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RESEARCH ARTICLE

ESTIMATING ABOVEGROUND BIOMASS IN FOREST'S ZONE OF TOGO (WEST AFRICA).

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ABSTRACT

The estimation of aboveground biomass (AGB) at the landscape level is necessary for estimating carbon pools in forest and provides baseline data for future studies. The objective of this study is to combine national forest inventory and remote sensing data to estimate aboveground forest biomass from remotely sensed data, and assess the accuracy of the method developed. The AGB maps 2015 across forest's zone in Togo were produced based on secondary data from national forest inventory (NFI) field measurement using open sources Landsat images. The 2015 national inventory data (168 plots) has served as the base for validation of the 2015 biomass map. Three measurements were made to quantify accuracy: root mean square error (RMSE), bias and the coefficient of determination (R2) of the linear regression between predicted and measured AGB values. A complete map of AGB maps at 30 metres spatial resolution was produced over 603'972 ha. The overall model shows 74% of variance. The predicted AGB values across the landscape are between 40.34 and118.71 Mg/ha, with mean equal to 75.83Mg/ha and standard deviation (S.D.) equal to57.93Mg/ha. The model has overestimated biomass of the AGB with low values (Forest plantation and Savanna) and underestimated the AGB with high biomass values (Fallow, Woodland, Dense forest and Gallery forest). The RMSE values vary between27.41 and 35.66 t/ha depending on the forest strata and the overall RMSE value is around 15 t/ha. The estimated mean biomass for the model ischosen from 40.34 (savanna) to 118.71 (dense forest) t/ha. This study can be considered as a reliable, cost-effective and reproducible approach to map AGB in dynamic forest landscapes and can support policy approaches towards reducing emissions from deforestation and degradation (REDD+).

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INTRODUCTION

An improved monitoring of forest biomass is needed to support requirements to sustainable forest management and carbon accounting (Houghton, 2007). Since the Kyoto protocol on greenhouse gas emission reduction, forests have been targeted for reducing carbon emissions because, they store great quantities of carbon and exchange it with the atmosphere through photosynthesis and respiration (Brown, 2011). As a consequence, a mechanism for Reducing Emissions from Deforestation and Forest Degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries (REDD+) has been developed under the United Nations Framework Convention on Climate Change (UNFCCC). REDD+ deploys results-based finance to incentivize emissions reduction, based on a functional forest carbon measuring, reporting and verification (MRV) system (UNFCCC. 2009). A functional MRV to support REDD+ requires estimations of the area of forest loss and gain and the corresponding carbon stock and changes (UNFCCC. 2009). These data are required for the estimation of the actual emissions and the construction of forest reference emissions level (FREL), a benchmark against which the actual emissions are being compared (UNFCCC. 2011). A combination of field inventory and remote sensing is expected to provide these data. The program requirement is the capability to accurately map and monitor changes in forest carbon by estimating gross emissions as a function of area of forest loss and density of carbon stocks within areas of forest loss (Tyukavina, 2013). The REDD+ mechanisms will then rely on accurate mapping and monitoring of Above Ground

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Carbone/biomass (AGC/B) (Houghton, 2010). However, scientific, technical and operational aspects of AGC mapping and monitoring are still in their infancy (Tyukavina, 2013). The suggested schemes for carbon credit incentive based on deforestation or carbon stock baselines require accurate estimation of biomass (Ern, 1979).

As tropical country Togo has recently joined the REDD+ mechanism with the ambition of creating a new incentive system to reduce forest loss and to restore the integrity of degraded forests (MERF 2013). The country has five ecological zones and the ecological zone IV which is the Togo's forest zone constitute the domain of the semi-deciduous dense forests (Ern, 1979) is now very degraded and is disappearing. Several previous studies (Adjossou, 2009; Adjossou, 2004) have shown that forests in the sub-humid mountainous area are very fragmented and have practically been reduced to hard-to-reach areas. Despite its degraded state, the ecological zone IV which extends over the plateau and central region of Togo is one of the main forest area in the country (MERF, 2016). Monitoring the biomass by remote sensing in the forest zone of Togo is a challenge because, of the effect of the relief and different forest types that mix up with fallows and secondary forests growing on agricultural land. The ability to map forest biomass is important for monitoring changes in forest structure and changes in the carbon account (Labrecque *et al*., 2006). These facts raise a research question: What aboveground biomass can be observed spatially in the study area over the last decades?

In the context of REDD+ in Togo, previous work on forest cover mapping has provided valuable insight into vegetation status and different maps were produced (MERF, 2018). However, few data are available on forest biomass mapping. In 2016, the World Bank funded the definition of the methodology and tools for biomass estimation in various compartments in Togo. Despite the estimation of biomass, further improvements in classification methods for biomass change are necessary in order to provide accurate and consistent estimations of biomass change at national and sub national levels. The year 2015 is a reference year in Togo because of the realization of the first national forest inventory. The result of this forest inventory was used to assess AGB for plots of different strata. According to Houghton (Houghton, 2005), it is critical to have reliable and current information on the spatial distribution of AGB in the forest's zone over the last decades in order to calculate the sources (and sinks) of carbon that result from converting a forest to cleared land (and vice versa) and to enable measurement of change through time. In recent decades, efforts have been made to estimate forest biomass, including field measurements and model simulations. Numerous regression models have been developed to estimate AGB while these models are accurate at tree, plot, and stand levels, they are limited when considering spatial pattern analysis of AGB across the landscape (Zheng, 2004). In order to scale AGB estimations to the landscape level, the estimations have to be linked with various vegetation indices derived by remote sensing data(16). As a result, a large number of research have focused on estimating biomass directly with moderate spatial resolution (e.g. Landsat, (Labrecque, 2006; Pflugmacher *et al*., 2014; Ji *et al*., 2012). Models derived from remote sensing need further calibration with ground data before they can be used appropriately to predict AGB for a given landscape. It has been demonstrated that the Landsat imagery is very useful for monitoring environmental change when combined with field measurements (19,20). This fact highlights a research question: How can aboveground biomass be mapped consistently, in the forest ecological zone 4 in Togo? The general objective of the study is to contribute to the monitoring of carbon stock and dynamics in the context of REDD+. The specificobjectives of this study is to combine national forest inventory and remote sensing data to developspatial map of aboveground forest biomass, and estimate aboveground biomassfrom the developed method.

MATERIALS AND METHODS

Study area: The study area is Togo's bioclimatic region "ecological zone IV" andis located in the southern part of the Atakora mountains, south-west of Togo, on the border between Togo and Ghana in the region called Togo Mountains or Togo highlands. The study area extends between the latitudes 6° 15 and 8° 20 and the longitudes 0° 30 and 1° and covers an area of 603'972 hectares (Figure 1).The climate prevailing in this area is a Guinean mountain climatecharacterized by a long rainy season (8-10 months). The mean annual temperatures range from 21° to 25°C and the total annual rainfall ranges varies from 1400 to 1700 mm. This zone contributes signi*fi*cantly to species richness in Togo (10). It is the current domain of semi-deciduous forests.The study area shows a strong topographic heterogeneity. The average altitude is 800 m, with peaks at Djogadjèto (972 m) and Liva (950 m). A succession of plateau (plateau of Kloto, Kouma, Danyi, Akposso, Akebou and Adele) where hills along with their valleys and caves are common. Landforms are diverse and complex. A network of complex secondary rivers covers the area with three catchment areas: the basin of the lake Volta in the west of the Mounts and basin of the Mono River and Zio River in the east of the mounts.Population distribution and land management vary across the area with implications for forest cover changes.

Overview of data and methods: The steps of this research are: (a) AGB calculation based on allometric equation and forest inventory data, (b) acquisition, preprocessing, and stacking of Landsat images, (c) AGB classification model using Random Forest and AGB values of NFI plots for calibration (d) application of the model for creating AGB 2015 based on AGB calculated and using Random Forest and (e) accuracy assessment of resulting maps using the national forest inventory plots.

Landsat's temporal and spatial coverage with moderate spatial resolution provide a unique opportunity for characterizing vegetation changes across large areas and longtime scales (Pflugmacher *et al*., 2014). A number of other national biomassmaps have been produced based onthe analysis of full coverage of Landsat data (Labrecque, 2006; Pflugmacher, 2014; Ji, 2012). Landsat data have been widely used in forest aboveground biomass (AGB) estimation, commonly through developing empirical relationships between AGB or other forest characteristics and spectral indices such as the normalized difference vegetation index (NDVI) derived from satellite data. The study area is covered by two WRS2 scenes with path 193 and rows 054 and 055. Landsat surface reflectance data at the end of the dry period (Jan - Feb) with less than 10% cloud cover were downloaded from the U.S. Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) portal (https://earthexplorer.usgs.gov/) at full spatial and spectral resolution (30 *x* 30 m resolution). The data selected was for the end of dry season as forests can then be best distinguished from other types of vegetation and classification tends to be more accurate than during the wet season (Liu *et al*., 2015). Furthermore, the availability of cloud-free images is limited in wet season in comparison to dry season. The final dataset obtained is made of Landsat 8/ OLI for the year 2015. The acquisition date of the image is 04/01/2015. For the date, the six spectral bands B, G, R, NIR, SWIR1 and SWIR2 of the Landsat images of scenes p193r054 and p193r055 were mosaicked and projected to the coordinate reference system WGS 84 - UTM 31. All data manipulation and analysis of satellite images were done using the R environment for statistical computing (Core Team, 2019) using the R-packages "raster".

Field measurements: In the framework of the national forest inventory of Togo, the sample plots are distributed in a random manner (MERF, 2016): A total of 945 national inventory plots are distributed on the whole country (MERF, 2016). In the framework of this study, the limit of forest zone of Togo was overlain on the map of Togo to extract the plots found there. A total of 168 plots were retained and spread over the study area (Figure 2). Field data were collected to estimate the following components of AGB: tree and shrub (both dead and alive) biomass and understory biomass. The field plots selected for the inventory is circular (better relationship between the sample area and its perimeter). The plots have been subdivided into three sub-samples (Figure 3) whose radius depends on the expected density of the vegetation to be measured:

- A 20 m radius for all sample trees with a breast height diameter (Dref) equal to or greater than 10 cm; the area of a plot of 20 m radius corresponds to about 1 256 m^2 or 12.6% of one ha; The expected average number of sample trees is 15;
- a radius of 4 m for all trees and shrubs with Dref between 5 and 9.99 cm (undergrowth);
- Four (4) circular subplots of 1 m radius for regeneration, ie for all trees / shrubs with a diameter of less than 5 cm and a height greater than or equal to 1.3 m.

Estimation of AGB from forest inventory: The basis for the assessment of biomass are the surveys made on 168 plots (r = 20m). AGB (Mg/ha) is defined in this study as biomass of trees greater than 10 cm DBH and taller than 1.3 m. The best taxonomic match wood density of each stem was extracted from a global database (Zanne *et al*., 2009). The above ground biomass was calculated using the Chave (Chave *et al*., 2014) 'moist forest' equation as following:$AGB = 0.0673 * (WSG * DBH^2H)^{0.976}$,where

AGB is the AGB (kg) at the tree scale, WSG (g cm^{-3})isthe tree wood density, DBH (cm)is the diameter breast height and H(m)is the tree height. AGB is then converted to dry matter Megagrams per hectare. Once AGB was calculated using the DBH of all trees species in each plot, we calculated the sum and converted to Megagrams per hectare (Mg/ha). The AGB of this study was compared to aboveground carbon (AGC) of other studies by divided the AGC by carbon content of dry biomass considering it as 47%(25). The AGB densities found in the national forest inventory (NFI) were used to calibrate a biomass map based on 2015 Land sat imagery. To obtain the necessary spectral values, the weighted averages of the values of the different pixels covered by the NFI plots were calculated.

Production of AGB map with Random forest: The 2015 above-ground biomass calculated on the basis of the national forest inventory as well as Landsat images from 2015 were integrated into the "Random forest" algorithm to produce the 2015 aboveground biomass map. The Random Forest algorithm, developed by Breiman (Breiman, 2001), was selected for its good predictive capabilities for regression (Gislason *et al*., 2006). Random Forest is a non-parametric supervised classification algorithm that combines the decision tree algorithm and an aggregation technique. The algorithm randomly selects a sample of observations and a sample of variables many times to produce a number of smallclassi *fi* cation trees (Breiman, 2001). "These small trees are then aggregated and a majority vote rule is applied to determine the final category (Breiman, 2001)". For this study we have used the Random Forest implementation provided by the R-package "Random Forest". In order to improve the discrimination of aboveground biomass, several remote sensing indices derived from the spectral bands G, B, R, NIR, SWIR1 and SWIR2 have been calculated:

- The normalized vegetation index (NDVI) is calculated as: NDVI= (NIR-red)/(NIR+red), where red and NIR stand for the spectral reflectance measurements acquired in the red (visible) and near-infrared regions, respectively (Rouse, 1974);
- The enhanced vegetation index (EVI) is computed following this equation:

EVI = 2.5×(NIR-red)/(NIR+C1× red - C2 × blue + L),(29) where NIR/red/blue are atmospherically-corrected, L is the canopy background adjustment that addresses non-linear, differential NIR and red radiant transfer through a canopy, and C1, C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in Landsat are; L=1, C1 = 6, C2 = 7.5;

The Normalized Difference Moisture Index (NDMI) is calculated with the following equation NDMI=(NIR−MIR)/(NIR+MIR) (30), where MIR is the middle infrared;

The Soil Adjusted Vegetation Index (SAVI) is calculated as SAVI= (NIR-red)*(1+L)/(NIR+red+L) (Huete, 1988), where NIR is the reflectance value of the near infrared band, red is reflectance of the red band, and L is the soil brightness correction factor;

The Normalized Burn Ratio (NBR1 et NBR2) calculated as: NBR = (NIR-SWIR)/(NIR+SWIR), where NIR is near-infrared and SWIR is short-wave infrared bands.

The utility of the different spectral bands and indices for the identification biomass has been tested with a recursive elimination of variables with the RFE algorithm available in the R-package "caret" (Kuhn, 2016). The recursive elimination of the variables shows that the best prediction is obtained by using the individual bands (blue, green, red, short wave infrared (SWIR-1 and SWIR-2)) (Figure 4).Many studies have shown that indices such as normalized difference vegetation index (NDVI) are useful predictors of leaf area index (LAI), biomass, and productivity in grasslands and forests (Zheng *et al*., 2004).

Accuracy assessment: The inventory field plots were used for validation of biomass estimates generated from the model. The accuracy of the model was assessed through both comparisons between the predicted AGB values and the measured AGB from the field. Three measurements were made to quantify accuracy: root mean square error (RMSE), relative RMSE (RMSEr) as a percent of the mean of the field inventory biomass, bias andthe coefficient of determination (R^2) of the linear regression between predicted and measured AGB values. RMSE is frequently used to assess the differences between values predicted by a model and the values actually observed or measured. It is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\gamma_i - x_i)^2}$$

Where,γ_i and x_i are the predicted AGB and measured AGB of the ithplot respectively, and n is the total number of plots. The reliability of the biomass estimates was assessed according to the RMSE between the predicted and observed biomass and the associated bias. A smaller RMSE indicates a higher accuracy. The relative RMSE (RMSEr) is define as RMSEr = $\left(\frac{RMSE}{y}\right) * 100,$ where,y is the mean of the observed values. The bias of the model is calculated as: Bias = e1-e2 wheree1 is the mean value of the estimated biomass and e2 is the mean value of the validation plots(33). The positive value of bias suggests an overestimate of AGB by the model, while negative value of bias indicate an underestimate of AGB by the model. The coefficient of determination (R^2)shows how well observed AGB are predicted by the model, as the proportion of total variation of AGB explained by the model. In addition, the mean biomass and the corresponding standard deviations were calculated for each forest strata, allowing the determination of which strata are most sensitive to errors.

RESULTS

Biomass assessed with inventory field plots: The aboveground biomass value was observed lowest (34.67Mg ha−1) in savanna strata while, it was highest of 129.31 Mg ha−1 in dense forest of the study area with an average value of 78.63 ± 68.75 Mg ha−1 across the studied forest area (Figure 5).

Models for estimating AGB: Remote sensing derived variables including all Landsat sensors (B, G, R, NIR, SWIR1, SWIR2) and derived indices were useful predictors of AGB (Figure 4).The regression model for AGB estimation had a good fit of R^2 = 0.74 (for all NFI) plots. In other words, the overall model explained 74% of variance observed between the 168 NFI plots however, high AGB values were slightly underestimated and low AGB value were overestimated (Figure 7).The predicted AGB (AGB derived from the predicted model) values across the landscape ranged from40.34to118.71 Mg/ha (Table 1), with amean value of75.83Mg/ha and standard deviation (S.D.) of 57.93Mg/ha; consequently, the total AGB in the study area was estimated at 47'488'814Mg/ha. The biomass classes with the highest area was 0– 25 and 26 to 50 Mg/ha (Figure 6). The AGB class distribution was skewed toward lower AGB values. Only 1.45 % of the landscape had AGB >200 Mg/ha (Figure 8).

Validation of modeled AGB: Total biomass and mean biomass values calculated for the model in addition to the error estimations (Table 1) provided an indication of the errors inherent in the biomass map. The mean biomass estimated derived from the model ranged from 40.34 (savanna) to 118.71 (dense forest) Mg/ha. These values suggested that the biomass map underestimated biomass when compared with the field data plots, which had overall bias values of -2.8 (Mg/ha). All forest strata had negative bias, except for forest plantation and savanna. The lowest bias registered occurred for fallow strata (-2.77 Mg/ha). The model overestimated biomass for the two strata (Forest plantation and Savanna) and underestimated biomass for the remain forest strata (Fallow, Woodland, Dense forest and Gallery forest). The RMSE values ranged from27.41 to 35.66 Mg/ha depending on the forest strata and the overall RMSE value is around 15 Mg/ha. The contribution of dense forest and gallery forest to the total above ground biomass was greater than those from all the other forest strata.

DISCUSSION

Aboveground biomass distribution: The estimated tree biomass values were comparable with values reported for tropical forests elsewhere. The above ground biomass of the studied ranges well within the range of other tropical dry deciduous forests of the world (30–262 Mg.ha−1)(34,35). The AGB values found in this study are close to the range of aboveground biomass carbon stocks (53 – 638 Mg.ha−1) reported from tropical forests of the world(36,37). The AGB values varied across different ranges of the study area could be due to variation in tree species compositions, diversity, forest age, disturbances, and forest management history.

Uncertainties in AGB estimation: The accuracies of our regression model and AGB estimates are similar to previous studies that used optical remote sensing to map biomass. RMSE of models using multiple predictor variables in our study ranges between27.41 to 35.66Mg/ha and $R^2$is 0.74. Ji *et al*(18) used Land sat-derived spectral variables and the field AGB data to generate a regression model and applied this model to map AGB for the ecoregionin Alaska and reported an $R^2$of 0.73.Labrecque utilized Land sat TM images to map forest biomass in western New-foundland by four methods and reported results with RMSE around between 47 and 59 Mg/ha. Zhu and Liu(38) utilized seasonal NDVI time-series derived from multi-temporal Land sat images to estimate AGB in the southeastern Ohio in U.S and reported an R^2 ranges from 0.49 to 0.58. Houghton(1) mapped forest biomass for Russia with 500-m resolution MODIS and forest inventory data using a regression tree method, which had an R^2 of 0.61. ForAGB mapping with intermediate resolution satellite data such as Landsat and System Pour l'Observation de la Terre (SPOT), the model R^2 values are commonly between 0.50 and0.70 and the absolute errors of the estimates fall in the range of 30–60 Mg/ha (Zheng, 2004; Ji *et al*., 2012). Comparing our study with these previous studies using optical images at a single time and seasonal multi-temporal data, we can see that the use of Random Forest and several remote sensing indices derived from the spectral bands G, B, R, NIR, SWIR1 and SWIR2 for

Table 1. Evaluation of the produced map using the plots biomass Valeur (Mg/ha)

		AGB derived from fied data		AGB derived from the model		RMSE	Bias
	Number of plot	AGB	*SD*	AGB	*SD*		
Fallow	30	56.89	43.01	54.12	36.19	35.66	-2.77
Woodland	27	65.25	43.42	59.75	42.33	25.32	-5.5
Dense forest	69	129.31	88.23	118.71	65.19	34.35	-10.6
Gallery forest	18	114.97	51.86	111.75	48.47	27.41	- 3.22
Forest plantation	5	42.14	26.13	58.35	39.54	27.43	16.21
Savanna	18	34.67	24.37	40.34	31.20	28.15	5.67
All category	168	78.63	68.75	75.83	57.93	15.07	-2.8

AGB estimation are able to improve the accuracy of AGB modeling. However, the estimation of AGB in our study still contains some errors. These errors may result from the fact that the geographic matching between Landsat pixels and field plots is very challenging because, the plot size does not perfectly match the pixel size.

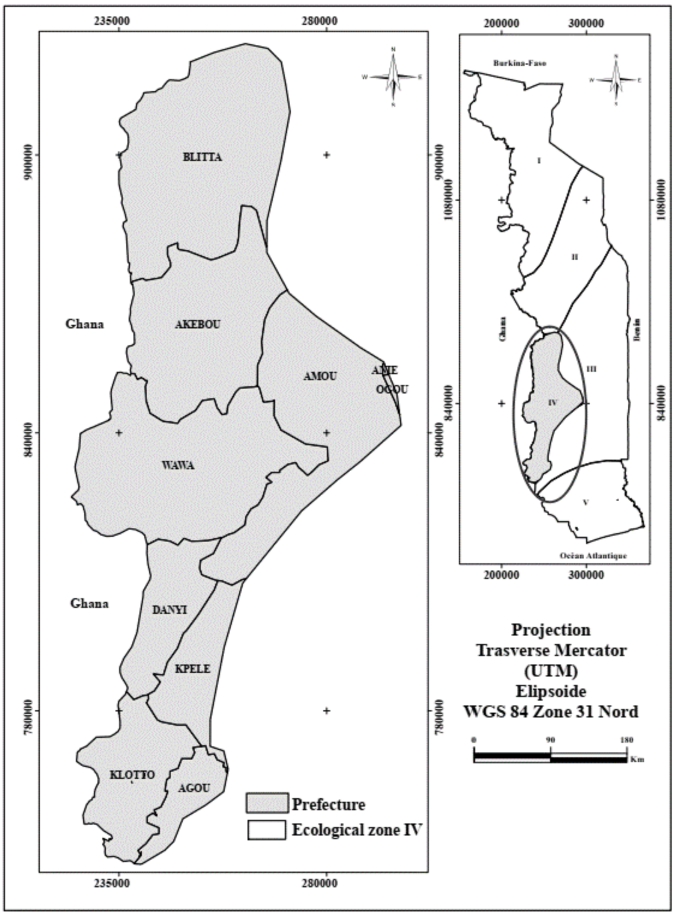

Figure 1. Study area Ecological zone IV

Mapping forest aboveground biomass: The model used for this study obtained small overall RMSE (15 Mg/ha) in the validation data. The mean value of AGB in the study area according to the model is 75.83 Mg/ha and the standard deviation is 57.93Mg/ha. The AGB values show clear spatial patterns in the study area (Figure 8): lower AGB values are found in relatively flat and low lands which are near roads, farming lands, and houses, while higher AGB values are distributed in mountainous areas with high elevations and in protected areas such as Missahoe forest. A possible reason for these patterns is that forests in mountainous areas and protected areas are with fewer disturbances than other areas and forest aboveground biomass in mature stands is higher than young stands (Zhu, 2015).

With optical Remote Sensing data (satellite imagery) we can determine crown-cover to a certain extent but not the height of the trees, which is also important for biomass estimates of forests (Hansen *et al*., 2019). Although our models tended to underestimate the AGB at high biomass values and overestimate the AGB at low values (Zheng *et al*., 2004) (Figure 8), the estimated AGB values corresponded well in general with the AGB value from the field. The skewed AGB distribution toward lower values (Figure 6) was caused by lack of old growth forests, high proportions of young growth and fallow, which usually had low biomass. Spatial patterns of AGB were clearly related to landscape structure and composition. Places with higher AGB are usually associated with mature forests (Zheng *et al*., 2004).

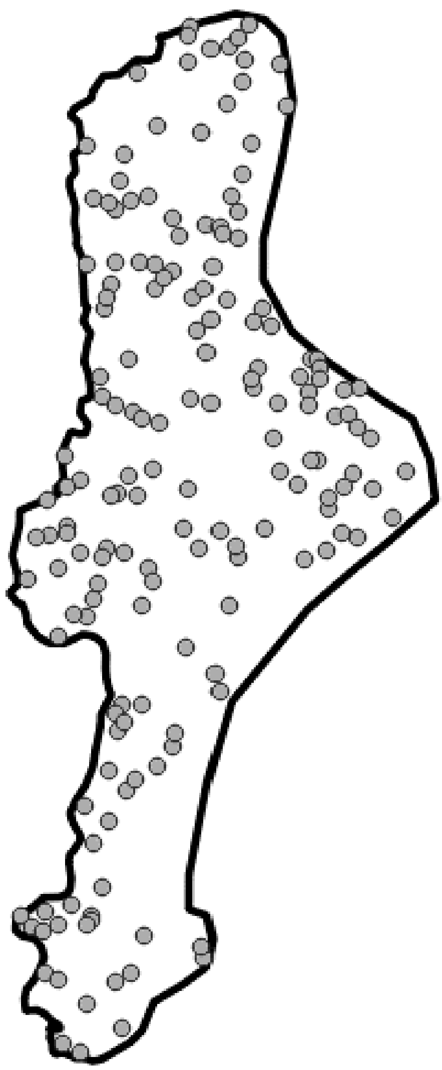

Figure 2. Distribution of NFI field plots in the study area

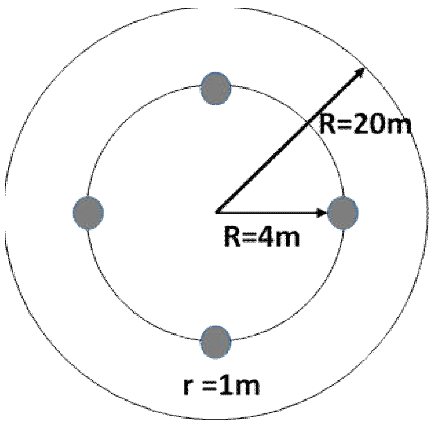

Figure 3. Illustration of field AGB data collection design

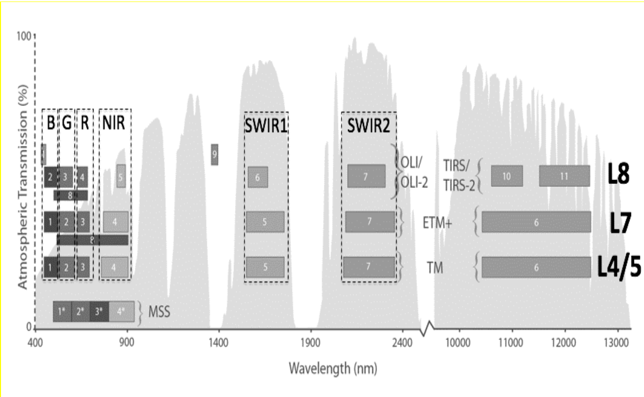

Figure 4. Bands used in this study: comparable bands on all Landsat sensors (B, G, R, NIR, SWIR1, SWIR2) and derived indices

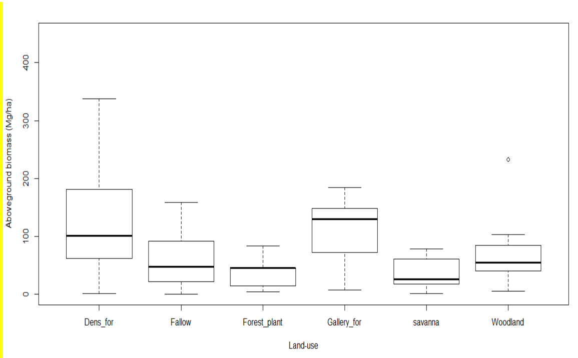

Figure 5. Distribution of AGB in different forest strata in ecological zone IV: Dens_for: dense forest; Forest_plant: forest plantation; Gallery_for: gallery forest

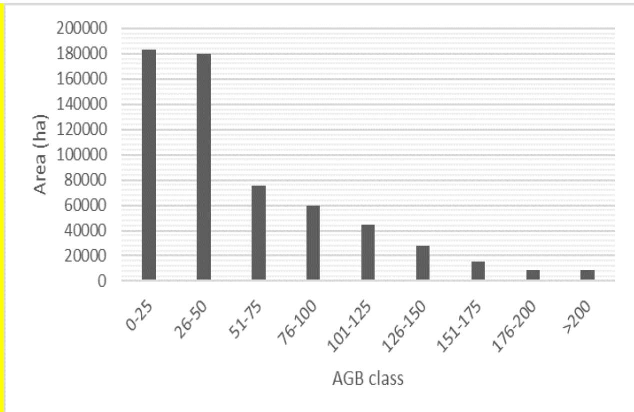

Figure 6: Area distribution of AGB (Mg/ha) classes

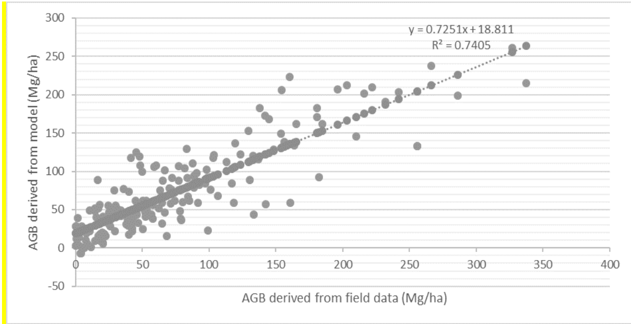

Figure 7. Field derived aboveground biomass density (Mg ha−1) versus landsat-based biomass estimates. Dots represent data used to fit the model. Each point represents the AGB for one of the 168 plots and the AGB for the pixel that the plot fall in

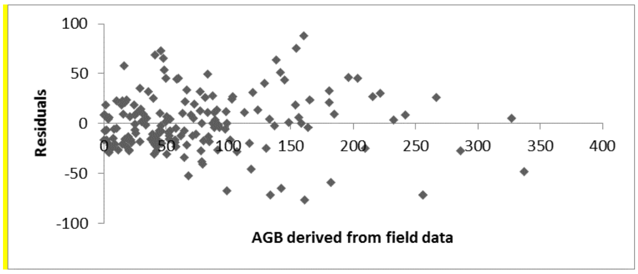

Figure 8. Residuals plots

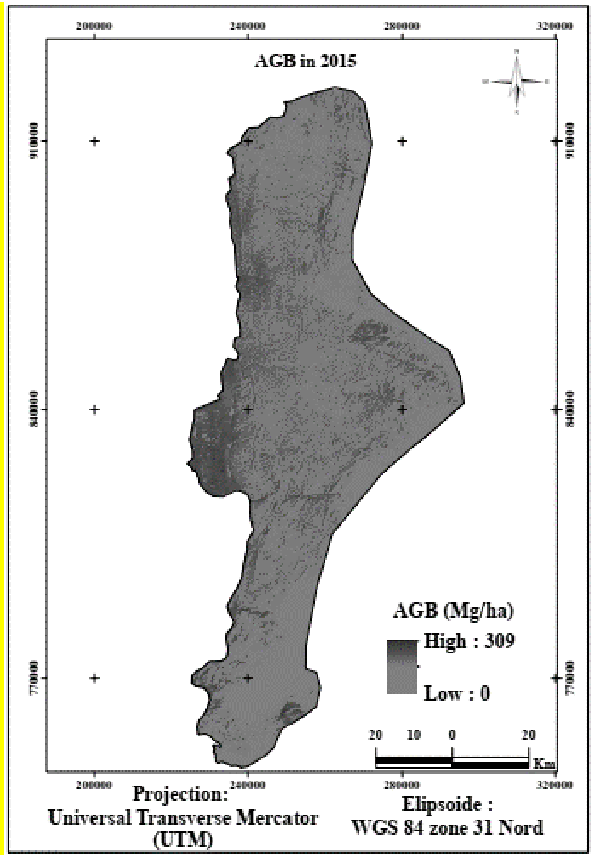

Figure 9. AGB map of the ecological zone 4

Implications for REDD+ process in Togo: The main strengths of the method from a practical perspective is its compatibility with forest inventories. Therefore, our results offer a great potential for increasing the understanding biomass distribution at local scale. This information is necessary for obtaining more reliable carbon estimates and for better planning, management and conservation of these ecosystems.

The methodological approach proposed here can help to identify potential conservation and restoration areas, when subjected to heavy anthropogenic pressure. The utility of the presented approach under REDD+ comes from the fact that Landsat data are available globally free of charge. Landsat data may remain the most viable option for national-scale REDD+ monitoring for a number of countries (Tyukavina *et al*., 2000). Using Landsat data, we followed recommended good practice guidance on the use of map-based activity data. In case of Togo RapidEye image to map the reference map may improve the model. Landsat resolution assessments of forest change may lead to significant underestimation of forest carbon loss (Tyukavina *et al*., 2013). The result of this study is a basis to map biomass change and to estimate emissions from deforestation and forest degradation in the country.

Conclusion

Information on forest biomass is relevant for global change research. In this context, remote sensing provides valuable data that can be related to field measurements for the development of environmental monitoring techniques.

Our results suggest that above-ground biomass in forest area in Togo can be estimated from Random Forest based on field data and Landsat 8 Oli data. In this work, several remote sensing indices derived from the spectral bands G, B, R, NIR, SWIR1 and SWIR2 of Landsat image appears as a good indicator of biomass mainly because, it is more sensitive to canopy parameters related to absorption of photo synthetically active radiation. This work not only contributes to the assessment of the status of forest zone ecosystems, but also provides methodological approaches to be considered in future studies for biomass change mapping and to make comparisons among analogous forest ecosystems at global scale. Its provides needed baseline information for landscape level analyses relating to regional carbon budget (i.e., monitoring changes of carbon pool over time). Additionally, this work represents a valuable contribution to international initiatives to forest conservation and climate change (e.g. REDD+) in Togo.

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Conflict of Interest statement

The authors declare that there is no conflict of interests regarding the publication of this paper.

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