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Research Article
Field Validation of Land Cover and above Ground Carbon Mapping Using the Landsat OLI in Tropical Region

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Abstract
Background and Objective: Land use information is increasingly essential for knowledge of the environment mainly in the context of global change. The objective of this study was to investigate the benefits of using field-collected ecological data and high-resolution images to map different types of land cover and vegetation from a Landsat OLI 8 image. **Materials and Methods:** The selection of training areas was made without and with the use of GPS data collected in the field and the google Earth tool. The supervised classification was applied using the maximum likelihood algorithm Spectral Angle Maping. In addition, data collected in the field made it possible to estimate above-ground biomass. **Results:** The results obtained showed that land use maps made without input from both ecological field data and Google Earth images have classes that are highly contaminated with pixels from other classes. The overall accuracy was estimated by applying the Intergovernmental Panel on Climate Change (IPCC) good practices It goes from O = 92.7% for the first map produced to O = 89.8% for the second map. In addition, the average carbon stock in our study area is estimated at 112 MgC ha^{-1} while it varies from 84 -213 MgC ha^{-1} in areas of land forests to and in areas of seasonally flooded forests. **Conclusion:** This small-scale study highlights several challenges to be addressed in reducing emissions from deforestation and forest degradation (REDD+) before arriving at a very accurate final map of land use in the intertropical zone.

Key words: Field validation, land cover, above-ground biomass, landsat OLI, carbon mapping

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Land use information is increasingly essential for knowledge of the environment, its development and management[1,2]. It is a fundamental variable for regional planning as well as for studying and understanding the environment[3]. According to the FAO[4], land use refers to quot the biophysical cover of the surface of the land" and therefore, the type of use (or non-use) made of the land by humans. Indeed, the mapping of the different types of land use is an important and indispensable tool in several fields such as: the environment, inventory, ecosystem management and land use planning. This makes it possible to take an inventory of the resources of an environment, to understand, analyze and monitor the evolution and changes in land cover[5,1].

The department of Likouala, is the department with the largest area of forests in the Republic of Congo, nearly 85% of the department. Recent studies have shown that population growth, the influx of civilian war refugees from the Democratic Republic of the Congo, Central Africa and Rwanda, population growth, urban growth and the development of both artisanal and industrial agriculture are profoundly changing the face of land use in this department [6,7]. All these activities have impact not only on the floristic biodiversity of forest species, on forest structure, but also on the aerial carbon stock[8-10].

The possibility offered by remote sensing technology to access an overview of vast territories offers the possibility of mapping the different types of land use to an overview of large areas but also to complex and dangerous territories[1,11,12]. This technique allows, using one or more sensors, to acquire information on an object, surface or phenomenon without direct contact with the object, surface or phenomenon being investigated, satellite images obtained by this technique are the main source for the production of the various land use maps[11,13].

However, it is still difficult to really identify from satellite images provided by remote sensing, the different types of vegetation land use that exist without prior knowledge of the terrain. The acquisition of field data is necessary to achieve a supervised classification of satellite images[14]. Decent field conditions are therefore important in order to really describe the different types of vegetation land use. Sellin *et al.*[15] using high-resolution images (Spot 5, Worldview-2 and BDORTHO IRC) in their study state that: Regardless of the image, the results show too much confusion between vegetation for the procedures to be used as they are. This, is particularly true in tropical areas in general and in the Likouala department where several studies highlight not only the existence of a high floristic biodiversity, but also several types of vegetation[16,17,9]. The field truth in this field and the few studies that exist address this subject in a lapidary way with the exception of Regrain's study[18] which made an in-depth study on the field truth in the process of map making. It is in this context, this study was done in order to highlight the importance of field truth in the validation of the final maps. The objective of this study was to map the different types of land use in the study areas and to present statistics on the accuracy of these maps in both cases: (a) Production of the map without coupling field data, (b) Production of the map with input not only from images provided by Google Earth, but also ecological data collected during field visits and (c) Compare the global carbon map with the carbon map from *in situ* with the data collected in the study area in the context of REDD+.

MATERIALS AND METHODS

Location of the study area: This study was carried out in the northern part of the Republic of the Congo, more specifically on the Impfondo-Dongou axis located in the department of Likouala (Fig. 1). The climate of this department is similar to the equatorial and humid tropical climates of the Guinean forest type (Fig. 2). This climate is characterized by: rainfall of 1600-1800 mm with interannual variability of 10-15%, a dry season of 40 days from December-January, an intra-rainfall decrease in July, an average annual temperature of 25-26°C with an amplitude of 1-2 and a diurnal amplitude of 9-140, a relative humidity of 84-86% throughout the year[19].

The vegetation around this department is mainly forest. There are species of great commercial value such as Sapelli (*Entandrophragma cylindricum* (Sprague) Sprague, Sipo (*Entandrophragma utile* (Dawe and Sprague) Sprague, Wengué (*Millettia laurentii* (Welw.) C. C. Berg and Padouk (*Pterocarpus soyauxii* Taub).

Methods

Land cover mapping: This study was made possible by downloading a Landsat Operational Land imager (OLI) image of the Impfondo area in February, 2016, scene 181-59 from the USGS website (Earth explorer, https://earthexplorer.usgs.gov/). The image has a spatial resolution of 30 m. The images have the same spatial resolution, i.e., 30 m. A set of pre-processing operations was performed on the selected image of the study area before classification. Then the post classification was done on this image before the final map was produced. All these steps were completed using the free software QGIS

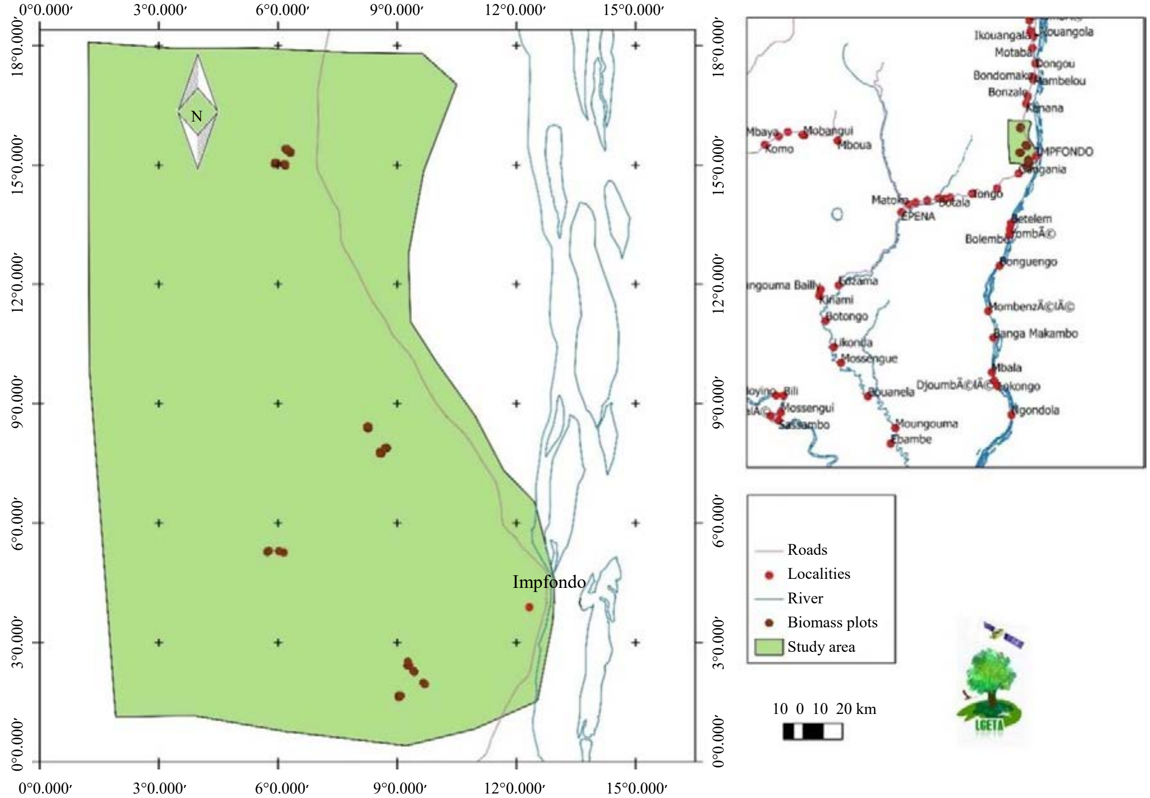

Fig. 1: Location of the study area

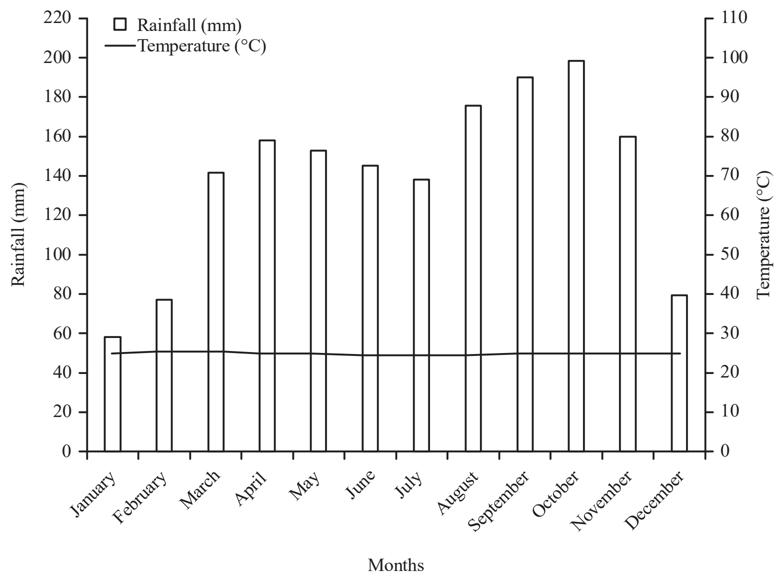

Fig. 2: Umbrothermal diagram of Likouala (1932-2015 average), ANAC Congo (2016)

version 2.18. The technique of colour composition was used to obtain the best visualization of the objects in the image. The Landsat OLI sensor has eleven spectral bands. This large number of channels allows to try multiple combinations of 3 channels to obtain synthesis in additive colors highlighting the different themes. In the context of our study, whose main objective is to analyze plant spaces, several combinations were used. The following strip composition 7.5 and 4 was

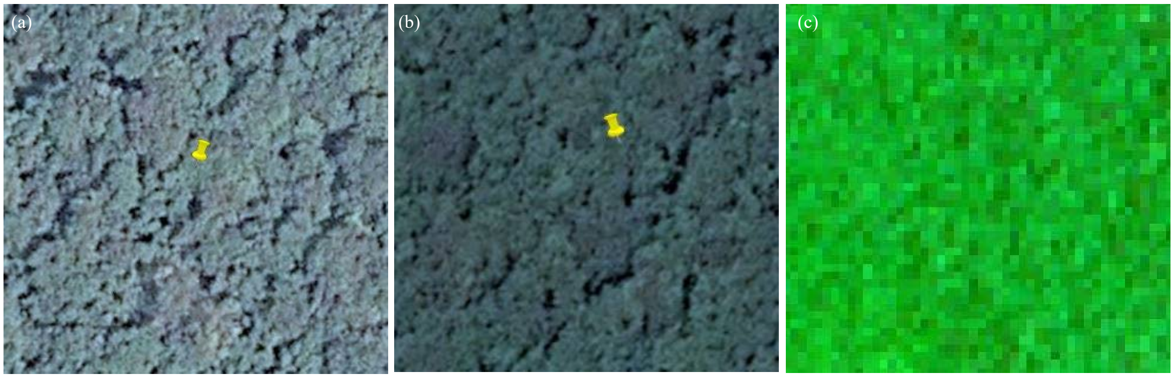

Fig. 3(a-c): View of the dense forest on Google Earth and landsat image, (a) Dense forest (2013), (b) Dense forest (2016) and (c) Pixel (2016) (composite color)

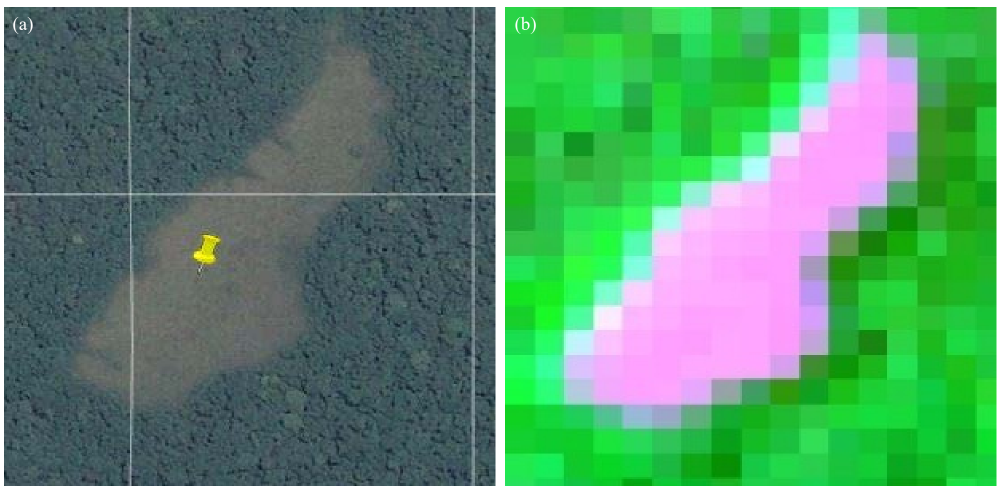

Fig. 4(a-b): View of the Savannah on Google Earth and landsat image (2016), (a) Image Google Earth (2016) and (b) Pixel (2016) (composite color)

applied to obtain a final composite image for this study. The visual interpretation of the images after the colour composition made it possible to identify training areas. The delimitation of these training areas was reinforced by the network of GPS point data collected in the field and Google Earth images (Fig. 3-5 and 6). The latter made it possible to go back a few years before 2016 in order to verify if the land use in 2016 was the same as in previous years by displaying historical images in the same GPS point.

To this tool, the data collected in the field during the 2015 and 2016-2017 descents were linked. This method made it possible to categorize 7 land use classes: secondary forest (FS), dense forest (DF), savannah, water, urban, degraded area and agriculture. Dense forest is a main class with 2 subclasses: primary land forests, as well as semi-flooded primary forests that are fairly well responded to in the study area. The secondary forests in the study area developed mainly on land, as most of the land conversion takes place on land forests. The secondary forest is identified from the spectral signature at a given point and confirmed using the Google Earth tool.

The supervised classification was applied to the image of the study area after selecting the different training areas for the different land cover classes using the Spectral Angle Maping algorithm. The quot, Spectral Angle Mapper" algorithm is a physics-based spectral classification that uses an n-D angle to match pixels to reference spectra. The algorithm determines the spectral similarity between 2 spectra by calculating the angle between the spectra and treating them as vectors in a space whose dimensionality is equal to the number of bands. This technique, when used on calibrated reflectance data, is relatively insensitive to illumination

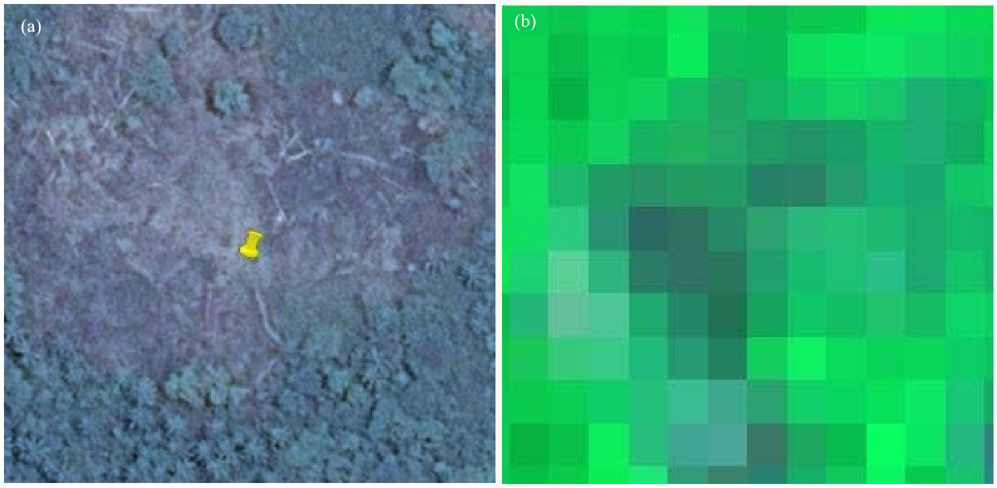

Fig. 5: View of the burnt area on (a) Google Earth and (b) The landsat image (2016)

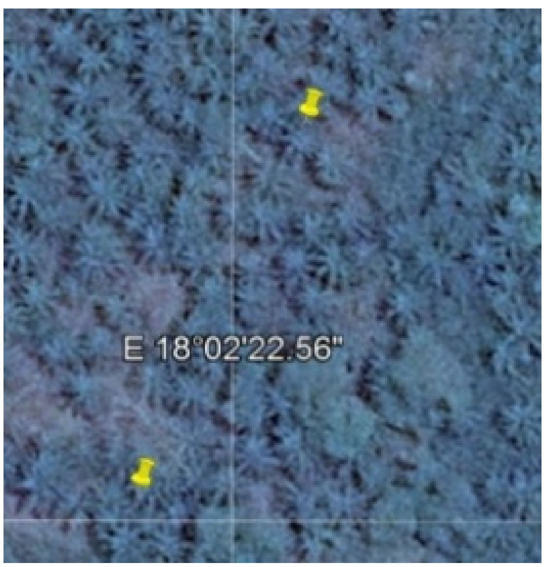

Fig. 6: View of the agricultural zone, oil palm on Google earth and on the Landsat image

and albedo effects[20]. This made it possible to highlight the different types of land use and then to edit the land use map.

The first land use map was made based only on training areas based on the visual appearance of Landsat pixels. Thus, 5 land use class points had been selected: urban area, dense forest, degraded area, savannah and water.

The second land use map of the same area was made by combining both Google Earth data and ecological data collected during field visits. This made it possible to map the agriculture class and the secondary forest class.

Assessment of the accuracy of the land use map: For the assessment of the accuracy of the land use map, the good practices established by Olofsson *et al.*[21] were applied to the final land use map. The objective of the accuracy assessment is to quantitatively assess the effectiveness of the classification, i.e., to verify whether the pixels sampled in the land cover classes on the image have been correctly classified in relation to the land cover. For this study, 320 control points were distributed in the different classes on the classified map to measure the accuracy of the classification. The verification of sampling points is done by combining data from Google Earth tools with data collected in the field during previous missions in 2015, 2016 and 2017. The number of points per class is unevenly distributed according to the size of each class. The producer and user error were calculated as well as the overall accuracy of the analysis.

Forest inventories: A total of 17 plots of unit 25×25 m were installed from across the study area in secondary, dense forests (dry land forests, seasonally flooded). In order to avoid any bias in the estimation of above-ground biomass, four points, representing 25×25 m plots, were generated and distributed in the Impfondo urban area using QGIS 2.18 software. These plots were physically installed in the field to collect the data required to calculate the above-ground biomass.

Within each 25×25 m plot, all trees with a diameter of $\geq$10 cm have been inventoried. For each tree, the following data were collected: the diameter (dbh) of the tree measured at 1.30 m from the ground, with a tape measure, the name of the species with the help of a local guide through the vernacular names, the height of the trees with a vertex (Laser)

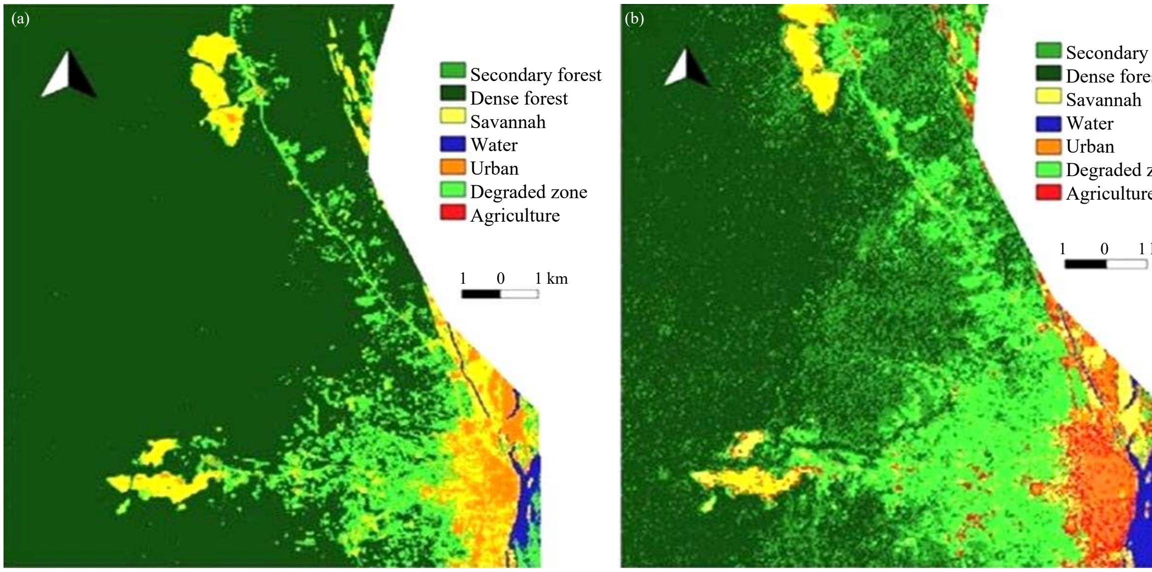

Fig. 7(a-b): Land occupancy (a) Map 1 and (b) Map 2 of the study area

In plots where the height values were not measured with the laser, the allometric equation (Eq. 1) had been applied[22]:

$$H = 45.1\text{-}42.8 * \exp(-0.025 * D) \quad (1)$$

where, D is the diameter of the tree in cm measured at 1. 30 m from the ground.

Above-ground biomass estimation: The above-ground biomass of the various trees in the study area was estimated by applying the allometric equation of Chave *et al.*[22], (Eq. 2). This equation takes into account the diameter, specific density of the wood and the total height of the tree and provides a better estimate of the above-ground biomass of trees compared to the equations of Feldpausch *et al.*[23] and provides accuracy of up to 90% in biomass estimates in 0.25 ha plots in humid tropical forests. The total height of the trees was estimated from Eq. 1. The specific wood densities of each tree inventoried were extracted from a global database[24]. The above ground carbon stock of each tree is obtained by applying the fraction of carbon 0. 49 t MS^{-1} applied for woods and trees of DBH greater than or equal to 10 cm in diameter. Aerial carbon stocks were calculated for the different forest types in the study area but also for the different forest groupings.

$$AGB = 0.0673 * (di * (Dbhi)\^{}2) * H\ total \quad (2)$$

Where:

Dbhi = Diameter of the tree in centimetres (cm) measured at 1.30 m

di = Specific density of the wood, H total: Total height of the tree

RESULTS

Primary land use map of the study area and precision analysis: The first land use map (Fig. 7a) before Google Earth field data and tools were considered revealed the presence of three vegetation types in the study area with a dense forest class dominance. This map shows that 80% or nearly 17860.14 ha of the study area, was covered by dense forest, followed by the degraded area class which covered 10% of the study area with 2228.4 ha. The urban area occupied 606.78 ha of the study area. Analysis of high-resolution images of the study area by Google Earth archives showed that some of the degraded area was actually a mosaic of several types of vegetation including both type 1 fallows, type 2 fallows but also small islands of forested area including both local forest species, but also fruit trees, oil palm trees, small agricultural plots, which are very difficult to map.

Indeed, in the study area, the land problem means that not all families have access to large areas to carry out their agricultural activities. This observation made in the field makes it possible to say that the high precision of the user's precision for the degraded forest class (U = 90. 90%) must be put into perspective for the reasons mentioned above. The user

Table 1: Land occupancy Map confusion matrix 1

	References								
Map classes	Water	Dense forest	Savannah	Urban	Degraded zone	Total	Area	Water	Users
Water	2	0	0	0	0	2	187.92	0.009	
Dense forest	0	98	0	1	5	104	17860.14	0.809	0.942308
Savannah	0	0	4	1	0	5	1186.65	0.054	0.8
Urban	0	0	1	3	0	4	606.78	0.027	0.75
Degraded zone	0	1	1	0	20	22	2228.4	0.101	0.909091
Total	2	99	6	5	25	137	22069.89	1	
Water	0.009	0	0	0	0	0.0085	187.92	0.009	
Dense forest	0	0.7626	0	0.0078	0.039	0.8093	17860.14	0.809	
Savannah	0	0	0.043014	0.0108	0	0.0538	1186.65	0.054	
Urban	0	0	0.006873	0.0206	0	0.0275	606.78	0.027	
Degraded zone	0	0.0046	0.00459	0	0.092	0.101	2228.4	0.101	
Total	0.009	0.7672	0.054477	0.0392	0.131		22069.89	1	
Producer's	0.99	0.99	0.79	0.5266	0.702				
Overall	0.927								
Area estimates	188	16.931	1.202	864.15	2884	22.070			

accuracy varies from 75-94% while the producer accuracy varies from 52-99%. The dense forest (DF) class has a user accuracy of 94.23% (Table 1), suggesting that this class is stable where there are fewer disturbances. This is not the case near the urban area. Also, field investigations have shown that in some places some pixels have been wrongly attributed to the dense forest when they are actually secondary forests to *Musanga cecropioides* R. Br. or plots of forests rich in *Macaranga spinosa* Müll. Arg. It should also be noted that not all classes with a minimum mapping unit of less than 4 pixels were selected during mapping. Despite the fact that the overall accuracy of this map is 92.7%, it did not allow other classes of sub vegetation under the degradation class to be properly mapped. Certainly, the source data used to prepare the reference data with the help of a Landsat image did not allow all vegetation subclasses in the degraded area to be identified.

Secondary land use map of the study area: The second land use map (Fig. 7b) made with the support of very high-resolution images in the choice of training areas allowed us to improve the quality of the selected polygons before launching the classification using the Spectral Angle Maping algorithm. The images provided by Google Earth archives made it possible in this case to distinguish different types of vegetation in the degraded area class such as oil palm plantations, agricultural fields. Thanks to the historical image tool, this tool has also made it possible to monitor the dynamics of the occupation of certain parcels of forest land that have been converted into secondary forest. However, the field data made it possible to better understand the high biodiversity of the vegetation in the degraded area with the existence of several types of fallows (type 1, 2) but also to collect GPS points which, coupled with existing data, improved the quality of the selection of training areas. The following classes were selected: secondary forest, dense forest, savannah, sand, water, urban, degraded area and agriculture class. The overall accuracy of this second land use map is 89.68%. User accuracy ranges from 57-98%, while producer accuracy ranges from 57.14-84.62 (Table 2) for the main land use classes in the study area. The classification results showed that the dense forest and secondary forest classes are the two most important first classes in the study area occupying 60.35 and 12.45% of the total area, respectively. The secondary forest class thus represents a very large area of the study area (Fig. 7b). This in the study area was found in sometimes very unexpected areas within the dense forest class as shown in Fig. 8 (Fig. 8a-c) where an area of 19.15 ha of forest land was cut during 2008 for agricultural activities in 2008. This agricultural land, which was later abandoned, has undergone a recolonization of forest vegetation (Fig. 8b). Ecological data collection in the field had indicated that this abandoned land 8 years earlier is a secondary forest *Musanga cecropioides* R. Br. with the presence of some growing natural forest species. In this case, remote sensing by Landsat images cannot provide details on the nature of the growing plant species in the area, details that only *in situ* data collection has provided.

A comparative analysis of the results of the first and second land use maps of this study area showed that the different land use classes show fairly significant changes in forest cover from one class to another. Thus, the area of the dense forest class increased from 17860.14-13321.10 ha, a difference in area of 4539. 04 ha. On the other hand, the area of the degraded area increased from 2228.4 ha in the first map to 3824.55 ha in the second map, an increase of 1596. 15 ha in the area estimate for this class. The agricultural class has a

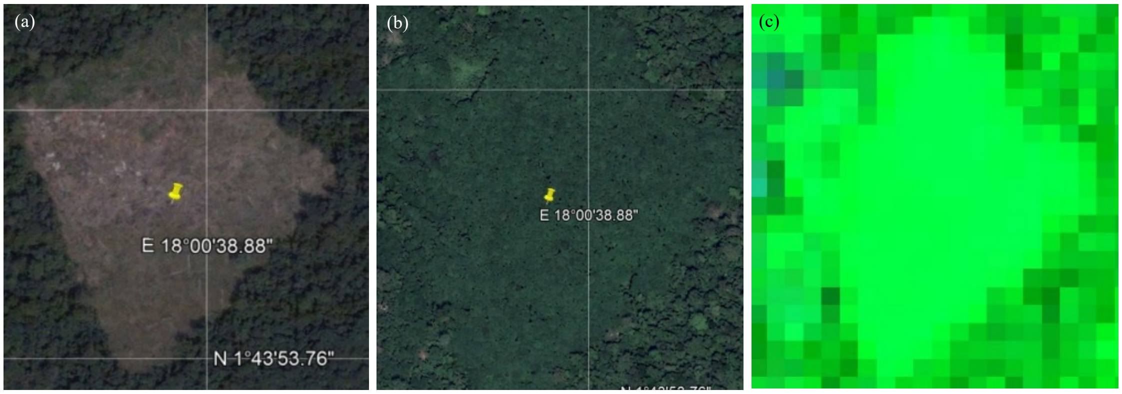

Fig. 8(a-c): Vegetation dynamics at a given point in the study area (a) Google Earth (2008), (b) Google Earth (2016) and (c) Image OLI (2016)

Table 2: Soil occupancy Map confusion matrix II

	References										
Map classes	Secondary forest	Dense forest	Savannah	Water	Urban	Degraded zone	Agri	Total	Area	Water	Users
Secondary forest	33	0	0	0	0	5	2	40	2748.78	0.124548876	0.82799
Dense forest	1	190	0	0	0	2	0	193	13321.1	0.603586153	0.9837
Savannah	0	1	6	0	0	1	2	10	716.31	0.032456437	0.5777
Water	0	0	0	3	1	0	0	4	267.12	0.012103368	0.77458
Urban	0	0	0	0	3	0	0	3	239.94	0.010871826	0.86232
Degraded zone	8	0	1	0	0	44	2	55	3824.55	0.173292663	0.79346
Agriculture	1	0	1	0	0	4	8	14	952.11	0.043140677	0.5795
Total	43	191	8	3	4	56	14	320	22069.9	1	
Secondary forest	0.103125	0	0	0	0	0.0156	0.00625	0.124548876	2748.78	0.124548876	0.82799
Dense forest	0.003125	0.59375	0	0	0	0.0063	0	0.603586153	13321.1	0.603586153	0.9837
Savannah	0	0	0.01875	0	0	0.0031	0.00625	0.032456437	716.31	0.032456437	0.5777
Water	0	0	0	0.00938	0	0	0	0.012103368	267.12	0.012103368	0.77458
Urban	0	0	0	0	0.0094	0	0	0.010871826	239.94	0.010871826	0.86232
Degraded zone	0.025	0	0.00313	0	0	0.1375	0.00625	0.173292663	3824.55	0.173292663	0.79346
Agriculture	0.003125	0	0.00313	0	0	0	0.025	0.043140677	952.11	0.043140677	0.5795
Total	0.134375	0.59375	0.025	0.00938	0.0094	0.1625	0.04375	1	22069.9	1	
Producers	0.76744186	1	0.75	1	1	0.8462	0.57143				
Overall	0.896875										
A (pixels)	2965.64147	13104	551.747	206.905	206.91	3586.4	965.558	22069.89			
A (ha)	266.907732	1179.36	49.6573	18.6215	18.621	322.77	86.9002				

total area of 952 ha. This agricultural area could not be easily extracted in the first map because it was mixed with the degraded area, which is a complex mixture of fallow land, forest islets, small abandoned agricultural plots of <0.09 ha in size.

Carbon stock in the study area and carbon map: The average carbon stock in the current study is estimated at 112 MgC ha^{-1} while it varies from 84-213 MgC ha^{-1} in the land forest areas of *Celtis adolfi-friderici* Engl and in the seasonally flooded forest areas. The differences are quite significant between the carbon stocks of the different forest types. Indeed, in the MSDS (secondary forest) at *Musanga cecropioides* R. Br. and the FTF (land forest) which are forests at *Celtisadolfi-friderici* Engl., carbon stocks range from 83-141 MgC ha^{-1}, have a significantly low carbon stock than the seasonally flooded forest with which carbon stocks range from 110-212 MgC ha^{-1}. In the area where ecological biomass data have been collected, the regular presence in some plots of either the species *Lophira alata* Banks ex P. Gaertn. or the species *Guibourtia demeusei* (Harms) J. Léonard have noted in the study area of Impfondo.

In addition, there is significant carbon stock variability within the secondary forest between study plots. Carbon stocks range from 21 MgC ha^{-1} in young forests at *Macaranga spinosa* Müll. Arg. to 84 MgC ha^{-1} in adult secondary forests of *Musanga cecropioides* R. Br.

DISCUSSION

This study once again shows the importance of using satellite images and Landsat in particular to map the different types of land use in a given territory. Several authors in the Congo Basin, West Africa and around the world have made efforts over the past decade to map different types of land use[25-28]. These images have the ability to have a synoptic view of the landscape and have the ability to inventory the geographical objects that make up the space[29]. However, the production of these maps suffers from a problem of cartographic accuracy related to several factors: image resolution, the type of satellite sensors, the software used to process the images, but also errors related to image users.

The accuracy of the card gave a value of 0.99% for the first card and 0.89% for the second occupancy card of the card. The difference in accuracy values can be explained by the fact that during the production of the first map a set of small land use classes were combined into a single land use class of the degraded area class. The breakdown of the homogeneous class degraded area into other subclasses makes the distinction between agriculture and secondary forest classes more complex. This could explain the decrease in the overall accuracy of the study area obtained in the second land use map obtained by combining both field data and Google Earth images.

The differences in user precision obtained in the land use map 2 show the difficulty of being able to map classes with great accuracy where there are pixel confusions. This is the case for the agriculture class in the study area with an accuracy of 0.5795, a relatively low accuracy compared to the other occupation classes where we noted for the dense forest (DF) class 0. 98% and for the secondary forest 0.82%. The difficulty in visually discriminating between the agricultural and savannah classes is due to the similarity of spectral signatures. This justifies the confusion noted between savannahs and agricultural plots.

Several authors had to perform the validation using high-resolution images[1,30,31]. However, field data are important to better understand the different types of land use in the study area and to allow for proper validation of the final maps[32]. According to FAO[33], remote sensing is not a substitute for collecting good and always important field data, but by combining these two techniques, the best results are obtained than one or the other employee alone. Also, the high cost of very high-resolution images is an obstacle for these studies in our working environment where access to the Internet. This prevents this study from having access to the Internet to use Google Earth.

However, it should also be noted that within the framework of the gaps that exist between the map and the points collected in the field, it is important to ensure that the image used is recent, <2 months before the descent into the field on the one hand and on the other hand it is necessary to check the season of shooting the image as well as the period when the team decides to go to the field for data collection because, the climatic conditions generally favour the growth of vegetation. The study area is characterized by heavy rainfall around 1700 mm and relative humidity around 85%[19]. These parameters promote the emergence of seed dormancy, the stimulation of plant growth especially since temperatures are around 26.5 °C[19]. These confusions have also been noted by some authors in the literature who had stated that medium resolution images (30 m) have some limitations, some classes are not well discriminated, confusion is inevitable[32].

The problem of the truth of the terrain is important in the intertropical zone because of the dynamics of the vegetation, which is very positive. Several authors in the literature had demonstrated that field truth is very important for classification studies by remote sensing[34,18,14].

According to Godard[35], despite the use of high-resolution satellites such as SPOT1 or Landsat TM, to produce land use maps, land reconnaissance is essential. This was also highlighted by Hassan[11] in his study, who stated that while satellite images and aerial photographs are very useful for studying the evolution of land use for a given environment, there must also be field study to validate satellite images and complete them with photographs that allow a good approach to be taken for certain phenomena". Field truth allows the correction of errors in the different classes due to image processing and improves the accuracy of the final cartographic product, it is very important in map validation[36,33,18,14]. The significant degradation observed in the study area reflects the impact of anthropogenic activities on the decline in dense forest area. Studies conducted in the area have highlighted the following socio-economic activities: burning cultivation, timber and fuelwood exploitation, urban growth[6,7].

Several authors[37,38] have questioned population growth and certain farming methods as being responsible for land degradation resulting in the disruption of local or regional ecological and climate balances. This is particularly remarkable in sub-Saharan Africa, where high population densities and the crisis in agricultural space are leading people to seek new land[39,40], which explains why the level of degradation is increasing significantly from the forest to the urban area, leading to the loss of forest plant biodiversity but also to the loss of biomass[8,9].

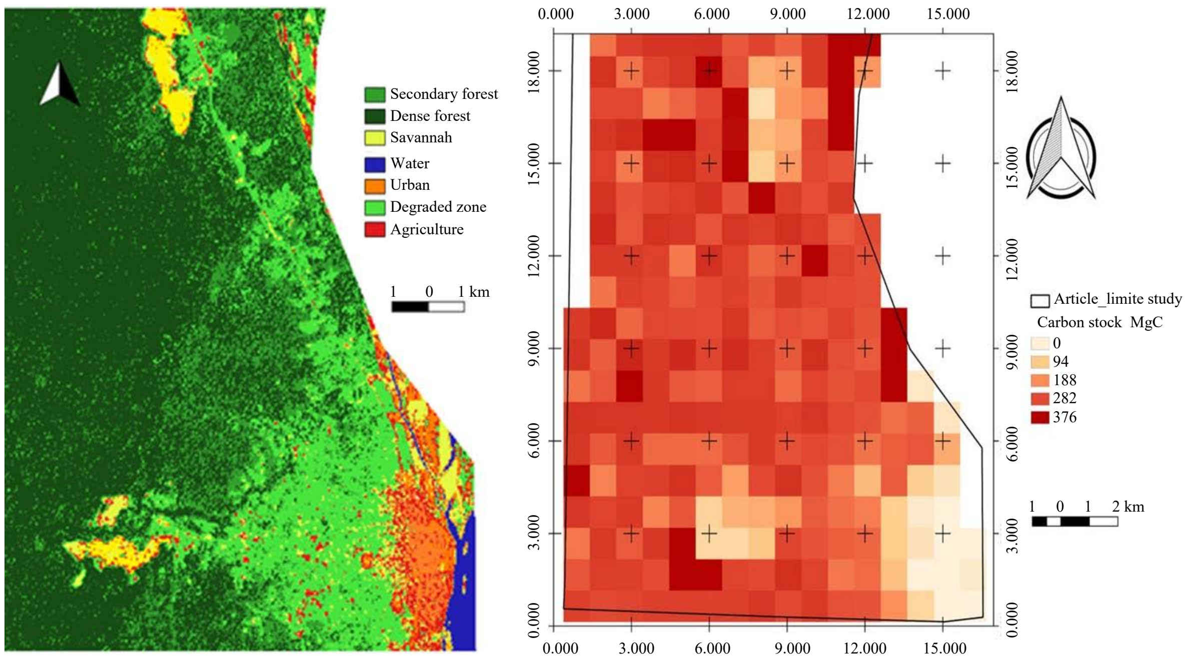

Fig. 9: Above-ground biomass of the study area

Comparison of *in situ* carbon stocks with the global carbon map: The comparison of carbon stocks between field data collected in the study area and the values extracted from the map from the Avitabile *et al.*[41] shows a very significant differences across the entire study area in forest vegetation and savannah vegetation areas (Fig. 9). In urban areas, carbon stocks are low and close to zero according to this study by Avitabile *et al.*[41]. A recent study stated that around some cities of the north of the Republic of the Congo above-ground stocks range[8] from 0.1-5.75 MgC ha^{-1}.

While the maximum carbon stock in our study is 213 MgC ha^{-1}, it is 376 MgC ha^{-1} in this study. Similarly, in savannah areas, carbon stocks are 8 MgC ha^{-1}, studies on the estimation of above-ground biomass by Yoka *et al.*[42] in the savannah of the Congolese Basin indicate a biomass of 04 MgC ha^{-1}.

Several forest structural parameters explain this difference in biomass between the mature forests in the study area and secondary forests: number of stems, number of species, number of families, basal area, density/hectare within forest types, which influences their carbon stocks. Structural parameters such as density and basal area decrease with the level of forest disturbance[10],

These results revealed the need for the REDD+ process and the assessment of efforts to reduce greenhouse gas emissions from the forest sector not to use the globally published carbon maps for calculating greenhouse gas emissions because of significant differences in carbon stocks at the pixel scale or at any given point.

CONCLUSION

The results of this study show that remote sensing is an important tool for discriminating between different types of land use, but this requires a field trip to verify the validity of interpretations made from the images and improve classification results. The homogeneous classes have been well classified. In addition, heterogeneous vegetation classes are a problem in distinguishing between different types of actual land use regardless of image resolution. The field mission carried out in the study area allowed us to know the importance of the field truth, on the one hand to capture the real land use types that exist and on the other hand to improve the estimation of overall accuracy but also to collect biomass data that compared to global data show very significant gaps. As part of the REDD+ process, more efforts should be made to achieve a high level of accuracy in the development of forest carbon maps.

SIGNIFICANCE STATEMENT

This study discovers the importance to combine field truth data with high-resolution image to produce vegetation/biomass maps in intertropical areas where forest vegetation is characterized by the very high variability of flora biodiversity but also of the flora structure. This study is very beneficial for the Republic of Congo in the context of climate change mitigation and the production of different vegetation and carbon maps, mainly if we consider REDD+ processes. This study will help the researcher to discover critical areas of remote sensing and the use of ecological data in the tropical zone that many researchers have not been able to explore.

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