Mapping the stratification of vegetation classes in the Miombo forests and assessing the accuracy of their classification in Katanga province in the Democratic Republic of the Congo

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Abstract: The mapping of the stratification of vegetation classes in the Miombo forests was carried out with the aim of assessing the land-use dynamics of these ecosystems in the Upper Katanga Province in the Democratic Republic of Congo (DRC), which are facing one of the strong anthropogenic pressures due to slash-and-burn agriculture, galloping exploitation of fuelwood (carbonization), late bush fires, artisanal exploitation of minerals and, to a large extent, demographic pressure. Landsat 8 images from June 2018 were processed and analyzed in this study. To ensure the quality of the accuracy of the vegetation class classification, **516** points from random and stratified sampling were generated using the Random tool in ArcGIS. In addition, high-resolution Google Earth images and data collected in the field were used as a reference (ground truth) during the analyses on the validation of the stratified vegetation class map of the Miombo forests. By comparing the reference data (Ground Truth) and the spatial map resulting from the classification, it was possible to make a statistical validation of the produced map. The analysis on the assessment of the accuracy of the different strata of the Miombo forest vegetation classes was performed using the Kappa index (Goshen coefficient) calculated from a confusion matrix. As shown in the Confusion Matrix Table (see Table 8), of the 519 control points, **343** points were correctly classified. This gives a mapping accuracy of 70% (**343/516**) and a Kappa coefficient of **0.58**. However, it should be noted that there are some difficulties in discriminating certain classes, such as between degraded and non-degraded open forest and savannah and anthropogenic areas. Overall, with reference to Cohen's (1960) [2] table on the Kappa index, the results of the mapping of Miombo forest strata in Haut-Katanga Province can be considered consistent (good). The mapping of the stratification of plant classes in the Miombo forests revealed three (3) main strata: (1) Non-degraded open forest (primary forest), (2) Degraded clear forest (Secondary forest) and (3) Savannah zones (which include shrubby savannah, grassy savannah, savannah forests and agricultural zones) and Other land use classes: Water and entropized area.

Keywords: Normalized difference vegetation index, Kappa Index, Confusion Matrix, Miombo forest, Landsat - 8

1. Introduction

The Democratic Republic of Congo (DRC) has a vast forest area, estimated at about 155 million hectares representing 67% of the national territory. Dense rainforests alone occupy nearly 99 million hectares (OSFAC, 2010; Eba'a, et al., 2008) [30-8, 40]. The forests of the Congo Basin, particularly those of the DRC, positively influence the rainfall regime of the sub-region. The diversity of the DRC's forests makes them a distinguished landscape (Debroux, et al., 2007) [12]. According to White's (1983) [35] phytogeographic classification, the forest vegetation of the DRC is subdivided into 4 centers of endemism (the Guinean-Congolese region, the Zambézian region, the Sudanian region, and the fragmented mountainous region). The Zambézian center occupies Haut-Katanga and the extreme south of the Kwango Plateau. It is a region of open forests and grassy formations. According to the DRC's Forest Code, forest is defined as land covered by a plant formation based on trees or shrubs capable of providing forest products, sheltering wildlife and exerting a direct or indirect effect on the soil, climate or water regime (Code Forestier, 2002)[38].

This ecosystem is rich in animal and plant biodiversity, is characterized by nutrient-poor soil and records rainfall of around 700 mm per year (Mpundu, 2015; Pienaar, et al., 2015) [24-15]. The miombo forest is generally referred to as a homogeneous ecosystem, but some differences in species composition, diversity and structure occur locally (Ribeiro, et al., 2015; Chidumayo, and Frost, 1996) [27-9]. They provide goods and services for more than 70% of the region's rural and urban populations (Ribeiro, et al., 2017; Mpundu, 2015) [14-24]. In the Democratic Republic of Congo, miombo open forests account for about 26% of the national forest cover, or nearly 14 million hectares (WWF, 2012) [37]. The miombo forest habitat covers a large part of the former Katanga Province and the southern part of the current Kwango Province (Kabulu, et al., 2008) [19]. The majority of miombo species grow (regrow vegetatively or coppice) in a persistent subsoil rootstock, or the base of the stem, as an adaptation to a variety of browsers. This allows them to persist on the site after some trauma (World Bank group, 2018) [36]. Extensive horizontal root systems and clonal reproduction from root shoots facilitate rapid regeneration after cutting. New individuals are recruited a few meters around the parent tree (Matowo, et al., 2019; Frost, 1996) [22-18]. Miombo forest is rich in precious wood species that are widely traded locally and internationally. China is the main importer abroad. Local consumption of timber (usually with the species Pterocarus angolensis, Afzelia quanzensis, Dalbergia melanoxylon) is estimated at more than 10 times the amount exported internationally (World bank group, 2018; Campbell, et al., 1996) [36-7].

Miombo's forests provide a wide range of ecosystem goods and services essential for the well-being of rural and urban communities. They are direct sources of food (fruits, seeds, leaves, mushrooms, berries, bark extracts, beans and roots, herbs, wild meat, caterpillars, honey, etc.) (Pierre, 2019; De Kesel, et al., 2017) [16-13]. They filter drinking water by reducing biological and chemical pollutants. Miombo forests play an indispensable role in maintaining climate balance, purifying the air, reducing noise, regulating rainfall patterns, reducing wind speed, maintaining soils against erosion, providing wood energy, etc. (Campbell, et al., 1996; Clarke, et al., 1996; Pienaar, et al., 2015) [7- 11-15]. However, the Miombo forests are increasingly facing many threats without any measures aimed at sustainable management. Trees are cut down to meet present needs (Nduwamungu, et al., 2015; Malmer, 2007) [25- 21].

Trees in Miombo are cut for conversion to agricultural land, mining, carbonization, fuelwood, etc. (Nduwamungu, et al., 2015; Malmer, 2007) [25-21]. Due to the lack of stable and permanent electricity, wood energy is more demanded by bakers, blacksmiths, restaurants, brick makers and households (Mpundu, 2015; Tréfon, et al., 2010; FAO, 2003; Misana, et al., 1996) [24 – 29 – 34- 23]. As a result, the area is exposed to the risk of soil erosion and climatic disturbances. Fuelwood, misuse of bush fires and urbanization due to population expansion are the main drivers of pressure on the miombo open forest (Pelletier, et al., 2018; Sikuzani, et al., 2017; Campbell, 1996) [17-28-7]; with the major consequences being habitat fragmentation and destruction, biodiversity loss, savannah development and soil erosion. For the year 2010, the annual rate of regression of miombo open forest cover is estimated to be around 2.4% (Chomba, 2018; Lupala, et al., 2015) [10- 20].

More than 70% of these populations use the products of these open forests on a daily basis to generate energy (charcoal and firewood), to treat themselves (medicinal plants), to feed themselves (non-timber forest products: fruit, mushrooms, honey, etc.) (www.ofcc-rdc.org) [39]. Furthermore, the main question that the study, like other projects in the region, is answering is: how to contribute to the reduction of the irrational exploitation of dry and clear forests in DRC in order to protect and manage them in a sustainable way"? This of course requires prior knowledge of the composition of its strata (vegetation classes). The main objective of this study is, on the one hand, to produce a general and stratified map describing the different vegetation classes of the Miombo forests of the Upper Katanga province from Landsat8 satellite images, collected in June 2018, and, on the other hand, to evaluate the quality of the accuracy of the map of vegetation strata of these forests produced using the confusion matrix (Goshen coefficient). The study presented in this paper aims to make a contribution with a view to serving as a necessary tool for the sustainable and responsible management of these forest ecosystems threatened by the drivers of deforestation as mentioned above.

2. Study area and data

2.1. Study area

Located in the south-eastern part of the DRC on the border with Zambia, the Upper Province - Katanga is situated at 11° 40′ 11″ South latitude and 2°10' and 27° 29′ 00″ East longitude (figure 1) and its surface area has been estimated at 132,425 Km². It has a desert climate (BWh) according to the Köppen-Geiger classification. Over the year, the average temperature is 22.4°C and precipitation averages 512.7 mm. Administratively, it is subdivided into 3 territories including: Kasenga, Kambove and Kipushi. The city of Lubumbashi is its capital.

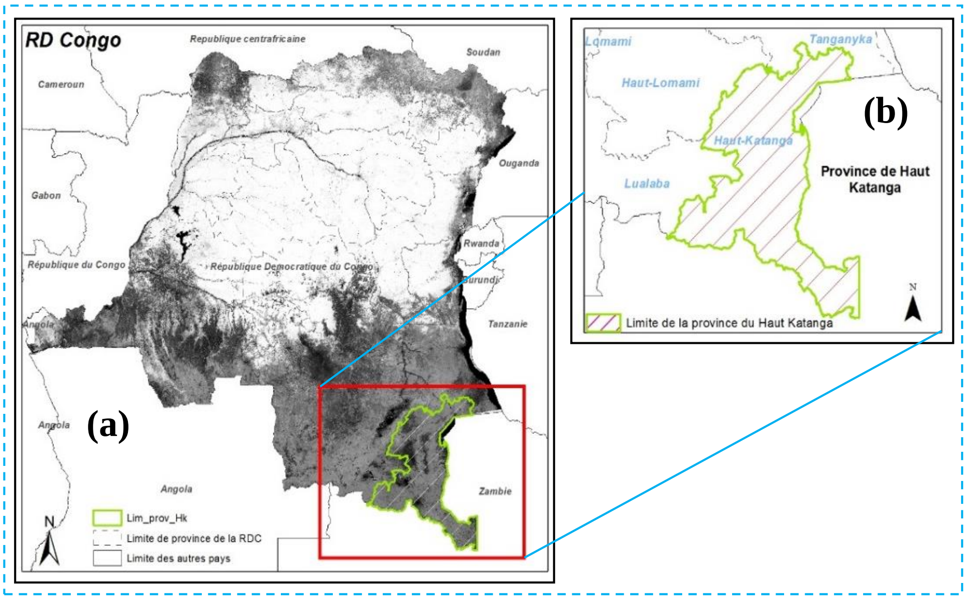

Figure 1. Study area showing, **(a)** the location of the study area in the Democratic Republic of the Congo, and **(b)** the study area location in Katanga province within the Democratic Republic of Congo.

2.2. Data

Data from LANDSAT 8 sensors were used in this study. Landsat satellites have a spatial resolution of 30 m in multi-spectral and 15 m in panchromatic. The spectral domains explored during this study are particularly in the Red, Near Infrared and Middle Infrared radiometric bands. In addition, 516 control or validation points were generated using the HQIS Random tool and verified in the field during the field truth collection mission [42].

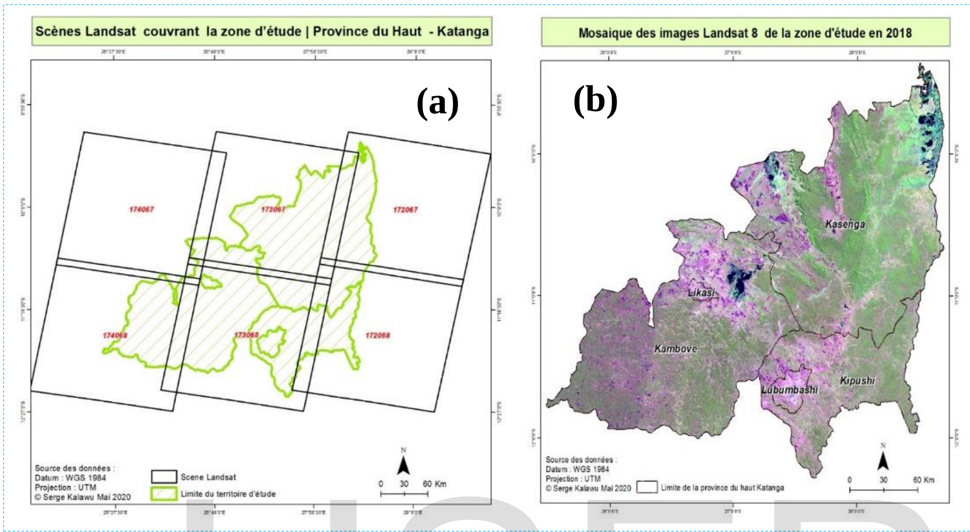

Figure 2: Study area showing **(a)** Landsat grid covering the study area. A total of 6 scenes of 180Kmx180Km Landsat images cover this area with Path (172, 173 and 174) and Row (066, 067 and 068) and **(b)** The Landsat 8 image mosaic covering the study area for the year 2020.

3. Materials and Methods

3.1. Materials

To carry out this study, we used certain data collection, analysis and processing equipment, including satellite data processing software (ENVI, Arc GIS and QGIS) and the Map 62c GPS receiver for collecting validation data in the field, in addition to a complete kit of Microsoft Word and Excel products for producing statistics.

3.2. Methods

The methodological approach used in this analysis is based on satellite image processing (Landsat 8), collection of validation data in the field, and the principles of interpreting validation points derived from random sampling and interpreted using high-resolution Google Earth images. It consists of six main steps: **(1)** data preparation (collection of existing data), **(2)** selection of Landsat 8 satellite images of the study area, **(3)** atmospheric correction of selected bands, color composition of radiometric bands and creation of the Image Mosaic, **(4)** calculation of the vegetation index, **(5)** processing of selected images (supervised classification), and **(6)** validation of the results obtained using the Goshen Index (Confusion Matrix).

3.2.1. Preparation of geographical data

The data used in this study mainly include Landsat 8 satellite images, GPS surveys collected in the field (Waypoint of land use classes), high-resolution image from Google Earth, and Administrative boundaries of the DRC provinces.

3.2.2. Selection of satellite images of the study area

Data from LANDSAT 8 sensors were used in this study. Landsat satellites have a spatial resolution of 30 m in multi-spectral and 15 m in panchromatic. The spectral domains explored during this study are particularly in the Red, Near Infrared and Middle Infrared radiometric bands. In remote sensing, these radiometric bands are among the most appropriate for highlighting vegetation. All the images used in this study were taken in June 2020. The choice of images was made taking into account three constraints, namely the percentage (%) of cloud cover, the proportion of scratches on the images and the availability of the image in relation to the year of study. A total of six (6) Landsat scenes of 180 Km X 180 Km cover our study area (**figure 2**).

3.2.3. Atmospheric correction of selected bands

The selected radiometric bands have been subjected to prior radiometric and atmospheric corrections to reduce atmospheric effects including the absorption and scattering process due to gases such as ozone, water vapor and aerosols.

3.2.4. Calculation of the Normalized difference vegetation index

In order to minimize the effects and/or influence of the seasonality of vegetation in the Miombo project area on reflectance, it was important to take into account the vegetation index variable (NDVI), which allows better discrimination of forest cover compared to other land use classes. In addition, NDVI is often used around the world to monitor drought, forecast agricultural production, and assist in forecasting fire zones and desert offensive maps. Farming apps, like Crop Monitoring, integrate NDVI to facilitate crop scouting and give precision to fertilizer application and irrigation, among other field treatment activities, at specific growth stages. NDVI is calculated in accordance with the formula:

$$\mathbf{NDVI = (NIR-RED)/(NIR + RED)} \qquad \mathbf{(1)}$$

NIR: reflection in the near-infrared spectrum and RED: reflection in the red range of the spectrum

According to this formula, the density of vegetation (NDVI) at a certain point of the image is equal to the difference in the intensities of reflected light in the red and infrared range divided by the sum of these intensities. This index defines values from -1.0 to 1.0, basically representing greens, where negative values are mainly formed from clouds, water and snow, and values close to zero are primarily formed from rocks and bare soil. Very small values (0.1 or less) of the NDVI function correspond to empty areas of rocks, sand or snow. Moderate values (from 0.2 to 0.3) represent shrubs and meadows, while large values (from 0.6 to 0.8) indicate temperate and tropical forests. Crop Monitoring successfully utilizes this scale to show farmers which parts of their fields have dense, moderate, or sparse vegetation at any given moment. (https://eos.com/ndvi/)[55].

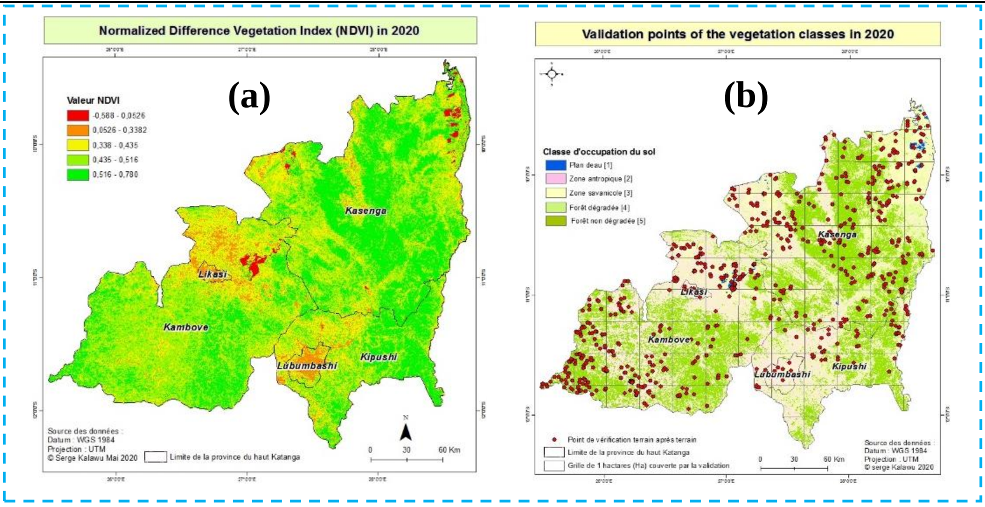

Figure 3. Study are showing **(a)** Range of Normalized Difference Vegetation Index values covering the study area for the year 2020 and **(b)** The Ground truth for the accuracy assessment of the three territories of the province of Haut Katanga.

3.2.5. Processing of selected images (supervised classification)

The processed Landsat images were classified with the Maximum Likehood algorithm to obtain the different strata of vegetation classes of miombo forest.

3.2.6. Validation of the results obtained using the Goshen Index (Confusion Matrix).

516 points from random and stratified sampling were generated using the Random tool (Figure 12). Thus, there are 42 control points for class 1 (Waterbody), 162 for class 5 (Non-degraded open forest), 89 for class 4 (Degraded open forest), 103 for class 4 (Savannah zone) and 120 for class 2 (Anthropogenic zone).

(a)

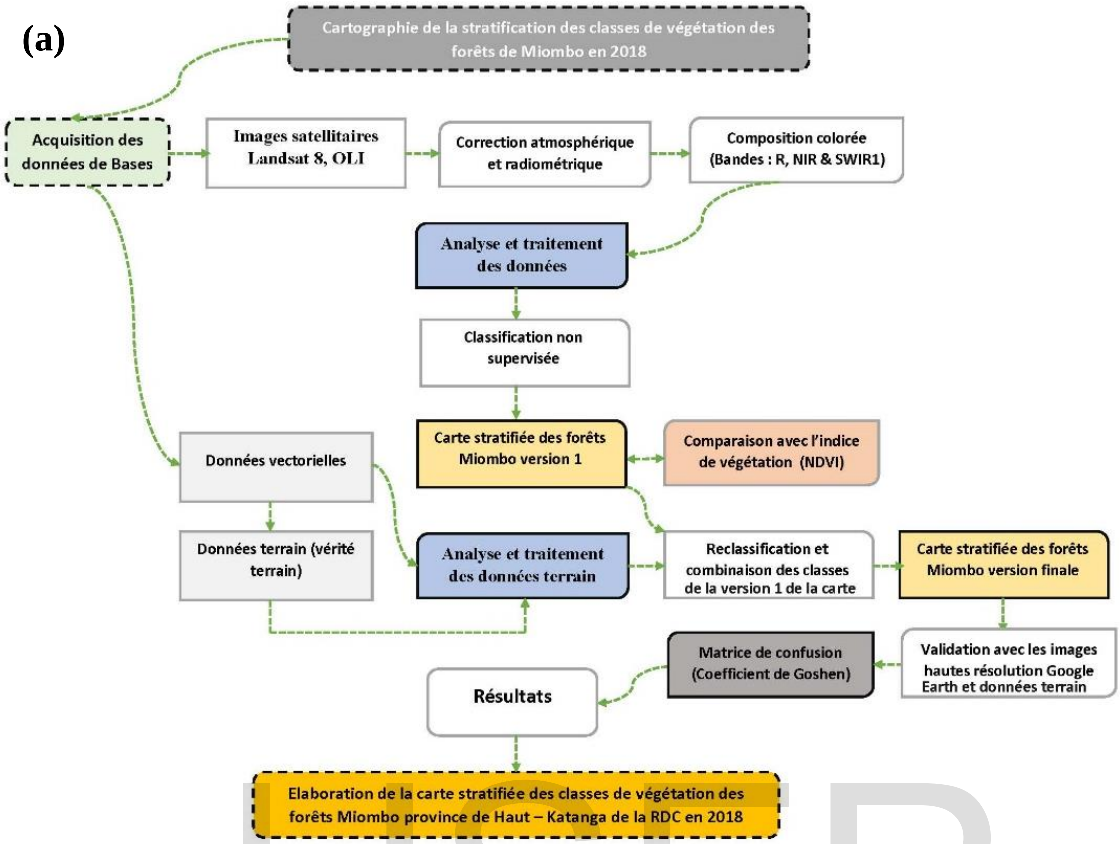

Figure 4. The graph illustrating the summarizes of the methodological approach used to map the strata of Miombo forests in the study area.

2.2.7. Field data collection (Ground truth)

A total of eight (8) villages located in the intervention zone of the Miombo project were visited during this mission and their forests categorized (Table 1).

Table 1. The villages visited in the field during the data collection for the validation of the stratification map of forest vegetation classes of Miombo in 2020.

N°	Village	Groupement	Sector	Territory
1	Mushibwe	Sapwe	Kisamba	Kasenga
2	Sapwe 1			
3	Kibundu			
4	Kyunga	Katanga	Lufira	Kambove
5	Milando			
6	Satumba	Kyembe		
7	Kibuye	Kasongo	Kaponda	Kipushi
8	Kialubamba			

4. Results

The national stratification of the DRC consists of ten classes presented in Table 3, with their correspondences to the IPCC 2006 land use categories. The first four classes relate to natural forests (class 1 to class 4) and the other classes relate to non-forested land (class 5 to class 10). Miombo forests are part of class 4 called open forest or dry forest (NERF, 2018) [31]. The production of the stratified map of the Miombo forests was done by integrating the information and data collected in the field into the final classification. The results presented in this study were obtained from the land use analysis and the confusion matrix analysis.

4.1. Analisis of results

4.1.1.Land use analysis

The processing and analysis of Landsat 8 images collected in June 2018 has enabled the production of the stratified map of vegetation classes of the Miombo forests of the Upper Province - Katanga. Five (05) classes were discriminated and their areas calculated. They are as follows: (1) Degraded open forest, (2) Non-degraded open forest, (3) Savannah, (4) Anthropogenic zone, and (5) Water plane. Below are the different classes or strata highlighted. It is important to note that the quality of a classification depends on (i) the choice of attributes to best discriminate between classes and (ii) learning data (Postadjian et al., 2018).

(a)

Figure 5. Different strata of the Miombo forest vegetation classes highlighted in this study in 2018.

It is important to note that the quality of a classification depends on (i) the choice of attributes to best discriminate between classes and (ii) learning data (Postadjian et al., 2018) [1].

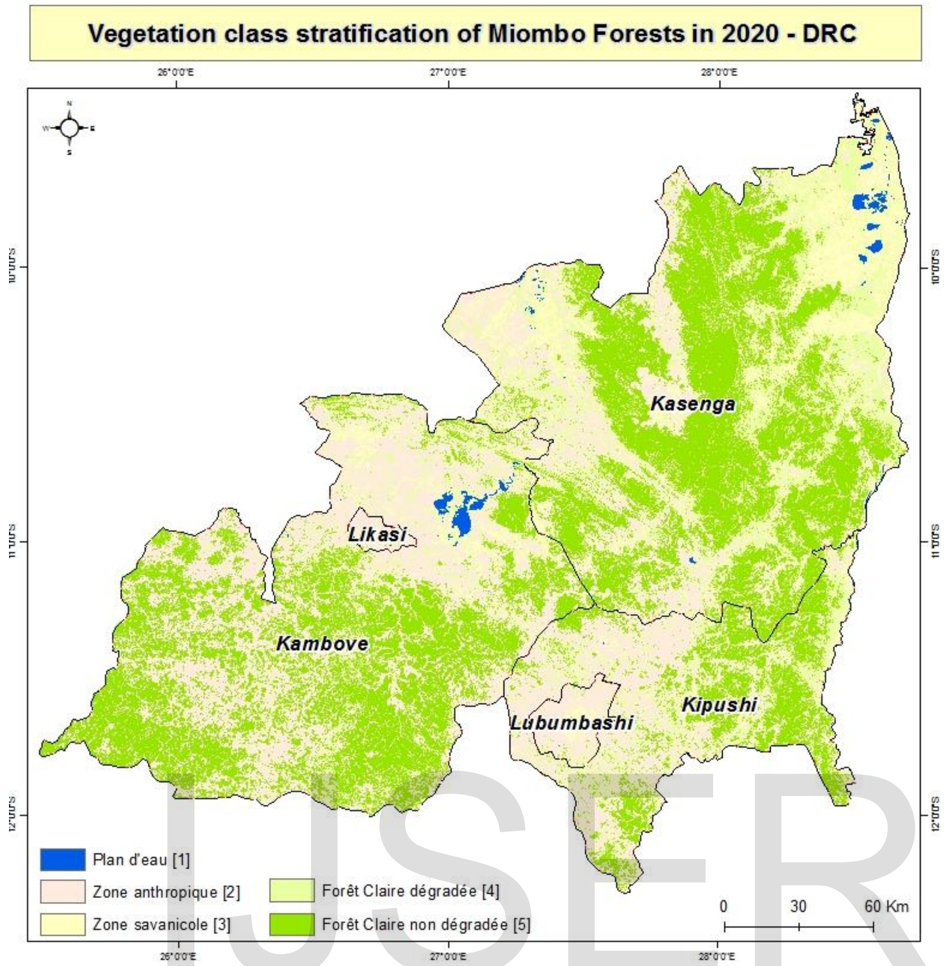

Figure 6: Stratum map of Miombo forest vegetation classes in 2020.

Analysis of the statistics table below shows that: (a) he land use class (savannah) occupies the first position with 2,240,081, 46 ha either 39.76% in the range of 0.33882 - 0.4352 NDVI (b) In second position is the degraded open forest stratum with 1,746,094.86 ha either 30.99% it is in the range of 0.4352 - 0.5161 NDVI; (c) The non-degraded open forest stratum occupies the third position with 1,244,094.48 22.08 %, it is identified in the NDVI range of 0.5161 - 0.7802. (d) Apart from these 3 identified forest strata, we can also note the anthropic zone class with 356,419.71 ha either 6.32% in the range of 0, 05263 - 0, 3382 and the water body class with 48,232.44 ha or 0.85% in the range of - 0, 5887 - 0, 05263.

Table 2 shows the areas of the land use classes or different vegetation classes of the Miombo forests in 2018 and their percentage proportion.

No	Land use class	Area (ha)	%	NDVI Values
1	Body of water	48232,44	**0,85**	**- 0,5887 - 0,05263**
2	Anthropogenic Zone	356419,71	**6,32**	**0,05263 - 0,3382**
3	Savannah Zone	2240081,46	**39,76**	**0,33882 - 0,4352**
4	Degraded Clear Forest	1746094,86	**30,99**	**0,4352 - 0,5161**
5	Unspoiled clear forest	1244094,48	**22,08**	**0,5161 - 0,7802**
	Total	**5634922,95**	**100**	

4.1.2. Confusion matrix analysis

- Preparation of validation points

After the development of a space map, it is often important to evaluate the classification. Thus, in this study, 516 points from a random and stratified sampling were generated using the Random tool (Figure 12). Thus, there are 42 control points for class 1 (Water body), 162 for class 5 (Non-degraded clear forest), 89 for class 4 (Degraded clear forest), 103 for class 4 (Savannah zone) and 120 for class 2 (Anthropogenic zone).

- Estimation of the accuracy of the classification

Validation of the classification results is an important step in the process, as it ensures the performance of the results obtained and thus the significance of the analyses that follow them (Masse A., 2013). Despite the availability of methods to refine class extent estimates for classification errors, the pixel counting approach continues to be widely used. Consequently, the full potential of the accuracy assessment data is not being utilized. In fact, it is not being used at all for estimating area in a pixel counting approach. An accuracy assessment does more than indicate the accuracy of the map, it provides sample data that can be used to avoid the measurement bias of pixel counting and to decrease the standard error of the estimated area. As such, the accuracy assessment results should not be the final step of the quality evaluation but an integral part of the overall analysis of accuracy and area (Olfsson at, al., 2012) [3].

By comparing the reference data and the spatial map resulting from the classification, it was possible to perform a statistical validation (confusion matrix and Kappa index) of the map produced. As a reminder, the confusion matrix (contingency table) is a tool for measuring the concordance between a set of observed elements and a set of reference elements. Here the observed elements correspond to the pixels from the classification and the reference elements to our verification samples (Masse, 2013) [6]. The confusion matrix allows us to statistically evaluate the intensity of the link between the reference data and the result of a classification. Similarly, the Kappa coefficient also estimates the quality of the classification. It was used to assess the accuracy of the adopted classification described above (Mama, V.J. and Joseph O., 2003) [4]. According to Pontius (2000), in a study of land use, when the Kappa index evaluated in classification operations is between 50 and 75%, the adopted classification is valid and the results can be judiciously used.
Table 3. Confusion matrix

		Producer's					
User's	Class	Degraded light forest	Non Degraded light forest	Water	Savana	Anthropic area	**Total 2**
	Degraded light forest	**58**	6	0	25	0	89
	Non Degraded light forest	70	**93**	1	0	0	164
	Water	0	0	**42**	0	0	42
	Savannah	9	0	1	**91**	0	101
	Anthropic area	0	0	2	59	**59**	120
		137	99	46	175	59	**516**

As shown by the results presented in Tables 3 and 4, some vegetation classes in Miombo forests are classified much more accurately than others. Except for the water bodies which show 100% accuracy, the savannah zone shows an accuracy of 93.2% in the classification. On the other hand, the lowest precision was observed in the degraded open forest class and the undegraded open forest class with 48.3 and 63.0 precision respectively. From Table 3, the errors of confusion and omission were determined for each vegetation stratum of the Miombo forests and are presented in Table 4. Errors of omission and confusion in classification were estimated at 24.4% (Table 4). The highest errors of omission were recorded at the level of degraded open forest classes (55%) and savannah classes (46%). On the other hand, the lowest errors of omission were observed in the water body and anthropogenic zone strata. Confounding errors were recorded for some vegetation classes. The largest values were obtained in the following strata: Degraded open forest 52%, human-induced 33% and undegraded open forest 30%. The lowest value of the error of confusion concerns the water body and savannah classes 0% and 7%.

In order to reduce the errors of confusion and omission, the land use classes were grouped together. All classes representing vegetation were merged to form the vegetation class, while the others were grouped together to form the land use class. As a result, the more detailed a classification is, the greater the errors that are made (Anderson et al., 1976) []. As shown in the confusion matrix, of the 519 control points, 365 are correctly classified. This gives a mapping accuracy of 70% (365/519) and a Kappa coefficient of 0.62. However, it should be noted that there are some difficulties in discriminating certain classes, such as between degraded and undegraded open forests and between savannah and anthropogenic areas. Overall, with reference to Cohen's (1960) [2] table on the Kappa index, the results of the mapping of the Miombo forest strata in Haut-Katanga can be considered consistent (good). Errors of omission and confusion were calculated for each stratum as identified after classification of Landsat 8 images. The values obtained reflect the accuracy of the interpretation of each class. When considering a stratum as degraded open forest, an omission error occurs when this forest stratum has been omitted from the map. On the other hand, it is considered a commission error or confusion when the area of degraded open forest has been classified into another class on the map.

Global Precision = 66,47 % and Kappa Coefficient = 0,58 %

Precision is the ratio of WSI that were correctly classified as malignant and all WSI that were classified as malignant (https://www.sciencedirect.com/topics/computer-science/classification-accuracy) [56]
Precision = TP/ TP+FP

No	Class	Commission Error (%)	User's Accuracy (%)
1	Body of water	0	100,00
2	Anthropogenic zone	33	66,67
3	Savannah	7	93,20
4	Degraded open forest	52	48,31
5	Non-degraded open forest	37	63,03

Table 9. Confusion, omission error and producer and user clarification of land use class classification

	User's Accuracy	%	Producer's Accuracy	%
	Degraded open forest	48,31	Degraded open forest	45,26
	Non-degraded open forest	63,03	Non-degraded open forest	88,89

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	Body of water	100,00	Body of water	95,45
	Savannah	93,20	Savannah	53,63
	Anthropogenic zone	66,67	Anthropogenic zone	95,24

5. Discussion

The mapping of the stratification of the vegetation classes of the Miombo forests resulting from the analysis of Landsat 8 satellite images of June 2018 has highlighted three main strata, namely: (1) undegraded open forest, (2) degraded open forest and (3) savannah areas (shrub, grassland, savannah forest and agricultural areas). The confusion matrix shows that this map has an overall accuracy of 70.33%. Moreover, if the results are deemed worthy and acceptable, they should not make us lose sight of the constraints encountered during the analysis and processing of the satellite images used. For the simple reason that the errors recorded during the classification of satellite images stem from several sources, notably the availability of images of the area with low cloud cover and the difficulty of discriminating certain strata.

Using the Kappa index, whose value is 0.58, we can conclude that the results of this study are statistically and cartographically acceptable. Thus, by referring to the table by Cohen (1960) [2] and Pontus (2000), on the Kappa index, whose value is higher than 0.50, we can judge the result of the mapping of the strata of the Miombo forests in Haut-Katanga in DRC to be consistent (good). As an index of overall quality, it also allows comparison of classification with random allocation of labels (Postadjian T. et al., 2018) [1]. Therefore, the classification used in this study, which resulted in five vegetation classes, is considered acceptable and workable. The analysis of the errors recorded at the level of the different vegetation classes, as shown in Figure 8, shows that the errors of omission are much lower at the level of some classes (water body, anthropogenic zone and undegraded open forest) while the errors of confusion are low in the water body and savannah classes. Classes that are difficult to discriminate visually are those with similar spectral signatures. This explains why the degraded open forest class is confused with the anthropogenic and undegraded open forest classes. Furthermore, the values of the confounding errors recorded are also considered acceptable as long as none of these errors is above 70%, which is the limit value.

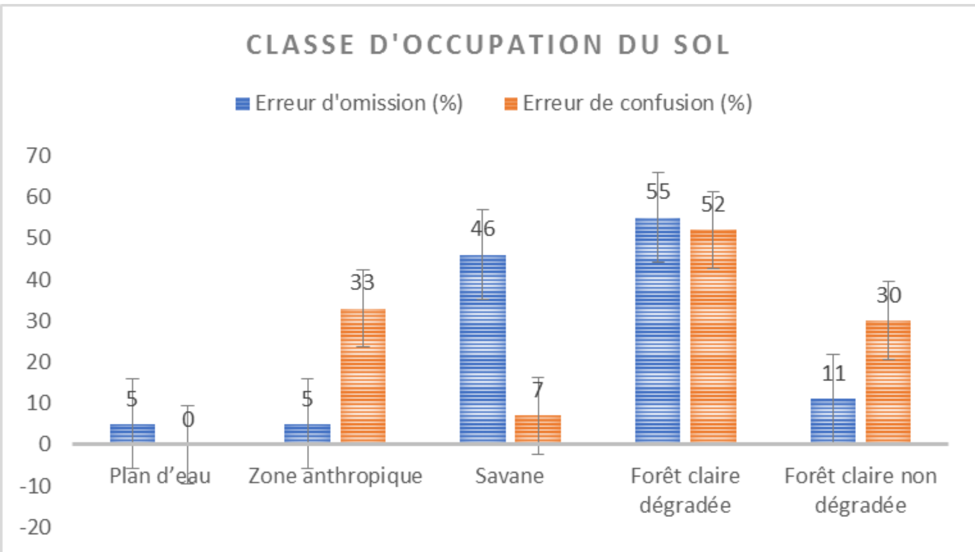

Fig11. Error of omission and confusion

6. Conclusions

The mapping of the stratification of plant classes in the Miombo forests revealed three (03) main Savannah areas (shrubby, grassy, savannah forest and agricultural areas); other land use classes: Water and entropized area. The stratification map of vegetation classes of the Miombo forests was statistically validated. The confusion matrix shows that this map has an overall accuracy of 66. 48 % and the Kappa coefficient is 0.58. The map produced can be used as a guide in the framework of sustainable management of the Miombo forests in DRC, more specifically, on issues related to land use (grazing, agriculture, reforestation, etc.).

7. Patents

We used some field data from OSFAC on behalf of FAO in the framework of the implementation of the project entitled: Miombo Community-Based Forest Management Project in Southeast Katanga.

Author Contributions: S.M.K conceived the experiments and processed the all of data such Landsat-8 data undertook the all analysis and prepared all the results with assistance from M.K.N. However, I.O, S.M.K and M.K.N participated in collection the field data for the accuracy assessment of the results. Also, S.M.K structured and drafted again the manuscript all authors have read and agreed to the published version of the manuscript.

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

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