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Mapping of Wood Carbon Stocks in the Classified Forest of Wari-Maro in Benin Center (West Africa)

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***Abstract*—*The Emissions Reducing program related to Deforestation and Forest Degradation (Redd +) calls for the development of approaches to quantify and spatialize forest carbon in order to design more appropriate forest management policies. The mapping of carbon stocks was done in the Wari-Maro Forest Reserve. To achieve this, forest inventory data (in situ) and remotely sensed data (Landsat 8 image) were used to construct a wood carbon stock forecasting model. Simple linear regression was used to test the correlation between these two variables. In situ surveys indicate that 64% of carbon stocks are contributed by forest formations, 32.72% are provided by savannah formations and 3.27% are from anthropogenic formations. The quantitative relationship between NDVI and carbon in situ shows a very good correlation with a high coefficient of determination R^2 = 91%. The carbon map generated from the model identified fronts of deforestation through their low carbon content. This remote sensing approach indicates that forest formations sequester 60% of forest carbon. The savannah formations reserve 33%, the anthropic formations bring only 6% of the stocks. Mapping has further captured the spatial variability among land use types, thus providing arguments to fully meet the objectives of Redd +.*

***Keywords* - Cartography, Classified Forest, Linear Regression, Surveyed in situ, Carbon Stocks, Wari-Maro.**

I. INTRODUCTION

The desire to build a reliable approach to mapping and spatial monitoring of plant biomass has gained a lot of importance, especially since the advent of new environmental issues such as sustainable forest management and carbon footprint modeling. Forest ecosystems help to mitigate climate change through carbon sequestration and the substitution of fossil fuels with bioenergy products (Migolet, *et al.*, 2007). These forest ecosystems have been at the heart of the climate change negotiations for some years now.

The impact of human activities on the environment has reached unprecedented proportions in just over a century, resulting in significant changes in the biosphere. At the current rate, deforestation is responsible for nearly a quarter of greenhouse gas (GHG) emissions (Grinand, 2010). By 2050, an estimated global warming of about 2.5 ° C and a significant change in climatic parameters are expected (IPCC, 1995). The significant increase in greenhouse gases in the atmosphere, caused by industrial discharges and deforestation, is partly responsible for global warming (Brown, 1997). However, forests are important in the global carbon cycle because they store large amounts of carbon in vegetation and soil. They exchange carbon with the atmosphere through photosynthesis and respiration and they are atmospheric carbon sink (net CO_2 absorption of the atmosphere), they become sources of atmospheric carbon when disturbed by human or natural actions (wildfires, logging due to poor logging procedures, brushing and burning for conversion of the forest to other uses).

Proposed mechanisms for Reducing Emissions from Deforestation and Forest Degradation (REDD) are of interest to many actors in both Southern and Northern countries. For several years, under the impetus of international organizations, the problems concerning global changes have been studied in particular. Based on the results already achieved, a research strategy has been defined for the monitoring of terrestrial ecosystems and forests in particular (GOSSP 1997, TOPC 1997). The orientations described strongly encourage coordinated remote sensing research actions with in situ measurements (GCOS, 1996, GTOS, 1997). Remote sensing is almost unanimously suggested as a tool for measuring avoided deforestation and GHG emissions associated with deforestation. The importance attached to

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remote sensing by the international community has led space agencies, scientific and methodological research institutes in developing countries to become interested in REDD + and to become involved in the development of remote sensing for the implementation of this mechanism.
In addition, the destruction of natural resources has evolved at a disturbing rate in Benin. Already in 1991, estimates indicated an average annual destruction of 100,000 hectares of natural vegetation in Benin for cultural purposes with a conversion rate of 2.3% per year according to FAO (2002). Between 1975 and 2010, the national forest cover experienced a conversion of 48.7% (World Gazeteer, 2013).
Generally, about half the weight of a mature tree is carbon. As long as this tree is alive and productive, it retains more carbon than it releases into the atmosphere. Forests are therefore considered carbon sinks. The amount of carbon trapped in terrestrial ecosystems is about 3 times higher than atmospheric. This carbon on the ground is 700 times greater than the annual increase in CO_2 (CIRAD, 2002). Therefore, even minor changes in the sequestration capacity of this huge reservoir could have a significant impact on the evolution of atmospheric CO_2 levels. Knowing more precisely the quantity and distribution of forest carbon will help to more accurately assess the CO_2 emissions associated with deforestation and at the same time combat poverty through the carbon credits that would be created by avoided deforestation. This article provides baseline and monitoring data for REDD + pilot projects.

II. STUDY AREA

The Wari-Maro classified forest belongs to the phytogeographic district of South Borgou (Adomou, 2005) and is located in the extreme south of the department of Borgou between8 ° 50 'and 9 ° 20' of northern latitude and between 2 ° 10 ' and 3 ° 10' east longitude (Fig. 1). It is contiguous and borders the south by the Kouffé Mountain classified forest, to the east by the Tchaourou-Bétou road, to the north by the Parakou-Djougou road and to the west by the Wari-Maro / Igbèrè road. The classified forest of Wari-Maro, subject of the order of classification n ° 9 190 / SE of November 25, 1955, covers an area of 111,095.38 ha and straddles the communes of Bassila and Tchaourou (PAMF, 2007).
The Wari-Maro Classified Forest is influenced by Sudan's subhumid tropical climate characterized by a dry season with average annual rainfall of 1,150 mm and annual average evapotranspiration (ETP) of around 1,500 mm. The average annual temperature oscillates around 27 ° C between 1965 and 2010. Pedoclimatic and anthropogenic conditions allowed the establishment of forest formations, savannah formations and anthropozoic formations (Issifou *et al.*, 2017). There is a rising temperature trend between 1965 and 2010 in the study area, which is indicative of the level of global warming in this region. These temperature changes are due to the deforestation and degradation that are leading to an increase in the emission of greenhouse gases (Issifou, 2016).

III. MATERIAL AND METHODS

3.1. Data used

Two different sets of data were used to construct the carbon stock estimation model for tree and shrub Biomass: the in situ data (forest inventory), which is the variable to be explained, and the data obtained by remote sensing are explanatory variables (Landsat 8 OLI images from 2013). A predictive model is constructed from the observed data and was used to infer stored carbon values using only remote sensing data.
The in situ data come from field campaigns carried out in 2014 in the Wari-Maro classified forest. Inventory plots installed by the PAMF project in 2003 are used. 60 of them were rallied from their geographical coordinates using the Etrex GPS 10 and 10 other plots were installed at the gallery forests. The remote sensing data are from the 2013 Landsat 8 OLI / TIRS images classified under Envi 5.2. The images were acquired on 02/11/2013 in Geotiff format downloaded on the EarthExplorer-USGS.GOV/USA website with the following characteristics: Path = 192 and Row = 54. The resolution is 30 m × 30 m. The extraction of land use units and their areas was done with ArcGIS 10.4.

3.2. Data collection equipment

Data collection required:
- A GPS to rally the plots from their geographical coordinates;
- One decameter for measuring the circumference of species ($C \geq 30$ cm);
- A clisimeter for measuring the height of trees;
- Record sheets to record the data in situ.

3.3. Data collection method

The observation unit is a circular plot of 15 m radius. The inventories are therefore carried out in circular plots of 15 m radius in the period from November to December 2014. The inventory plots installed by the PAMF project in 2003 are used. 60 of them were rallied from their geographical coordinates using GPS and 10 other rectangular plots were installed at the gallery forests. All trees with a breast height diameter (dbh) exceeding 10 cm were considered in each plot. Scientific or vernacular names of trees, total height and circumference ($C \geq 30$ cm) are the main data collected. Added to this are the type of vegetation formation, the type of soil and the topographical situation.

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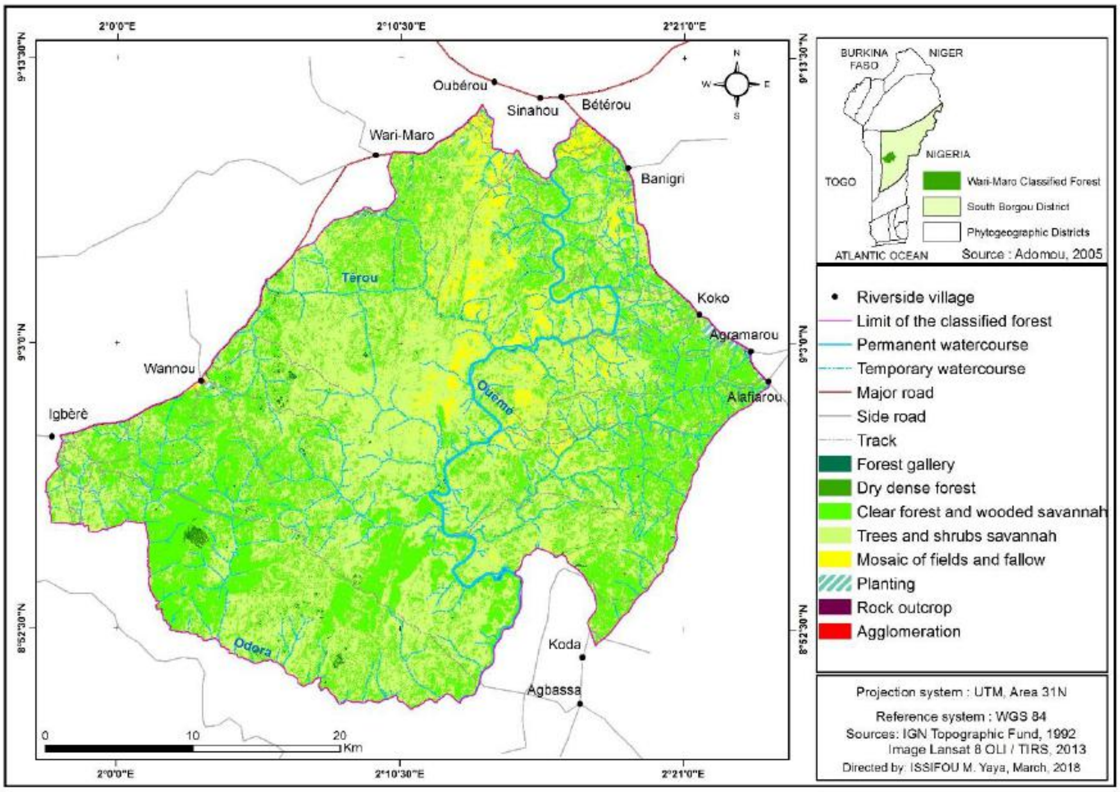

Fig.1: geographical location of the Wari-Maro classified forest

3.4. *Data processing method*

The Wari-Maro classified forest is located in the Sudano-Guinean transition region, which has a tropical climate with a rainfall of less than 1,500 mm / year, the allometric equation of the dry forest dry forests of Chave *et al.* (2005) was used to estimate the above-ground woody biomass of the Wari-Maro Classified Forest. It is expressed by:

$$\mathbf{AGB = 0.112 \times (\rho D^2 H)^{0.916}} \qquad \mathbf{(1)}$$

Where AGB: biomass is expressed in kg; D: the diameter in cm to 1.30 m; H: the height of the tree in m and ρ: the specific density of the wood in g.cm-3.

The estimation of the carbon stock in the forest depends on the knowledge of the dry aerial biomass (Vieira *et al.*, 2008). It has been reported that the carbon content of dry tree biomass is 50 % (Brown and Lugo 1992, Malhi *et al.*, 2004). However, it should be noted that the fraction of carbon in wood has some small variations according to species (Elias and Potvin 2003, Chave *et al.*, 2005) and according to plant formations. Carbon (C) has been quantified through equation (2) considering that 50 % of the biomass is carbon. We have:

$$\mathbf{C = 0.5 \times AGB} \qquad \mathbf{(2)}$$

3.5. *Normalized Difference Vegetation Index or Tucker Index (NDVI)*

The standardized difference vegetation index expresses the chlorophyll activity of plants. This type of index can be calculated from data from any satellite capturing the spectral responses in the visible and near infrared. It is expressed by:

$$\boldsymbol{NDVI = \frac{\mathrm{PIR}-R}{\mathrm{PIR}+\mathrm{R}}} \qquad \mathbf{(3)}$$

PIR = reflectance in the near infrared band of the electromagnetic spectrum;

R = reflectance in the red band of the electromagnetic spectrum.

NDVI values theoretically range from -1 to +1, with negative values for areas other than plant cover, such as rocky surfaces, water, or clouds, for which red reflectance is greater than near infrared. For bare soils, the reflectances being of about the same order of magnitude in the red and the near infrared, the NDVI has values close to 0. The vegetal formations as for them, have values of NDVI positive, generally between 0.1 and 0.7; the highest values correspond to the densest cutlery.

3.6. *Choice and description of the statistical model*

The choice of model was preceded by the preparation of the forest inventory sampling plots database so that it could be used for the remote sensing carbon stock method. The first step was to extract for each of the 70 plots the spectral value of the bands in the Landsat 8 image. These values were then added to the plots database. The second step was to remove from the database the plots that were not representative of the stands in which they were located. The first criterion for

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eliminating plots is negative or no spectral values that correspond to non-forest areas, such as water, bare soils, or rocky outcrops. The second criterion relates to the identification of changes that occurred between the time the measurements were taken in the field and the date of acquisition of the image. These changes include disturbances such as total or partial cuts, defoliation or wind throw. They cause the spectral variability between the plot and the surrounding pixels. If the variability is high, the plots were not considered representative of their surroundings. They would therefore be located on the boundary between stands or too close to rocky surfaces, streams, roads and bare soils, or the in situ measurements were underestimated or overestimated, or simply the plots were poorly georeferenced.

This approach was chosen because it made it possible to eliminate the most heterogeneous plots while keeping a sufficient number for the rest of the analysis The incompatibility of several plots with the remote sensing data can be explained in large part by the fact that the forest inventory carried out in 2014 was not designed specifically to correlate with this type of remote sensing data. After this screening phase, 51% of the inventory plots were selected (36 out of the 70 plots) for further analysis.

From a statistical point of view, the approach consists in constructing a model by cross-referencing remote sensing data and field observations, the aim being then to use this model to predict the quantities of carbon stored from remote sensing data alone. The predicted values are then used under GIS to obtain a map of the study area. This modeling aims to understand the carbon storage potential of the different land-use units from the selected data. By predicting values on field surveys carried out through the plots, the model provides a map for the entire forest from a few sampling points.

There is a growing variety of successful statistical methods for predicting biomass, forest carbon stocks, land cover, or soil types (CSE 2017, Garba 2017, Grinand 2010; Labrecque, 2004, McBratney *et al.*, 2003). Among the most used are regressions (41 %), methods of discrimination or classification (32 %), kriging (19 %) and tree-based models (14 %) (Grinand, 2010). In this study the linear regression model was used to test the correlation between carbon stocks from field measurements and spectral values (NDVI) from Landsat 8 images covering the Wari-Maro classified forest. The regression analysis was conducted for the pixels corresponding to the position of each plot of the database as well as for the valuesobtained for the 3x3 pixel windows around the plot. The input regression analysis procedure was used, with the carbon mass as the dependent variable and the spectral values as independent variables. A regression line is established between NDVI and woody aerial carbon stocks from field measurements. It is of the form:

$$\mathbf{Cp = (a \times NDVI + b) \times 0.5} \qquad \mathbf{(4)}$$

Cp: predicted carbon; a: constancy and b: slope.

The application of this regression equation to the satellite image generated the forest carbon map classified by land use category (forest formations, savannah formations, anthropogenic formations) for better visualization and for analyzes. More complete. This approach has the merit of being used in several studies as part of ecological monitoring of ecosystems (CSE, 2017, Garba, 2017, ILWAC, 2013, Diallo *et al.*, 2002, Sawadogo *et al.*, 1994, Labrecque, 2004). For the application of this model, we used the algebra Map algorithm of Spatial Analyst tools in the AcrGIS 10.4 Arctoolbox.

IV. RESULTS AND DISCUSSION

The quantification of carbon stocks with in situ data and the mapping of stocks with remote sensing data are the main axes of the results.

4.1. Quantification of carbon stocks through in situ data

Assuming that 50 % of the total biomass of a tree is carbon, surface carbon stocks in the study area were quantified through the pan-tropical allometric model put in place in 2005 by Jérome Chave and allies as illustrated in Table 1.

Table.1: Changes in carbon stock by plant formation

Type of vegetation	Carbon stock (T / ha)	Number of trees
Ja	17.46	10
Pl	43.68	54
Ch	59.88	36
Sa	80.72	53
SB	221.90	185
FC	542.97	337
FDS	723.52	289
SA	907.30	522
FG	1099.90	386
Total	**3 697.31**	**1 872**

From the observation in Table 1, it appears that the forest formations have the highest carbon content per hectare, followed by the savannah formations and finally the anthropic formations. There is a clear decrease in the carbon content of forest formations towards anthropogenic formations.

Indeed, gallery forests constitute the largest carbon reservoir with an overall stock of 1,099.90 T / ha. The overall carbon storage potential is 723.52 T / ha for dry dense forests. As for the open forests, they bring about

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542.97 tons of carbon per hectare. The carbon content of trees under savanna trees is 907.30 T / ha. Woody savannas contain an overall stock of 221.90 tonnes of carbon per hectare. Then come shrub savannas with a global stock of 80.72 tons of carbon. In contrast to these high levels, the lowest carbon content in fallow land is observed at only 17.46 T / ha. Plantations sequester 43.68 tonnes of carbon per hectare, while fields sequester about 59.88 tonnes of carbon per hectare.

Overall, the Wari-Maro classified forest constitutes a reservoir of 3,697.31 tonnes of carbon per hectare, with 64 % (or 2,366.38 T) of stocks brought by forest formations, 32.72 % supplied by the savannah formations (1,209.91 T), compared to only 3.27 % (or 121.02 T) for anthropic formations.

4.2. NDVI-carbon stock correlation in situ

The quantitative relationship between NDVI values and in situ carbon measurements has been established through the simple linear regression whose equation line is in the form of:

$$\mathbf{Cp = (33.126 + 294.74 \times NDVI) \times 0.5} \quad \mathbf{(5)}$$

The fit of the linear regression line between the NDVI and the corresponding wood carbon stocks in the field is presented in fig. 2. The high coefficient of determination R^2 = 90 % reflects the good correlation between the two parameters studied.

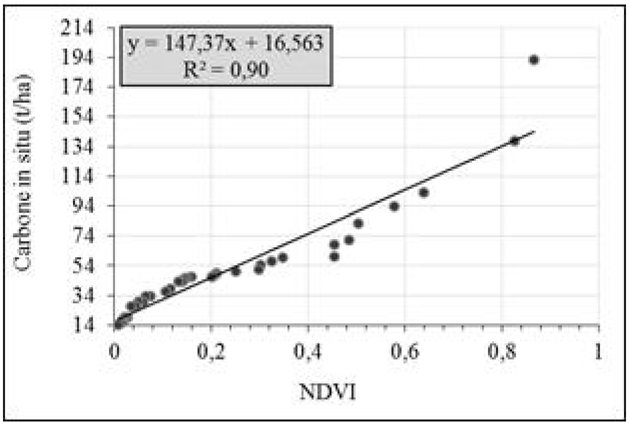

Fig. 2: Linear regression between the NDVI and the stocks of corresponding woody carbon
Sources: 2014 Field Data and Landsat 8 Images from 2013

The regression of Fig. 2 indicates good correlation of carbon values with NDVI values extracted around the 36 sample plots. The intensity of the correlation is more pronounced for NDVI values less than or equal to 0.3. Values greater than 0.3 tend to overestimate the mass of carbon around the plots. The Fisher statistical test calculated Fc = 323.221 was read at a threshold of 0.001, well below the critical threshold of 5% allowed. The standard error of the estimate is 16%. According to Labrecque, (2004), one of the simplest methods for estimating biomass using remote sensing images involves the development of empirical relationships between the sensor's radiometric signal and the structural features of the forest. The most used sensor in such studies is the Landsat TM sensor (Cohen and Spies 1992, Jakubauskas and Price 1997, Cohen *et al.*, 2003), or TM data simulated using an airborne sensor. (Franklin, 1986, Peterson *et al.*, 1986). The most commonly used means of linking spectral information to forest parameters is single or multiple regression (Franklin 1986, Puhr and Donoghue 2000, Lefsky *et al.*, 2001). Another way to develop direct relationships between radiometric signal and forest cover attributes is to use spectral indices such as NDVI (Peterson *et al.*, 1986, Dong *et al.*, 2003). Jakubauskas and Price (1997) obtained good relations between NDVl and total biomass (R^2 = 0.59) and between band 7 and total biomass (R^2 = 0.58) in natural forests. These studies on the spectral relation with the forest variables do not allow to conclude to a general and adequate relation, especially for a site of study comprising several species. In a mapping study of carbon stored in vegetation for the spatialization of an ecosystem service Oszwald *et al.* (2013) reported that the fit quality of the linear regression model measured by R^2 is 60%. The regression model therefore seems more efficient in predicting the carbon stock variable.

The map of fig. 3 shows the spectral values from the Landsat 8 image.

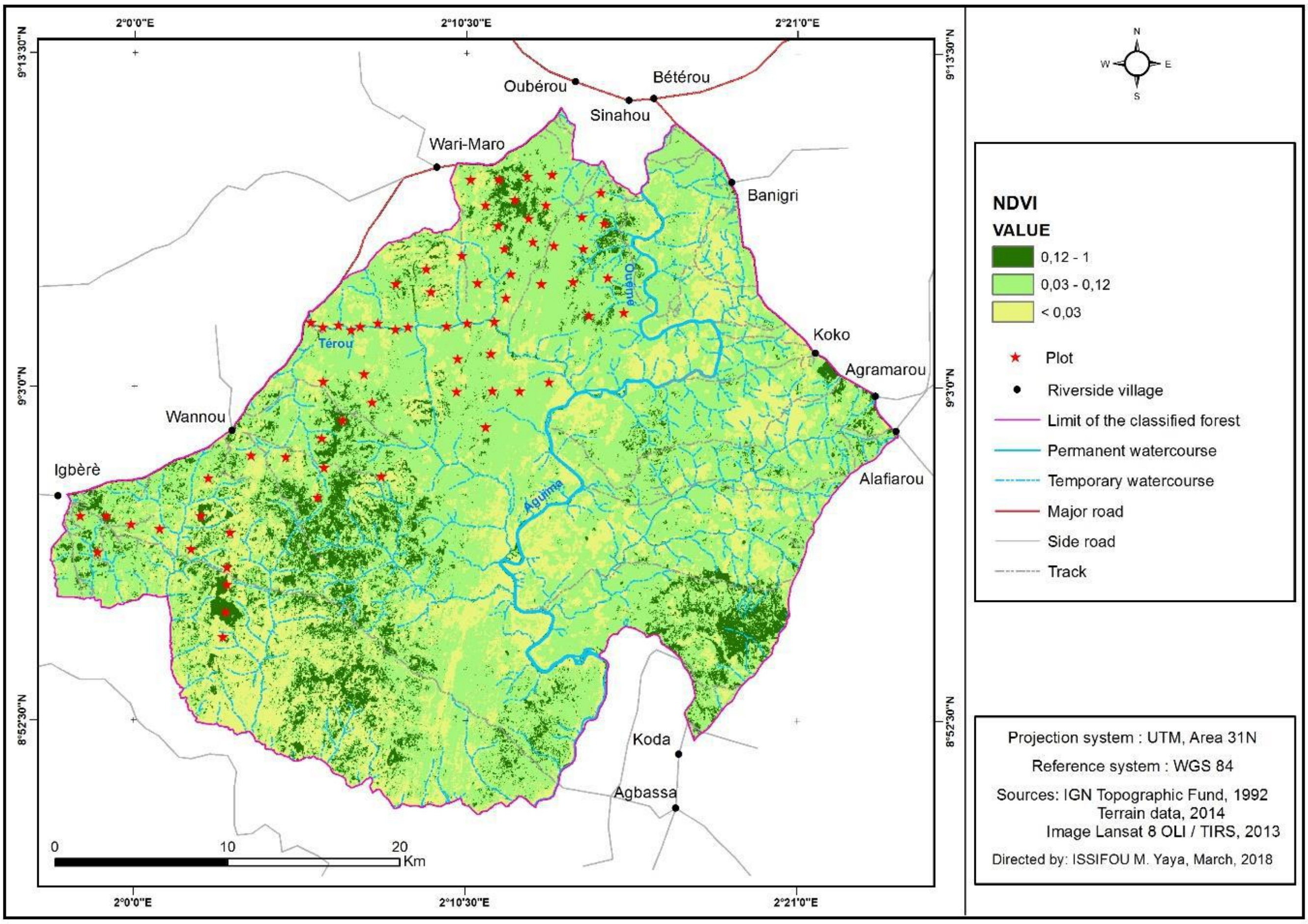

Fig. 3: Standardized Vegetation Index (NDVI) extracted from plots

The plots in situ are represented by the red dots, the greenish or dark green layers with NDVI between 0.12 and 1 are areas of dense forest cover (dense forest, forest gallery). Areas with low forest cover and NDVI ranging between 0.03 and 0.12 (clear forest, wooded savanna, tree and shrub savanna) are represented by light green and yellowish color indicates non-forest formations (fields, fallow etc.) (Fig. 3). The model then distinguishes pixels of heavily forested formations from other types of land use with significantly different values. Pixels with very low values (<0.03) correspond to highly anthropised areas such as fields, pastures, bare ground, built-up areas.

4.3.Mapping of carbon stocks

The carbon map produced from the linear regression model shows more differentiated carbon storage values across the entire Wari-Maro classified forest. The predicted values are presented by class, thus allowing to represent more finely the variations of quantity of carbon stored.

At the scale of the forest, the map allows to distinguish large amounts of carbon in the most wooded areas and much smaller amounts at the deforestation front. The cartography reveals a new phenomenon that the scale of fig.4 does not allow to visualize: the hydrographic network is highlighted with larger quantities of stored carbon.

This phenomenon is explained by the presence of gallery forests. Indeed, the mapping obtained makes it possible to analyze the human / environmental relationships since it offers a better understanding of the distribution of carbon stocks in the areas being deforested. Fig. 4 illustrates the different changes in carbon stocks in the Wari-Maro classified forest.

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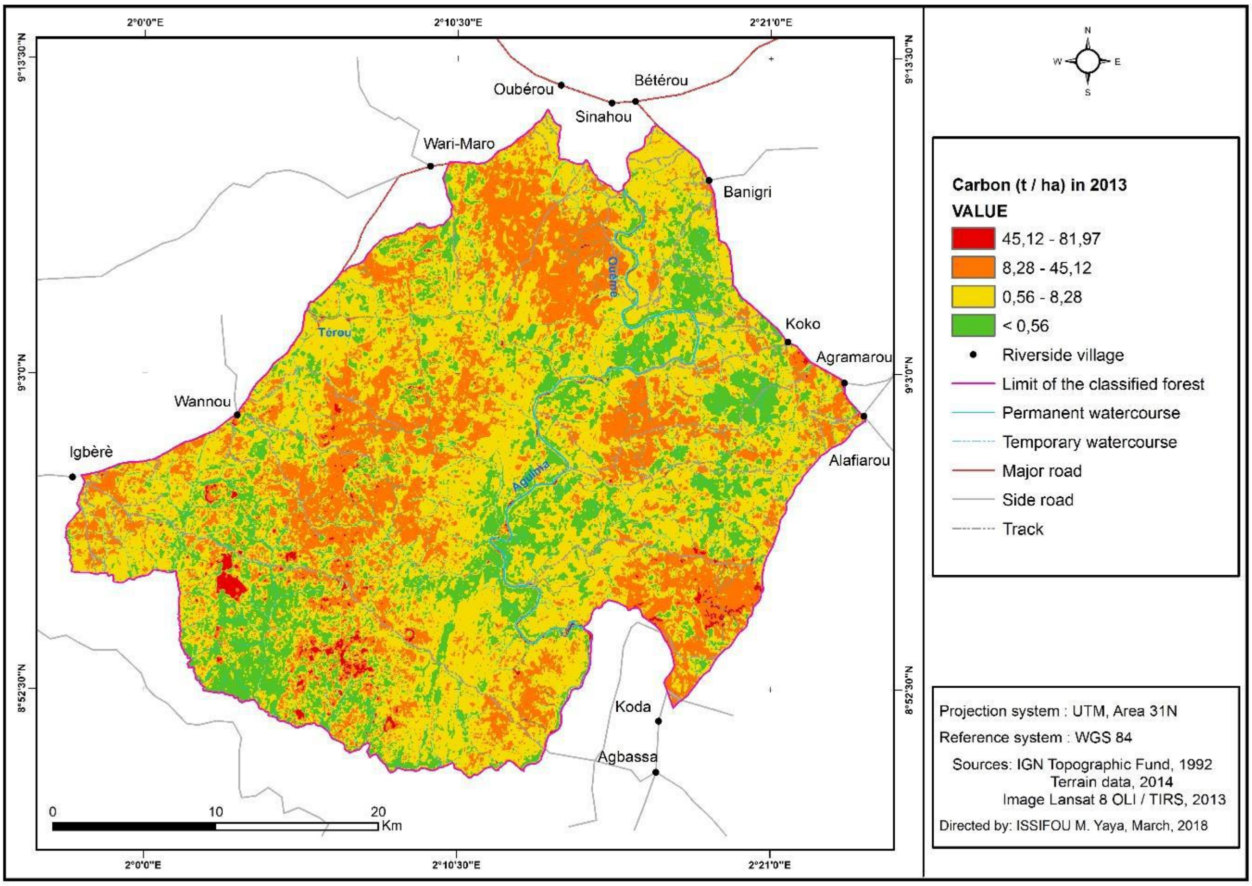

Fig.4: Carbon map of the Wari-Maro classified forest

The examination of the carbon map of fig. 4 shows a high concentration of carbon in forest formations (dense forests, gallery forests) with 45.12 tonnes at 81.97 tonnes per hectare, an average carbon content (8.28 at 45.12 t / ha) in open formations (clear forest and wooded savanna, tree and shrub savannahs) which are actually the most dominant occupying units in the forest. Anthropogenic formations sequester less than 0.56 tonnes of carbon per hectare according to the prediction made using remote sensing data. Overall, with this remote sensing approach, forest formations sequester 60% of forest carbon. The savannah formations reserve 33%, whereas the anthropogenic formations bring only 6% of the carbon stocks and 1% are brought by the other units of occupation (Agglomeration, denuded soils, etc.). Estimating the change in carbon stock with remote sensing data only confirms the observed trend with field data. However, there is a difference between the carbon values obtained in situ and those obtained with remote sensing data for the three main categories of formations considered globally (forest formations, savannah formations and anthropogenic formations).

This situation could be explained by the overestimation made in measuring the dendrometric parameters of the trees in the field. In fact, in the Wari-Maro classified forest, the spaces along the road network were deforested earlier and correspond to areas cultivated since 1990-2002 before the PAMF project. In these predominantly grazed areas, there is little tree and shrub vegetation. The quantities of carbon stored are therefore lower. Moving away from the runway, the human influence is less marked, but remains present. This leads to the creation of a mosaic of grazed / cultivated areas. These are transition spaces marked by a strong heterogeneity in the spatial distribution of the quantities of carbon stored. As the human influence is weak on the most remote areas of the road, plant cover is mostly dense and homogeneous. The quantities of carbon stored are, therefore, the most important. At the scale of a locality in the Brazilian Amazon Oszwald *et al.* (2013) reported that the highest carbon stocks are in the most afforested areas (dense forests and burned forests) while the lowest amounts, between 14.52 and 87.51 Mg / ha, correspond the deforestation fronts of recent years.

Linear regression mapping allows much finer analysis to better account for spatial variability within each type of land use. it indicates areas of high carbon content (45.12 to 81.97 t / ha) that actually correspond to the expanses of dense forests, gallery forests, open forests and wooded savannas that occupy a small portion of the forest compared to wooded and shrubby savannas that dominate the forest landscape with also average carbon concentrations (8.28 to 45.12 t / ha). This is due to the superior predictive ability of this method and especially to the use of Landsat 8 satellite imagery which is relevant, whether in terms of identifying land cover types or in terms of spatial resolution. in fact, by working with high spatial resolution images, the mappings produced make it possible to identify carbon stock changes at the fine scales and thus to better understand the statistical relationship maintained between the field surveys, and therefore the physical processes. , and remotely sensed data. Thus, local scales constitute an important scale of analysis complementary to large-scale studies based on inaccurate spatial data (Oszwald *et al.,* 2013, Dupouey *et al.,* 1999, Metzger *et al.,* 2006). Several recent studies of the vegetation carbon estimate are based on a LiDAR dataset (Asner *et al.,* 2012). These data, although more precise, are very expensive, not very reproducible and spatially small. This makes it a poor tool for Redd + objectives. In contrast, Landsat 8 imagery is easy to acquire, freely accessible, covers large geographical areas, and has the latest advantage of providing images at multiple dates, making it a reproducible tool. despite the uncertainties presented by these images, this model takes into account landscape diversity this makes it an essential tool for the actors of the territory who can take ownership of the phenomenon and develop the territories effectively by adapting to the local specificities, the public policies put in place and the realities of the studied field. This complementarity of scales would make it possible to fully meet the objectives of Redd +.

V. CONCLUSION

The mapping of carbon stocks in the Wari-Maro classified forest was done through the linear regression model used to test the correlation between carbon stocks from field measurements and spectral values (NDVI) from Landsat 8 imagery covering the classified forest. The results from the field measurements indicate a high carbon content of gallery forests and dry dense forests, although not very representative in terms of area. This is what makes all forest formations the best carbon storage reservoir in the Wari-Maro classified forest. The carbon map produced from the linear regression model shows more differentiated carbon storage values across the entire Wari-Maro classified forest. At the scale of the forest, the map has been able to distinguish large amounts of carbon in the most forested areas and much smaller amounts at the deforestation front. The prediction of carbon stock change with remote sensing data alone confirmed the observed trend with field data. Linear regression mapping has favored much finer analysis to better account for spatial variability within each type of land use. The regression model therefore seems very efficient in predicting the carbon stock variable. Despite the negligible bias of the linear regression adopted, this model takes into account the landscape diversity of the environment. The map obtained makes it possible to analyze the relationships between man and the physical environment, since it offers a better understanding of the distribution of carbon stocks in sectors that are being deforested and can thus be used by managers with the aim of more sustainable development of the Wari-Maro Classified Forest.

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