Above ground biomass and tree species richness estimation with airborne lidar in tropical Ghana forests

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Abstract

Estimates of forest aboveground biomass are fundamental for carbon monitoring and accounting; delivering information at very high spatial resolution is especially valuable for local management, conservation and selective logging purposes. In tropical areas, hosting large biomass and biodiversity resources which are often threatened by unsustainable anthropogenic pressures, frequent forest resources monitoring is needed. Lidar is a powerful tool to estimate aboveground biomass at fine resolution; however its application in tropical forests has been limited, with high variability in the accuracy of results. Lidar pulses scan the forest vertical profile, and can provide structure information which is also linked to biodiversity. In the last decade the remote sensing of biodiversity has received great attention, but few studies focused on the use of lidar for assessing tree species richness in tropical forests.
This research aims at estimating aboveground biomass and tree species richness using discrete return airborne lidar in Ghana forests. We tested an advanced statistical technique, Multivariate Adaptive Regression Splines (MARS), which does not require assumptions on data distribution or on the relationships between variables, being suitable for studying ecological variables.
We compared the MARS regression results with those obtained by multilinear regression, and found that lidar was able to successfully estimate both biomass (R^2 = 0.72) and species richness (R^2 = 0.64), with MARS providing higher accuracies. We also noted strong correlation between biodiversity and biomass field values. Even if the forest areas under analysis are limited in extent and represent peculiar ecosystems, the preliminary indications produced by our study suggest that instrument such as lidar, specifically useful for pinpointing forest structure, can also be exploited as a support for tree species richness assessment.

1. Introduction

The estimation and monitoring of the carbon stored by tropical forests is of great relevance for understanding the global carbon cycle and the effects of climate change on forest resources, as well as to fulfill the reporting requirements of international programs, such as the United Nations Reducing Emissions from Deforestation and Forest Degradation (REDD+) (Gibbs et al. 2007). In tropical countries, such as Ghana, where more than half of the forested areas are selectively logged and the anthropogenic pressure on forest resources is increasing (Hawthorne and Abu Juam 1995), carbon density data are needed at high spatial resolution, both for conservation purposes and for selective logging planning.

Forest monitoring is considered a difficult task in remote tropical regions: field surveys are resource demanding and necessarily very restricted in extent and frequency. Remote sensing can support the estimation and monitoring of forest resources upscaling the information coming from limited field data over much larger extents (Turner et al. 2003; Zolkos et al. 2013). However, in order to provide fine scale data able to capture the local variability, and thus useful for management purposes, the use of advanced instruments such as lidar (light detection and ranging) is recommended (Corona 2016~~5~~). Lidar pulses penetrate the canopy providing very detailed forest structure information in three dimensions, which is closely related to forest carbon content and habitat spatial heterogeneity (Asner et al. 2012).

Previous studies showed the usefulness of lidar for aboveground biomass (AGB) estimation in tropical forests (Asner et al. 2012; Asner and Mascaro 2014; Leitold et al. 2015), including in West Africa (Vaglio Laurin et al. 2014a; Chen et al. 2015). However, various reasons justify the need for additional research in the tropical biome. First, lidar has been much more tested in boreal than in tropical regions, for which the number of available literature is still limited. Moreover, in the tropics a high variability in the accuracy of the estimates, and often lower accuracies, has been observed (Zolkos et al. 2013). This variability can be attributed to the use of different instruments, field data and forest types, with more results needed to derive generalizations on best methods and expected accuracies. With the present research we aim at contributing in increasing the number of data useful to clarify limitations and advantages in tropical lidar-based AGB estimation.

Monitoring biodiversity is another urgent priority in tropical forest. Biodiversity has an irreplaceable value and its conservation is the objective of different international agreements and efforts, with 2011-2020 being the United Nations decade on biodiversity; it is an important function of forests and its preservation is critical in forest management. Tropical forests are one of the major repositories of biodiversity, increasingly threatened by human impacts and climate change (Chapin et al. 2000). These impacts are evident in West Africa, where only fragments of the original Upper Guinean forest belt, a hotspot of biodiversity that once entirely covered this region, remain (CEPF 2003). Biodiversity can also directly influence carbon sequestration (Corona et al. 2011; Diaz et al. 2009; Strassburg et al. 2010). High variability exists in standing biomass and tree species diversity in tropical African forests (Day et al. 2013). Despite this variability, forests with a greater tree species diversity are likely to have higher biomass content, and therefore greater carbon storage: such evidence has been proved worldwide in tropical forests (Poorter et al., 2015), and distinctively reported for Africa (Vroh et al. 2015). Previous studies suggest that the biomass-diversity relationship is also influenced by different factors, including successional stage or disturbance level (Asase et al. 2012; Lasky et al. 2014). Data useful to clarify the relationship between biomass and tree species richness can have important forest management and policy implications, e.g. with respect to the assertion that UN-REDD schemes can provide significant co-benefits for biodiversity conservation.

In the last decade several studies have been directed toward estimating biodiversity with remote sensing data (Foody and Cutler 2006; Gillespie et al. 2008; Rocchini 2007); among the different diversity measures available, species richness was the most commonly adopted.

The majority of the previous studies used information derived from the optical spectral domain, and related to species foliar biochemistry variations or environmental heterogeneity. For instance, the variation in the spectral responses of optical images has been proposed as an indicator of plant species richness (Rocchini et al. 2007). Hyperspectral data are considered the most suitable tool to capture tree species diversity (Feret and Asner 2013; Nagendra and Rocchini 2008), thanks to the ability to detect fine variations in biochemical foliar composition, and have been successfully used to estimate species richness in different vegetation types (Lucas and Carter 2008; Psomas et al.

2011) including in West African forests (Vaglio Laurin et al. 2014b). Measures of environmental heterogeneity derived from optical data have also been associated to the species richness of other taxonomic groups, such as bird (Tuanmu and Jetz 2015) and dung beetle (Aguilar-Amuchastegui and Henebry 2007).

Active sensors, such as radar and lidar, can generate information on vegetation structure and topography. Specifically, the lidar pulses penetrate the canopy and scan the forest from the canopy top down to the ground. Adding lidar to hyperspectral data, accurate classification at the species level has been obtained in different forest ecosystems, through the exploitation of both structural and spectral information (Asner and Martin 2008; Clark et al. 2005; Dalponte et al. 2012; Ghosh et al. 2014; Jones et al. 2010; Leutner et al. 2012; Zhang et al. 2016).

The use of the sole lidar for tree species classification has been tested with very few species, and methods usually relied on geometric and vertical distribution features used to detect differences in stems and crowns structure (Hovi et al. 2016; Holmgren et al. 2004; Ko et al. 2012; Korpela et al. 2010; Li et al. 2013; Vaughn et al. 2012). Innovative approaches to information extraction include the use of computational geometry, and the development of metrics related to texture, foliage clustering and gap distribution (Kent et al. 2015; Li et al. 2013; Vauhkonen et al. 2012). However, it has been noted that increasing the species number (over 4-5) is associated with a consistent loss in overall accuracy (Vaughn et al. 2012), a fact which makes single species classification unfeasible in tropical areas, characterized by a large number of species.

Different authors suggested that lidar can be used to monitor biodiversity (Bergen et al., 2009; Dees et al. 2012; Gibson et al. 2011; Koch 2010; Turner et al. 2003). The potential of lidar to model animal biodiversity components, such as the assemblage and diversity of insects, spiders and birds have been previously investigated (Goetz et al. 2010; Muller et al. 2009; Muller and Brandl 2009; Vierling et al. 2011). Tree species diversity is considered a good proxy for diversity of other taxonomic groups (Gentry 1988), and Bergen et al. (2009) suggested lidar as a useful proxy for species richness in forests with high vertical complexity. However, the use of lidar for tree species richness estimation has been tested in an exiguous number of studies. Successful results were obtained in marsh, meadow and woodland habitats in Mississippi (Lucas et al. 2010), in Mediterranean forests (Lopatin et al. 2015; Lopatin et al. 2016; Simonson et al. 2012), where lidar also outperformed hyperspectral data for species richness estimation (Ceballos et al. 2015); and in two tropical forest cases (Herandez-Stefanoni et al. 2014; Wolf et al. 2012).

Lopatin et al. (2016) illustrated the theoretical suitability of lidar, considering that this datatype relates to three types of information which interacts with plant species richness: micro-topographical, macro-topographical and canopy structural information. Macro-topography factors are related to climate and geomorphology, which are known to influence species distribution through the differentiation of soil, hydrology, illumination or temperature conditions. Micro-topography such as local slope or roughness (also influenced by understory) can act as a proxy of small scale habitat structures, as in the case of shaded humid sinks or areas with deeper soils, which can accommodate peculiar species. Differences in canopy structure, such as height, leaf size and leaf orientation, lead to different canopy closure percentages and ground light conditions, and in turn influence species composition and richness. Stein et al. (2014) also supported this view, suggesting that biodiversity is positively influenced by environmental heterogeneity; while Gilbert & Lechowicz (2004) noted that variations in vegetation structure can lead to multiple niches and increased biodiversity, such as in the case of uneven forest stands.

We recognize that optimal results in species diversity estimation are obtained when both spectral and structural forest information is exploited (Turner et al. 2014; Vaglio Laurin et al. 2014b). However, based on the capability of lidar to inform on environmental heterogeneity, micro-habitats and forest height variability, and considering the encouraging results obtained by previous lidar-based studies, we aim at further contribute in understanding how lidar can support biodiversity monitoring in tropical forests. We suppose that in our sites, affected by disturbance which causes structural changes such as forest openings and increased height variability, lidar can provide relevant information.

The use of advanced modeling techniques has proved to be valuable in forest attributes prediction. For instance, mixed effects models outperformed other lidar-based AGB regression models in Sierra Nevada (Chen et al., 2012), and in Alaska (Temesgen et al. 2015). Partial least square regression improved the results obtained with multiplicative power model in AGB estimation from lidar and hyperspectral data in West Africa (Vaglio Laurin et al. 2014a). Random Forests was successfully used to estimate the Shannon diversity index of a forest canopy from hyperspectral data in West Africa (Vaglio Laurin et al. 2014b). Another advanced statistical technique is the Multivariate Adaptive Regression Splines (MARS; Friedman 1991), a nonparametric regression procedure that allows the modelling of complex relationships between a response variable and its predictors combining piecewise linear basis functions. MARS fits an adaptive non-linear regression, computing the functions in pairs and connecting them to a knot. MARS technique does not assume a priori a specific function and is characterized by high analytical speed and simplicity of the produced models (Hastie et al. 2009). These characteristics make MARS suited for ecological applications in which the variables may not always be normally distributed, as in the case of both AGB and species richness; in these circumstances MARS could be a convenient statistical tool for regression and prediction. Few previous studies have used MARS in and forestry and terrestrial ecology: Moisen and Frescino (2002) compared five modelling techniques for retrieval of forest parameters from remote sensing data and found that MARS and generalized additive models performed best; Munoz and Felicisimo (2004) found that MARS was the best of four advanced statistical techniques for predicting the distribution of a moss genus and a forest tree species; Filippi et al. (2014) used MARS for biomass estimation from hyperspectral data in floodplain forests. Our research represents an additional opportunity, using different data types, to test the suitability of this statistical tool for ecological estimations.

The main aim of this research is to estimate AGB and tree species richness, two key variables for monitoring climate change effects and biodiversity loss, in Ghana forests using discrete return airborne lidar. Specifically, our objectives are:
(i) to test lidar for the estimation of AGB;
(ii) to test lidar for the estimation of species richness, underlying that the aim is an estimate at plot level and not of the overall richness in the study sites, for which a much larger sampling area (from 1.28 to 3.27 ha) is needed (Vaglio Laurin et al. 2016a);
(iii) to evaluate MARS as an effective modeling approach, compared to multilinear regression as benchmark;.
We additionally reported the correlation found between AGB and species richness to increase the information available on these forests, and finally discuss our results in the framework of those obtained in other tropical areas, considering perspectives for high spatial resolution carbon and diversity monitoring in view of future remote sensing data availability.

2. Materials and methods

2.1 Study areas

This research was carried out in two forest sites (The Bia Conservation Area –BCA, and Dadieso Forest Reserve -DFR) located in Southwestern tropical Ghana (Fig. 1), which were surveyed in 2012-2013 in the framework of the ERC Africa GHG project.
BCA, also commonly named Bia, is the northern site and covers approximately 306 km^2; it includes the Bia National Park (77 km^2 in the northern range) and Bia Resource Reserve (228 km^2 in the southern range). The site is characterized by a mean annual precipitation between 1250 and 1750

mm, and a mean annual temperature between 24˚- 28˚C, and a hilly topography with elevations between 168-238 m. Bia hosts two forest types: moist evergreen in the south and moist semi-deciduous in the north (Hall and Swaine 1981). In Bia National Park timber extraction was prohibited, while selective logging was applied in Bia Resource Reserve from 1985 to 1990 approximately. Fire and elephants damages, as well as anthropogenic disturbance for firewood collection and small scale agriculture at forest edges, are commonly reported by local rangers. DFR, also named Dadieso, covers 171 km^2 including 4.50 km^2 in which farms are admitted along the border with Ivory Coast; the mean annual temperature is 25-27°C while mean annual precipitation ranges from 1500 to 1750 mm. The vegetation is transitional between moist evergreen and wet evergreen types, with presence of swampy areas. The terrain is mostly flat. Dadieso forest has not been officially logged but is degraded in many areas due to anthropogenic pressure, still reported in present days and caused by the presence of several villages and cocoa farms in its surroundings (Hawthorne and Abu-Juam 1995).

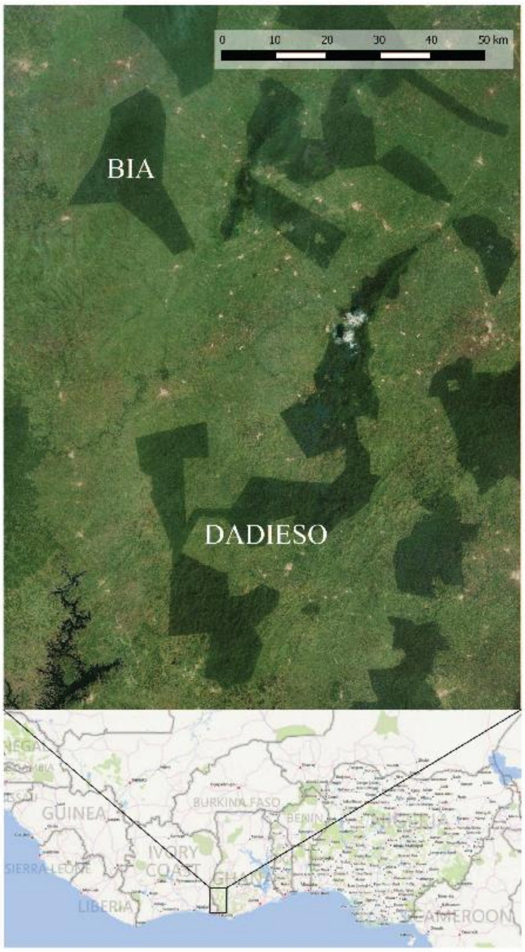


Figure 1. Lower part: southwestern Ghana region. Upper part: Bia and Dadieso study sites; forested areas are in dark green.

2.2 Field data

The field survey was conducted in 2012-2013 in the framework of the ERC Africa GHG project, and set up 20 plots of 40 x 40 m in Bia, and 20 plots of 40 x40 m in Dadieso. In each plot diameter at breast height (DBH), height and species information was gathered for trees with DBH >20 cm. Information for trees in the 10-20 cm DBH range was collected by the project only in smaller subplots, and therefore not used in the present study. Previous research in the same areas indicates that the AGB included in the 10-20 cm DBH range is 6% of the total AGB in Dadieso and 5.4% in Bia (Vaglio Laurin et al. 2016a); we therefore considered that the sampling of trees >20 cm DBH is still useful for calibrating and validating the lidar AGB estimates. From the project survey, we excluded those plots covered mainly by palms, for which biomass calculation was not performed, and a plot with the presence of a very large dead tree. In total we retained 35 plots: 18 and 17 of 1600 m^2 from Dadieso and Bia, respectively. We calculated above ground biomass (AGB) for all living trees using the Chave equations for moist and wet species (selected according to our forest types) based on height and DBH records (Chave et al. 2005), and wood density values as reported in the Global Wood Density Database (Chave et al. 2009). For one plot, with the presence of a very high tree and reported difficulties in height measure, we replaced the Chave' equation with the one from the same author based on DBH only.
For the collection of data on tree species richness, we simply counted the number of species occurring at plot level among trees with DBH > 20 cm (Magu~~a~~rran 2004).
Overall, the AGB values in our plots covered a broad range from 14 to 405 Mg/ha; the number of species in the plots ranged from 5 to 20; ~~and mean plots height ranged from 12.08 to 22 m, while~~ the total range of tree heights was from 5 to 47 m . Table 1 summarizes the field plots observed values by area, for trees with DBH > 20 cm:

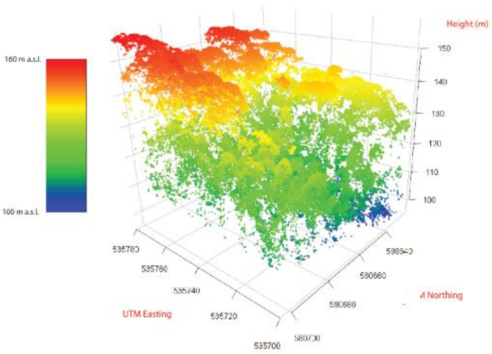
Table 1: field plots observed values by area (DBH > 20 cm).

Tree ~~A~~aboveground biomass ~~(AGB)~~		
	Bia	Dadieso
Plots mean ~~AGB~~	186 Mg/ha	128 Mg/ha
Tree ~~H~~height		
Plots mean ~~height~~t	16.65 m	17.09 m
Tree ~~S~~species richness		
Number of species	7 ~~to~~ -20 ~~species~~	5 ~~to~~ -20 ~~species~~

The available dataset can only provide indication for plots richness based on trees > 20 DBH: these trees represent dominant and sub-dominant canopy layers, and it is known that a large proportion of variation in richness can be attributed to smaller trees (Fricker et al. 2015). It has to be noted that the lidar pulses density decreases while penetrating the canopy and thus the capability of sampling very small and low level trees is reduced. However at the plot scale lidar might still be able to sample a certain amount of lower vegetation and thus limitations in our dataset might occur with respect to the contribution of smaller trees to richness analysis.

2.3 Remote sensing data

An aerial survey in March 2012, during the dry season, collected discrete return lidar data over the plots (fig. 2). The lidar sensor was the Optech Ltd. ALTM GEMINI, which includes a 1064-nm wavelength laser emitting at 167-kHz max pulse repetition frequency and 0.25-mrad (1/e) beam divergence, and is able to collect up to 4 range measurements. The mean laser density was 12 points per square meters, and ranged from 11 to 20 points. The average footprint that reaches the canopy and the terrain surface at that flight height (about 650-850 meter) is ~0.15 m. The swath of the lidar strips on the ground was 280 m, with the plots located at the center of two overlapping strips; for this reason, the maximum scan angle of the laser beam in the plots was below 11°. The positional errors of the laser returns in the horizontal and vertical dimensions were lower than 0.27 m. The all-returns point cloud was processed using the Toolbox for Lidar Data Filtering and Forest Studies (TIFFS) (Chen, 2007) to derive the following lidar metrics for each plot: mean height, quadratic mean height, standard deviation height, skewness and kurtosis, height bins at 5 m intervals, and 10% percentile heights. TIFFS generated a Digital Terrain Model and calculated the relative height above terrain of each laser return by subtracting the corresponding DTM elevation from its original Z value.



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igure 2. Lidar data collected over a 40 x 40 m plot, with height in meters above sea level (a.s.l.).

2.4 Data analysis

For AGB estimation, we used a multilinear regression (MLR) approach on log transformed values to estimate biomass from stepwise selected lidar metrics, validating the model with leave-one-out (LOO) procedure and back transforming in the original scale with bias correction (Backersville 1982). We then tested the MARS algorithm, implemented in the *earth* R package (Milborrow 2014), using all the available lidar metrics as input. The parameters to set are the degree of interaction among predictors, the maximum number of basis functions allowed, and the minimum number of observations between knots; we built models without interactions, with maximum number of basis function equal to 15, and minimum number of observation between knots equal to 3. All models were validated with LOO.

For species richness estimation, we used a multilinear regression (MLR) approach on untransformed values to estimate richness from stepwise selected lidar metrics, validating the model with leave-one-out (LOO) procedure. We then performed AGB estimation using MARS, implemented in the *earth* R package (Milborrow 2014), using all the available lidar metrics as input. We built models without interactions, with maximum number of basis function equal to 15, and minimum number of observation between knots equal to 3. All models were validated with LOO.

In addition to the estimation research objectives, we calculated the degree of correlation between field AGB and tree species richness using Pearson' correlation coefficient, considering the plots grouped by area, and all together.

The analyses were performed using the R Core Team (2012) and Matlab statistical packages.

3. Results

For AGB estimation with MLR, stepwise selection retained the kurtosis, the 15 to 20 m height bin and the 50^{th} percentile of height; the model validated with LOO obtained an R^2 of 0.60 and a RMSE of 63.1 Mg/ha equal to 36.2%. Using the MARS *earth* package the variables automatically selected were the kurtosis, and the 15 to 20 m and 40 to 45 m height bins. The model validated with LOO obtained a R^2 of 0.72 and a RMSE of 47.1 Mg/ha equal to 26.9%.

For tree species richness estimation with MLR, the stepwise selection retained the 0 to 5 m height bin; the model validated with LOO obtained an R^2 of 0.62 and a RMSE of 2.7 species equal to 20.2%. The use of 'earth' model resulted in the selection of the 15 to 20 m height bin and the 30^{th} percentile of height; the R^2 was equal to 0.64 and the RMSE to 2.6 species equal to 19.5% (Table 2).

Model **(LOO validated)**	$\mathbf{R^2}$ 35 plots	**RMSE %** 35 plots
MLR AGB	0.60	36.2%
MARS AGB	0.72	26.9%
MLR Richness	0.62	20.2%
MARS Richness	0.64	19.5%

Table 2. Results for aboveground biomass (AGB) and species richness estimation using the multilinear regression (MLR) and the MARS *earth* model validated with leave-one-out (LOO) procedure.

The Pearson coefficient of correlation between AGB and richness for the joined Bia and Dadieso plots was equal to 0.73 (p= $8.27e^{-007}$; confidence intervals of 0.52 and 0.85). When the areas were considered separately, the coefficient for Bia was 0.79 (p= $1.76e^{-004}$; confidence intervals of 0.49 and 0.92), and for Dadieso 0.75 (p= $3.2e^{-004}$; confidence intervals of 0.44 and 0.90).

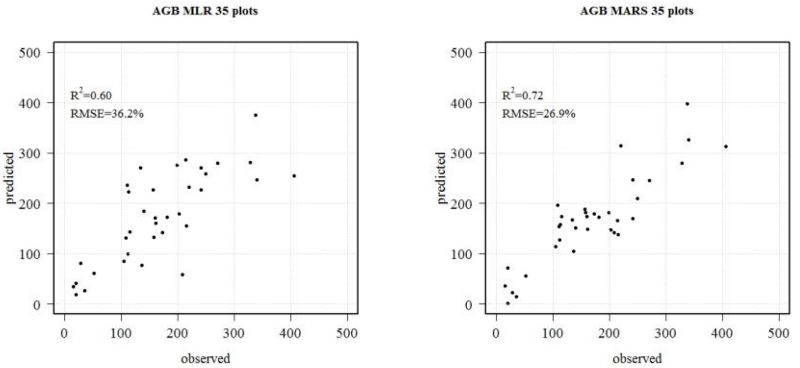

Figure 2. Scatterplots of the estimations for above ground biomass (AGB), with multilinear regression (MLR) and MARS *earth* model.

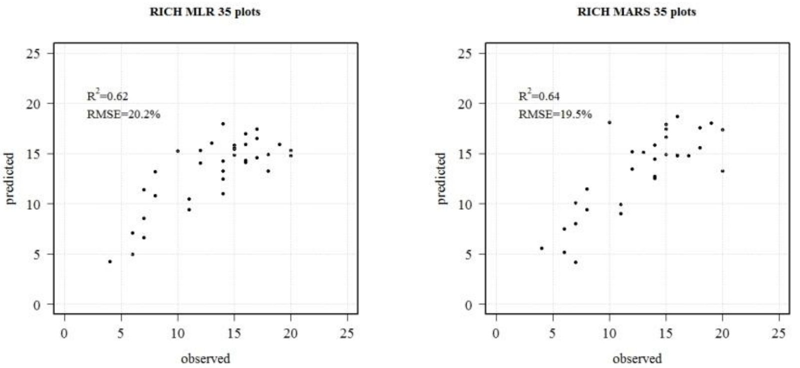

Figure 3. Scatterplots of the estimations for tree species richness (RICH), with multilinear regression (MLR) and MARS *earth* model.

4. Discussion

The MLR result for AGB estimation (R^2=0.60, RMSE=63.1 Mg/ha) indicates that lidar is a useful tool in these tropical forests. Zolkos et al. (2013) conducted a global review on AGB estimation finding a mean R^2 of 0.76 from lidar studies in different biomes; they also reported systematic differences in accuracy found between types of lidar systems used, and due to the selected forest types, plot size, and DBH thresholds, with studies from tropical forest characterized by lower accuracies than those from other biomes. Our result is in the range of those obtained by airborne lidar in other tropical forests. For instance, in recent tropical researches, the R^2 value was included in the 0.48-0.71 range in Tanzania using different combinations of lidar-derived metrics (Hansen et al. 2015); and it was equal to 0.7 in Panama rainforest (Mayer et al. 2013). In West African forests results were also similar: Vaglio Laurin et al. (2014b) obtained an R^2 of 0.64 which improved to 0.7 with the addition of hyperspectral to lidar data; and Pirotti et al. (2014) obtained an R^2 of 0.65 using full waveform lidar. The reasons behind the accuracy range observed in tropical forests might be multiple, as different sources of error characterize the workflow from field data collection to lidar-

based AGB estimation. A recent study conducted in African forests reviewed the large set of possible error sources and estimated a total uncertainty > of 20% at 1 ha spatial resolution, which is larger than what commonly requested for reporting purposes (Chen et al. 2015). In the tropics, these sources might be more relevant than in other forests, and more difficult to correct. In our study, one of the major uncertainties is possibly caused by the lack of specific African allometric equations, with pan tropical allometric relationships derived from data collected outside Africa (Brown et al. 1989; Chave et al. 2005; Vaglio Laurin et al. 2014a). For tropical AGB estimation the plot size is also very important as larger plots (> 0.5 ha) decrease between-plot variance, reduce edge effects due to large crowns, and minimize GPS positional errors (Mauya et al. 2015). However, the remoteness of most tropical forest makes it often difficult to set up and monitor large plots (Hansen et al. 2015). Our plots were 0.16 ha, not large even if in the recommended range of size (Riuz et al. 2014), but very large crowns were observed in these forests (Vaglio Laurin et al. 2016b) . GPS positional errors are also larger under dense canopy cover; and in tropical areas the GPS fixed bases for differential correction are less abundant or absent, as in the Ghana case. The AGB estimates improved consistently when using the MARS *earth* model, producing a result (R^2=0.72) in the upper part of the range usually found for tropical areas (Zolkos et al. 2013). To try to understand why MARS produced better results with respect to MLR we compared the inputs selected by the two algorithms. Two inputs were selected by both models. The first one is the 15 to 20 m height bin: this variable represents the proportion of returns (or cover percentage) at that interval of height. Considering that the mean height of our plots is also found in the same interval of height, the selected metric carries on information on the density and variability of trees at mean forest height. Indicators related to mean forest height are commonly selected in many lidar-based surveys of forest biomass (e.g. Corona et al. 2012; Montaghi et al. 2013). The second commonly selected input is the kurtosis, which provides information on the shape of the distribution of heights, and specifically on the 'tailedness' of the curve and thus on the propensity of extreme AGB values presence. Only the thirdly selected input differed when using MLR or MARS, being the 50^{th} percentile of height and the 40 to 45 m height bin, respectively. While the former is again a measure related to mean plot height, the second is an indication of maximum forest height not previously exploited; MARS used more varied information with respect to MLR.
Our results, coming from a restricted study area with limited ground truth, can provide relative indications to be evaluated in the framework of the available tropical lidar literature, which overall suggest that the accurate estimation of AGB in tropical forests using discrete return lidar data remains a challenging task, with accuracies usually lower than those obtained in temperate or boreal regions (~~Corona 2015; ~~Naesset and Gobakken 2008; Popescu 2007; Thomas et al. 2006). This has to be reminded when planning the use of lidar as surrogate ground truth, or as a tool to assist forest inventory in tropical forests (Gautam et al. 2013; Naesset et al. 2013; Nelson et al. 2003). As it is unlikely that resources will be available in the short future in the tropics to set up a considerable number of large forest plots, or to develop specific tropical allometric equations, the use of highly performing lidar instruments and advanced statistical modeling, such as MARS, can represent a way to treat complex field datasets and improve the accuracy of AGB estimates.

The results we obtained for tree species richness estimation are encouraging. The MLR result (R^2=0.62), and the limited improvement obtained using MARS (R^2=0.64), are values similar or slightly above the range of those obtained by other tree species richness studies. For instance, Hernandez-Stefanoni et al. (2014), using the standard deviation of lidar metrics (which indicate topography and vegetation height variability), reached a R^2 of 0.39 and 0.49 in two different tropical dry forest sites; Simonson et al. (2012) found a significant association between lidar-measured vegetation height and diversity of species in a Mediterranean oak forest, with a R^2 equal to 0.5; Ceballos et al. (2015) reached an accuracy with R^2 of 0.59 for the prediction of plant richness in a deciduous Chilean forest, using various topographic and vegetation structure indices that outperformed indices derived by hyperspectral data.

In our case, the input metric selected by MLR was the lowest (0 – 5 m) height range available, that includes information on the density of the above canopy (with denser canopy corresponding to lower values in this range) and micro habitat variability. In fact, differences in canopy closure are related to different amounts of light that penetrates down to the ground, being a proxy of small scale habitat structure (Lopatin et al. 2016).

MARS selected two other inputs: the 15 to 20 m height bin and the 30th percentile. The first is an indication of the variability in height of the majority of trees, as this is the height bin in which mean tree height is found; interestingly this input was selected also for the AGB model. The second input indicates the variability at the sub-canopy level where smaller trees are found.

The inputs selected by both algorithms have a theoretical relationship with richness, as suggested by Lopatin et al. (2016). Moreover, micro habitat information provided by terrain structure data was found related to plant species composition spatial patterns in various tropical (Bohlman et al. 2008; Liu et al. 2014) and subtropical (Yasuhiro et al. 2004) forests researches. Furthermore, vegetation height variations, especially at subcanopy level, are directly related to disturbance, which opening gaps in the forest may allow the establishment of new species. This is in agreement with the Intermediate Disturbance Hypothesis (Connell 1978) which justifies that local species diversity is maximized at moderate disturbance levels; this view is also in agreement with the species richness levels found in our study region: Bia is characterized by higher environmental heterogeneity with a hilly topography and a more retrained disturbance level than Dadieso, and has higher tree species richness.

All the previous species richness estimations are based on lidar metrics carrying on information on vegetation height variations and habitat or topographic heterogeneity, independently from the forest type under examination. Besides the indices useful in the studies already mentioned above (Ceballos et al. 2015; Hernandez-Stefanoni et al. 2014; Simonson et al. 2012), indices related to vegetation height and structural complexity were used by Lucas et al. (2010), Lopatin et al. (2015), and Wolf et al. (2012); while altitude above sea level, standard deviation of slope and mean canopy height were the most important predictors in the Lopatin et al. (2016) research.

However, the limited number of studies conducted in tropical forests (Hernandez and Stefanoni et al. 2014; Wolf et al. 2012), the moderate accuracy obtained by all the previous studies, the limited amount of ground data analyzed, as well as the fact that the two algorithms we tested produced different selections, calls for additional research in this topic. For instance, among the possible factors limiting the accuracy of the estimates there is the fact that height variations can also be produced as a result of different growing stages of a single species. Being this a young research topic, more results are needed to understand the strength and weakness of the relationship between species richness and lidar-derived information.

Finally, the Pearson correlation coefficients, reported mainly to provide additional information on the biomass-biodiversity link in these scarcely studied forests, indicated a strong positive relationship between AGB and tree species richness. This positive relationship is supported by complex forest structures (e.g. Wang et al., 2011), which allow greater light infiltration and promote a more efficient use of resources by trees, thus leading to an increase in biomass production. However, the AGB-richness relationship in forests can be stronger for smaller plots (Chrisholm et al. 2013), and influenced by succession (Lasky et al. 2014), both factors being present in our study. Considering that we sampled the vascular component of forest richness for trees having DBH > 20 cm, our correlation observation can only ~~provide~~ convey ~~only~~ preliminary information.

5. Conclusions

Lidar successfully estimated AGB and species richness at very high spatial resolution in our study sites, and MARS proved to be a useful tool for this purpose. Considering that remote sensing has been devised as an essential tool by UN-REDD (UN-REDD 2013), the outcomes of our work are relevant, suggesting the suitability of lidar for biomass estimations and to support tree species richness assessments.

However, the present research has been conducted in a limited area characterized by peculiar forest types. Even if there are increasing evidences of the link between specific environmental variables, that could be captured by sensors penetrating the vertical profile, and forest attributes, the estimation of forest variables in tropical areas remains a complex task. Furthermore, the accuracy of the results seems highly dependent on the specific site characteristics, with amount and quality of field data collection remaining a critical issue. Nevertheless, the gathering of detailed forest information is fundamental for local resource management and conservation, and urgently requested. Even in the case of accurate field data being available, airborne surveys are very expensive, limited in extent, and require expert knowledge for data processing. The real possibility to monitoring forest resources with airborne sensors is still limited to sites where specific funding is present.

For AGB monitoring, new spaceborne missions are planned, such as the European Biomass Earth Explorer and the United States Global Ecosystem Dynamics Investigation (GEDI) lidar. Thus, in the coming years new biomass data will hopefully be available, not at such high spatial resolution as requested for local monitoring but covering the entire tropical range. Considering the links between AGB and species richness, these missions also have the potential to provide important biodiversity and ecosystem information. Additionally, the use of stereo imagery from very high resolution optical satellites data for AGB monitoring deserves further investigation (Maack et al. 2015).

For canopy species richness monitoring, at present lidar can be considered a useful tool, already able to provide information but possibly better suited to be used together with other remote sensing data. The forthcoming hyperspectral missions such as the NASA HyspIRI, the Italian Space Agency PRISMA (PRecursore IperSpettrale della Missione Applicativa), and the German Environmental Mapping and Analysis Program (EnMAP) are further optimal opportunities to provide detailed forest diversity information.

In the future very high resolution forest resource monitoring could be performed using Unmanned Aerial Veichles (UAV), equipped with lightweight lidar, hyperspectral camera, or acquiring stereo imagery. Preliminary studies have already been conducted in this sense (Esposito et al. 2014; Getzin et al. 2012; Wallace et al. 2014). Even if additional research is needed, also with respect to the feasibility of using such instruments in inaccessible tropical forest, this could be another very promising opportunity for local analyses, in the light of the very fast expansion and decreasing costs of the UAV sector.

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