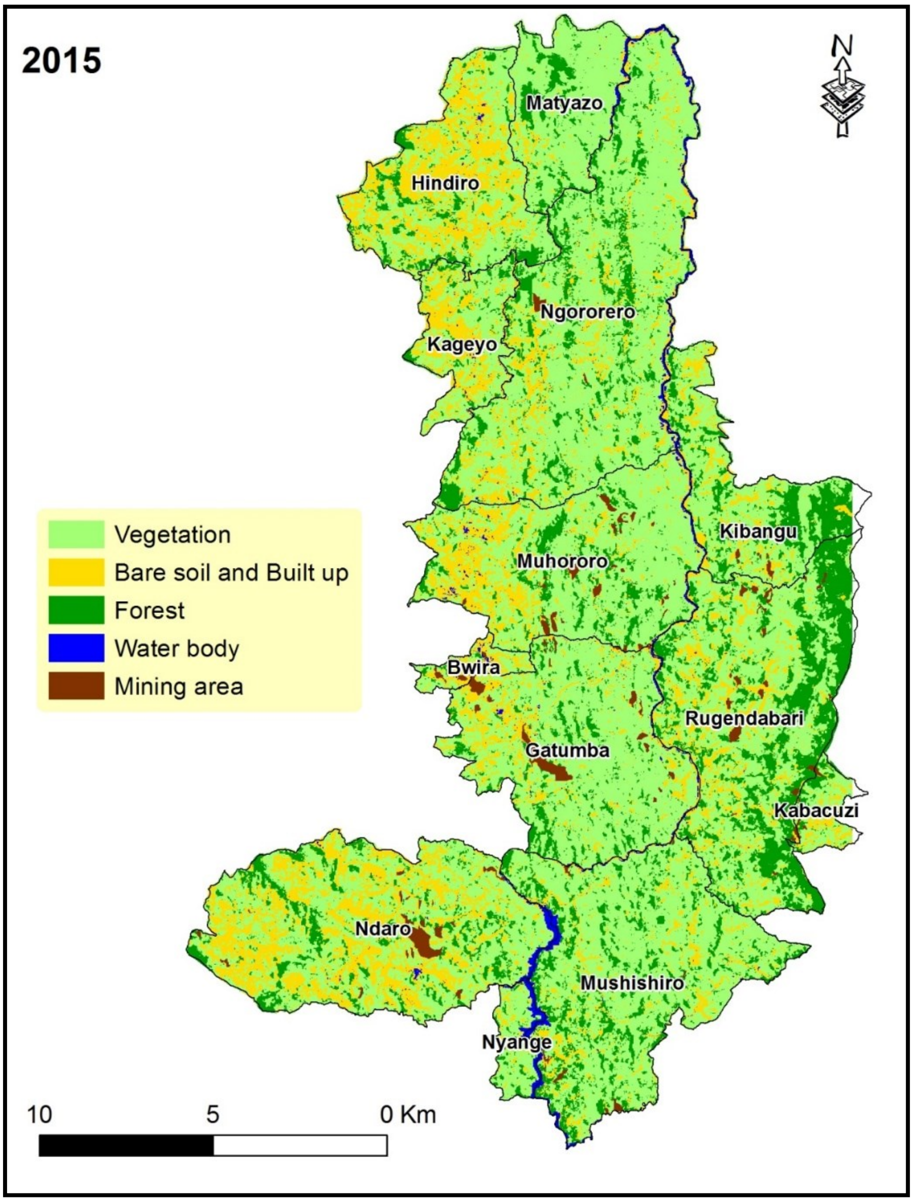

Figure 6: Land use/land cover pattern and extent in Gatumba region in 2015

The accuracy assessment results indicated reliable values (Table 2). Kappa Coefficient is a robust statistic useful for either interrater or intrarater reliability testing. It can range from -1 to

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+1, where 0 represents the amount of agreement that can be expected from random chance, and 1 represents perfect agreement between the raters (Foody 2020).

Table 2: Accuracy assessment of classified Landsat images

Dataset	Overall accuracy	Kappa Statistics
1999 Landsat 7 ETM+	70.21%	0.54
2008 Landsat 5 TM	69.30%	0.53
2015 Landsat OLI/TIRS	83.20%	0.73

Based on the appropriate threshold of Kappa values (Foody 2020), this study has proved moderate accuracy assessment for the map because it falls in the range of 0.4 to 0.8.

3.2. Land use/land cover changes

The pattern of land use/land cover distribution in Gatumba region for a period of 16 years starting from 1999 to 2015, exposed substantial changes both positive and negative. Therefore, mining activities recorded progressive increases.

Table 3: Land use/land cover change overall magnitude in Gatumba from 1999 to 2015

Classes	1999 Area in Km^2	%	2015 Area in Km^2	%	Change Km^2	Change in %	Remark
Mining area	2.85	0.91	5.55	1.76	2.7	3.95	Increase
Water body	2.93	0.92	3.36	1.06	0.43	0.63	Increase
Bare soil and Built up	29.59	9.35	60.67	19.18	31.08	45.43	Increase
Forest	83.26	26.33	50.84	16.08	32.42	47.38	Decrease
Crop and Vegetation	197.61	62.49	195.82	61.92	1.79	2.62	Decrease
Total	**316.24**	**100%**	**316.24**	**100%**	**68.42**	**100**	

The overall magnitude of changes is summarized in Table 3. It shows that out of the total size of Gatumba region (316.24 Km^2), mining area, water body, bare & built-up areas increased by 3.95% (2.7Km2), 0.63% (0.43Km^2) and 45.43% (31.08 Km^2) respectively. With the advent of mining operation, portion of the forest plantation was converted to non- forest area such as settlement, roads and grasslands. Most of the dense forest areas and agricultural fields were converted into mining areas. Thus, the increase in mining area can be attributed to the decrease in forested areas. The increase in mining activities caused population increase in settlement by migration of people into the area. Given the land use competition, high population growth rate,

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land for settlement and land for cropping are increasing and reduce both the capability of the land resulting in increased soil erosion. This can be considered when taking acceptable decision toward land resources use and management for a sustainable development. In the same line, vegetation land decreased by 2.62% (1.79 Km^2) and the forest cover decreased by 47.38% (32.42 Km^2). The mining areas were increasing and competing with other land use/land cover patterns. A previous observed by Lehmann et al.(2017) there was a drastic land cover changes with the highest mining activities in 1974. From 1958 to 1974, woodland decreased and cropland increased rapidly. From 1974 to 2009, the process reversed, with woodland increasing while cropland decreased. This was mainly due to enforced legal regulations of the Government of Rwanda to control land degradation and a decline of mining activities.

3.3. Mining impacts on soil and landscape degradation in Gatumba

The most important environmental concern from mining activities relates to land degradation associated with operating and abandoned mine sites and the multiple trenches found across the hillsides. This can have impact on residents when reducing land available for farming, while the open and un-fenced shafts and pits scattered across the area pose hazardous risk to livestock and humans (Barreto *et al.* 2018). Due to soil excavation, translocation and exposure of bare soil, new geomorphic processes are initiated and naturally running processes are accelerated in mine sites. This results in new geomorphic landforms and alteration of landscapes. The most visible erosive features include rills, gullies, slides, topples, slumps and sinkholes. Depositional features include debris flows and tailing fans at the outlets of mine pits and interconnected channels that develop in downstream sedimentation (Byizigiro *et al.* 2015, Byizigiro *et al.* 2020). In most cases, mining affected soils have low base and higher acid saturations compared to the soil of unaffected land (Imanirareba and Naramabuye 2018). The extent of landscape degradation depends on the magnitude of human activity including the mining operations. If the disturbed landscape is not properly reclaimed, the removed topsoil, which would be necessary for subsequent reclamation measures, is not preserved. Given the increasing demand for arable land by an ever-increasing population, adequate mitigation strategies using environmentally friendly reclamation techniques are becoming increasingly important (Byizigiro *et al.* 2015).

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Figure 7: Water pond and degraded mountain in Gatumba
Source: Picture taken by authors, May 2015

Major geomorphic processes to the land scape in open cast mining in the Upper-Nyabarongo catchment, such as in the Gatumba area, include excavation (cutting, trenching, pitting, striping, and sometimes shallow tunnelling), construction resulting in features like tailings dam, mine waste piles, rock dump and terraces, and diversion of stream flow. Specific landforms emerge and natural pathways of the landscape are altered. Mining landscape is often characterized by denudation and the most visible erosive features include rills, gullies, slides, topples and slumps and sinkholes (Byizigiro 2016).

3.4. Need for best practices in mine closure and rehabilitation

While many sites have been allocated to mining operations that are responsible for their rehabilitation, the abandoned mine sites in Gatumba Region present a considerable challenge related to the lack of environmental rehabilitation and financial burden for the Government. According to the Guidelines for Environmental Impact Assessment for Mining Project in Rwanda, the objective of the final closure and rehabilitation is to ensure that the mine area is left in a functioning status with respect to the ecological, physical and chemical characteristics, with the pre-mining status as the reference. The core aim is to make it available and ready for future land uses (REMA 2012). For most of the mine sites, the big challenge in the abandoned mine sites in Gatumba is the existing of destroyed mountainous massif exposed to erosion which requires urgent actions for environmental rehabilitation as shown in Figure 8.

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Figure 8: Biggest old mine site in Gatumba, mined from 1940s
Source: Picture taken by authors, May 2015

The legacy of bad mining practices from the colonial and immediate post-independence era has also made environmental impacts of mining a sensitive topic in Rwanda. Mining and quarry operations require on-going site rehabilitation and management of the potential post closure environmental and social impacts and risks. However, the identification of the appropriate post-mining land use options is an important component of a mine closure plan for achieving the sustainable land use. The mine closure encompasses rehabilitation process designed to restore physical, chemical and biological quality disturbed by the mining to a level acceptable to all concerned. It shall aim at leaving the area in such a way that rehabilitation does not become a burden to the society after mining operation is over. It shall also aim to create as self-sustained ecosystem (RBS 2011). Environmental friendly practices have to be adopted in order to minimize mining impact on the landscape. These best practices may include for example reshaping the topography by properly filling or closing the open pits, and re-arranging the overburden stockpiles. It is also important to regularly inspect the status of pits to prevent erosion and weakening of the embankments. The excavation of the new pits should begin after closing and refilling the existing open pits. There is also a need to minimize the cost the

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potential runoff by channeling water in less risk zone, and by increasing the land vegetation cover. The creation of a vegetation buffer zone along the watercourse to prevent siltation, sedimentation and collapsing of banks can help to stabilize the disrupted drainage system.

4. Discussions

4.1. Land use and land cover changes from mining activities

The classified images resulted in five distinct classes which are mining areas, forest cover, vegetation, water body and bare soil & built up. The overall accuracy shows a moderate classification of 70.21% (1999), 69.30% (2008) and 83.20% (2015). The corresponding Kappa values were stated 0.54 – 0.53 and 0.73 respectively. The trends and patterns found were almost close to what was obtained in previous studies concerning land use/land cover changes in other localities. For example, Chitade & Katyar (2010) evaluated the impact of open cast mining on land use/land cover for two different years with the accuracy assessment of 95.81% (Kappa: 0.93) and 93.71% (Kappa: 0.91). The same exercise was performed by Ruiz-Luna & Berlanga-Robles (2003) who found the accuracy of 73% (Kappa: 0.7) and 84% (kappa: 0.72) while assessing the land use, land cover changes and coastal lagoon surface reduction associated with urban growth in Mexico.

Moreover, the approach of using remote sensing data is widely recognized. In this research, for a period of 16 sites assessed for Gatumba region (316.24 Km^2), mining area, water body, bare & built-up areas increased by 3.95% (2.7 Km^2), 0.63% (0.43 Km^2) and 45.43% (31.08Km2) respectively. In the same period, vegetation land decreased by 2.62% (1.79Km2) and the forest cover decreased by 47.38% (32.42 Km^2). The same trend was remarked in Bukuru, Plateau State, Nigeria according to Ndace & Danladi (2012). The authors indicated that for the 30 years intensive mining between 1975 to 2005, degraded area/land (mining area), built-up area, and water bodies increased by 24.58%, 18.51% and 7.57% respectively. Whereas arable land (farm and grazing land) decreased by 106.60sq.km (14.16%), and forest reserve decreased by 264.89sq.km equivalent to a loss of 35.18%. The same trend was identified by Mallupatu & Reddy (2013) who declared that land use/land cover changes were significant during the period from 1976 to 2003 in Tirupati, India. There was significant expansion of built-up area noticed. On the other hand, there was a decrease in agricultural area; water spread area, and forest areas. In Singrauli, India, the mining experienced an increase of 11.84 km^2 during nine years which is due to the rapid increase in the coal production, dense forest areas decreasing while plantations on post-mined sites have also been observed (Javed and Khan 2012).

4.2. Conclusion

This study integrated multispectral Satellite Imagery for Monitoring Landuse and land Cover Changes for the period of 1999, 2008 and 2015 in Gatumba mining area in Western Province of Rwanda. Due to the limitations of pixel based approach adopted, it was particularly difficult to distinguish bare land from mining areas. Vector overlay rectification applied to distinguish mining areas from bare land could yield the desirable accurate information. We recommend repeating the study by using high resolution imageries and applying modern machine learning techniques such as Artificial Neutral Network, Random Forest and Support Vector Machines with object-based tools for precise and consistent outputs. We used Focus Group Discussions to determine the environmental impact caused by mining activities in the region mainly by focusing on vegetation and soil; however, an extended quantitative research on the impact of mining land should indicate a strong warning effect in the study area by considering other variables like water and air pollution. In this study, we have confirmed that surface mining development on land use/land cover a changes can be detected using free low resolution satellite imagery.

Generally, the forest cover witnessed a decreasing trend while other land use/land cover classes witnessed up and down variations. This study also showed the contrasting aspect of mining activities competing with other land use/land cover patterns leading to severe environmental changes and landscape degradation. The information obtained from change detection of land use/land cover can help to optimize land management options, planning for mine sites, monitoring environmental effect of mining and restoring the degraded mining landscapes in Rwanda.There is therefore a need to develop the guidelines for minerals extraction and mine site development to boost the management of environmental impacts of mining for sustainable post-mining land use. In that regards, the implementation of the revised land-use masterplan should take into consideration the national land use guidelines regarding the treatment of mining tailings and post mining land use management and use in order to contribute to sustainable and long-term productive land. Enforcement of the rehabilitation and restoration of mining sites should be strictly applied for further development according to the mining law in Rwanda. The mine closure and reclamation should be conducted progressively and planned from the early stages of a mining project in order to maximize the beneficial outcomes after

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post-mining land use. The mine closure plans should be prepared by mining companies and regularly updated in order to ensure that the environment bonds are enough to finance mine closure and mine rehabilitation.

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