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The use of Normalized Difference Vegetation Index (NDVI) to assess urban forests dynamics in West Africa: A case study of Mbao Classified Forest, Dakar (Senegal)

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Abstract

Mbao Classified Forest is the largest urban forest in Dakar. It covers an area of 720 hectares and is the most important green lung of the city. This forest plays a key role in terms of carbon storage and sequestration, air pollution removal, and more generally in ecosystem services provision. Hence it is urgent to monitor the dynamic of this forest over the past twenty years (1998-2018) because a lot of infrastructures including a water pumping station and a highway were established inside during this period. These installations make it subject to encroachments and the risk of depletion that could compromise its existence. The aim of this this paper is to assess urban forest dynamics using artificial intelligence and vegetation indices. To achieve this goal the first step is to perform a forest inventory. We opted for a sampling rate of 0.5%. The area of a plot in the i-Tree Eco inventory is 391 m^2 with a radius of 11.16 m, which resulted in a total number of 90 plots. The variables measured for each tree are D.B.H, total height, crown width. The allometric equations were used to compute the above-ground biomass. The NDVI of every plot was computed from Landsat datasets followed by the development of a linear regression model with NDVI as the independent variable and biomass as the dependent variable. Landsat imagery enables the NDVI computation of each plot during the twenty past years and using the regression model, the biomass was determined over this period. Our results provide a sound basis to advocate the safeguarding of Mbao Classified Forest.

Keywords:
Urban forest, biomass, NDVI, inventory.

Introduction, scope and main objectives

Urban forestry and greening offer a multitude of benefits to the inhabitants of towns and cities. Hence the monitoring of these forest stands remains a very important pursuit (citation).

Most urban forest studies use classic methods which are very time-consuming and less accurate. Thus, in the 21st century, it is necessary to take advantage of advanced earth observation technologies such as cloud computing to enable rapid assessments of the state of urban forests in West Africa.

Accordingly, urban forest monitoring using remotely sensed vegetation indices have been recommended to remove variability caused by canopy geometry, soil background, sun view angles and atmospheric conditions when measuring biophysical properties (biomass, Leaf Area Index (LAI) and percent green vegetation cover) of vegetation at canopy scale (Tucker, 1979). Santonu (2015)showed evidence of NDVI saturation above a biomass of 100 g/m^2 and an LAI of $2m^2/m^2$. Although ALOS PALSAR images that contain L band, that can penetrate the canopy and is sensitive to the total above ground biomass in many urban forests in West Africa this rate is far from being reached (Diankha, 2021). Hence the NDVI remains a reliable surrogate for monitoring the dynamics of urban forest biomass.

The main objective of this research was to carry out a multi-temporal analysis of the vegetation of Mbao Forest to determine its biomass trend from 1988 to 2018. Such information is needed for forest policy formulation in relation to ecosystem conservation and climate change mitigation.

Methodology/approach

1. Study area

Covering an area of about 1000 ha when it was created in 1908, Mbao Classified Forest now covers an area of 720 ha. It is located in Dakar region West of Senegal, between 17 ° 10 and 17 ° 32 LW and 14 ° 53 and 14 ° 35 LN. The classified forest of Mbao, located in the department of Pikine, has been set up as a reforestation area for soil fixing and conservation objectives. The classified forest of Mbao is bounded to the north by the traditional villages of Bourne, Darou Misseth, and Médina Kell, to the south by Petit Mbao and Grand Mbao, to the east by Kamb and Keur Mbaye Fall, and to the west by the National Road N °1 and the Petit Mbao and Fass Mbao roads.

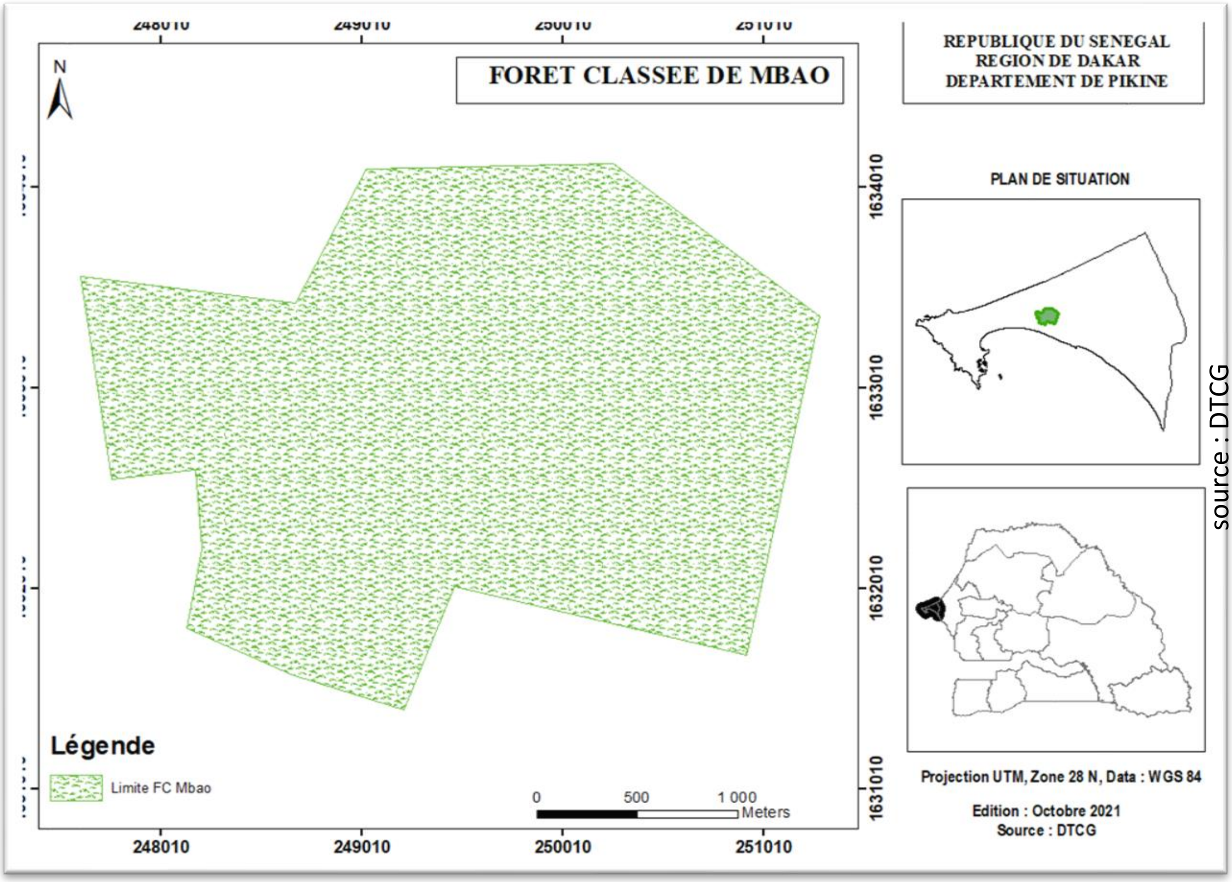

Figure 1: Localization of the study area in Senegal (1) and Dakar region (2)

2. Methods

The first activity was a forest inventory to obtain the aboveground biomass using allometric equations**:** AGB (Kg/tree) = Volume of tree (m^3) x Wood density (Kg/m^3) (Jaiswal et al., 2014). The inventory rate was 0.5% in a forest area of 7.2 km^2; hence, the area surveyed was 36000 m^2. The area of each circular plot was 391 m^2 (Nowak, 2020), with a radius of 11.16 m. The number of plots (92) was obtained by dividing the survey area (36000 m^2) by the plot size. We obtained the area of influence for each plot ($\sim$0.08 km^2) by diving the forest area is divided by the number of plots. The distance between the plot centers ($\sim$282 m) was obtained by taking the square root of the area of influence. We had the flexibility to choose the method to distribute the plots in the study area. For this study the grid points method was adopted. The computation to get the biomass with the inventory data was carried out in Microsoft Excel.

Secondly, the mean normalized difference vegetation index (NDVI) values of the same plots were computed from Landsat surface reflectance data on the cloud-based geospatial computational platform – Google Earth Engine (GEE). NDVI is a dimensionless index that describes the difference between visible and near-infrared reflectance of vegetation cover based the equation

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}},$$

where ρ_{NIR} and ρ_{RED} are the reflectance in the near-infrared and red bands of the electromagnetic spectrum, respectively.

Finally, a linear regression model between biomass (as the dependent variable) and NDVI (as an independent variable) was developed to determine the strength of the correlation between the two variables. Previous studies (e.g., Cabrera-Bosquet et al., 2011) have reported strong correlations between NDVI measurements and aboveground biomass, especially in semi-arid areas of the world NDVI does not saturate. The modelling procedure was carried out in R statistical software.

Results

The study sampled a total of 418 stems (between January 1st, 2021 and February 10, 2021) with DBH ≥ 2.54 cm (1 inch) (Nowak, 2020) that belong to 10 families and 18 species. A total of 51 sample plots covering 19,957 m^2 were measured.

Table1: Results for all species combined

PARAMETER	QUANTITY
Number of stems/ha	204.902
Volume (m3)/ha	47.311
Above Ground Biomass (Kg/ha)	30.193
Below Ground Biomass (Kg/ha)	7.85
Total Biomass (Kg/ha)	38.043
Carbon stored (Kg/ha)	19.022
Tree cover (%)	13.46%

For the same period, the NDVI values computed for the 51 plots is summarized in the table below. The complete table is available in Appendix 1.

Table 2: Descriptive statistics of NDVI values

Statistic	*Value*
Mean	0.429216373
Standard Error	0.017017792
Median	0.436346
Standard Deviation	0.121531347
Sample Variance	0.014769868
Minimum	0.147052
Maximum	0.689256

Table 2: NDVI and AGB of the surveyed plots

num	x	y	NDVI	AGB(Kgha^{-1})
1	248841	1631803	0.457582	3.404582
2	248559	1632085	0.494603	0.50092
3	248841	1632085	0.635408	7.31095
4	249123	1632085	0.405582	0.155344
5	249405	1632085	0.556549	3.163511
6	249687	1632085	0.20641	2.664363
7	249969	1632085	0.315591	0.519741
8	250251	1632085	0.319227	0.057183
9	250533	1632085	0.377855	2.159232
10	248559	1632367	0.549676	0.85949
11	248841	1632367	0.355916	0.111962
12	249405	1632367	0.340684	0.698379
13	249687	1632367	0.298399	0.308969
14	249969	1632367	0.254388	0.517528
15	250251	1632367	0.42229	0.541588
16	250533	1632367	0.476758	2.495665
17	249123	1632649	0.384441	0.547178
18	249405	1632649	0.439004	0.038312
19	249687	1632649	0.681047	0.305229
20	250815	1632649	0.458297	0.150227
21	247995	1632931	0.243804	5.978465
22	248277	1632931	0.147052	0.891155
23	248559	1632931	0.589015	9.290705
24	248841	1632931	0.542565	2.915419
25	249123	1632931	0.36604	0.850906
26	249969	1632931	0.689256	0.443229
27	247995	1633213	0.338468	1.761268
28	248277	1633213	0.537068	0.778214
29	248559	1633213	0.460106	1.336509
30	248841	1633213	0.598582	0.707798
31	249123	1633213	0.29755	0.352686
32	249405	1633213	0.2578	0.586981
33	249687	1633213	0.371893	2.065759
34	249969	1633213	0.399665	1.017465
35	250251	1633213	0.499743	0.370063
36	250533	1633213	0.47806	0.326705
37	248841	1633495	0.466527	0.278492
38	249123	1633495	0.406897	0.916726
39	249405	1633495	0.284499	0.144851
40	249687	1633495	0.343347	0.717946
41	249969	1633495	0.364028	1.543348
42	250251	1633495	0.520645	4.119342
43	250533	1633495	0.433798	0.770658

44	250815	1633495	0.305281	0.466062
45	248841	1633777	0.613105	6.743225
46	249123	1633777	0.508497	0.69343
47	249405	1633777	0.473735	1.026507
48	249687	1633777	0.454321	1.947208
49	249969	1633777	0.436346	0.32135
50	250251	1633777	0.466837	1.031652
51	250533	1633777	0.565798	0.092669

The correlation between biomass and NDVI ($R^2 = \sim 0.073$) as obtained from the linear regression model was lower than expected, possibly due to the limited number of observations and the spatial resolution of Landsat which is slightly more than the size of the sampled plots. The regression equation obtained was:

$$\boldsymbol{Biomass} = -\mathbf{0.3859} + \mathbf{4.4165} \times \boldsymbol{NDVI}.$$

Table 3 below summarizes the results of the correlation.

Table 3: Summary of linear regression parameters

Coefficient	Value
Intercept	-0.3859
Slope	4.4165
P-value	0.0553
$\boldsymbol{R^2}$	0.07292

Finally, using the linear regression model, we estimated mean biomass for the years 1988 – 2018 based on the mean NDVI values for each year over the same period (see Table 4).

Table 4: Mean NDVI and Aboveground Biomass from 1988 to 2018

Year	Mean NDVI	Aboveground Biomass (Kg/ha)
1988	0.4362354	1.54073365
1989	0.45363465	1.61757744
1990	0.4159384	1.45109194
1992	0.40050239	1.3829188
1994	0.207302	0.52964927
1995	0.23653952	0.65877678
1998	0.24581765	0.69975363
1999	0.49260825	1.78970432
2000	0.26239797	0.77298065
2001	0.4065525	1.40963912
2002	0.42811586	1.50487368
2003	0.3376492	1.10532771
2004	0.36023724	1.20508776
2005	0.28110469	0.85559886
2006	0.33061245	1.07424987

2007	0.32933096	1.0685902
2008	0.2297427	0.62875862
2009	0.34858126	1.15360914
2010	0.31414412	1.0015175
2011	0.36212927	1.21344393
2012	0.2831544	0.86465142
2013	0.27052444	0.80887117
2014	0.40190328	1.38910582
2015	0.30629753	0.96686304
2016	0.33357741	1.08734462
2017	0.34807966	1.15139384
2018	0.28471436	0.87154096

A graphical representation, as shown in Figure 2, reveals a decreasing trend in biomass over the period, even though it is not homogeneous.

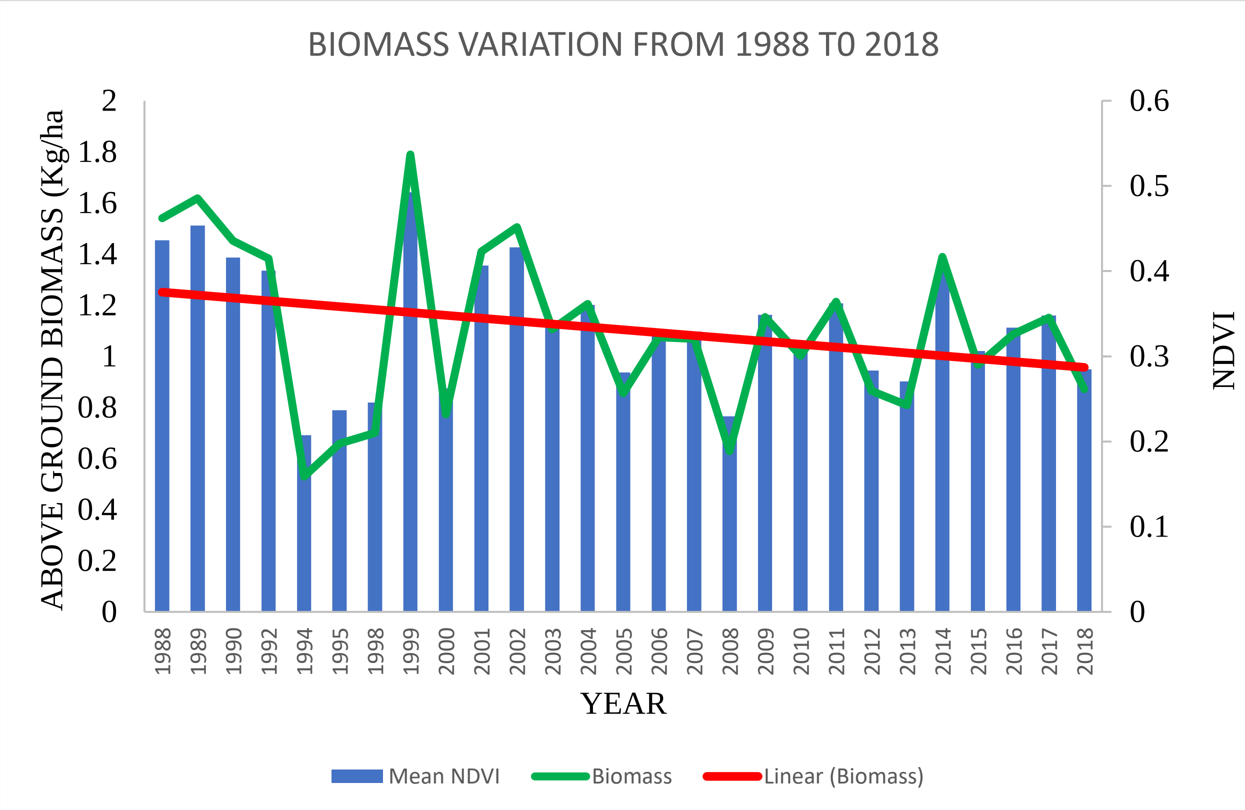

Figure 2: Trend of the biomass variation between 1988 to 2018

Discussion

About the forest composition, large-diameter trees are not important, and this fact demonstrates the reforestation and regeneration efforts undertaken by managers. Urban forests are composed of a mix of native and exotic tree species. Thus, urban forests often have a tree diversity that is higher than surrounding native landscapes.

The regression model between the above ground biomass and the NDVI gives a relatively low R^2 value (R^2 = 0.07292). The result is not consistent with Morel et al.,(2012) with R^2 = 0.6 in "Monitoring aboveground biomass in Sabah, Malaysia". Several reasons including the inconsistency between the plot size (radius = 11.16 m) and Landsat pixel size of 30 m, and the limited number of samples could account for this. Unfortunately, because of persistent clouds in Sentinel-2 images, which would have better suited this project, it was impossible to get a clean image composite for the data collection period. A similar study conducted by the Ecological Monitoring Center (CSE) in Senegal utilized data from NOAA-AVHRR, SPOT, and MODIS and found a regression the model, **Biomass = 11750 * NDVI – 3120,** in 2011 with a correlation coefficient R = 0.87 (CSE, 2011). This is not consistent with our results.

Our results indicate a decreasing trend in biomass between 1988 and 2018 because, in 1988 we had a biomass density equal to 1.5 Kg/ha while in 2018 the quantity of biomass fell to 0.8 Kg/ha, i.e., a decrease of 46.66%.

This may be due to the activities of traditional healers who, according to Gueye (2015), harness trees with 47% followed by shrubs at 33% and lianas at 20%. The road infrastructure development has contributed to the loss of the vegetation cover because the toll highway establishment required the declassification of 35 ha (Gueye et al., 2008). Hansen et al. (2013) has reported a global forest loss of 2.3 million km^2 and gain of 0.8 million km^2 from 2000 to 2012 due to forest degradation. The forest monitoring deficit linked to the staffing problems of the Forest Service of Senegal also contributes to the biomass loss because of the illegal logging of eucalyptus plantations by local populations. These results are consistent with a previous inventory done by Ngom (2010) who, during a stratified stocktaking with 8 classes, found an average biomass of 8269.98 Kg/ha in 2010 due to illegal loggers.

This approach for spatially and temporally estimating AGB dynamics at a land management scale, using single-date forest inventory plots and an annual Landsat time series (1988–2018) can be particularly useful in forest regions where only single-date and sparse inventory data are available. This can aid forest managers and policymakers in measuring and reporting on forest biomass changes, especially in developing countries, because high resolution images are freely available. The emergence of cloud-based data and computation platforms like Google Earth Engine even makes such endeavours achievable within limited timeframes.

In charcoal forest management, the forest is first divided into blocks and each block is divided into plots. For a rotation of eight (08) years, the block is divided into eight plots. In the first year of implementation, 50% of the woody potential is exploited. It is in the ninth year that the operators will go back to cut 50% of the remaining potential. Thus, a harvested species has sixteen (16) years to reconstitute itself and therefore the sustainability of the forest is ensured. The use of this method would make it possible to follow the evolution of the plot and give the alert in case that the reconstitution of the plant cover is not sufficient. This activity is very important in West Africa as forests are made up mainly of indigenous species (Combretum *glutinosum* Perr. ex DC., *Terminalia macroptera* Guil & Perr., *Anogeissus leiocarpus* (DC) Guill & Perr.*, Terminalia avicennioides Guill. & Perr, etc.)* whose silviculture is not yet well mastered.

Conclusions/ wider implications of findings

For monitoring the evolution of forests over time, NDVI could be a less expensive alternative since the images (Landsat, Sentinel, ALOS PALSAR) are currently easily accessible and free of charge on Google Earth Engine (which eliminates the need to download the data from different data platforms) but only a few local researchers use it. What appears to be the challenge is that the user should know the basics in programming either in JavaScript or Python.

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