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RESEARCH ARTICLE

REVISITING THE DEMOCRATIC REPUBLIC OF THE CONGO STRATIFICATION MAP FOR THE YEAR 2000 USING CLOUD-BASED COMPOSITING AND OBJECT-BASED CLASSIFICATION ALGORITHMS

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Abstract

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National stratification maps are essential to improve forest management systems. For the Democratic Republic of the Congo, the existing maps derived from remote sensing techniques do not allow an optimal representation of the diverse land cover classes constituting the national stratification scheme. This situation is inherent to the cloud persistence, the seasonality effects and the spatial resolution of the input satellite imagery used that is not always adequate for the discrimination of certain land cover classes. This paper explores a cloud-based median luminance best pixel approach to obtain a cloud-free mosaic of optimal quality. The mosaic produced has necessitated nearly 2,500 Landsat scenes and a following object-based classification enabled the generation of a stratification map for the year 2000 according to the national stratification theme. A stratified random sampling approach that required 1,141 reference samples allowed estimating the map accuracy at 79.32%. Land cover classes areas computed using standard good practices recommendations to estimate land areas indicated that the dense moist forest area was about 158,810,975 ± 7,460,671 ha representing 68.40% ± 3.21% of the country area. Thanks to the free, user-friendly and cloud-based platforms for satellite images processing, the methodology implemented is easily replicable for other tropical countries.

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Introduction:-

The forests of the Democratic Republic of Congo (DRC) represent around 60% of the overall Congo Basin forest estate and play an important role in the sequestration of atmospheric CO2, thus contributing to balancing the flow of global greenhouse gas emissions [1,2]. Monitoring the dynamics of Congolese forests is therefore of importance, particularly since the advent of the REDD+ mechanism [2,3]. In order to progress in meeting the requirements of the Warsaw Framework for REDD+, the DRC recently submitted to the United Nations Framework Convention on Climate Change (UNFCCC) its first Forest Reference Emission Level (FREL) covering the period 2000-2014 [4]. The year 2000 was chosen as the base year of the DRC's FREL as it corresponds to the reference year for several map products at the national level [4].

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The DRC, like several other Congo Basin countries including Congo-Brazzaville [5] and Equatorial Guinea [6] and many other tropical forest countries [7], was confronted with the lack of reliable historical data on land cover and land cover change during the establishment of its FREL [4]. The data included a homogeneous national stratification map for the base year 2000, allowing to distinguish different land cover classes described in the country's national forest classification operational guide [8]. Indeed, the 2000 national stratification map included in DRC's FREL is the result of merging two maps. The first map covers the extent of three western provinces namely Mai-Ndombe, Kwilu and Kwango while the second map spans over the remaining DRC territory. These two maps differ in terms of (1) the classification techniques used (i.e., object-oriented classification and visual interpretation for the first vs. pixel-based classification for the second map), (2) the labeling systems of the land cover classes, and (3) the types of satellite images used as inputs to produce them [9].

An additional constraint in obtaining a homogeneous national stratification map for the DRC is the classes aggregation found in existing maps, which do not adequately represent the classes described in the national stratification scheme. As an example, the class known as dense rainforest found in many land cover maps [10,11,3] is in fact an aggregation of several classes of the national stratification scheme, notably the dense moist forest, the edaphic forest, the secondary forest as well as the closed to open deciduous woodland (Miombo). Such aggregation is either the direct consequence of the spatial resolution of each map i.e. 1-km for [11] or it is tributary of the main objective pursued by the authors i.e. [3] whose vegetation map at 60 m spatial resolution mainly aimed at representing the major land cover classes at the national level.

Recently, [12] have developed a national stratification map for the year 2000 at 30 m spatial resolution. Although at this spatial resolution it is theoretically possible to discriminate the different land cover classes constituting the DRC's forest classification system, this map only represents two general classes (i.e., forest and non-forest) and therefore cannot meet the requirement of obtaining a homogeneous and detailed cartography of the national stratification scheme.

In turn, cloud-based geo-spatial data display and processing platforms, such as Google Earth (GE), Collect Earth (CE), Google Earth Engine (GEE), and System for Earth observation, data access, Processing, Analysis for Land monitoring (SEPAL) [13], have significantly reduced the time required to process spatial data for deriving homogeneous and detailed vegetation maps [14]. In fact, those free, user-friendly and cloud-based platforms for satellite images processing make the use of remote sensing techniques more accessible to a larger number of practitioners. SEPAL for instance, is a cloud-based supercomputer platform that is part of the Openforis tools such as Collect Earth [15]. SEPAL provides access to and processing of historical and recent satellite images archives of the USGS (United States Geological Survey) Landsat (L4-5, L7 and L8) and ESA (European Space Agency) Copernicus (Sentinel-1 and 2) programs. CE for its part is a tool for querying high and very high spatial resolution satellite images and collecting various data through the GE archives in conjunction with Bing Maps and GEE [16].

There is therefore a need to demonstrate how cloud-based geo-spatial processing algorithms can be routinely used to improve capacities in producing reliable classification maps that reflect national stratification schemes. Such demonstration is of paramount importance in developing countries where computation capacities to process a large amount of satellite imagery are still low and where adequate infrastructures and standard operating protocols to produce consistent land cover maps trough time are still lacking.

The objective of the present research is to use these cloud-based platforms to produce a DRC-wide stratification map for the reference year 2000 that discriminates the land cover classes as described in the country's national stratification scheme. The specific objectives of the research are threefold: (1) using the best median pixel approach to produce an annual composite which excludes the seasonality effects and the lack of data (i.e., clouds, poor quality image, atmospheric haze, etc.); (2) conducting an object-oriented supervised classification for producing a historical map of the year 2000 with an improved spatial discrimination of the vegetation types described in the national stratification scheme; and (3) generating reliable land cover classes areas at the national scale. In addition, the approach developed in the research is meant to be straightforward so that it can be easily replicated for other tropical countries that are still facing challenges in producing reference maps that comply with national stratification schemes.

Materials and Methods:-

Data

Producing a DRC-wide mosaic for the year 2000 required the use of almost 2,500 Landsat 4-5 (L4-5) and Landsat 7 (L7) scenes (Table 1) to cover the entire country area spanning over 2,345,409 sq.km. These scenes with a spatial resolution of 30 m were acquired around the year 2000 and selected through the SEPAL platform. Three spectral bands were used for these analyses: (1) Medium Infrared [MIR]: 1.55 - 1.75 µm; (2) Near Infrared [NIR]: 0.76 - 0.90 µm and Red [R]: 0.63 - 0.69 µm. These bands were preferred to other spectral bands because: (i) the R can distinguish between vegetated and bare areas; (ii) the NIR is sensitive to the structure of healthy or disturbed vegetation, including cultivated areas; and (iii) the MIR is sensitive to the reflectance of vegetation and soil, in addition to being able to capture the reflectance at the peak of chlorophyll absorption [11]. In addition to the L4-5 and L7 images, nationwide SRTM (Shuttle Radar Topographic Mission) images at 30 m spatial resolution were acquired from the OSFAC (ObservatoireSatellital de Forêtd'Afrique Centrale) database [17]. This data was used to characterize the vegetation types based on the altitudinal gradient [11,2].

Methodology:-

The Figure 1 summarizes the methodology consisting of five steps that are: (1) delineation of blocks; (2) generation of mosaics; (3) segmentation and calibration of classification models; (4) object-based classification and (5) evaluation of results including the calculation of the number of reference samples to be collected and the production of land cover area statistics. These different stepsare detailed below.

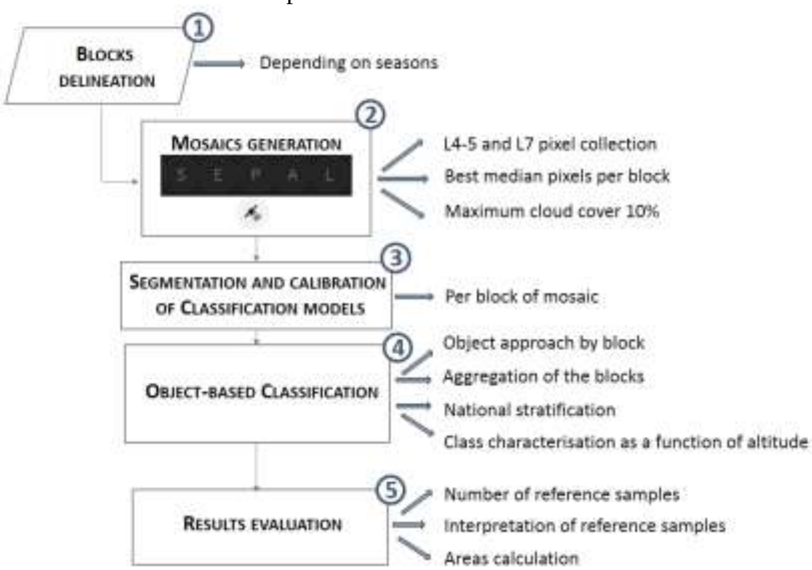

Figure 1:- Methodological approach for producing the DRC stratification map for the year 2000 according to the national stratification scheme.

Delineation of blocks

The DRC's geographic location straddling the Equator causes an inversion of the seasonality between the North and South, making it difficult to map simultaneously the totality of country ecosystems using satellite-based remote sensing techniques [11]. To circumvent that issue, the country was divided into three blocks (Figure 2) to stratify the seasonality. The northern block (in blue) corresponds to the area covered by the Sudanian and Sudano-Guinean savannah, while the central (in orange) and southern (in red) blocks correspond respectively to the areas of dense humid forest and Zambézian savannah [2].

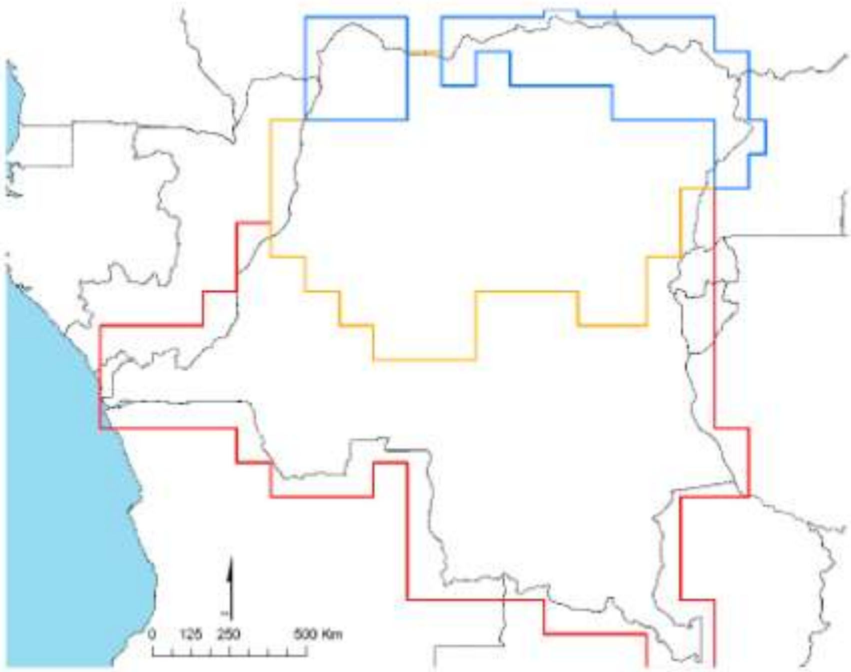

Figure 2:- Delimitation of DRC into three seasonal blocks (blue, orange and red).

Mosaics generation

The collection of Landsat scenes was conducted per block according to specific Julian Days (JD) to generate per block mosaics within the SEPAL platform [13]. The selection of images was constrained with a maximum threshold of 10% cloud cover in order to generate a high quality and cloud-free composite for the year 2000. To achieve the could-free composite objective, the strategy consisted in increasing the number of scenes collected per block and extending the time series around the year 2000, i.e. 1996-2003 for the northern block, 1995-2003 for the central block and 1996-2003 for the southern block (Table 1).

Table 1:- Specific parameters for the collection of scenes and the production of mosaics per block.

	Satellite	**Sensor**	**Julian Day**	**Date Gregorian Calendar**	**Time series**	**No. of Landsat scenes covering the block**	**Average acquisition per scene**	**No. of scenes collected/block**
North	L4-5	TM	350	15-Dec	1996-2003	36	14	75
	L7	ETM+						426
Sub-Total								**501**
Center	L4-5	TM	167	15-June	1995-2003	56	17	202
	L7	ETM+						551
Sub-Total								**753**
South	L4-5	TM	93	02-April	1996-2003	90	14	859
	L7	ETM+						379

Sub-Total		**753**
Grand Total		**2,492**

Segmentation and calibration of classification models

Multi-resolution segmentation by region [18] was used to partition the mosaics of each block into homogeneous segments [19-22]. These segments were constructed by merging the spectral and spatial information of adjacent pixels using the MIR, NIR and R Landsat bands [23,24,21]. The segmentation was carried out under the constraint of obtaining segments or objects whose sizes are finer (here referred as S-N1 segments of about 3,41 ± 4,80 hectares) in heterogeneous landscapes and larger (i.e., S-N2 segments of about 22,40 ± 22,41 hectares) in homogeneous ones [25,21,26,22]. A S-N2 segment corresponds to an aggregation of several S-N1 segments and represents a dense and spatially homogeneous vegetation cover. The aggregation of homogeneous segments was considered to reduce the time required to calibrate the classification model.

The classification model calibration for dense and homogeneous landscapes of the central block (Figure 3) and certain areas of the southern block was carried out based on S-N2 segments from which so-called reference segments (RS) within each block were extracted. The RSs were visually identified within each block on landscapes that are characteristic of a specific targeted vegetation. The calibration thus consisted in assigning the type of vegetation corresponding to the RSs considering the following information as inputs for decision-making: (i) expert knowledge from the authors, (ii) NDVI (Normalized Difference Vegetation Index) indices [27] (equation 1) and (iii) NDWI (Normalized Difference Water Index) [28] (equation 2). These two indices are commonly used in remote sensing respectively for their sensitivity to characterize vegetation cover and water availability[29,30]. They have already been successfully applied in the characterization of certain types of vegetation in DRC, notably edaphic forest and grassland classes [11].

$NDVI = (\rho NIR - \rho R)/(\rho NIR + \rho R)$, (1)

with : ρNIR : luminance of the Near Infrared spectral band and ρR : luminance of the Red spectral band

$NDWI = (\rho NIR - \rho MIR)/(\rho NIR + \rho MIR)$, (2)

with : ρNIR : luminance of the Near Infrared spectral band and ρMIR : luminance of the Medium Infrared spectral band

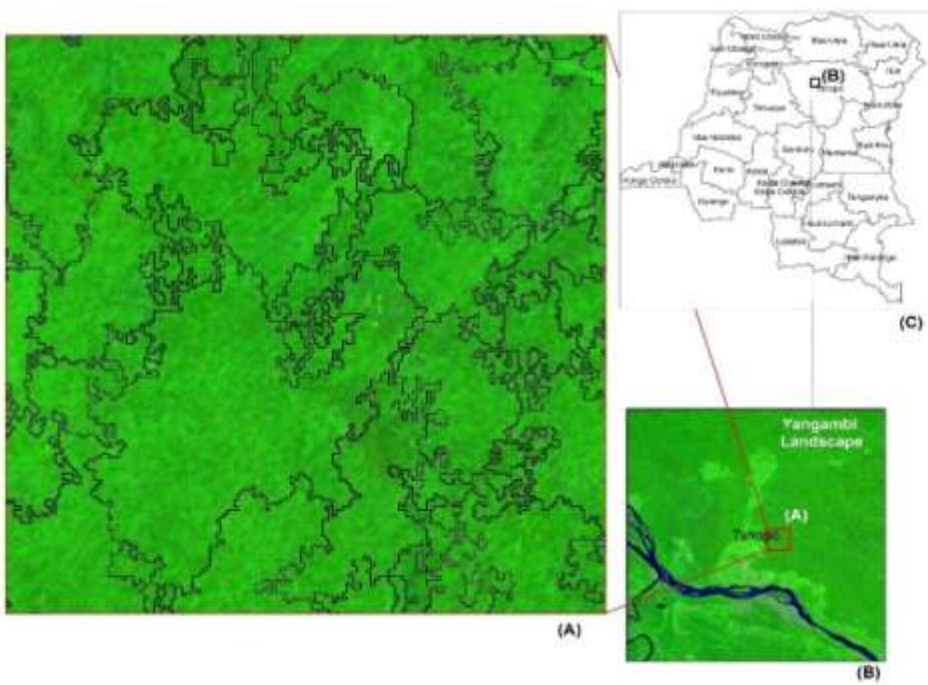

Figure 3:- Overlay of S-N2 segments on the best median pixel mosaic around the City of Yangambi in the Tshopo Province.

For landscapes that are less dense and more homogeneous, the calibration of the classification model was carried out at the S-N1 segments level, especially in the northern and southern blocks.

In addition to parameters of homogeneity and density, other information available in the scientific literature and in the country's national stratification standards [8] were considered to distinguish certain types of vegetation in the RSs. These include canopy texture (i.e. rough or coarse vs. smooth) [10,11] which was used to improve the calibration of the classification model, particularly in the case of certain highly heterogeneous landscapes in the northern and southern blocks.

Object-based classification:-

A supervised object-based classification [31] using the nearest neighbor maximum likelihood algorithm was applied to derive vegetation types by block. This algorithm has proven to be efficient for mapping vegetation types [32,33] and the classification approach preferred has the distinct advantage of requiring only a few set of training samples per vegetation types within each block.

The labeled objects (segments or polygons) resulting from the classification process were subsequently converted to a raster format at a spatial resolution of 30 m, equivalent to the Landsat spatial resolution, to obtain the stratification map of the whole country.

Results Evaluation:-

The evaluation of the classification output was carried out through a stratified random sampling design of reference samples throughout the whole DRC.

Number of reference samples;

Equation (3) [34,35] was used to calculate the number (n) of samples required per class of the stratification map.

$$n = \left(\frac{\sum W_i S_i}{S(\hat{o})}\right)^2, \quad (3)$$

$$S_i = \sqrt{U_i * (1 - U_i)},$$

where: n is the total number of samples ; $S(\hat{o})$ is the standard error of the overall acceptable accuracy: i.e. 0.01; W_i is the proportion area of the class i; S_i is the standard deviation of class i and U_i the user accuracy of class i.

The expected user accuracy (U_i) for each class has been set as follows based on expert knowledge and the expected complexity to distinguish each vegetation type: 0.50 (dense forest on dry land); 0.45 (edaphic forest); 0.99 (secondary forest); 0.90 (open forest); 0.60 (submontane forest); 0.45 (mountain forest); 0.20 (mangrove forest); 0.70 (wooded & shrubby savannah); 0.99 (grassland); 0.90 (urban area) and 0.90 (water body). The standard error of the overall precision for the whole country was set at 0.01.

The n samples were then allocated to different classes according to each class area and a minimum of 100 samples was allocated to any minority class [36].

Interpretation of reference samples;

Reference samples were visually interpreted on Collect Earth (CE) [16] through a squared evaluation unit of 0.09 ha [37] corresponding to the spatial resolution of the stratification map. The interpretation was mainly carried out on images from the year 2000 and in priority on any high-spatial resolution satellite images when available [38]. In case where images for the year 2000 were missing, images acquired around this year were used (Table 1).

To guarantee the independence of reference samples, their interpretation was carried out regardless of the class predicted by the automated classification process (Section 2.2.4). Furthermore, the assignment of the vegetation class corresponding to each reference sample was based on the majority rule within each evaluation unit. The comparison of reference samples with the results from the automated classification led to a confusion matrix that was used to calculate common map accuracy indices that are typically the user accuracy, the producer accuracy, the overall accuracy and the Kappa index [39,36].

Areas calculation;
Two approaches were used for calculating the areas of different classes: pixel count and statistical estimation. The pixel count was conducted at the provincial level and summarized at the national level. The statistical estimation of class' areas and the associated errors were performed using SEPAL's Stratified Area Estimator Analysis module[13], following the good practices approach for estimating land areas proposed by [35].

Because the forest class is of major interest in particular for operationalizing the REDD+ mechanism at the national level, the final stratification map was subsequently aggregated into two major classes namely Forest (i.e., Dense moist forest, Edaphic forest, Mangrove forest, Secondary forest, Close to open deciduous woodland (Miombo), Submontane forest and Mountain forest) and Non-Forest (i.e., Savana woodland &Shrubland, Grassland and Urban & Bare areas) to estimate the reference forest area for the year 2000 (i.e., Forest 2000).

Results:-

Landsat mosaic
Figure 4 shows the mosaic for the year 2000 at 30 m spatial resolution, resulting from the aggregation of three blocks (i.e., north, center and south)mosaics using a total of 2,492 Landsat scenes. Despite the large number of Landsat scenes required, the mosaic necessitated very little memory space allowing its easy display and processing on standard computers that are commonly available in most of developing country remote sensing national institutions. The mosaic covers homogeneously the entire country thanks to the median luminance best pixel mosaicking process. Common cloud persistence in the southwestern was significantly reduced so that remaining clouds on the mosaic represent only 0.2% (No Data in Table 2) of the country area.

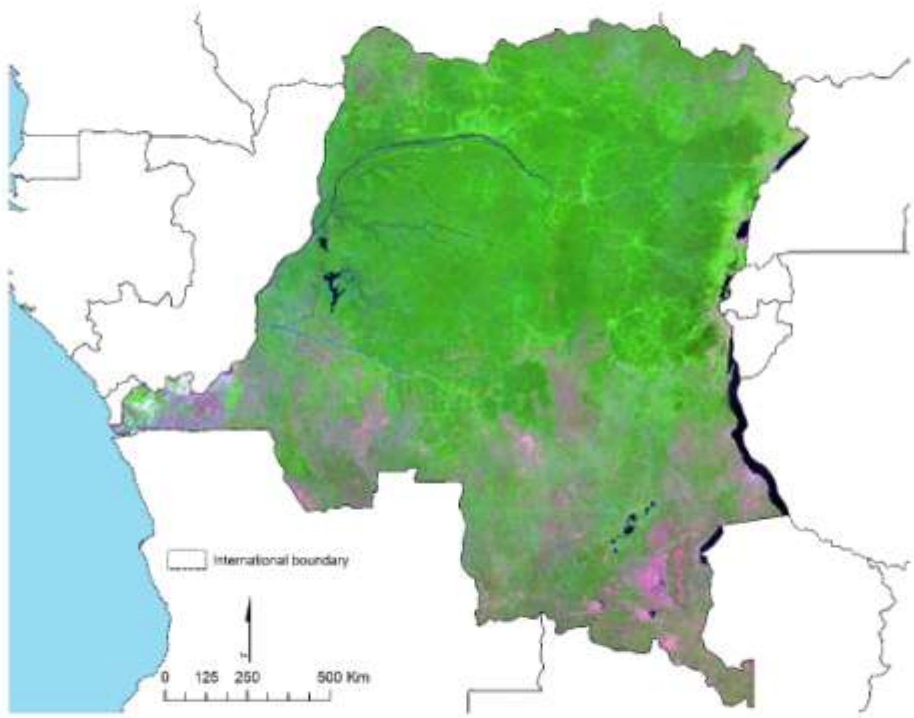

Figure 4:- Median luminance best pixel mosaic for the year 2000 in RGB mode - R=Medium Infrared, G=Near Infrared and B=Red.

Vegetation class areas
Figure 5 below shows the stratification map (i.e., Vgt DRC 2000) for the year 2000 with a spatial resolution of 30 m comprising 12 land cover classes. The pixel count-based surface area of the forest class (called Forest 2000) was estimated at 160,684,890 ha representing 69.08% of the national territory.

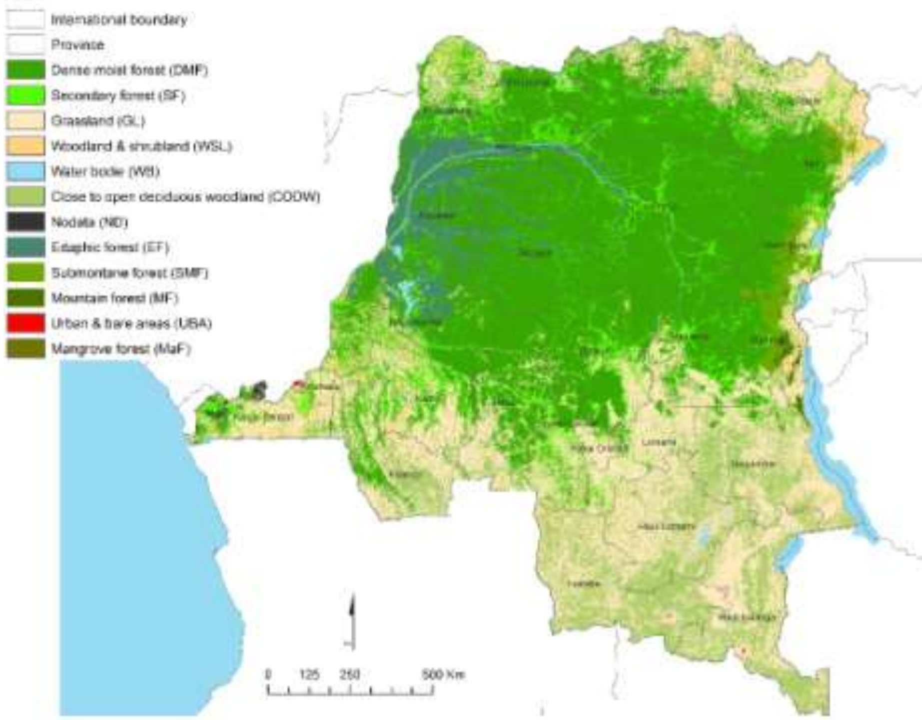

Figure 5:- Map Vgt DRC 2000.

Table 2 below shows pixel count-based areas of different classes by province and their relative proportions at both national and provincial levels.

Table 2:- Pixel count based-land cover classes'1 areas per province and relative proportion areas at both national and provincial levels.

Provinces	DMF (ha)	%	SF (ha)	%	GL (ha)	%	WSL (ha)	%	WB (ha)	%	CODW (ha)	%	ND (ha)	%	EF (ha)	%	SMF (ha)	%	MF (ha)	%	UBA (ha)	%	MaF (ha)	%
Kinshasa	61,049	5.8	151,463	14.3	613,869	58.0	187,489	17.7	1,129	0.1	15,518	1.5	233	0.0	0	-	0	-	0	-	27,648	2.6	0	-
Kongo-Central	517,483	9.5	1,045,287	19.2	2,399,930	44.0	855,879	15.7	52,018	1.0	116,831	2.1	428011	7.9	0	-	0	-	0	-	6,047	0.1	27,268	0.5
Mai-Ndombe	7,162,705	55.6	1,515,779	11.8	929,500	7.2	1,148,212	8.9	385,626	3.0	145,995	1.1	0	-	1,590,933	12.4	0	-	0	-	0	-	0	-
Kw	1,	2	1,	1	3,	4	78	9	83	1	31	4	8	0	0	-	0	-	0	-	0	-	0	-

ilu	734,784	1.8	478,037	8.5	577,209	4.9	4,658	.8	,438	.0	6,538	.0	1	.0										
Kwango	1,649,550	18.1	411,600	4.5	4,215,424	46.3	369,658	4.1	54,496	0.6	2,407,554	26.4	0	-	0	-	0	-	0	-	1,099	0.0	0	-
Equateur	4,341,631	42.5	408,972	4.0	129,386	1.3	43,704	0.4	353,304	3.5	3,019	0.0	0	-	4,927,677	48.3	0	-	0	-	0	0.0	0	-
Sud-Ubangi	2,181,050	41.8	884,375	16.9	882,218	16.9	255,875	4.9	23,218	0.4	-	-	0	-	993,285	19.0	0	-	0	-	2	0.0	0	-
Nord-Ubangi	3,156,834	58.0	902,943	16.6	965,489	17.7	350,538	6.4	48,221	0.9	-	-	0	-	19,209	0.4	0	-	0	-	1,432	0.0	0	-
Mongala	3,461,446	61.5	890,503	15.8	11,563	0.2	3,060	0.1	143,810	2.6	-	-	0	-	1,099,329	19.5	0	-	0	-	15,343	0.3	0	-
Tshuapa	11,494,580	86.4	434,436	3.3	1,975	0.0	0	0.0	64,115	0.5	-	-	0	-	1,302,997	9.8	0	-	0	-	0	-	0	-
Tshopo	18,023,329	89.9	1,212,676	6.0	24,408	0.1	0	-	210,495	1.0	-	-	0	-	570,042	2.8	0	-	0	-	14,660	0.1	0	-
Bas-Uele	10,095,557	67.7	1,121,326	7.5	2,529,209	16.9	954,302	6.4	204,853	1.4	-	-	0	-	12,955	0.1	0	-	0	-	4,771	0.0	0	-
Haut-Uele	3,348,285	36.5	914,091	10.0	3,920,554	42.8	711,840	7.8	20,824	0.2	-	-	0	-	0	-	249,949	2,7	0	-	817	0.0	0	-
Itur	3,	5	22	3	1,	1	63	1	18	0	-	-	0	-	0	-	67	1	9	0	2,	0	0	-

i	707,209	9.0	1,242	.5	027,052	6.3	3,312	0.1	,221	.3							2,475	0,7	85	,0	563	.0		
Nord-Kivu	2,583,236	45.1	558,969	7.0	708,768	12.4	87,632	1.5	53,546	0.9	34,418	0.6	0	-	0	-	1575,885	27,5	115,947	2,0	5,171	0.1	0	-
Sud-Kivu	2,179,106	36.7	394,112	5.6	952,536	16.1	418,553	7.1	11,450	0.2	269,084	4.5	0	-	0	-	1,235,236	20,8	468,816	7,9	1,759	0.0	0	-
Maniema	7,770,284	60.7	1,239,950	9.7	2,841,058	22.2	90,298	0.7	66,606	0.5	663,585	5.2	0	-	0	-	127,967	1,0	0	-	3,692	0.0	0	-
Lualaba	129,530	1.0	2	0.0	5,347,789	42.6	410,494	3.3	36,985	0.3	6,579,875	52.5	0	-	0	-	0	-	0	-	39,823	0.3	0	-
Haut-Lomami	181,336	1.6	15,310	0.1	6,054,902	54.4	345,983	3.1	203,645	1.8	4,311,909	38.7	0	-	0	-	0	-	0	-	24,240	0.2	0	-
Tanganyika	241,309	2.0	178,119	1.5	5,564,852	45.5	419,685	3.4	34,740	0.3	5,719,075	46.7	0	-	0	-	43,256	0,4	42,022	0,3	1	0.0	0	-
Haut-Katanga	1,699	0.0	2,218	0.0	63,76,243	50.4	153,688	1.2	66,709	0.5	6,035,400	47.7	0	-	0	-	0	-	0	-	15,244	0.1	0	-
Kasaï-Oriental	41,267	4.0	107,515	10.4	774,067	75.2	46,487	4.5	3,775	0.4	56,538	5.5	0	-	0	-	0	-	0	-	0	-	0	-
Sankuru	7,879,84	72.5	1,210,31	11.1	1,509,66	13.9	108,281	1.0	24,818	0.2	131,892	1.2	0	-	0	-	0	-	0	-	0	-	0	-

	9		2		7																			
Lomami	429,659	7.9	415,308	7.6	4,026,198	73.7	148,381	2.7	12,402	0.2	429,252	7.9	0	-	0	-	0	-	0	-	1	0.0	0	-
Kasaï-Central	1,797,701	31.1	1,035,042	17.9	1,903,120	32.9	396,713	6.9	15,518	0.3	628,362	10.9	0	-	0	-	0	-	0	-	0	-	0	-
Kasaï	5,490,912	56.4	705,918	7.2	2,730,533	28.0	129,553	1.3	58,756	0.6	626,928	6.4	0	-	0	-	0	-	0	-	0	-	0	-
Pixel count	**99,661,380**		**17,455,506**		**60,017,518**		**9,054,277**		**2,252,714**		**28,491,772**		**428325**		**10,516,427**		**3,904,768**		**627,769**		**164,311**		**27,268**	
% / country	**42.8**		**7.5**		**25.8**		**3.9**		**1.0**		**12.2**		**0.2**		**4.5**		**1.7**		**0.3**		**0.1**		**0.0**	

1DMF: Dense Moist Forest; SF: Secondary Forest; GL: Grassland; WSL: Woodland &Shrubland; WB: Water Bodies; CODW: Closed to Open Deciduous Woodland; ND: No Data; EF: Edaphic Forest; SMF: Submontane Forest; MF: Mountain Forest; UBA: Urban and Bare Areas; MaF: Mangrove Forest.

The dense moist forest on land is the predominant country vegetation with an area equivalent to 99,661,380 ha, which is close to 43% of the national territory. This class is mainly present in the provinces of Tshopo, Tshuapa, Bas-Uelé, Sankuru, Maniema and Mai Ndombe. The edaphic forest class is mainly present in the provinces of Equateur, Mai Ndombe and Tshuapa and remains flooded almost all year, and includes the extent of DRC peatlands [40]. The secondary forest for its part results from the anthropogenic pressure and is generally found along the main roads, close to farming communities, rural agglomerations and urban centres [11].

The Close to open deciduous woodland is a combination of Close to open deciduous forest with an open canopy and as an undergrowthgrassland layer. It is also called "Miombo forest" which is found in the south-east and south-west of the country, respectively in the Lualaba provinces, Haut-Katanga and Kwango. Submontane forest and mountain forest are found exclusively in the eastern provinces of the country, mainly North and South Kivu. The grassland is one of the most represented vegetation in the north and south of the central forest massif as well as in the west of the country in the Kongo-Central province.

Finally, Woodland and Shrublandwere aggregated into a single class due to the lack of auxiliary information, particularly the respective ranges of canopy heights, which could improve their discrimination. These two types of savannas form a buffer zone at the frontier between dense moist forest and grasslands that are predominant in the Kasai Oriental province.

Statistical estimation of class areas

Table 3 below presents the results of the statistical area estimation and the associated errors for each class. The Forest 2000 class was estimated at 158,810,975 ± 7,460,671 ha representing about 68.40% ± 3.21% of the national area.

Table 3:- Area estimates of vegetation types and associated errors.

Land cover class	Pixel count (ha)	Area estimate (ha)	± 90% IC (ha)	Relative error (%)
Dense moist forest	99,661,380	95,486,748	4,865,011	5.0
Secondary forest	17,455,506	18,229,040	3,494,241	19.1
Grassland	60,017,518	50,266,714	4,945,162	9.8
Woodland &Shrubland	9,054,277	17,844,567	4,018,111	22.5
Water bobies	2,252,714	3,038,740	1,367,186	44.9
Close to open deciduous woodland (Miombo)	28,491,772	30,775,268	3,931,362	12.7
Edaphic forest	10,516,427	10,332,160	2,061,707	19.9
Submontane forest	3,904,768	3,233,979	246,659	7.6
Mountain forest	627,769	732,192	128,398	17.5
Urban & Bare areas	164,311	2,212,715	1,602,527	72.4
Mangrove Forest	27,268	21,587	1,869	8.6
Total	**232,173,711**	**232,173,711**	**10,037,415**	**4.32**

The area estimate of the Urban & Bare areas class is significantly different from that obtained using the pixel count method, with a relative error of about 72.42%. This difference is due to omission errors, notably 4 samples of Urban & Bare areas class on the Vgt DRC 2000 map that corresponded in fact to secondary forest (1 sample) and grassland (3 samples) according to the visual interpretation of reference points.

Accuracy assessment

The confusion matrix shown in Table 4 originates from the cross-comparison of the DRC 2000 Vgt map and the visual interpretation of reference samples.

Table 4:- Confusion matrix between the Vgt DRC 2000 map and the reference samples

		Reference samples 2000												
		D MF	**SF**	**GL**	**WS L**	**W B**	**COD W**	**EF**	**SM F**	**MF**	**UB A**	**Ma F**	**Tot al**	**UA[1] (%)**
Vgt DRC 2000	**DMF**	108	5	1	3	1		2					**120**	90,00
	SF	11	69	7	11		2	1			1		**102**	67,65
	GL	2	1	77	12		17				3		**112**	68,75
	WSL	1	12	24	64		1						**102**	62,75
	WB					98		2					**100**	98,00
	CODW	3	2	16	5		79				1		**106**	74,53
	EF	16		4				82					**102**	80,39
	SMF	7	3	3					83	4	1		**101**	82,18
	MF	2	1		1				4	92			**100**	92,00
	UBA	5	4	9	5						77		**100**	77,00
	MaF	4	3	7	2	2		2				76	**96**	79,17
	Total	**159**	**100**	**148**	**103**	**101**	**99**	**89**	**87**	**96**	**83**	**76**	**1,1 41**	
	PA[2] (%)	67. 92	69. 00	52. 03	62. 14	97. 03	79.80	92. 13	95. 40	95. 83	92. 77	10 0		

	OA3 (%)												79.32	
	Kappa Index												0.78	

1UA: User Accuracy; 2 PA: Producer Accuracy; 3 OA: Overall Accuracy;

The Vgt DRC 2000 map has an overall accuracy estimated at 79.32%, with a Kappa index of 0.78. The Mountain forest and Dense moist forest classes have the highest user accuracies respectively of 92 and 90% whereas the Woodland &Shrubland stratum has the lowest user accuracy of about 63%.

Discussion:-

Parameters for selecting Landsat scenes per block

The quality of the median luminance best pixel mosaic is primarily a function of the quality of Landsat scenes that were selected as inputs and therefore of the choice of the JD specific to each block [11,2]. The ultimate objective of the Landsat scenes selection was to minimize both the effects of seasonality and the presence of no data pixels [41,42,11,2].

In the northern block, the selected Julian day (JD =350) corresponds approximately to the beginning of the dry season (JD =335), while for the central (JD = 167) and southern (JD = 93) blocks, they correspond to the periods of the year with the lowest rainfall. The Landsat scenes were therefore collected during the low rainfall period for the three blocks. The main reason for using this period is that Landsat satellite images acquired during the rainy season in the northern block could bias the signal analysis of herbaceous land cover classes, which would then present higher NDVI values. The direct consequence would be the difficulty to discriminate herbaceous from woody vegetation within the northern block.

In the central and southern blocks, the JDs were chosen to maximize the depiction of deciduous woody vegetation, particularly the Close to open deciduous woodland (Miombo) class, whose foliage matures during the dry season. Thus, the use of rainy season scenes in these blocks would lead to an underestimation of deciduous forests.

Beyond the choice of JD per block, the relevance and representativity of the mosaic for the target year (2000) is important to evaluate. Such representativeness is a function of the number of scenes from the year 2000 that have been used in comparison to those from other years. In fact, the selection of input images has been extended before and beyond the year 2000 in order to obtain the best scenes with regard to the criteria set, i.e. a maximum of 10% cloud cover. Table 5 below illustrates that 43.5% of the scenes used for the mosaic in the northern block were from the year 2000, 43.3% for the central and 34.2% for the southern blocks. Thus, most of the scenes for all three blocks were from the year 2000, which indicates that the final mosaic produced for this study is representative of the target year as compared to other years (Table 5).

Table 5:- Landsat scenes (n) collected per block during the period 1995-2001 to produce the mosaic for the year 2000.

	1995		**1996**		**1997**		**1998**		**1999**		**2000**		**2001**		**Total**	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**N**	**%**
North			8	1.6			29	5.8	145	28.9	218	**43.5**	101	20.2	**501**	**100**
Center	17	2.3	35	4.6	26	3.5	52	6.9	147	19.5	326	**43.3**	150	19.9	**753**	**100**
South			136	11.0	199	16.1	287	23.2	193	15.6	423	**34.2**			**1,238**	**100**

Calibration of classification models

Four main parameters were used to calibrate the classification models: landscape homogeneity, density and roughness of the canopy, and altitude. The classification model was calibrated by block, based on RS-N1 segments for heterogeneous environments and SR-N2 for more homogeneous landscapes. The preliminary identification of vegetation types to drive the classification model was also based on the density, which, together with homogeneity, provides information on the horizontal physiognomy of the landscape, particularly the degree to which the canopy is open. The horizontal physiognomy was a key parameter for the discrimination between dense and open forests.

The vertical physiognomy was characterized by canopy texture based on the shape of tree crowns. It was used to distinguish edaphic forest from dense moist forest or even secondary forest. Indeed, the smooth texture which is specific to the edaphic forest is due to the persistence of water in the undergrowth throughout the year whereas the canopy texture of dense moist forest is rougher.

Altitude, also used by several authors including [11,7], made it possible to discriminate between low and high altitude vegetations, particularly mountain and submontane forests.

Minimum number of samples per land cover class

The accuracy assessment of the VgtDRC 2000 map was carried out according to good practices recommendations from [35]. These practices relate to three main elements: sampling design, response design and analysis of reference data.

The most used sampling methods are the systematic and random stratified samplings [43]. The first method selects the samples based on a regular spatial distance while for the second one the samples are selected randomly either equally or proportionally to the land cover classes areas on the map [44]. The latter was used in this research even though it generates a few samples in the land cover classes represented in small proportions [43]. To address the potential under-representativeness of samples in land cover classes covering small areas, [36] proposed allocating between 20-100 samples to these classes. Thus, for the VgtDRC 2000 map, 100 samples were allocated to each class considered as a minority class, namely mountain and submontane forests, mangroves and water bodies.

Mapping evaluation and products comparison

The conversion of the object-based stratification map to a raster format resulted in a final product at 30 m spatial resolution. This conversion did not induce any significant loss of information in terms of each class area (Table 6).

Table 6:- Areas comparison between the object-based and the pixel-based stratification map.

Land cover class	**Object-based area (ha)**	**Pixel-count based area (ha)**	**Absolute difference (%)**
Dense moist forest	99,661,913	99,661,380	- 0.001
Secondary forest	17,455,756	17,455,506	-0.001
Grassland	60,019,321	60,017,518	-0.003
Woodland &Shrubland	9,054,622	9,054,277	- 0.004
Water bodies	2,253,588	2,252,714	- 0.039
Close to open deciduous woodland (Miombo)	28,492,257	28,491,772	- 0.002
No Data	428,425	428,325	- 0.023
Edaphic forest	10,516,427	10,516,427	-
Submontane forest	3,904,797	3,904,768	- 0.001
Mountain forest	627,770	627,769	-
Urban & Bare areas	164,341	164,311	- 0.018
Mangrove Forest	27,269	27,268	- 0.003
Total	**232,606,486**	**232,602,037**	

However, the area estimates comparison between the pixel count and the statistical approaches showed significant differences for the classes Woodland &Shrubland and Urban & Bare areas (Table 3). These differences are mainly tributary of the 30 m spatial resolution of the final map that is still too coarse to allow discriminating tree and shrub savannas at the frontier with dense moist forest. The same applies to the discrimination between the Urban & Bare areas and the Grassland class, especially in provinces where the latter class is predominant (i.e., Kasai-Oriental, Lomami, Haut-Lomami, etc. see Table 2). Furthermore, the low precision found for Woodland &Shrubland in the confusion matrix (Table 4) is also a direct consequence of the low level of discrimination for these two classes. However, with all the savannas aggregated into a single class, the pixel count and statistical area estimates for that class are much closer, leading to about 14% decrease of the map overall relative error from 4.32% (Table 3) to 3.71% (Table 7), which is significant.

Table 7:- Area estimates of vegetation types and associated errorswith the savannah classes aggregated into a single class.

Land cover class	Pixel count (ha)	Area estimate (ha)	± 90% IC (ha)	Relative error (%)
Dense moist forest	99,661,380	95,294,536	4,790,060	5.0
Secondary forest	17,455,506	20,823,910	3,829,227	18.4
Grassland, Woodland &Shrubland	69,071,795	69,736,731	4,536,415	6.5
Water bodies	2,252,714	3,038,740	1,367,186	45.0
Close to open deciduous woodland (Miombo)	28,491,772	27,386,476	2,966,111	10.8
Edaphic forest	10,516,427	10,332,160	2,061,707	20.0
Submontane forest	3,904,768	3,233,979	246,659	7.6
Mountain forest	627,769	732,192	128,398	17.5
Urban & Bare areas	164,311	1,573,399	1,056,745	67.2
Mangrove Forest	27,268	21,587	1,869	8.7
Total	**232,173,711**	**232,173,711**	**8,619,652**	**3.71**

Figure 6 presents a visual comparison of the map Vgt DRC 2000 (map A) with those produced by [11] (map B), [3] (map C) and [4] (map D).Three locations are targeted, namely the province of Tshopo in the north of the country (Location 1), the province of Kwango in the south-west (Location 2) and the province of Tanganyika in the south-west (Location 3). These areas were chosen because they are characteristic of specific landscapes in DRC. In fact, the Location 1 shows intrusions of secondary forest within the dense forest massif which illustrates the intensity of anthropogenic activities, while the Locations 2 (southwest) and 3 (southeast) illustrate how open forests can be adjacent with dense forests along the watercourses in the south of the country.

The visual comparison illustrated in Figure 6 shows that the map Vgt DRC 2000 (Figure 6, A-1) discriminates the secondary forest intrusions in the core of the dense moist forest at the difference of the map produced by [11] (Figure 6, B-1). The main reason of that difference being that the latter map’s coarser spatial resolution does not allow to distinguishing detailed land cover shapes. The Vgt DRC 2000 map is in turn very similar to the map produced by [3] (Figure 6, C-1) that is at 60-m spatial resolution. The same similarity is observed with the [4] (Figure 6, D-1) which is at the same spatial resolution as the Vgt DRC 2000 even though the latter assimilates secondary forest to a non-forest area, unlike the three other maps.

The four maps are very similar considering the discrimination of the vegetation types in the Kwango Province (Figure 6, A-2; B-2; C-2 and D-2), while only the first three maps (Figure 6, A-3; C-3; D-3) are convergent about the land cover classes found in the Tanganyika Province.

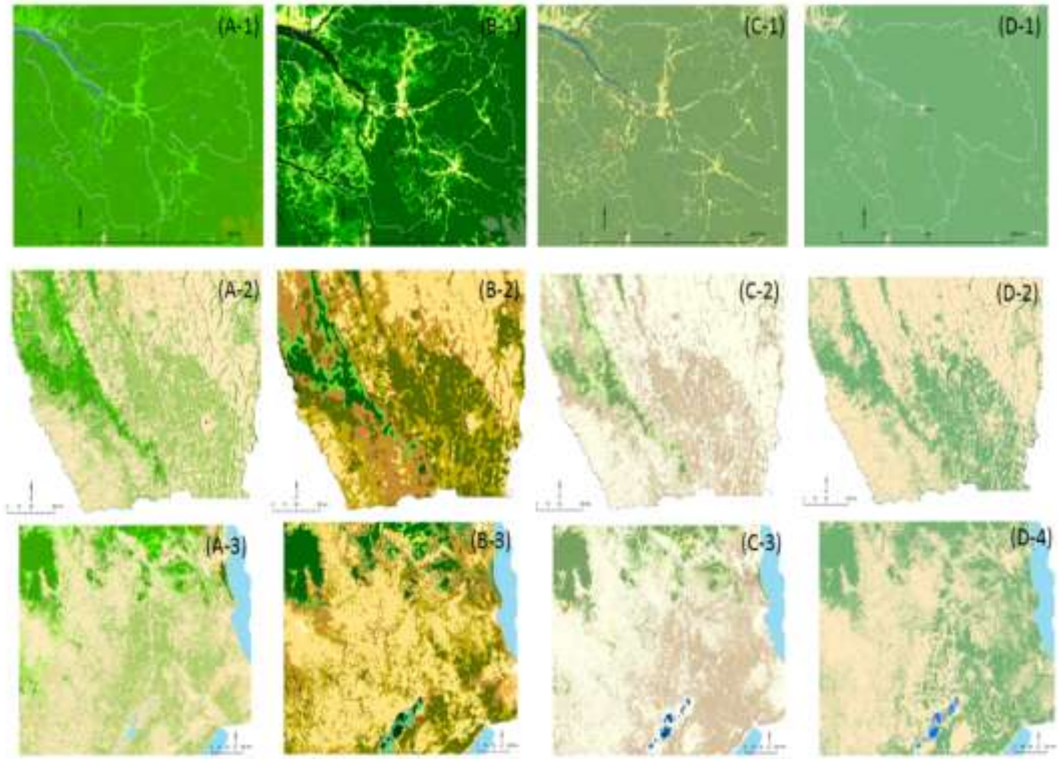

Figure 5:- Visual comparison of maps in the province of Tshopo: (A to D -1), Kwango (A to D - 2) and Tanganyika (A to D - 3) for the products: Vgt DRC 2000 (Map A), [11] (Map B), [3] (Map C) and [4] (Map D).

The comparison of pixel count-based areas between the four maps also shows some discrepancies for the major land cover class that is the dense humid forest here considered as the aggregation of all forest classes, i.e. dense moist forest, edaphic forest, secondary forest, close to open deciduous woodland (Miombo), submontane forest and mountain forest (Table 8).

Table 8:- Comparison of the dense humid forest area for the year 2000.

Vegetation type	Areas (Ha)	National proportion (%)	Study scale	Data sources
Dense humid forest	160,684,890	69.08	DRC	Map Vgt DRC 2000
Dense humid forest	159,529,000	68.58	DRC	[3]
Dense humid forest[1]	133,437,600	57.36	DRC	[11]
Dense humid forest[2]	147,273,000	63.31	Africa	[10]

1aggregation of the following classes: edaphic forest, dense moist forest, old secondary forest, young secondary forest, rural complex, close to open deciduous woodland (Miombo).
2 aggregation of the following classes: dense forest and forest/other mosaic.

The area of the dense humid forest class for the year 2000 is very close when comparing the map Vgt DRC 2000 and the map produced by [3], whereas the two products result from two different methodological approaches, notably an object-based classification for the first and a pixel-based approach for the second. Such finding was also corroborated by [45] who observed that these two classification approaches lead to similar area estimates in homogeneous and poorly fragmented landscapes such as the dense moist forest.

Conclusions:-

This paper proposed an alternative methodology to produce a 30 m DRC-wide stratification map according to the land cover classes defining the national stratification scheme as described by [8]. This research showed that the median luminance best pixel approach allowed to obtain a cloud-free mosaic of optimal quality and which minimizes the seasonality effects. The mosaic has also proven to require very little memory space on standard computers whereas the time series used comprised nearly 2,500 Landsat scenes. The areas of the different land cover classes and associated errors were estimated according to the good practices recommendations to estimate land areas [35] based on a set of 1,141 reference points spread over the entire national territory using a stratified random sampling. The precision indices indicated that the map was indeed representative of the different classes' areas for the year 2000, particularly the dense moist forest which is of paramount interest. The area of this class was therefore estimated at 160,684,890 ha (pixel count-based area) and 158,810,975 ± 7,460,671 ha (area statistical estimation), i.e. approximately 68.40% ± 3.21% of the country area. Thanks to the use of free, user-friendly and cloud-based platforms for satellite images processing,the methodology implemented in the research can be replicated in other Congo basin countries where stratification maps are still an issue in order to fully operationalize the REDD+ mechanism and for other forest management purposes.

Author Contributions:

The two authors contributed equally.

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Conflicts of Interest:

The authors declare no conflict of interest.

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