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Assessing Forest Cover Change and Deforestation Hot-Spots in the North Kivu Province, DR-Congo Using Remote Sensing and GIS

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Abstract Since the advent of plant and animal domestication, humans have been alternating the land cover to satisfy their needs. In many developing countries, the forest patterns have been reduced in replacement to non-forest areas such as agriculture land. This study assessed the change in the land cover/use and analysed the deforestation hot-spots of the North Kivu province in the Eastern part of the Democratic Republic of Congo (DRC). Landsat 7 ETM+ and Landsat 8 OLI/TIRS images were used to quantify temporal change between 2001 and 2015. Supervised classification techniques were performed using ArcGIS 10.3 ESRI software and Change Detection was performed with the Remote Sensing software ERDAS Imagine 2014. Getis–Ord (Gi*) spatial statistics tool of ArcGIS 10.3 software was used to identify deforestation hot-spots whose presence was confirmed by the Spatial Autocorrelation (Global Moran I). With reference to forest cover change, the results reveal an overall change, from 2001 to 2015, of 1,381,003 ha (30%) for forest loss and 404,380 ha (9%) for forest gain. The study concluded that agriculture is the major factor impacting 89.66% of the forest loss due to agriculture expansion. It also revealed the presence of hot-spots areas with a Z score of 92 and P-value of 0.0000 especially along the main roads and major towns.

Keywords Land use/cover, Change detection, Forest, Remote Sensing, GIS, Hotspot analysis, North Kivu

1. Introduction

Humans have been alternating the Land cover, since the advent of plant and animal domestication, through clearance of land for agriculture and livelihood [1, 2]. The last decade human impacts on land cover have increased with effects on natural resources, hydrological cycle and climate [1]. Economic, institutional, technological, cultural and demographic variables have been affecting the land cover, especially the forest cover [3]. The population growth affects the humans' demand of food, energy and other economic interests [4, 3] and has negative or positive impacts on the forest cover.

Humans are recognized as the key factor of global environment change. Land cover change, especially the conversion of forested areas to other use, has been a consequence of human activities and they are identified as a contributing factor to climate change and loss of biological diversity [1].

Currently, there is a growing necessity of studying the land use/cover change as part of the global environment study [5]. Thereby various studies relating to land cover change have been conducted using different techniques [6]. Some of these studies concern understanding key factors driving change in the land cover [1] to improve resources management and decision making [6]. For instance, modelling is used to simplify the complexity of socio-economic and biophysics factors that influence the change in the land cover [7].

The strong interest in land use / cover results from their direct relationship to many of the planet's fundamental characteristics and processes including the productivity of land, the diversity of plant and animal species, and the biochemical and hydrological cycles [1]. Remote sensing techniques have been used to classify and map the land cover change using satellite images such as Landsat, which have played an important role in identifying change [7, 8].

The change in the land cover, especially the conversion of forested areas to other use, does not have the same magnitude over the world. Some developing countries in the tropical forest regions are known to possess the highest rate of deforestation although they have possibility of interring the carbon market [1].

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The North Kivu was selected for change detection for this study being one of the DRC provinces with an important area of tropical forest. In addition, except Kinshasa city-province, the North Kivu had the highest annual population growth rate in DRC in 2010 [9] and its population increased by more than 15% between 2010 and 2015 [10]. Consequently, the agricultural activity, which is the major economic activity of North Kivu [11], has increasingly lead to the forest cover loss.

Assessing forest cover change requires remote sensing and geographic information system (GIS) techniques. Multi-temporal and multi-spectral satellite images are processed to map the forest cover and monitor the forest patterns dynamics over a period of time. It allows the forest cover change to be observed spatially and historically [5] for a better decision-making. Remote Sensing data helps to monitor change and its driving factors [12].

Hot-spot analysis known also as Getis-Ord Gi* [13] is a method used to analyze the location related tendency (clustering) in the attribute of spatial data [14]. The method focuses on calculating the value of each feature (polygon or points), taken in the context of neighboring features, in a dataset. The neighboring features which return the highest value of the Getis-Ord Gi* statistic is considered as the hot-spot area. The hot-spot analysis method has been used in rainfall, epidemic and agriculture modelling and has been recently applied in assessing spatio-temporal patterns in forest cover loss [14, 15].

The objective of the present study was to use Remote Sensing and GIS techniques to map the land cover and assess its forest cover change occurring in North Kivu province, Eastern part of DRC for 2001 and 2015. The study also aimed at identifying and analyzing the deforestation hot-spots that should be the forest conservation priority regions in the study area.

2. Study area

2.1. Location of the Study Area

The North-Kivu province is located in the Eastern part of the DRC at latitude 0° 58' - 2° 3' and Eastern longitude 27° 14' - 29° 58' (Figure 1). It is one of the provinces of DRC that extends on both sides of the Equator in East of the country.

The North Kivu area extends over 59,483 km^2 that covers approximately 2.5% of the DRC area. The province has six territories (Beni, Lubero, Rutshuru, Walikale, Masisi, Nyiragongo), and three major cities (Goma, Butembo and Beni). It shares its boundary with Uganda and Rwanda countries in the eastern part.

2.2. Relief, Climate and Hydrography of North-Kivu

The North-Kivu topography varies between 800 and 2,500 meters of altitude. However, some mountains raise up to 2,500 meters such as mount Ruwenzori (5,119 m), Nyamulagira volcano (3,056 m) and Nyiragongo volcano (3,470 m) [16]. The physiology of North Kivu is the result of the rifting and seismicity in the Albertin Rift valley that created low and up lands from Lake Albert in North-East DRC to Lake Malawi [17].

The diversity of climate in North Kivu is a result of the heterogeneity of the topography. Below 1,000 meters the average temperature is 23°C, around 1,500 meters the temperature is close to 19°C and around 2,000 meters the temperature is close to 15°C. The average annual rainfall varies between 1,000 mm and 2,000 mm. The lowest monthly precipitation is recorded between January and February and July and August. The North Kivu climate is characterized by four seasons: two wet seasons and two dry seasons. The first wet season appears between mid-August and mid-January and the second in mid-February to mid-July. However, the two dry seasons appear in a very short time. The first is observed between mid-January and mid-February and the second between mid-July and mid-August [16].

The North Kivu main hydrographic network includes the Lake Edouard, which is one of the African great lakes and four lakes inside the province (Ndalaha, Lukulu, Mbalukia and Mbila). The Lake Kivu makes border of the southern part of the province. Apart from these lakes, the province has the following big rivers: Rutshuru, Rwindi, Semliki, Osso and Lowa [16].

Figure 1. Location map of the North-Kivu province

3. Material and Methods

3.1. Data Acquisition

LANDSAT 7 ETM+ for 2001 and **LANDSAT 8**

OLI/TIRS for 2015 satellite images covering the study area were downloaded from http://earthexplorer.usgs.gov. The five scenes used are described in Table 1. The data extracted from LANDSAT 7 ETM+ and LANDSAT 8 OLI/TIRS satellite images acquired on 2001 and 2015 were used to assess the dynamics of the land use of North Kivu province. A total of ten scenes over the space of two years was downloaded considering their cloud cover rates less than 15%. Four additional scenes (Table 1) were downloaded to fill the areas covered by the cloud. Table 1 shows the details of the acquired images including the path and row information. All the images are on the scale of 30 meters of resolution.

The main Landsat images were acquired for the months of November, December, January and September during the rainy season in the study area to facilitate the easy comparison of extracted information for 2001 and 2015. In addition, true color SPOT images with a scale of 2.5 meters of resolution acquired in 2013, where ground objects are clear, were used for interpretation to support the false color Infra-Red key interpretation for the Landsat 8 OLI/Tirs. Ancillary some data was collected in Beni and Lubero territories using Global Positioning System (GPS) in April 2015 to discriminate spectral signatures of Eucalyptus and oil palm plantations from SPOT images and Landsat during the interpretation. Eucalyptus plantations were integrated in forest cover area class and oil palm in Agriculture area.

A strong correlation between ground truth data collected from the field and those collected using Google Earth Pro was noticed [18, 19]. The landcover maps for 2015 were validated using 435 georeferenced points collected using Google Earth Pro. These points were collected using a random sampling technique to assess the accuracy of maps used for this study.

3.2. Image Pre-Processing and Classification

It is advised to perform pre-processing techniques for satellite imagery prior classification and analysis. The pre-processing operations helps to reduce errors due to solar, topographic and atmospheric effects. Before applying atmospheric correction to enhance the quality of the images, different scenes were mosaicked and clipped by the GIS polygon representing North-Kivu boundaries.

We implemented the atmospheric correction to the near infrared, red and green bands separately using Equations 1 and 2 applied in the Raster Calculator (Spatial Analyst) tool of ArcGIS 10.3 software. For Equation 1, DN2ToAr is Digital Numbers to Top of Atmosphere, B_Mult_B is Band specific of multiplicative bands, DN_V is Digital Numbers value and Ref-Add is Reflectance Additive and for Equation 2, CoSun is correction for sun elevation, ToAr is Top of atmospheric reflectance and SinSunE is Sinus of sun elevation.

$$\text{"DN2ToAr} = \text{"((B\_Mult\_B)" "* (DN\_V) + Ref\_Add))"} \quad (1)$$

$$\text{CoSin} = \frac{\text{ToAr}}{\text{SinSunE}} \quad (2)$$

However, geometric correction was not performed as Landsat images from USGS website have accurate pixels [20] that do not need the geometric correction. The false colour composition using Near Infrared, Red and Green bands were created to discriminate diverse patterns needed for supervised classification using the maximum Likelihood Classifier tool of ArcGIS 10.3 software. Thus, following interpretation key in Table 2, two Landcover maps were extracted for 2001 and 2015 years respectively with the forest cover land and non-forest cover land including agriculture, Settlement, Shrub or bare soil, volcanic lava and Water body.

Table 1. Landsat time series scenes used in the study

SCENE			LANDSAT7 ETM+		LANDSAT8 OLI/TIRS	
			ACQUISITION DATE		ACQUISITION DATE	
PATH	ROW	RESOLUTION	MAIN IMAGE	USED TO FILL GAP	MAIN IMAGE	USED TO FILL GAP
173	**59**	30 m	25/11/2001		9/2/2015	
173	**60**	30 m	11/12/2001		8/1/2015	9/2/2015
173	**61**	30 m	11/12/2001	9/12/2001	9/2/2016	
174	**60**	30 m	1/12/2001		16/2/2015	
174	**61**	30 m	1/12/2001	9/4/2002	16/2/2015	9/9/2014

Table 2. Image interpretation key [21]

Landcover class	Tone	Texture	Shape	Pattern
Forest	Dark or Light red	Medium	Varying	Rough
Agriculture	Pinkish or Light green or light blue	Smooth	Regular	Smooth
Scrub	Light red (mottled)	Coarse	Varying	Rough
Bare soil	Grayish/ Whitish	Fine	Irregular/ Regular	Smooth
Water body	Blue or Black	Smooth	Irregular	Scattered

The false colours resulted from the band composite were interpreted using their tone, texture, shape and patterns [19, 21]. Samples of known identities, prior identified from SPOT images with 2.5 meters of spatial resolution were used to classify unknown identities from **LANDSAT 8 OLI/TIRS** as suggested by Potapov P. et al. [22] while the AFRICOVER Landcover maps produced in 2000 helped to confirm training samples from LANDSAT ETM+ [23].

3.3. Land Cover Change Detection and Modeling

After the Supervised classification of Landsat images, a post-classification change detection was performed using ERDAS IMAGINE 2014 software to determine changes. The changes concerned only the forest spatial extent converted to other types of Land cover to determine the forest cover loss. At the end, table describing the forest gain and loss was generated as result for discussion.

ArcGIS 10.3 data Management tool was used to create a fishnet, which is a polygon feature class of rectangular cells that was cropped to the North Kivu boundary for statistical analysis (Figure 2). A total of 6812 cells of 3000 meter by 3000 meters, except the cropped ones, were generated for this fishnet covering the study area. Moreover, the Zonal statistics as table tool were used to calculate the value of pixels of forest cover loss (Figure 3-C) within each cell of the fishnet. The output was a table with values of forest cover loss listed in a field and whose data were added to the North Kivu fishnet feature using "joint table" tool of ArcGIS 10.3.

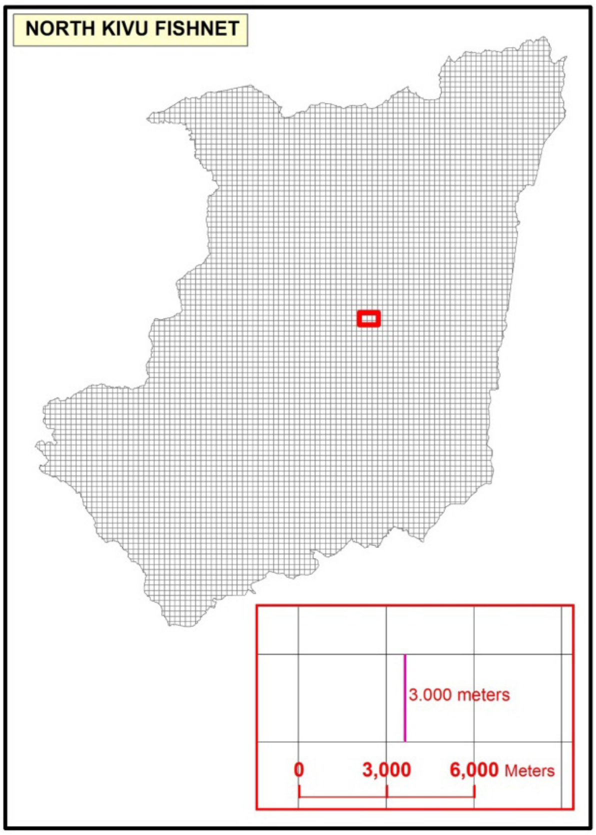

Figure 2. Fishnet map of North Kivu

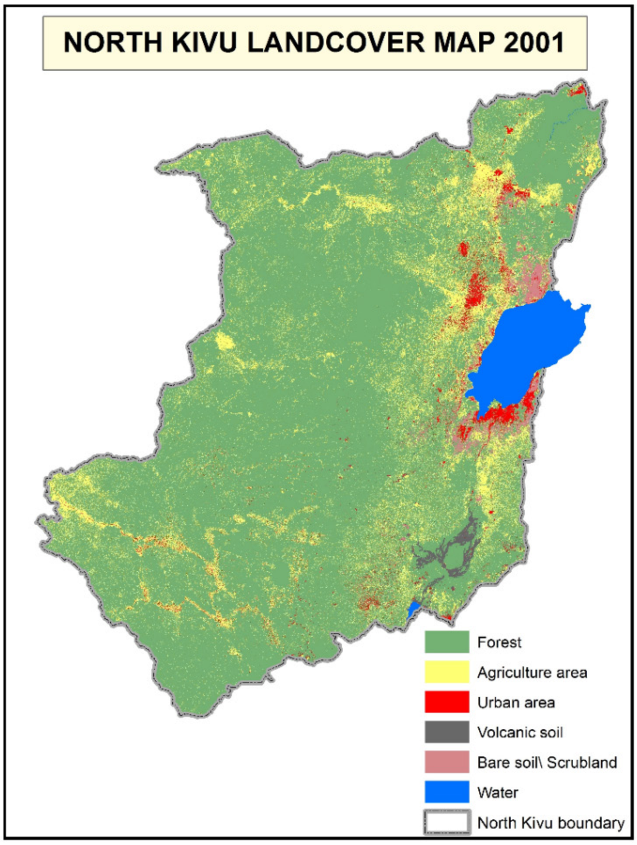

Figure 3. Land cover/ use map of North Kivu 2001

3.4. Hotspot Analysis Assessment

Prior to perform hop-spots analysis, a feature class containing a rectangular cells (fishnet) covering the study area was created using the "create fishnet" tool from ArcGIS 10.3 software. The cell size has been set to 3 km x 3 k m before the fishnet map was clipped to fit the study area (Figure 2).

Each polygon (cell) in the fishnet has an attribute used to record percentage of pixels representing forest loss which occurred inside between 2001 and 2015. The pixels containing forest cover loss were counted from change detection map using the "Zonal Statistic as a table" tool of ArcGIS 10.3 and output values were integrated in the fishnet map for analysis.

The fishnet mapping approach is a grid thematic mapping in which data are related to within a spatial weighted matrix. This quadrat-based technique is appreciated by many researchers because it avoids problems associated with different sizes and shapes of administrative geographical zones [24]. The approach uses uniform comparable grids over the study area drawn as a GIS layer, which leads to an easy identification of hotspots. Especially for the North Kivu province, administrative geographic zones (collectivities or health areas), which could be used to perform hotspots analysis, have sizes and shapes which are so irregular that could negatively affect the analysis results.

High or low distribution of geographic can be identified visually or using statistic tests. However visual identification can lead to wrong information [26]. Thus, the Z-scores and P-value statistic test are very important to detect the presence of hot-or-cold spots [27].

The Spatial Autocorrelation is a statistic test used for study of map patterns and geostatistics [25]. For this study, Getis-Ord hotspots analysis was used to investigate critical areas and test the deforestation spatial autocorrelation over the study area. Its output results a Z-score and a P-value which confirm statistically significant hot and cold spots across the study area. The approach told where fishnet cells with either high or low values of forest cover loss where clustered spatially, looking at each cell in the context of neighboring feature [26]. Because a fishnet cell with high value of forest cover loss should also be surrounded by other cells with high value as well to be considered as hotspot.

A P-value is a probability associated with a Z-score, which are defined before launching a hot-spots analysis algorithm. With "< -1.65 or > +1.65", < -1.96 or > +1.96 and < -2.58 or > +2.58 as critical Z-values, are associated 0.10, 0.05 and 0.01 theoretical P-values for 90, 95 and 99 percent confidence levels respectively. A Z-score above 2.58 means that the spatial autocorrelation of Moran I shows a statistically significant hot-spots (high values) and a Z score below −2.58, a statistically significant cold-spot (low values) at a significance of $P < 0.01$ [28]. If a P-value of 0.05 is considered, the statistically significant hot-spot are tested with a Z score of 1.96.

Developed in 1990's, the hotspots analysis approach was commonly applied in rainfall and epidemic modelling. In recent years, the method has been used in many research fields [14] including deforestation modelling [29, 30, and 31]. Since then, it has been integrated in many GIS software such as ArcGIS (version 10.3) used for the current study to identify the presence of spatial clustering of forest cover loss for the period 2001-2015 in North Kivu province. The confirmation of hot-spots of deforestation was tested using the Complete Spatial Randomness (CSR) of 2.58 to confirm the deforestation hot-spots in the study area at a 99% confidence interval.

The function used to calculate the Getis-Ord Gi* statistics using ArcGIS software is represented by the Equation 3 Ord JK [24] where $\boldsymbol{G_i^*}$ statistic is the Z-score, $\boldsymbol{x_j}$ is the attribute value for feature $\boldsymbol{j}$, $\boldsymbol{w_{i,j}}$ is the spatial weight value between feature $\boldsymbol{i}$ and $\boldsymbol{j}$ and **n** is equal to the total number of features [25, 28, 32].

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{x}\sum_{j=1}^{n} w_{i,j}}{s\sqrt{\frac{\left[\sum_{j=1}^{n} w_{j,1}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)\right]}{n-1}}}$$

$$\text{with } x = \frac{\sum_{j=1}^{n} x_j}{n} \tag{3}$$

$$\text{And } s = \frac{\sum_{j=1}^{n} x_j^2}{m} - (\bar{x})^2$$

4. Results and Discussion

4.1. Land Cover/ Use Patterns

Using **LANDSAT 8 OLI/TIRS** and **LANDSAT 7 ETM+** six major land cover types viz: Forest, Agriculture, Settlement, Volcanic lava, Shrub/bare soil and Water body delineated as described in Table 3 and illustrated in Figure 3. Comparing the **A**, **B** and **C** maps on Figure 3, the agriculture was the main driver of forest loss in North Kivu province.

In 2001 the forest cover of North Kivu was accounted to 4,593,902 hectares (78.12%) and was changed to 3,613,177 (61.42%) in 2015 (Table 3).

Within a period of fourteen years, a forest loss of 1,238,198 ha (89.66%) was observed due to agriculture expansion and, a forest gain of 404,380 ha (Table 4). The agriculture area accounting to 855,818 ha (14.55%) of the study area in 2001 was increased to 1,785,211 ha (30.35%) in 2015.

Table 3. Land cover/ use classes of North Kivu and area calculated from classified images

	2001		2015	
Class	**Area (ha)**	**Area (%)**	**Area (ha)**	**Area (%)**
Forest	4593902	78.12	3613177	61.42
Agriculture area	855818	14.55	1785211	30.35
Settlement	118891	2.02	217223	3.69
Volcanic lava	41552	0.71	36537	0.62
Shrub/ Bare soil	99326	1.69	58561	1.00
Water body	170898	2.91	171555	2.92
TOTAL	**5880387**	**100.00**	**5882264**	**100.00**

The Volcanic lava area and the bare soil/ Shrub decreased from 0.71% to 0.62% and from 1.69% to 1% respectively in the same period while the settlement area increased from 2.02% to 3.69% (Table 3). In 2015, the overall change in reference to the 2001 forest cover was 1,381,003 ha (30%) for forest loss and 404,380 ha (9%) for forest gain. The accuracy assessment was carried out on the land cover map for 2015 using Ground Control Points (GCP) from Google Earth Pro to express the quality of the classification results. An overall accuracy of 87% was found in 2015 data (Table 5) that is greater than 85% what Anderson R. J. et al. [33] proposed as the minimum classification accuracy. The forest and agriculture categories have a Producer Accuracy of 71% and 80% respectively and a User Accuracy of 81% and 82%.

The accuracy assessment of the thematic map of 2001 could not be performed owing to the lack of GCP in the study area. However, the same interpretation keys used to classify the LANDSAT 8 OLI/TIRS were used for the LANDSAT 7 ETM+ in 2001. Potapov P. et al. [22] assessed the forest cover area in North Kivu and found 4,590,000 ha in 2000. The findings in the current study were almost the same as the forest cover in 2001 was around 4,593,000 ha (Table 3).

Table 4. Forest gain and lost in the Land cover/ Use of North Kivu

Forest Cover	Agriculture	Settlement	Volcanic Lava	Bare soil/Shrub	TOTAL
Loss (in Ha)	1238198	104472	11210	27123	1381003
Loss (%)	89.66	7.56	0.81	1.96	100
Gain (in Ha)	302000	37142	13499	51738	404380
Gain (%)	74.68	9.19	3.34	12.79	100

Table 5. Accuracy assessment of classification

Class	Forest	Agriculture	Settlement	Volcanic lava	Bare soil/ Shrub	Water body	Total	User Accuracy
Forest	52	10	1	0	1	0	64	81%
Agriculture	5	69	8	0	2	0	84	82%
Settlement	11	7	149	0	0	0	167	89%
Volcanic lava	2	0	0	35	0	0	37	94%
Bare soil/ Shrub	2	0	4	0	22	0	28	79%
Water body	1	0	2	0	0	52	55	94%
Total	73	86	164	35	25	52	435	
Producer Accuracy	71%	80%	32%	100%	88%	100%		87%

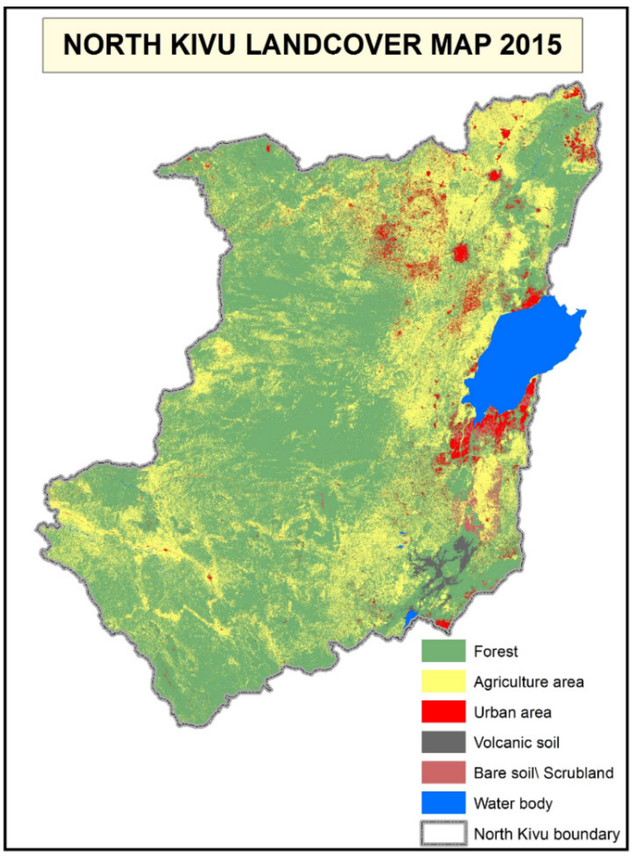

Figure 4. Land cover/ use map of North Kivu 2015

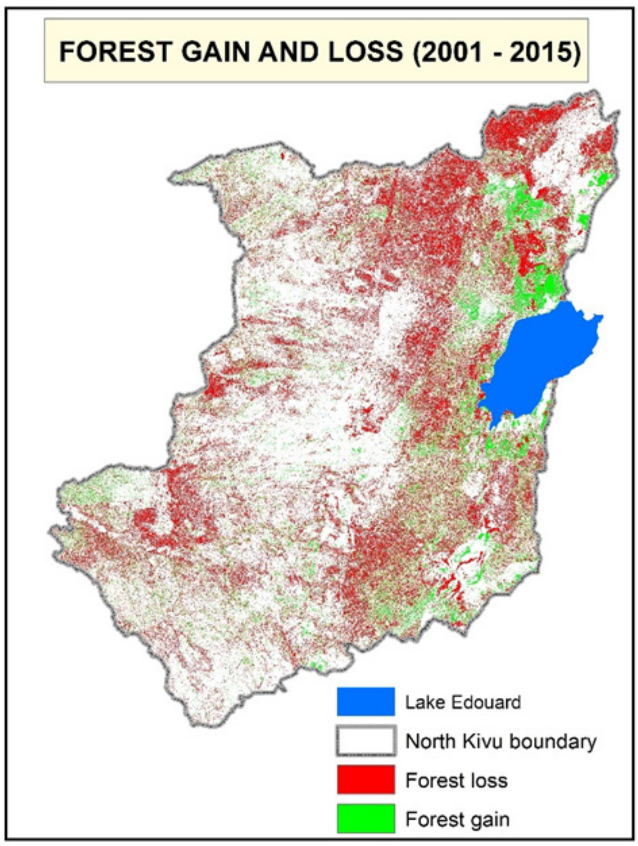

Figure 5. Land cover/ use change map of North Kivu 2001-2015

4.2. Forest Loss and Deforestation Hotspots

The study revealed the loss of forest during the period between 2001 and 2015, and 89.66% of this forest cover loss was converted to agriculture area. In the Panama Canal corridor, Ghislain R. [34] found that 86% of forest loss was explained by agriculture expansion. Helmut J. G. and ERIC F. L. [3] found that agriculture expansion is the leading land use change and is associated to 96% of deforestation cases in the whole tropical forest. During a 2002 actor-based survey, Agriculture was reported as the second cause of deforestation after charcoal extraction in North Kivu province and the first cause in all the ten other DRC provinces [35]. However, in the same report agriculture is reported as the main cause of deforestation in Lubero and Masisi territories, North Kivu province.

Results obtained by the Getis-Old algorithm allowed identification of cold and hot-spots in the study area. The algorithm indicated the spatial entities (fishnet cells) with high and low values which tend to cluster in a geographic area (Figure 4). This means that the occurrence of grid cells with high or low values, for a specific attribute in the North Kivu fishnet, are surrounded by other cells with high or low values for that attribute. However, for the result to be statistically significant, a Z-score and P-value had to be calculated.

The spatial autocorrelation (Moran I) used with the forest loss variable returned a P-value of 0.0000 and a Z score of 92. The P value is greater than 0.01 and the Z score greater than 2.58, which means that there is a statistically significant hot-spots with 99% of confidence level. The Fig VI shows that the magnitude of the forest cover loss was not the same all over the geographic area of the North Kivu province. Many of these deforestation hot-spots are located along major roads (national and provincial roads) in the study area. These results corroborate those of Harris Nancy et al. (31), which demonstrated that many of the hot-spots of the DRC's forest cover loss are situated along the country's road network. The same study revealed the deforestation hot-spots around Beni city located in center of Beni territory in the North Kivu province.

Many hot-spots were also identified in the eastern part of the study area (Figure 6). The cold-spots, however are found far from the North Kivu main roads and major towns on the same figure. The highest population density and the most populated cities are located in this part of the North Kivu province (Figure 7).

However, some cold-spots areas were observed in the north-eastern part of the study area around the mount Rwe-nzori and in the extreme east which is covered by the Lake Kivu.

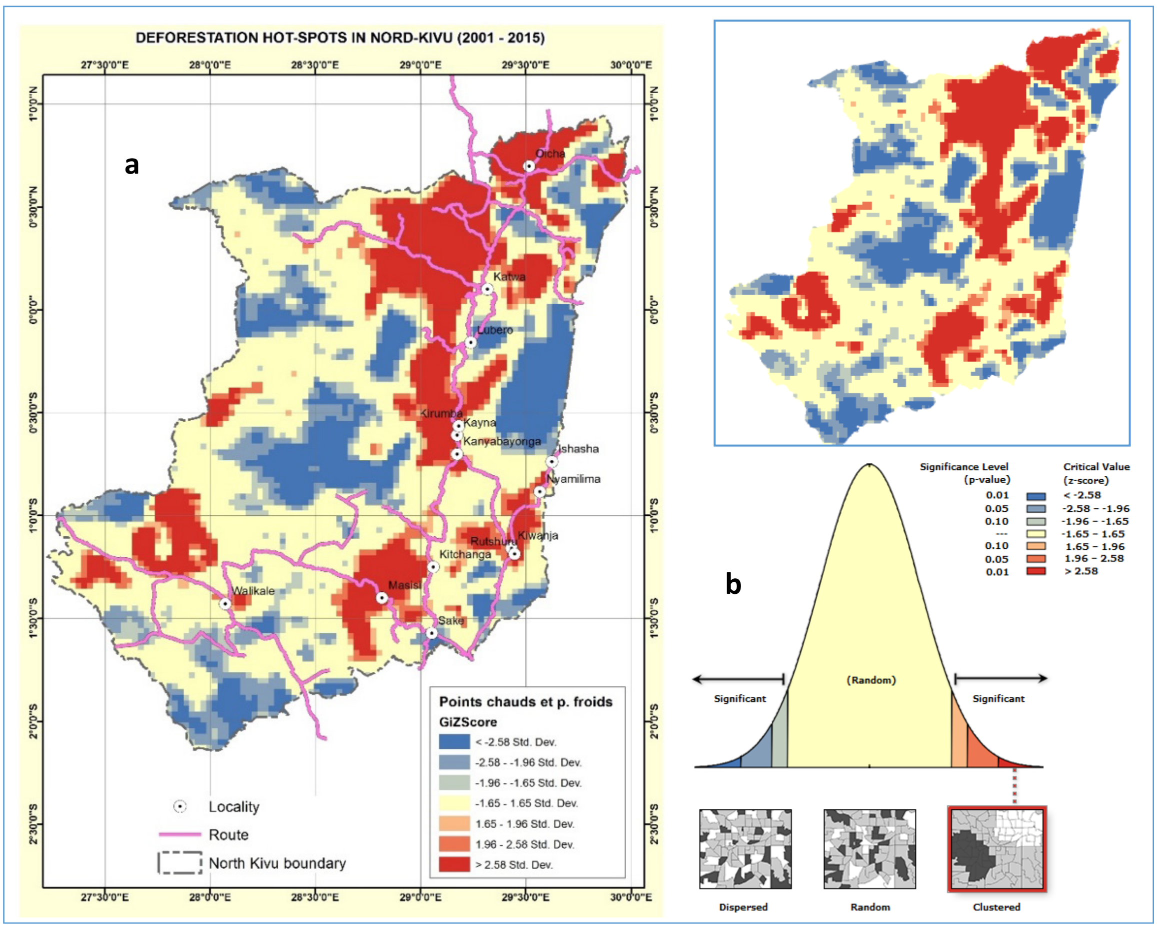

Figure 6. North Kivu province a) hot and cold-spots and b) Normal distribution of the p-values and z-scores

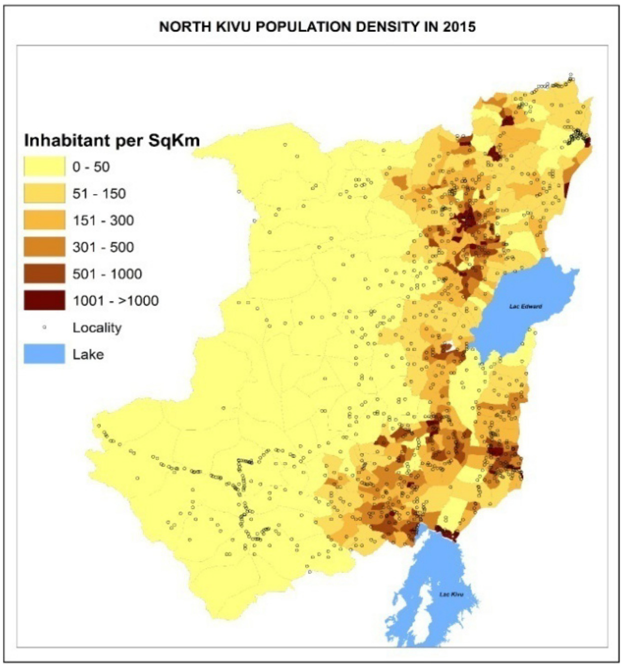

Figure 7. North Kivu population density per Square Km in 2015

4.3. Forest Loss and Gain Driving Forces

During the period 1984-2010, the North Kivu population annual growth was 3, 59 percent, the highest of all DRC provinces, except Kinshasa. The population growth dynamics passed from 894,838 capita in 1958 to 6,090,723 in 2010 [9]. In 2015 the number of people inhabiting the province was estimated to 7,754,196 while more than 60 percent relies on agriculture [11]. The overall density which was 15 inhabitants per Sqkm in 1984 increased to 130 inhabitants.

Thus, more change occurred in areas with high population density (Figure 7) especially around main cities due to the expansion of urban and agriculture areas. The Figure 7 illustrates change occurred around Oicha city in Beni territory in seven maps with a scale of 1: 65,000. The landcover change map (LCC 2001-2015) shown was detected from landcover maps (LC-2001 and LC 2015) classified using false color Infrared composition of Landsat images acquired in 2001 (LS-2001) and 2015 (LS-2015). Similar situation occurred around many towns where forest cover was converted to urban and agriculture area.

Change areas are also located alongside main roads (Figure 8). Forest cover near principal roads is more exposed to deforestation than inaccessible forest areas. Moreover, the same Figure 8 reveals a decrease in settlement area far from the road. This can be explained by insecurity caused by “Mai-Mai Simba” and “Raia-Mutomboki” armed groups, which have been influencing that area. Thus, population is forced to move from isolated settlements toward more populated and relatively secured localities around main roads.

In North Kivu, volcanoes eruptions had also driven deforestation in the Virunga mountain region during 2001 – 2015 period. During this period the Nyiragongo volcano erupted once in January 2002 and the Nyamulagira volcano erupted 6 times and its last eruption ended in April 2011. For each eruption, a huge area of forest cover had been destroyed converting into lava area (Figure 10). However, these volcanoes are in Virunga National Park and their lava is progressively and quickly transformed in fertile volcanic soil on which natural forest regenerates (Figure 11). These phenomena explain the presence of forest gain in volcanic region (Figure 10).

Figure 6 revealed more deforestation hotspots in the northern part area of North Kivu province, especially in eastern part of Beni territory and northern of Lubero territory. This part of the province is one of the fertile regions and is preferred for food and industrial crops. Many corporations settled in the area to promote agricultural products such as cocoa, vanilla, papain, rice, oil palm among others. For example, ESCO-Kivu, a corporation which has a cocoa pre-transformation factory in Beni, has been promoting cocoa and vanilla production in Beni territory and surroundings.

Since then, the cocoa production has progressively increased in Beni territory from 112,260 kgs in 2006 to 6,200,016 kgs in 2014. As many people were interested in cocoa agriculture, the number of farmers which was 9,291 in 2006 passed to 13, 4830 in 2014 (Table 6). Consequently, an important forest cover has been converted into cocoa field.

The lack of security situation in North Kivu negatively affected the industrial sector in general. Many factories especially dealing with coffee were closed due to insecurity in some areas and to tracheomycosis disease [36]. However, some factories were also created in secured areas thanks to the agricultural resources in some regions of the province. In 2012, Brasserie Simba (BRASIMBA), which is a member of CASTEL group brewing factory was installed in Beni city expecting to get raw material locally, especially rice. Many farmers were grouped into associations to enhance their ability of delivering commercial quantity of rice to BRASIMBA. Only LOFEPACO, which is a league of women’s organizations, involved in agriculture in Congo, could delivered more than 450 tons of rice in 2015 [37]. This situation is also one of reasons of the conversion of forest cover to agricultural land in this region. Some other factories such as SICOVIR (La Société Industrielle et Commerciale des Virunga) and SAIBU (Savonnerie Industrielle de Butembo) transforming and promoting palm oil were also created in the region.

Figure 12 and Table 4 indicate that there was also forest gain in some areas of North Kivu. The important part concerned by this forest gain is located in the Virunga National Park and surroundings.

This can be explained by change in the governance of this protected area since 2008 when Emmanuel de Mérode, a Belgian prince was appointed as national park Director. At that time many conservation actions were carried-out against deforestation.

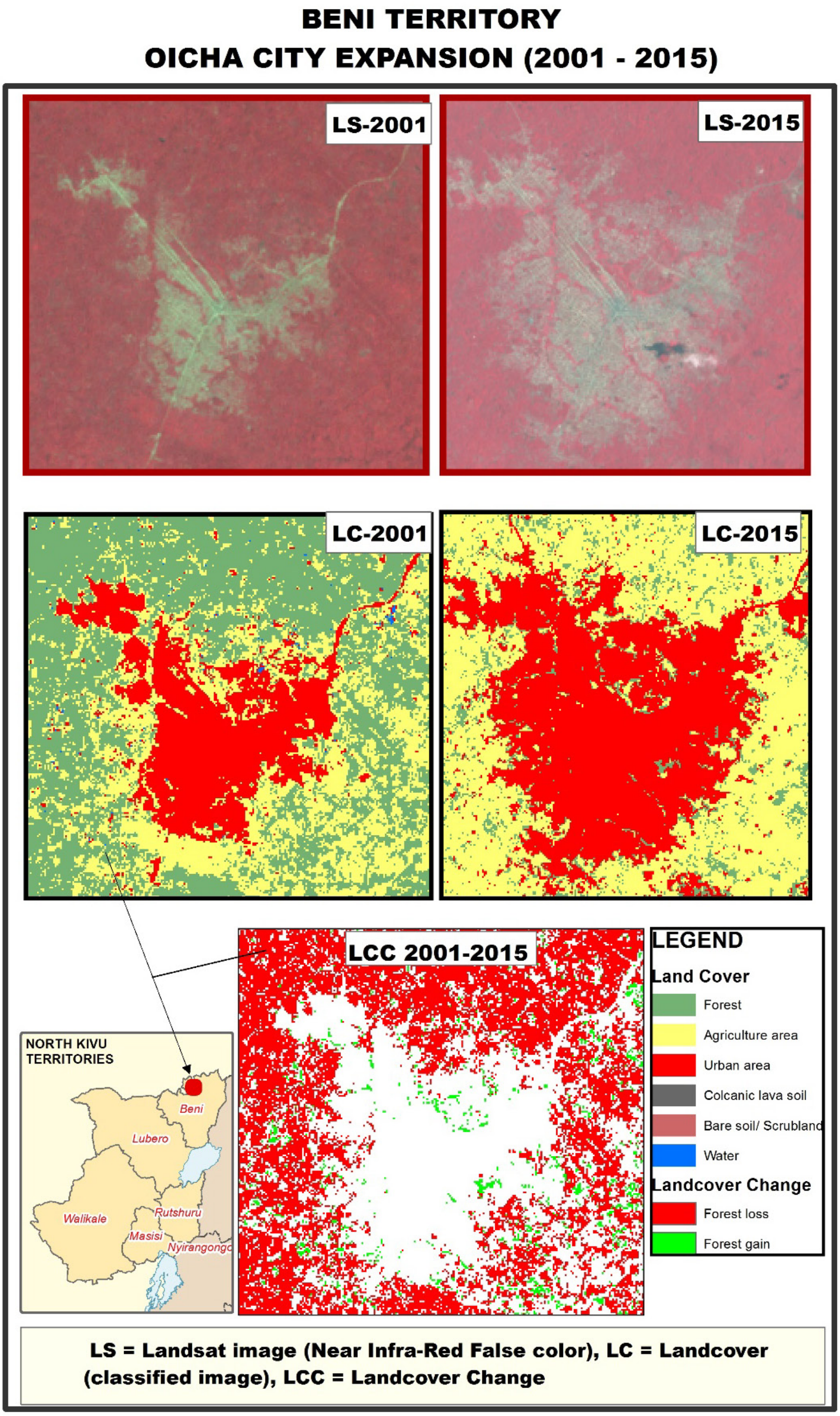

Figure 8. North Kivu: Oicha city expansion for 2001-2015 periods

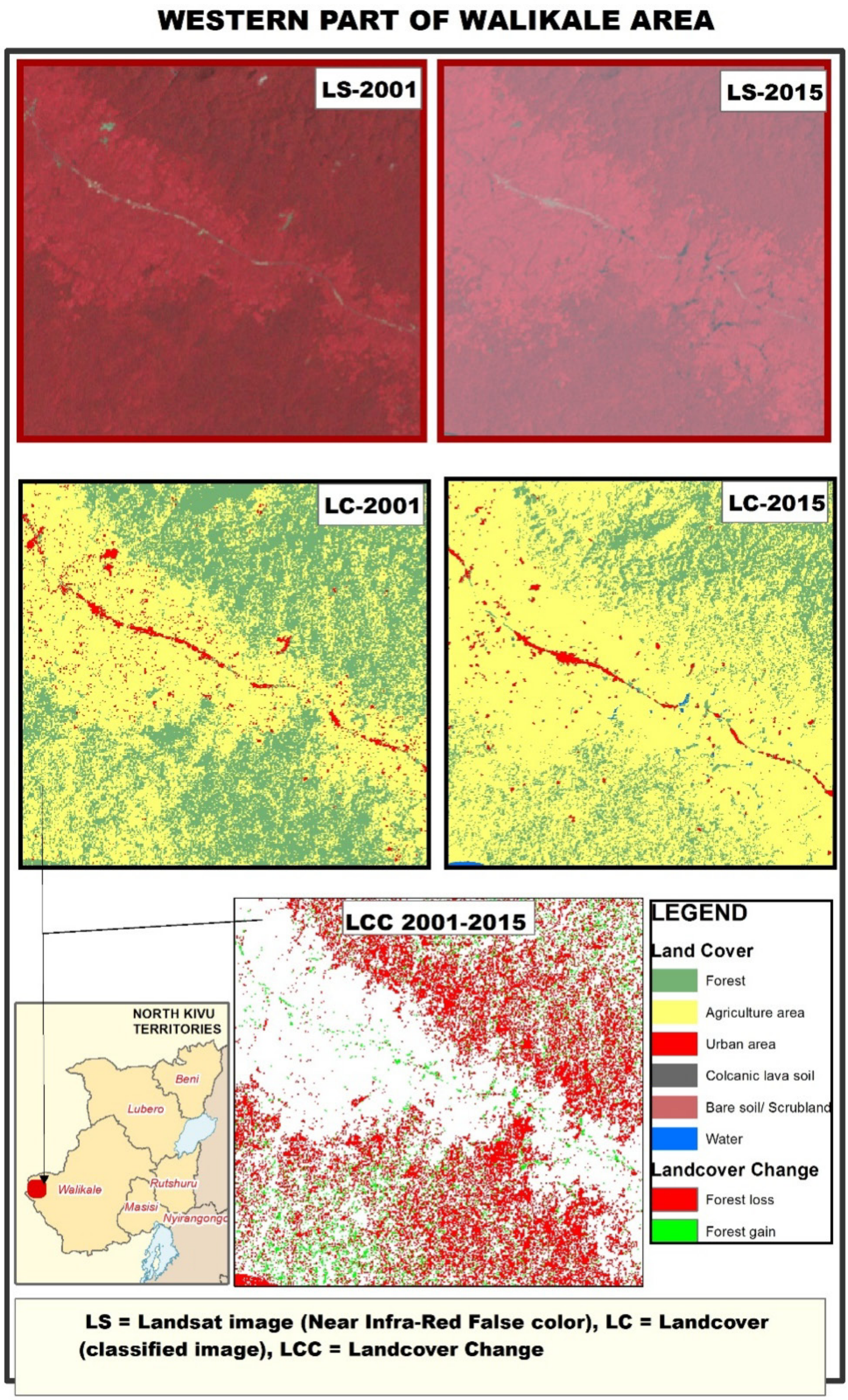

Figure 9. North Kivu: agricultural land expansion around main road in Walikale territory

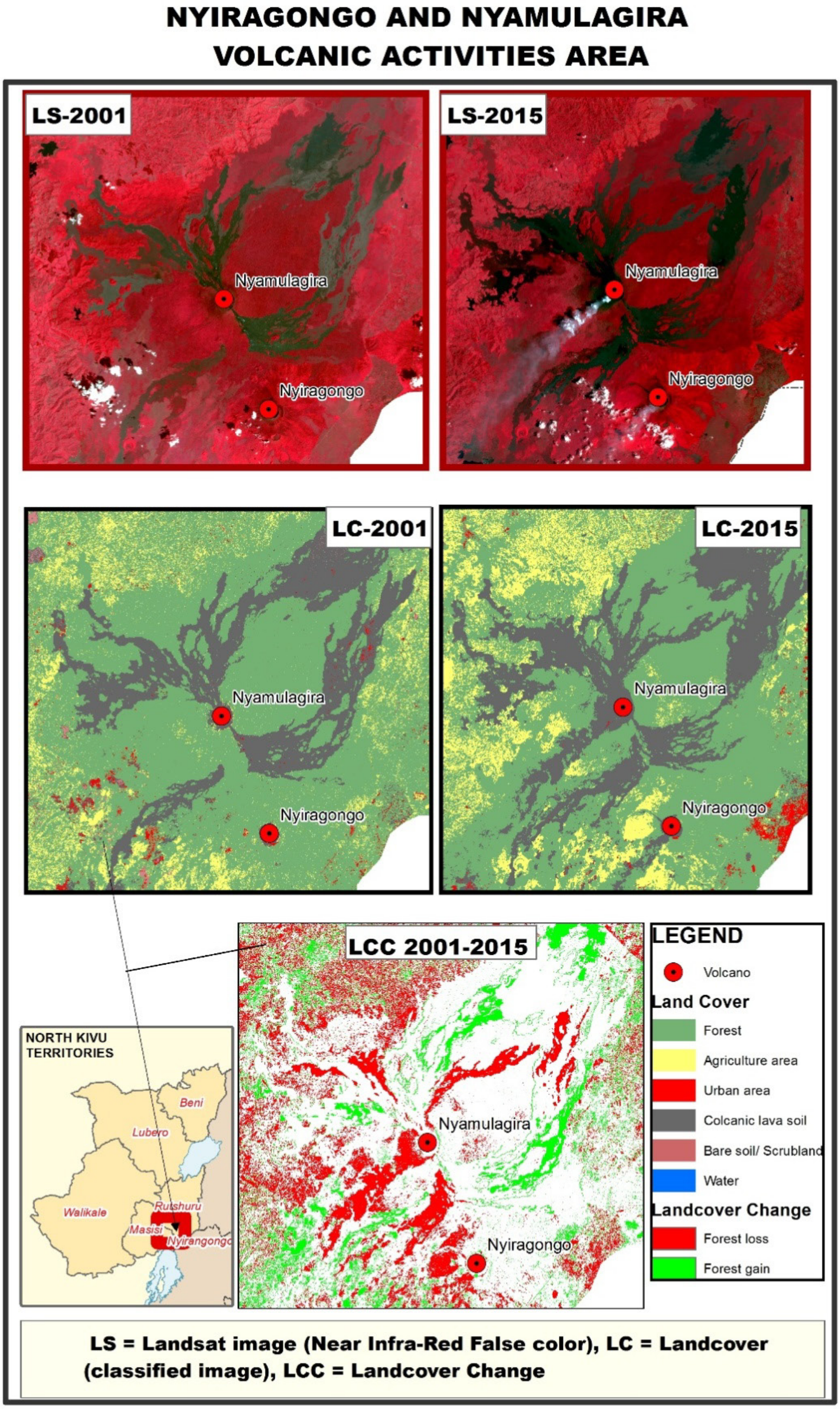

Figure 10. North Kivu: change around volcanoes area during 2001-2015 periods

Figure 11. North Kivu: regenerated forest around volcanoes area during 2001-2015 periods

An important part of population practicing agriculture in the Virunga National Park was successfully evacuated. These efforts allowed regeneration of forest in some area of the park. Also, many local initiatives dealing with afforestation, such as LCDP, CICEKI, OPEGL (Fig. XII) among others were created and invested funds from donors like WWF in reforestation around the park. Land owners interested in silviculture were solicited to convert their farms into forests. This explains the presence of many small planted forests areas as illustrated in Figure 13.

In general, the deforestation rate in the Congo Basin is law due to the lack or poor road infrastructure [38]. Despite its high forest loss, the North Kivu forest cover loss has been curbing in some areas due to poor condition of roads. About twenty years, DVDA had not received fund to maintain road leading to agricultural zones [39]. Maintenance of these roads will more unlock the agriculture in North Kivu and extend the access to wood market with the risk of increasing the deforestation rate.

The DRC has developed initiatives to encourage forest gain and stabilization. A forest code in respect to international standards and laws regulating activities relating to was developed and adopted in 2002. The DRC forest code emphasizes the protection of forest cover inside protected areas and community forests and encourages forests plantation [40]. The Environment Ministry has a special Department of Reforestation and Horticulture to promote forests plantation in rural and urban areas [41].

To promote forest stabilization and gain, DRC government also encourages the creation of new protected areas. In 2010, during the Nagoya protocol of biological diversity, DRC committed to increase its protected areas from 11% to 17% of the national area [40]. Apart from the known National parks (Virunga, Kahuzi-Biega and Maiko) in North Kivu, some natural reserves and community forests were recognized by the DRC Environment Ministry to fight again deforestation.

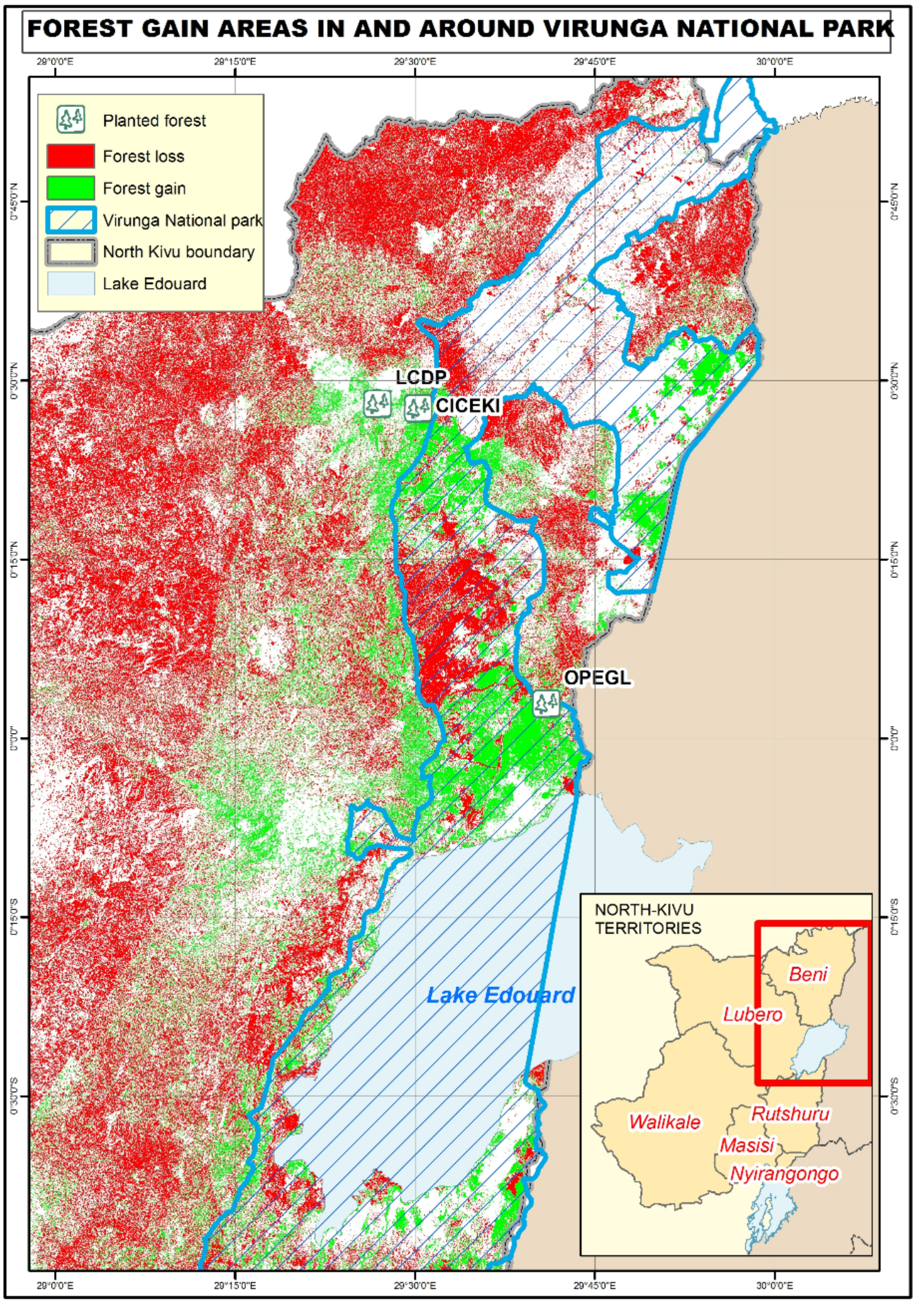

Figure 12. Change in the North-Eastern part of North Kivu during 2001-2015 periods

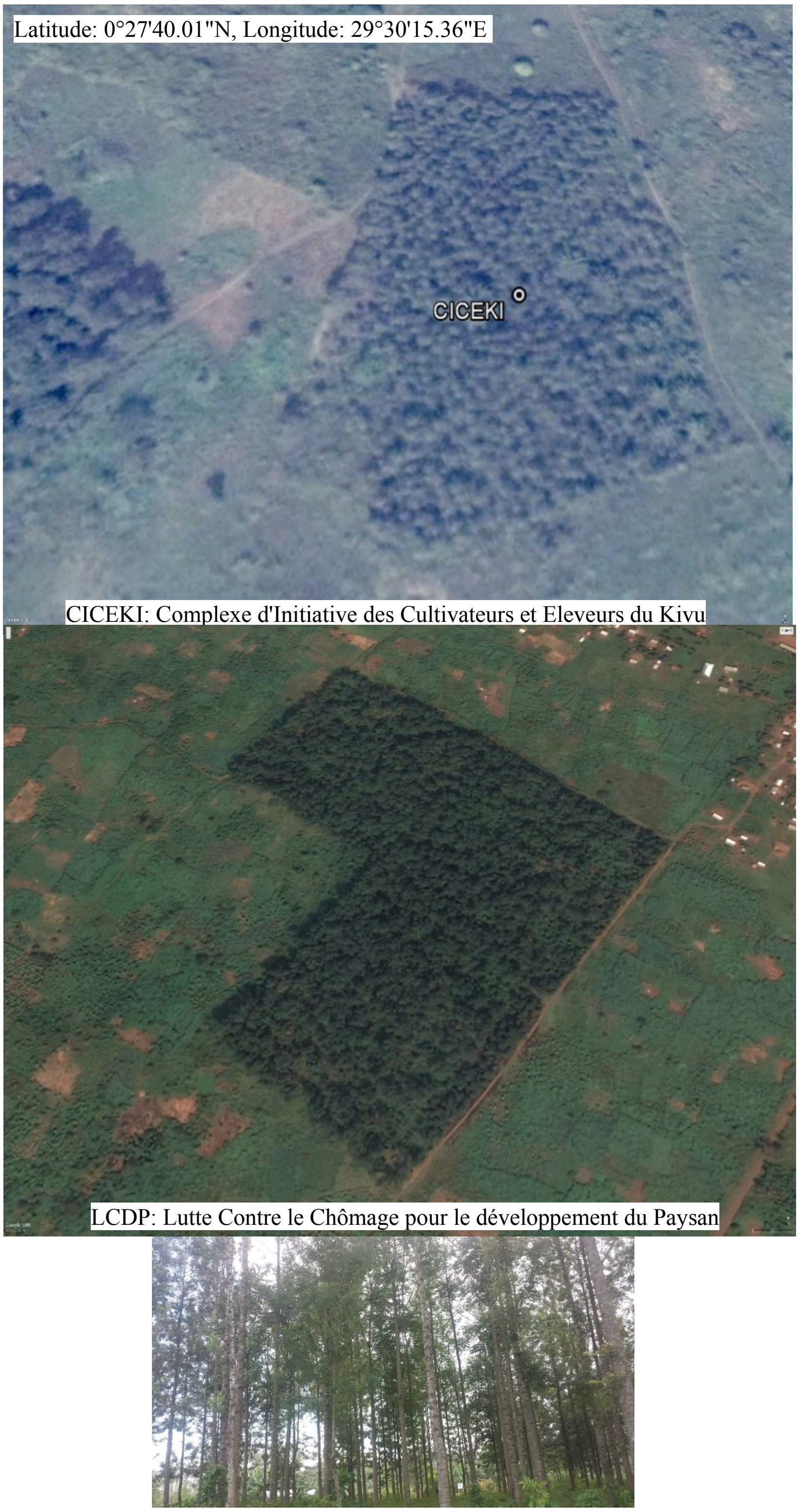

Figure 13. North Kivu: some planted forests during 2001-2015 period

5. Conclusions

This study assessed the land use/ cover change and identified the hot-spots in North Kivu province. The study was carried out in the province of North Kivu, Eastern DRC for 2001-2015 period.

Using ArcGIS 10.3 and ERDAS IMAGINE 2014 software, Findings reveal the overall change, in reference to the 2001 forest cover, of 1,381,003 ha (30%) for forest loss and 404,380 ha (9%) for forest gain. In 2001 the forest cover of North Kivu was assessed to 4,593,902 ha (78.12%) and to 3,613,177 (61.42%) in 2015.

Among the six classes: Forest, Agriculture, Settlement, Volcanic lava, Shrub/bare soil and Water body delineated for the study, agriculture expansion was revealed as the main driver of forest cover loss. Eighty-nine-point six percent of forest cover loss was due to agriculture expansion while 7.56%, 0.81% and 1.96% were due to Settlement, Volcanic lava and bare soil or Shrub expansion respectively.

The findings revealed the presence of deforestation hot-spots in the North Kivu province. These hot-spots presence were confirmed using **Getis–Ord (Gi*) spatial statistics algorithm.** The Moran I spatial autocorrelation returned a P-value of 0.0000 and a Z score of 92. With a P value greater than 0.01 and a Z score greater than 2.58 the hot-spots confirmation is statistically significant with 99% of confidence level. Many of these hot-spots are located along the main roads and major towns in the eastern part of the study area. The study also showed some forest gain reforestation and forest regeneration in the areas around the Virunga National Park.

Shifting and burning agriculture techniques should change to intensive agriculture to avoid the observed huge forest cover loss due to agriculture expansion. And the hot-spots regions should be given the first priority for forest conservation activities in the study area.

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