BIOMASS ESTIMATION BASED ON MULTILINEAR REGRESSION AND MACHINE LEARNING ALGORITHMS IN THE MAYOMBE TROPICAL FOREST, IN THE DEMOCRATIC REPUBLIC OF CONGO

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Abstract. Accurate forest aboveground biomass estimations have always been of crucial importance for sustainable forest management. However, a choice of the suitable statistical modelling method and predictor variables from remotely sensed data remains the cornerstone for providing accurate aboveground biomass estimates. The present study intended to compare the potential of four modelling techniques, including RandomForest, Support vector machine, multilinear regression, and K-nearest neighbour for estimating aboveground biomass using vegetation indices, spectral information, and both vegetation indices and spectral bands. The results have revealed that machine learning algorithms provide better results than the multilinear regression method. Indeed, the multilinear regression method produced the lowest R² and the greatest RMSE. Besides, the RandomForest performed better by providing accurate results compared to other machine learning algorithms. However, comparing the three sets of predictors, the vegetation indices have yielded accurate results of aboveground biomass and the strongest modelling power. Our results have also revealed that the RF is the best choice for predicting aboveground biomass for the purpose of reducing over- or under-estimation problems. This study has demonstrated the potential of the machine learning algorithms in predicting aboveground biomass in the tropical forest, using freely remotely sensed data derived from sensors with medium spatial resolution.

Keywords: aboveground biomass, Landsat 8 Operational Land Imager, Mayombe, machine learning

Introduction

Forest ecosystems store up to 80% and 40% of aboveground and underground carbon, respectively (Mohammadi et al., 2017) and can strongly contribute to mitigating effects of climate change (Moroni, 2013; Caputo, 2009; Brown et al., 1996; Zhang et al., 2014). Numerous studies have shown that biomass is an essential parameter for the carbon sequestration description. However, forest programs based on reducing carbon emissions require the accurate estimation of forest biomass.

In general, the biomass comprises of aboveground biomass (AGB) and belowground biomass (BGB) (Lu, 2006). Therefore, due to the difficult works related to the acquisition and calculation of the BGB, several studies are focused principally on AGB.

Forest biomass has already been measured using several allometric methods based on numerous tree measurements (Manyanda et al., 2019; Mohammadi et al., 2017; Vashum and Jayakumar, 2012). Therefore, forest biomass estimation relying on field inventory
is more expensive, arduous, and unrealizable in unreachable areas, thereby making it practicable only in relatively small and accessible areas. Currently, it is possible to optimize this inventory work and reduce the field measurement costs using techniques combining remote sensing technology and field inventories. Indeed, the remote sensing technology, with its capabilities of providing updated information on large areas, has been successfully used for spatial distribution and temporal variation of forest biomass. Several studies have reported that remote sensing variables are useful predictors of biomass because of a strong correlation between biomass and reflectance at different wavelengths (Phua and Saito, 2003; Lu et al., 2004; Zheng et al., 2004). Also, McRoberts et al. (2013) have stated that biomass models using remotely sensed data produce more accurate results than other traditional models. Previously, much research has been completed to estimate AGB in forest ecosystems (Zhang et al., 2014; Dixon et al., 1994; Saatchi et al., 2009; Pflugmacher et al., 2014; López-Serrano et al., 2016; Zhu and Liu, 2015; Glenn et al., 2016). In this research, different remote sensing data (spectral bands and variables derived from spectral bands) and various modelling techniques have been used. However, the remote sensing technology for modelling aboveground biomass implies several main issues. Some of them are related to the remotely sensed derived spectral information that is used as predictor variables (Wang et al., 2013; Lu et al., 2016; Frazier et al., 2014), while others are related to the suitable statistical modelling approach (Shao et al., 2016; Alrababah et al., 2011). According to Lu et al. (2006), two categories of techniques have been used for modelling forest biomass, including parametric and nonparametric methods.

The parametric methods are related to statistical regression, such as linear regression (Lu et al., 2016). In fact, multilinear models are frequently applied to estimate aboveground biomass. However, the relationships between aboveground biomass and predictor variables derived from remotely sensed data might not be linear; consequently, it can lead to overestimation or underestimation problems for small or high aboveground biomass values (Zhao et al., 2016). Therefore, much research has been conducted to examine the use or the potential of nonparametric algorithms, including support vector regression, K-nearest neighbour, and random forest (Li et al., 2014; Vauhkonen et al., 2010; Lu et al., 2016; Gleason and Im, 2012). However, Kumar and Mutanga (2017) have mentioned that among various AGB modelling methods based on different remotely sensed and field data, it is difficult to state or declare that there is one more suitable model than others without assessing their performance separately. In fact, in the field of aboveground biomass estimation using remote sensing technology, the result accuracy depends on different factors, including forest types, remote sensing sensors, and topographical features. Similarly, Feng et al. (2017) have reported that no single modelling method has been determined to be the best for predicting aboveground biomass. Also, Fassnacht et al. (2014) have demonstrated that in the frame of modelling forest biomass based on remote sensing technique, the modelling approach is as important as the data type in deriving accurate AGB estimates.

However, among all previous studies that have tackled the main methods for modelling aboveground biomass, it is unclearly known how data types, forest types, and modelling methods affect aboveground biomass prediction results, especially in the Mayombe tropical forest of the Democratic Republic of Congo, where less research has been carried out for aboveground biomass estimation.

In this research, the main objective was to compare different statistical modelling methods for generating estimates of AGB in the Mayombe forest. The machine learning
algorithms and multilinear regression method were then used to estimate the aboveground forest biomass based on remotely sensed data and field biomass measurement. After comparing the performance of the four different models, the suitable model was used to produce a forest biomass map of our study area.

Materials and methods

Study area

The study area is located in the central zone of the Biosphere Reserve of Luki (Fig. 1), in the Southwestern part of the Democratic Republic of Congo. It is located between 5.5-5.6°S in latitude and 13.08-13.24°E in longitude. Its total land area is estimated at 8347 ha, entirely located in the Congolese Mayombe tropical forest. The region is dominated by tropical forest and humid tropical climate (Aw5, according to Köppen’s classification). This climate is characterized by two seasons notably a rainy season of seven months (mid-October to mid-May) and a dry season of five months (mid-May to mid-October). The annual average temperature and the annual average precipitation are 28.8 °C and 1032.72 mm, respectively. The vegetation is dominated by the primary forest.

Data collection from the field and aboveground biomass estimation

One hundred fourteen square plots with size 30 × 30 m (corresponding to a Landsat pixel) were installed in the forest from June to July of the year 2019. We recorded the plot centre geographic coordinates using GPS (global positioning system) receivers. For the purpose of reducing the GPS horizontal locational error (∼5 to 10 m), we considered
final plot positions based on the criterion that the forest structure and composition in a 10-m buffer around the plot are the same as within the plot. The tree height (m) and tree diameter at breast height (cm) were measured on each tree inside of each sample plot. Also, the name of each tree with diameter at breast height (DBH) greater than 10 cm was reported. To compute the aboveground biomass of individual trees using diameter and tree height, allometric models were used. Several allometric models have been developed for the tropical forest. However, due to the literature review, no allometric model for estimating aboveground biomass is available locally for the Mayombe tropical forest of the Democratic Republic of Congo. Therefore, the allometric equation of Fayolle et al. (2013) was adapted to convert field data to AGB per tree. The predicted tree aboveground forest biomass within each plot was summed to represent plot biomass (expressed in Mg/900 m²). After that, the expansion factor was used to calculate the AGB per hectare for each plot.

**Remote sensing dataset and preprocessing**

Surface reflectance Landsat image of 2019 (the 18th of June), with 30 m resolution (path 183 and row 64), was acquired through the USGS Earth Explorer (earthexplorer.usgs.gov). The image was cloud-free and was corrected for atmospheric and topography conditions by the provider. Using the spectral bands (red, blue, and near-infrared bands), we calculated various vegetation indices (*Table 1*), which were used to estimate the aboveground biomass of the area under study. In this paper, based on the correlation between different spectral variables and biomass, numerous machine learning algorithms and a multilinear regression model were performed to predict aboveground biomass. Based on the geographic coordinates of the centre of each sample plot, the spectral variable values, were calculated within the area of each plot using R software; then, we established a database of predictors (vegetation indices and spectral bands) versus biomass values.

**Table 1. Information on remote sensing variables**

| Image spectral information | Band 2 (Blue), Band 3 (Green), Band 4 (Red), Band 5 (NIR), Band 6 (SWIR1), Band 7 (SWIR2) |
|-----------------------------|--------------------------------------------------------------------------------------------------|
| **Vegetation indices**      | **Equation**                                                                                      |
| Soil adjusted vegetation index (SAVI) | ((NIR – R) / (NIR + R + L)) × (1 + L) (Eq.1)                                                        |
| Normalized difference vegetation index (NDVI) | NIR – R / NIR + R (Eq.2)                                                                            |
| Ratio vegetation index (RDVI) | (NDVI × DVI)\(^{0.5}\) (Eq.3)                                                                    |
| Optimized soil-adjusted vegetation index (OSAVI) | (NIR – R / NIR + R + L) × (1 + L) (Eq.4) where L is the soil brightness correction factor; L = 0.5 works well in most situations and is the default value |
| Simple ratio (SR)           | NIR / R (Eq.5)                                                                                    |
| Modified soil adjusted vegetation index (MSAVI) | (2 * NIR + 1 – sqrt ((2 * NIR + 1)2 – 8 * (NIR – R))) / 2 (Eq.6)                                 |
| Difference vegetation index (DVI) | NIR – R (Eq.7)                                                                                   |
| Enhanced vegetation index (EVI) | 5 × (NIR – R) / (NIR + 6 R – 7.5 Blue + 1) (Eq.8)                                                   |

NIR: near-infrared; R: red band
Among the four models under study, we selected the best model based on the performance of each of them in terms of predictive power and the accuracy in AGB estimates. Then, we performed the selection of the most important variables using the best model. Finally, the best model was used to produce the map of the AGB spatial distribution in the study area.

**Modelling methods**

In this study, four different modelling methods were tested to estimate forest AGB including Random Forest (RF), Support vector regression (SVR), multilinear regression (MLR), and K-nearest neighbour (KNN).

MLR is one among parametric prediction methods commonly used to predict forest AGB using remotely sensed data (Zhu and Liu, 2015; Fassnacht et al., 2014; Lu et al., 2016; Zhao et al., 2016). For this study, we used the ordinary least squares regression method to predict forest aboveground biomass values. However, compared to the machine learning algorithm, the linear regression approach depends on certain assumptions, including the linearity in the relationship between explained and explanatory variables, independence, and normal distribution of errors with a mean value of zero and constant variance. Therefore, the non-respect of these assumptions leads to their violation. Thus, the method is less flexible when facing nonlinear problems (Li et al., 2017), and cannot adequately handle the multicollinearity problem (Ju et al., 2008).

The RF algorithm has been widely used to predict aboveground biomass (Avitabile et al., 2012; Chen, 2015; Pflugmacher et al., 2014; Vauhkonen et al., 2010; Hudak et al., 2012; Tanase et al., 2014). A random forest (RF) algorithm is a tree-based modelling method using a set of rule-based decisions to assess the relationships between a response variable and its predictor variables (Gleason and Im, 2012). This method can generate a large number of small trees built through a different randomly permuted sample from the input dataset (Breiman, 2001). The target data are categorized through two offspring at each node split to maximize homogeneity, and the best split is selected. Finally, the target data for each tree are achieved using bootstrap resampling (Were et al., 2015). Applying unique tree bagging and selection of a random subset of covariates results in minimization of within-group variance and overcoming the over-fitting problem (Park et al., 2016).

The nearest neighbour approach is one of the nonparametric methods used in remote sensing technology (Shataee, 2013), to predict the values of variables using the information of its neighbours (Cover and Hart, 1967). With these techniques, predictions are computed as linear combinations of observations for population units in a sample that are similar or nearest in the space of auxiliary variables to population units requiring predictions (Chirici et al., 2016). The performance of this algorithm depends on the number of neighbours retained by the model (López-Serrano et al., 2016).

The support vector machine (SVM) algorithm states that each ensemble of predictor variables has a unique relationship to the response variable, and sets of explanatory variables can be used to identify the rules to predict a response variable from a set of predictor variables (Mountrakis et al., 2011). It changes the input dataset into a multidimensional hyperplane space by using a kernel function to separate groups of input data with similar response variables to predict a response variable (Were et al., 2015). Indeed, hyperplanes are multidimensional space. In consequence, each explanatory variable is represented by axes from which hyperplanes are built. In that space, the explained variables are placed by projecting it following its explanatory.
variable values. The SVM applies support vectors to assign each target to a well-fragmented space (Görgens et al., 2015). The main idea behind SVM is to minimize structural risk and moderate the overfitting problem (Latifi et al., 2015).

**Model development and verification of estimation models**

In the field of biomass estimation, the assessment of the model’s performance and accuracy are of crucial importance in terms of selecting a suitable model (Mayer and Butler, 1993). Thus, the k-fold cross-validation approach was considered to examine the performance of the different models. In this research, the 10-fold cross-validation approach was mainly applied as it involves the random partitioning of the original dataset into k subsets (10) with equal size. Among k subsets, every single subset should be held out and used as testing data, while the others k subsets are used as training data. The procedure has a k-times number of repetitions. Also, every k subset is used one time for testing the model. Then, the results are averaged depending on the k number, to provide an overall accuracy. This technique provides many advantages, of which, all instances can be used for validating and training the model. In addition to the cross-validation method, number of validation measures (Eqs. 9-11), including the root mean square percentage error (RMSPE), root mean squared error (RMSE), R², were calculated to evaluate the model’s performance and assess the accuracy of the model using the testing dataset (25%). All statistical analyses were carried out using R software.

Root mean square error (RMSE):

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}
\]

(Eq.9)

Root mean square percentage error (RMSPE):

\[
RMSPE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( \frac{y_i - \hat{y}_i}{y_i} \right)^2} \times 100
\]

(Eq.10)

Coefficient of determination:

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}
\]

(Eq.11)

where \(y_i\) is the observed AGB, \(\hat{y}\) is the predicted AGB, \(n\) is the number of plots, and \(\bar{y}\) is the mean observed AGB.

**Results**

**Analysis of correlation between AGB and predictors subsection**

**Table 2** presents the Pearson’s correlation coefficient between all the explanatory variables and the forest AGB. Among all the vegetation indices, the forest AGB was significantly correlated with the NDVI, SR, and RDVI, respectively. For the spectral information, the forest AGB was significantly correlated with the Band4, Band3,
Band2, Band7, and Band6, respectively. However, it has been noted that the NDVI, SR, and RDVI had the highest positive correlation coefficient values among all the predictor variables retained for the present study. At the same time, all spectral bands were negatively correlated with AGB.

Table 2. Pearson’s correlation coefficients between independent variables and AGB

| Variables | r   | Variables | r   | Variables | r   | Variables | r   |
|-----------|-----|-----------|-----|-----------|-----|-----------|-----|
| DVI       | -0.069 | MSAVI     | 0.0005 | Band2     | -0.42*** | Band6     | -0.29** |
| SAVI      | 0.021  | OSAVI     | 0.13  | Band3     | -0.47*** | Band7     | -0.35** |
| EVI       | -0.020 | SR        | 0.53***| Band4     | -0.52*** | -0.12     |
| NDVI      | 0.81***| RDVI      | 0.42***| Band5     | -1.02     |

Level of significance, *** < 0.001; ** < 0.01; r, correlation coefficient

Field-based AGB estimates and predicted AGB estimates

Table 3 presents the descriptive statistics of the field-level forest aboveground biomass and predicted aboveground biomass. Table 3 indicates that the observed AGB biomass ranged between 192.22 to 301.11 t ha⁻¹, with a mean value of 250.34 t ha⁻¹, and a standard deviation of 29.39 t ha⁻¹. For the predicted biomass, it has been found some slight differences among different models and data sources. Also, the predicted biomass was slightly greater or smaller than observed biomass, implying the overall underestimation or overestimation problems.

Table 3. Plot-level aboveground and predicted biomass statistics of 114 plots

| Data            | Model | Min (t/ha) | Max (t/ha) | Mean (t/ha) | SD (t/ha) |
|-----------------|-------|------------|------------|-------------|-----------|
| Vegetation indices | MLR   | 187.77     | 286.91     | 251.26      | 26.29     |
|                 | SVM   | 204.10     | 290.53     | 251.41      | 25.61     |
|                 | RF    | 199.32     | 290.92     | 250.39      | 28.15     |
|                 | KNN   | 206.00     | 287.11     | 250.23      | 26.21     |
| Spectral information | MLR   | 193.98     | 279.44     | 250.03      | 18.79     |
|                 | SVM   | 204.90     | 284.33     | 248.61      | 21.53     |
|                 | RF    | 209.90     | 282.19     | 251.03      | 20.92     |
|                 | KNN   | 210.89     | 278.00     | 250.42      | 20.27     |
| Combination VI and SI | MLR   | 32.19      | 291.76     | 242.23      | 54.12     |
|                 | SVM   | 204.11     | 289.59     | 251.44      | 25.04     |
|                 | RF    | 200.74     | 291.75     | 250.62      | 27.91     |
|                 | KNN   | 212.04     | 279.01     | 251.08      | 22.80     |
| Field data      |       | 192.22     | 301.11     | 250.34      | 29.39     |

SD, Min, and Max represent standard deviation, minimum, and maximum

AGB estimates based on the machine learning and multilinear regression models

The performance assessment results of the different machine learning algorithms and multilinear regression based on different datasets, including vegetation indices, spectral...
information, and combination of both vegetation indices and spectral information, are presented in Table 4. Overall, the machine learning algorithms provide the best prediction performance of aboveground biomass compared to the multilinear regression method, but each algorithm has its performance in predicting aboveground biomass using different data sources. For example, for the support vector machine method, the vegetation indices-based predictors and the combination of both vegetation indices and spectral information produced the highest R² values and smallest RMSE and RMSEPE value; spectral information-based variables. For the K- nearest neighbours and RF algorithm, the conclusion is similar to the support vector machine, but for the RF, the R² value between vegetation indices-based variables and combination of both vegetation indices and spectral information-based variables were similar. For multilinear regression method, the highest R² was reached with vegetation indices-based variables. However, spectral information-based variables provide the greatest RMSE and RMSPE values compared with vegetation indices-based variables and a combination of both vegetation indices and spectral information, except for multilinear regression that has the greatest value with the combination of all predictors. Thus, in general, the vegetation indices-based predictors produced the most accurate results of AGB estimation regardless of which models were used, while the spectral information-based predictors yielded poor performance. The combination of both vegetation indices and spectral information could not improve the modelling performance. According to these results, the RandomForest algorithm provides the most accurate results in predicting biomass, but the accuracy decreases when using spectral information-based predictors. Besides, the Support vector machine yielded the best estimation of the aboveground biomass with spectral information-based predictors. Using the RF algorithm, the most important variables selected were NDVI, Band4, RDVI, SR, Band2, Band6, Band7, Band3, and SAVI, in decreasing order of importance (Fig. 2).

Underestimation and overestimation measure based on the machine learning and multilinear regression models

The goodness of fit can be visualized with the scatterplots showing the linear relationships between the predicted AGB and observed AGB from the sample plots (Fig. 3).

After computing the overestimation and underestimation mean values with regard to the mean observed values of aboveground biomass (Table 5), it was found that spectral data have much more significant overestimation and underestimation mean values than vegetation indices data and combination of both spectral information and vegetation indices data. The vegetation indices data have the smallest overestimation and underestimation mean values. The fact of combining both spectral information data and vegetation indices data improves the overestimation and underestimation problems regardless of which modelling approaches were used, compared to when the models use only spectral information. In view of the modelling algorithms based on the three datasets, in general, the machine learning algorithms have much smaller overestimation and underestimation problem than multilinear regression regardless of which data sources were used. Comparing the performance of machine learning algorithm in dealing with this issue, it was found that the RF and SVM have much smaller overestimation and underestimation problems than the KNN algorithm. However, the RF algorithm has produced the best performance with the lowest overestimation and underestimation problems.
Table 4. Comparison of AGB prediction performance

| Data                      | Model | RMSE (t/ha) | RMSE-CV (t/ha) | RMSPE (t/ha) | R²   |
|---------------------------|-------|-------------|----------------|--------------|------|
| Vegetation indices       | MLR   | 17.48       | 2.12           | 0.06         | 0.60 |
|                          | SVM   | 16.38       | 1.32           | 0.06         | 0.65 |
|                          | RF    | 10.22       | 1.08           | 0.04         | 0.86 |
|                          | KNN   | 14.75       | 2.05           | 0.06         | 0.72 |
| Spectral information     | MLR   | 27.89       | 2.25           | 0.07         | 0.15 |
|                          | SVM   | 24.72       | 2.04           | 0.10         | 0.20 |
|                          | RF    | 26.55       | 2.13           | 0.11         | 0.08 |
|                          | KNN   | 27.44       | 2.13           | 0.11         | 0.01 |
| Vegetation indices and spectral information | MLR | 89.13       | 1.51           | 1.58         | 0.25 |
|                          | SVM   | 16.95       | 1.42           | 0.07         | 0.62 |
|                          | RF    | 10.44       | 1.06           | 0.04         | 0.86 |
|                          | KNN   | 18.47       | 1.46           | 0.07         | 0.55 |

Figure 2. Important variable ranking by Random forest algorithm. (a) RandomForest with a combination of both vegetation indices and spectral information; (b) RandomForest with vegetation indices; (c) RandomForest with spectral information.
Figure 3. Observed AGB versus predicted AGB by KNN, SVM, RF and ML. The solid line indicates the optimal regression of observed versus predicted AGB and the dashed line indicates the 1:1 line of perfect agreement. (Note: (a) represents VI and SI, (b) represents VI and (c) represent SI)

AGB mapping using RF algorithm

Based on the RF algorithm, the suitable algorithm in this study concerning its best performance, as shown in Table 4 ($R^2 = 0.86$ and RMSE = 10.22 t ha$^{-1}$), the map of the
forest AGB was generated. *Figure 4* presents the spatial distribution of the forest AGB within our study area. The prediction results produced different statistics, notably 190.32 t ha\(^{-1}\), 274.02 t ha\(^{-1}\), 302.8 t ha\(^{-1}\), respectively minimum, mean, and maximum predicted biomass value.

**Table 5. A comparison of mean values of overestimation or underestimation from different data and algorithms**

| Data               | Model | Overestimation | Underestimation |
|--------------------|-------|----------------|-----------------|
| Vegetation indices | MLR   | 11.88          | 9.65            |
|                    | SVM   | 8.74           | 7.45            |
|                    | RF    | 5.17           | 5.62            |
|                    | KNN   | 8.67           | 11.35           |
| Spectral information | MLR | 18.96          | 18.92           |
|                    | SVM   | 10.62          | 14.08           |
|                    | RF    | 11.79          | 12.55           |
|                    | KNN   | 15.15          | 17.88           |
| Combination VI and SI | MLR | 9.81           | 23.13           |
|                    | SVM   | 8.52           | 8.05            |
|                    | RF    | 5.15           | 5.34            |
|                    | KNN   | 11.94          | 14.11           |

*Figure 4. Aboveground biomass of the study area using the RF algorithm*
Discussion

Satellite images with medium resolution represent an alternative method to estimate aboveground biomass, especially where the acquisition of hyperspectral images still has serious problems. In fact, up to now, the acquisition of hyperspectral images constitutes a severe problem due to their high costs, limited accessibility or availability, and their manoeuvrability. However, Forest aboveground biomass estimation using remote sensing approaches remains a significant challenge requiring numerous studies to find related solutions concerning different modelling approaches and remote sensing data. According to GAO et al. (2018), the AGB model performance depends on remote sensing data, modelling algorithms, and forest type. Lu (2006) has stated that in the field of the aboveground biomass estimation based remote sensing technique, researchers should take great attention regarding many parameters, among others, the remote sensing variables and the modelling technique or algorithms. In this study, we compared the potential of four methods, including RandomForest, K-nearest neighbour, support vector machine, and multilinear regression, to predict the aboveground biomass of tropical forest using the Landsat 8 multispectral OLI.

In general, the machine learning algorithms have demonstrated the higher ability to predict aboveground biomass in comparison with the multilinear regression method, regardless of data sources that were used (vegetation indices, spectral bands, and combination of both). Indeed, the multilinear regression method yielded the lowest $R^2$ and the greatest RMSE compared to all other models. Our results are in line with those found by Sadeghi et al. (2018) and Pandit and Dube (2018). Indeed, comparing the performance of the RF machine learning algorithm and the multilinear regression, the authors have reported that the RF algorithm provides high accuracy than multiple linear regression for mapping aboveground biomass. Another study conducted by Feng et al. (2017) has demonstrated the strong ability of RF and SVR to yield better aboveground biomass estimation than multilinear regression. Thus, many reasons were developed to explain the low accuracy of multilinear regression compared to the machine learning algorithm. Numerous studies have pointed out that the weaker performance of the linear regression method is based on the fact of the complexity and non-linearity between remote sensing-based variables and aboveground biomass (Baccini et al., 2004; Foody et al., 2003; Muukkonen and Heiskanen, 2005). Gao et al. (2018) stated that the multiple linear regression method was an essential tool of modelling aboveground biomass, especially for the biomass range of 40–120 Mg/ha. Another reason is that the linear regression method is less flexible when facing nonlinear problems (Li et al., 2017), and cannot adequately handle the multicollinearity problem (Ju et al., 2005).

Still, according to Safari et al. (2018), when the biomass value is lower than saturation values, such as 150-ton/ha, as stated by Feng et al. (2017) and Gizachew et al. (2016), and when the relationship between Landsat-derived predictors and observed aboveground biomass is expected linear, the linear regression approach can be more efficient. In our study, the biomass range is 192.22–301.11 t/ha, greater than 40–120 Mg/ha. This can explain why the linear regression performed poorly than the machine learning algorithm.

However, it is essential to point out that the RF algorithm improves the forest aboveground biomass estimation. Indeed, the RF algorithm provided better results in AGB estimation regardless of the data source that was used. Indeed, recently, numerous studies have successfully revealed the effectiveness of the RandomForest algorithm to estimate aboveground biomass, and their results are similar to ours. Supporting our
results, Liu et al. (2017) reported a significant improvement of the RandomForest algorithm compared with the multilinear regression and support vector machine. In this study, the RandomForest algorithm has produced better performance in terms of accuracy and predictive power of the model ($R^2 = 0.95$ RMSE = 17.73 Mg/ha). Another study carried out by Latifi et al. (2010), comparing the effectiveness of the K- nearest neighbour methods and the RandomForest algorithm to predict volume and biomass, have found accurate biomass estimation with the RandomForest algorithm, compared to all other nonparametric methods. Similarly, Sadeghi et al. (2018) also revealed that the RF algorithm could produce the accurate results in mapping aboveground biomass at the level of boreal forest stands ($R^2 = 0.62$, RMSE = 26 Mg ha$^{-1}$).

In this research, we also analysed the power of the RandomForest algorithm using the important variable selection method, completed using the parameter tuning procedure. The present study has demonstrated the advantage of parameter tuning in predicting AGB employing the RF model. For instance, using the vegetation indices-based variables, the $R^2$ value augmented from 0.86 to 0.91, while the RMSE value declined from 10.22 to 9.12 t ha$^{-1}$. According to Kuhn et al. (2008), removing the less important variables from the model has no impact on its performance. However, the results obtained in this study proved the opposite. Hence, Biau and Scornet (2016) have mentioned that due to its complexity, it is difficult to understand the computation of the Random Forest’s parameters.

Nevertheless, the RandomForest model provides the minimum number of subgroup input predictors that will improve the effectiveness of the model using the OOB method. Based on OOB data, the RandomForest algorithm produces an estimation error without bias for the testing data. Moreover, several parameters such as tree numbers (Oshiro et al., 2012), splitting at each node of each tree (Grömping, 2009), determine the performance of the algorithm. The sample numbers in each cell, below which the cell is not divided (Kuhn, 2008), but equals the default value of the node size (Tyralis and Papacharalampous, 2017). However, the present study used the default value, as suggested by the literature. The RandomForest algorithm variables have many limit factors, one of which is that the ideal number of predictors with the smallest error is not selected automatically (Adam et al., 2012). According to Grömping (2009), numerous parameters can affect variable importance in RandomForest, one of which is based on the choice of mtry.

Additionally, the author confirmed that it should be better to avoid redundancy to achieve a suitable model in finding a minimum number of variables for a good prediction. Thus, the model does not necessarily need to contain all the appropriate predictors, as long as the results are accurate. In line with Oshiro (2012), in the present study, the RandomForest algorithm identified 15 input predictors as the minimum subgroup with acceptable prediction power.

The percentIncMSE and IncNodePurity were used in ranking predictors concerning their performance to estimate forest AGB provided an improvement in the accuracy of the model. Though the present study accomplished a satisfactory result, it is essential to point out that several parameters influence the effectiveness of the model, including the number of trees (Genuer et al., 2010) and the split numbers. Kuhn and Johnson (2013) recommended considering a minimum number of trees at 1000 for optimizing the parameterization of the model. Likewise, as recommended by Verikas et al. (2011), optimizing variable numbers to divide a node, rather than default values, leads to numerous predictor rankings.
However, the performance of each machine learning algorithm varied depending on data sources. Indeed, vegetation indices were better related to aboveground biomass than spectral information-based variables. The use of spectral information-based predictors did severely increase the performance of the model. Our findings support those discovered by Pandit et al. (2018) and Lu (2006). In their studies, the authors found that the vegetation indices-based variables were better correlated to AGB than spectral bands. Indeed, some researchers have revealed the strong relationship between vegetation indices-based predictors and biomass (Pearson et al., 1976; Bedard and LaPointe, 1987; Hardisky et al., 1984; Deering and Haas, 1980). For example, Piao et al. (2007) have reported that vegetation indices computed from spectral information reflect the photosynthetic activity of the vegetation and are consequently used for biomass monitoring.

Nevertheless, the fact of combining both vegetation indices-based predictors and spectral bands-based predictors could not improve the modelling performance. Hence, using RandomForest and, according to the increasing order of importance as shown in Figure 2, the most crucial vegetation indices-based variables are NDVI, RDVI, SR, DVI, EVI, OSAVI, MSAVI, and SAVI. Our results are in line with those found by Shao and Zhang (2016) and Pandit et al. (2018). The authors have found similar variables for estimating forest biomass by using Landsat 8 OLI sensor.

Finally, the present study found that the biomass was more linked to the vegetation indices than the spectral bands. Indeed, the best models have been found through the use of vegetation indices-based predictors. However, the results based on the linear model were less precise compared to those found using machine learning algorithms. This may be due to the complex structure of tropical forests that sometimes makes linear models ineffective in estimating biomass under these conditions. It should be emphasized that, of all the different existing AGB modelling methods, using various sensors and field data, the choice of the best model should be preceded by a parsimonious evaluation considering the number of parameters of which the sensor type, the forest types, and other environmental conditions. However, as Kumar and Mutanga (2017) reported, several factors influencing uncertainties in the aboveground biomass estimation methods, including vegetation types, landscape types, seasons, and data availability.

Seeing that our study area is located in relatively steep terrain with almost homogeneity in the structure of the canopy, and containing high aboveground biomass, we suggest for further research to investigate the potential of these four methods for predicting forest biomass in various forest conditions, to fill the gap existing in the lack of aboveground forest biomass data.

Conclusions

The present study compared the potential of different machine learning algorithms (RF, KNN, and SVM) and the linear regression method for AGB estimation in the tropical forest using Landsat images and field data. Our study demonstrated that the machine learning algorithm has the potential to estimate AGB with high precision compared to the linear regression method. Comparing the three sets of predictors, the vegetation indices have yielded accurate results and the strongest modelling power in the present study. Our findings show that the RF algorithm is the best alternative for biomass estimation given its best accuracy and high modelling power, regardless of the
data source that was used. This study revealed as others the potential of machine learning algorithms based on Landsat images in predicting AGB in the tropical forest, using freely remotely sensed data, allied to field measurement data. This research confirms that machine learning algorithms, especially the RF and SVM, are powerful tools for aboveground biomass using variables derived from sensors with medium spatial resolution. However, we suggest for further research to examine the potential of these machine learning algorithms for predicting forest aboveground biomass in various forest conditions.

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