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Research Article

Aboveground Biomass Modeling of Forest Stands in Licuan-Baay, Abra, Philippines

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About Article

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ABSTRACT

Climate change induced by global warming is the most important environmental concern facing the globe today. The study aimed to develop a model in determining the aboveground biomass of forest stands through remote sensing in licuan-baay abra, Philippines. It determined the total carbon, carbon dioxide of the forest stands. The developed models of ndvi, savi, sri, and evi were also compared to select the best model suited for estimation above ground biomass of forest stand. The estimated above-ground biomass using the regression models developed is 8m mg/ha^{-1} for ndvi, sri and savi while evi has an estimated agb of 7m mg/ha^{-1} respectively. But the four-model developed has a correlation of above ground biomass and the vegetation index. Therefore, enhance vegetation index is highly recommended in this study since R squared among the four-vegetation index has the highest total value computed and has the lowest total value computed in the rsme (mg/ha^{-1}) which indicated as the most accurate to predict the above ground biomass of forest stand.

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1. INTRODUCTION

Climate change caused by global warming is the most pressing environmental problem of the world today. Carbon dioxide is one of the leading gases causing this climatic anomaly which is abundant in the atmosphere. Forest ecosystems have a significant potential in this respect. Carbon can be stored in the biomass, soil, litter, and coarse woody debris pools in forest ecosystems. Above Ground Biomass (AGB) and carbon uptake of a forest are key ecological indicators for various technical and scientific applications and sustainable forest management (Bao Huy *et al.*, 2022). The relationships amongst environmental conditions, stand age, tree diversity, and trait identity with Above Ground Biomass (AGB) remain highly debated in forest ecosystems, but these relationships across forest strata (i.e., over-story and understory) remain poorly assessed (Hae-In Lee *et al.*, 2022). Understanding the drivers of Above Ground Biomass (AGB) variation in present-day tropical forests can contribute to management strategies that help mitigate against CO_2-driven climate change and provide other services related to high AGB. Higher tree diversity can lead to higher woody productivity and carbon storage (Borges *et al*, 2021). At present, only limited studies have been conducted to identify and assess the Above Ground Biomass of mixed stand forest and pure stand forest, and even more research are needed to assess the Carbon stock of the forest stand in addressing the concerns on Carbon sequestration and adaptation to climate change. The result of this study provided basis in gathering data on Above Ground Biomass of forest stand. To estimate the biomass of the forest stand, the equation based on breast height diameter (DBH). The tree DBH was estimated using calibrated tape measure.

There are also many kinds of sensor that were used to gather information in the ground such as landsat 1-5 multispectral scanner while the latest satellite that were used today carried just one sensor was the landsat8 which acquires data in 11 bands from two separate sensors like the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) which was used in the study. The OLI and TIRS images consist of nine spectral bands with a spatial resolution of 30 meters for bands 1 to 7 and 9. The new band 1 (ultra-blue) is useful for coastal and aerosol studies. Landsat Surface Reflectance-derived Normalized Difference Vegetation Index (NDVI) is derived from Landsat 4–5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat8 Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS). NDVI is used to quantify vegetation greenness and is useful in understanding vegetation density and assessing changes in plant health. NDVI is calculated as a ratio between the red (R) and near infrared (NIR) values. It calculated using the reflectance value of red and near-infrared bands of optical imagery, and is widely accepted as an indicator of green foliage (Fraser *et al.*, 2011). Linking with that, the Landsat8 was used in this study to monitor the NDVI, EVI, SAVI, SRI of the forest stand of Licuan Baay. The area of the municipality is hilly and mountainous with a slope of ranging to 50 percent.

In this study, Above Ground Biomass of forest stands in Licuan-Baay, Abra was estimated. In order to estimate the Above Ground Biomass of the forest stand gathered data in the field the brown model (1997) was used in the study. Allometric functions at tree-level species and site-specific as sited in the study of Macedo *et al.* (2018) are most commonly used to estimate biomass, frequently with diameter at breast height and total height as explanatory variables. Data from forest inventory and vegetation indices (NDVI, EVI, SRI and SAVI) derived from high spatial resolution satellite images was used. The statistical analysis included correlation, variance analysis and linear regression (Macedo *et al.*, 2018).

Generally, the study aimed to develop a model in estimating the aboveground biomass of forest stands through satellite image. Specifically, it aimed to Quantify the Above Ground Biomass (ABG) and carbon sequestered by the mixed forest stand in the area, Determine the relationship of vegetation indices (NDVI, SAVI, SRI and EVI) acquired from satellite image and Above Ground Biomass (ABG) of forest stand obtained from field data, and Compare the total computed ABG and sequestered carbon of forests stand from the product of developed equation model. Since field measurement of carbon stock is costly and laborious, this study seeks cost-effective method of estimating carbon stock and estimate the Above Ground Biomass of forest stand. Determining the best resolution to be use in estimating the Above Ground Biomass and monitoring the vegetation cover of Licuan-Baay, Abra forest stands. The tools used in estimating the Above-ground Biomass is NDVI, EVI, SAVI, SRI.

2. LITERATURE REVIEW

2.1. Methods of estimating above-ground biomass (ABG)

Carbon exists as carbon dioxide in the atmosphere and constitutes about 0.04% of the atmosphere. In the recent past, it has gained a lot of attention as a greenhouse gas, as it has potential to influence the climate pattern of the world. Anthropogenic activities like industrialization, deforestation, forest degradation and burning of fossil fuel, has caused an increase in the level of carbon in the atmosphere and disrupted the global carbon cycle. However, nature has its own mechanism of sequestering and storing the carbon in its “reservoirs” or “sinks’’ (Vashum *et al.*, 2012). Estimates made by the Global Forest Resources Assessment as cited by Zhi *et al.* (2016) show that the world’s forests store more than 650 Gt of carbon and 289 Gt in biomass. The Assessment of C stocks can be aimed at a specific ‘area’, what-ever it’s vegetation or land use, or at a specific ‘activity’ or form of land use or land cover as found within a specified geographic domain. Allometric equations can be locally developed by destructive sampling, derived from literature for supposedly comparable forest types, or estimated from fractal branching analysis. They normally use the tree diameter at breast height (DBH, measured 1.3 m above the ground) as basis (Hairiah *et al.*, 2001). In destructive sampling, Xiaofang Wei *et al.* (2017) develop allometric equations by establishing the relationship between Above Ground Biomass with an average of basal diameter, tree height and the total basal area. The validity and the strength of the allometric models were examined with the adjust coefficient of determination (r^2), Standard Error of Estimate (SEE) and Akaike Information Criterion (AIC). In the study of Beets *et al.* (2012), Above Ground Biomass allometric equations were also developed through the equation based on breast height diameter (DBH) and tree height (H) provided acceptable estimates of stem plus branch (>10 cm in diameter over bark) volume, which was multiplied by live tree density to estimate dry matter. As studied by Hao Zhang *et al.* (2017), the data gathered was the trees of average size (i.e., height, stem, and crown diameter), located near the middle of each plot and as close to each other as possible, were selected for destructive sampling to determine tree biomass. Each selected tree was separated into foliage, stem, branch, root, and fruit. The fresh weights of ecosystem components (foliage, stem, branch, root, and fruit) were measured in situ, and six subsamples of each component from each collected plant were dried at 65°C to estimate dry biomass density (Mg ha^{-1}) and C concentration. The effects of stand age on C concentration, C storage, and biomass accumulation of ecosystem components were compared using one-way ANOVA, followed by Fisher's LSD method for testing the null hypothesis. On the other hand, non-destructive methods are the most common use by many researchers to study carbon stock in the forest because Quantification of carbon stocks using allometric equations is the most practiced method since destructive method is labor intensive, time and resource consuming. Kim Calders *et al.* (2015), emphasize that Allometric equations are currently used to estimate Above Ground Biomass (AGB) based on the indirect relationship with tree parameters. They develop an approach to estimate AGB from TLS data, which does not need any prior information about allometry. They compare these estimates against destructively harvested Above Ground Biomass estimates and Above Ground Biomass derived from allometric equations. They also evaluate tree parameters, diameter at breast height (DBH) and tree height, estimated from traditional field inventory and TLS data. In addition, in the study of Chaturvedi *et al.* (2013) in non-destructive methods, they compared biomass estimates of seven tropical tree species measured on the basis of two methods these are allometric equations relating destructively measured tree biomass and the circumference at breast height (CBH), and non-destructive equations having wood specific gravity in the estimator. It emphasizes also that once an allometric equation has been established for different classes of trees in a vegetation, one only needs to measure DBH (or other parameter used as a basis for the equation) to estimate the biomass of individual trees. The sum of the biomass estimates for all trees within the measurement transect can be converted to a biomass in Mg ha^{-1}.

2.2. Remote sensing

The used of remote sensing in gathering Above Ground Biomass are now popular and used by many researchers to know the status of one area. There are studies on Above Ground Biomass using satellite images have been collected to guide and strengthen this study on determining the Above Ground Biomass of forest stand located in the municipality of Licuan-Baay, Abra. According to Gunawardena *et al.* (2015), Remote Sensing (RS) is popular as a nondestructive method of biomass estimation since it can reduce the measurements and monitoring in the field to a considerable extent. Dengsheng Lu *et al.* (2014) says that Remote sensing-based methods of Above Ground Biomass (AGB) estimation in forest ecosystems have gained increased attention, and substantial research has been conducted in the past three decades. Biomass estimation methods using remote sensing data and discusses four critical issues – collection of field-based biomass reference data, extraction and selection of suitable variables from remote sensing data, identification of proper algorithms to develop biomass estimation models, and uncertainty analysis to refine the estimation procedure. Light Detection and Ranging (lidar) can remove data saturation, but limited availability of lidar data prevents its extensive application. Karakoc *et al.* (2019) study uses hyperspectral remote sensing techniques to predict Above Ground Biomass in grasslands. In order to reach this goal, biomass properties with different ecological features and altitudes of 550 m, 1200 m, and 1400 m above sea level. Wani *et al.* (2015) Realizing the importance of forest carbon monitoring and reporting in climate change. In their study, they derived spectrally modeled Above Ground Biomass and mitigation using Landsat data in combination with sampled field inventory data in the coniferous forest. After conducting preliminary survey in 2009, 90 quadrats (45 each for calibration and validation) of 0.1 ha were laid in six forest types for recording field inventory data viz. diameter at breast height, height, slope and aspect. Kumar *et al.* (2017) also says that the role of Remote Sensing in estimating grassland, forest and woody biomass using a plethora of data and processing methods. Seasonality information was successfully built into biomass models with improved accuracies. The fusion of microwave and multispectral/hyperspectral data also reduced uncertainty errors in biomass estimation, especially in environments with complex canopy structure. Of critical importance is that the special issue highlighted methods and data sets that solves the problem of saturation in biomass estimation using the conventional vegetation indices. The issue provides a platform for day-to-day methods and approaches to operationalize Remote Sensing in vegetation productivity management.

2.3. Vegetation indices

According to Liu *et al.* (2015) study Vegetation normalized difference vegetation index (NDVI) data from 1998 to 2012 and a field survey investigation in 2013, demonstrated that annual NDVI values varied greatly with an increasing trend. Goswami et, al. (2015) showed that the NDVI values for the six species studied varied within a range of ~ 0.3 with corresponding change in values in LAI and biomass. The strong relationships between NDVI and biomass and LAI for the species studied support the use of NDVI as a spectral index for indirectly measuring plant community structure. The strong relationship between NDVI and biomass found in this study is similar to studies conducted in other tundra ecosystems including tussock tundra (Boelman *et al.* 2003), shrub and high arctic tundra. While Boelman *et al.*, (2003) reported a linear relationship between NDVI and biomass, an exponential relationship between NDVI and biomass. Lumbierres *et al.* (2017) proposes a method to estimate standing Above Ground plant Biomass using NDVI Land Surface Phenology (LSP) derived from MODIS, which calibrate and validate in the Doñana National Park's marsh vegetation. Out of the different estimators tested, the Land Surface Phenology maximum NDVI (LSP-Maximum-NDVI) correlated best with ground-truth data of biomass production at five locations from 2001–2015 used to calibrate the models (R^2 = 0.65). Estimators based on a single MODIS NDVI image performed worse ($R^2 \leq 0.41$). The LSP-Maximum-NDVI estimator was robust to environmental variation in precipitation and hydroperiod, and to spatial variation in the productivity and composition of the plant community. The determination of plant biomass using remote-sensing techniques, adequately supported by ground-truth data, may represent a key tool for the long-term monitoring and management of seasonal marsh ecosystems. In Gunawardena *et al.* (2015) study, they use ALOS PALSAR, IRS LISS III and Thermal bands of Landsat OLI images to estimate Above Ground Biomass. There were 55 field sampling plots used and diameter at breast height, total tree height, and canopy cover percentage of all trees (dbh >10 cm), and slope and GPS locations of each sampling plots were collected. Previously developed relevant allometric equations were used to estimate biomass using DBH and height in each plot. In addition, Hogrefe *et al.* (2017) on their study, they use Tools that can monitor biomass and nutritional quality of forage plants are needed to understand how arctic herbivores may respond to the rapidly changing environment at high latitudes. The Normalized Difference Vegetation Index (NDVI) has been widely used to assess changes in abundance and distribution of terrestrial vegetative communities. However, the efficacy of NDVI to measure seasonal changes in biomass and nutritional quality of forage plants in the Arctic remains largely un-evaluated at landscape and fine-scale levels. They modeled the relationships between NDVI and seasonal changes in Above Ground Biomass and nitrogen concentration in halophytic graminoids, a key food source for arctic-nesting geese. The model was calibrated based on data collected at one site and validated using data from another site.

3. METHODOLOGY

3.1. Study area

The study area was in the municipality of Licuan-Baay, Abra (Figure 1). It is located at the Northern part of the Philippines with geographic coordinates of 17°35’08.60” N and 120°32’33.50” E. The area is 30,567.70 hectares with a population of 4, 864 during the 2015 census. Based on the Modified Coronas Classification, the study area is under climatic type II which is characterized by two seasons, dry during the months of November to April while wet during the months of July to November. The average annual temperature is 24.0°C while the average annual rainfall is 3,012 mm.

The land cover of the study area (Figure 1) shows that forests has the highest area (69.90%) as shown in table 1. Recently, it is observed that there is an increase in forest cover of the area as a result of various reforestation projects of the government such as the National greening program. In addition, the forest cover is maintained because of the implementation of traditional forest management in the municipality. The main possible threats to forest cover loss in the area are small scale illegal logging and forest fires.

3.2. Field Data Collection

3.2.1. Materials

The materials used in the gathering of field data are: diameter tape to measure the DBH of trees; tape measures used in determining the size and for lay-outing of the sample plots, Global positioning System (GPS) receiver determined the coordinates of the sample plots and camera was used to photo document the activities. Other materials such as cutting tools were used in clearing paths in the lay-out of plots.

Table 1. Land cover classes of the study area

Land Cover	Area (has)	%
Agriculture	552.93	1.81
Bare ground	85.30	0.28
Built-Up	440.10	1.44
Inland Water	28.32	0.09
Grassland/Shrubland	8,092.91	26.48
Forest	21,367.41	69.90
Total	**30,566.97**	**100.00**

3.2.2. Modified Plot Establishment

Biomass and carbon stock estimation was determined following the carbon stocks assessment protocol formulated by Hairiah *et al.* (2001) which was also used by other researchers in the Philippines with modifications (Figure 2). Sixty-nine (69) measuring 30 x 30 meters was established. Trees within the plot with DBH (1.3 meters above the ground) of more than 15 cm were recorded.

The coordinates of the established plots were taken at the center of the plot using a GPS receiver. Since GPS receivers have positional errors, it is nearly impossible to accurately locate every sample plot on the center of the 30 m by 30 m grid of Landsat OLI pixels. To remedy this, moving window techniques (Gunlu *et al.*, 2014) such as 3 by 3 pixels were used in the study. This technique used to determine the average index values of the various vegetation indices of each of the sample plots.

3.3. Mathematical equations and symbols

3.3.1. Above Ground Biomass Computation

In this study, aboveground biomass of the forest stand was determined by using the generalized allometric equation created by Brown *et al.* (1997) as cited by Lasco *et al.* (2006). Based on her study, Brown’s equation is a generic biomass regression used 170 trees with different species were destructively sampled in the moist forest zone of three tropical regions which have been used in local studies to determined indirectly the biomass and carbon storage of ecosystem.

Y (Kg) = exp (-2.134 + 2.53*InD) for Natural Forest and plantation

Where:

Y = biomass per tree in kg;

Exp (…) = “raised to the power of”;

In = natural logarithm

DBH = diameter at breast height (cm) at 1.3 m

3.3.2. Data Acquisition

Landsat 8 satellite images was downloaded from the United States Geological Survey (USGS) website and used in this study. Satellite image with less cloud cover was selected for this study which was coincide with the time of field data gathering. Landsat 8 was launched on February 2013 and it carries the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) instruments. The OLI sensor collects 9 shortwave spectral bands over a 190 km swath with a 30 meter (m) spatial resolution for all bands except the 15 m Pan band while The TIRS sensor collects image data for two thermal bands with a 100 m spatial resolution over a 190 km swath. The two thermal infrared bands encompass the wavelength range of the broader TM and ETM+ thermal bands and represent advancement over the single-band thermal data. The following table presents the spectral bands of Landsat 8 OLI/TIRS sensor.

Table 2. Features of landsat 8 OLI/TIRS spectral bands

Bands	Wavelength (micrometers)	Resolution (meters)
Band 1 - Coastal aerosol	0.43-0.45	30
Band 2 - Blue	0.45-0.51	30
Band 3 - Green	0.53-0.59	30
Band 4 - Red	0.64-0.67	30
Band 5 - Near Infrared (NIR)	0.85-0.88	30
Band 6 - SWIR 1	1.57-1.65	30
Band 7 - SWIR 2	2.11-2.29	30
Band 8 - Panchromatic	0.50-0.68	15
Band 9 - Cirrus	1.36-1.38	30
Band 10 - Thermal Infrared (TIRS) 1	10.6-11.19	100
Band 11 - Thermal Infrared (TIRS) 2	11.50-12.51	100

3.3.3. Image Preprocessing

The satellite image was used in this study undergo preprocessing in order to improve the accuracy of the quantitative values of the various vegetation indices. Image preprocessing involves geometric, and atmospheric corrections. For geometric correction, the satellite image was the geo-referenced to WGS 84/ UTM 51 N projection system. Atmospheric correction was done to remove atmospheric effects from satellite images. This was done by converting the DN values of the spectral bands to Top of Atmosphere (TOA) Reflectance using the following formula provided in the Landsat 8 (L8) Data Users (Ihlen & Zanter, 2019).

Formula 1. $\rho\lambda' = M\rho * Qcal + A\rho$

Where:

$\rho\lambda'$ = TOA Planetary Spectral Reflectance, without correction for solar angle (Unitless)

$M\rho$ = Reflectance multiplicative scaling factor for the band (REFLECTANCEW_MULT_BAND_n from the metadata).

$A\rho$ = Reflectance additive scaling factor for the band (REFLECTANCE_ADD_BAND_N from the metadata).

Qcal = Level 1 pixel value in DN

Formula 2. $\rho\lambda = \rho\lambda' / \cos(\theta_{SZ}) = \rho\lambda' / \text{in}(\theta_{SE})$

Where:

$\rho\lambda$ = TOA planetary reflectance

θ_{SE} = Local sun elevation angle; the scene center sun elevation angle in degrees is provided in the metadata

θ_{SZ} = Local solar zenith angle; $\theta_{SZ}=90°-\theta_{SE}$

3.3.4. Vegetation Indices

After preprocessing the images, the images were processed and analyzed to determine the quantitative values of the various vegetation indices. QGIS 3.22.5 software utilized the data processing.

Table 3. Vegetation indices

Vegetation Indices	Equation	References
NDVI	NIR - RED/NIR + RED	Gunlu *et al.* (2014); Estoque *et al.* (2017); Wahlang and Chaturvedi (2020)
EVI	2.5 x (NIR-RED) (NIR + 6 x RED -7.5 x BLUE +1)	Das and Singh (2012); Eckert (2012); Gigachew *et al.* (2018); Macedo *et al.* (2018)
SRI	NIR/Red	Jordan, 1969; Chen, 2018
SAVI	(1 + L) (NIR - Red) (NIR + Red + L)	Huete, (1988)

4. RESULT AND DISCUSSION

NDVI, SAVI, SRI, and EVI model equations are developed in this study by using linear regression analysis. Since linear regression is a commonly used method to estimate Above Ground Biomass in most studies. The four vegetation indices model equations developed used to predict the entire Above Ground Biomass of the study area. The study located at the Municipality of Licuan-Baay, Abra. The four-vegetation index which is the NDVI, SAVI, SRI, and EVI derived from Landsat 8 image served as the dependent variables and field data gathered served as the independent variables data in developing the model equations to estimate or predict the Above Ground Biomass of forests stand. The following are the results and discussion based on the objectives of the study.

The sixty-nine (69) sample plots were used in the study has a total biomass of 2,844.36 Mg/ha^{-1} and a total of 1,279.96 Mg/ha^{-1} carbon and a total of 4,697.46 Mg/ha^{-1} carbon dioxide. The mean of the biomass is 41.22 and carbon mean is 18.55 and carbon dioxide mean is 68.08. The average biomass tons per hectares is 458.03 Mg/ha^{-1} and the carbon average is 206.11, and carbon dioxide average is 756.43. Consequently, the overall total estimated biomass of the forests stand of Licuan-Baay Abra is 9,786,273.78 tons based on the field data gathered. With that, the estimated biomass of Licuan-Baay forest stands from actual data will be served as inputs and update data of the municipality to be used by the DENR and other agencies concerned.

The correlation between VIs and AGB was calculated to determine the relation between the two variables. Correlation exists if a change in one variable affects the other variable. If increase in one variable increases the other variable, then these variables are considered to have positive correlation and vice-versa. There is various statistical measures to determine the degree of correlation. In this study, the Pearson's correlation was used. The degree of relationship is represented by correlation coefficient (r). Figure 1, 2, 3 and 4 shows the scatterplot between the measured ABG and VI values derived from Landsat 8. It also shows the relationship between vegetation indices acquired from Landsat8 images and Above Ground Biomass of forest stand obtained from field data.

Table 4 presents the result of the correlation analysis. The coefficient of correlation ranges from 56.7 % to 59.4 %. The result shows a negative correlation between the vegetation indices values and Above Ground Biomass. Compared to other studies, vegetation indices are positively correlated with Above Ground Biomass. For instance, the studies of Das and Singh (2012); Gizachew *et al.* (2016); Askar *et al.* (2018); Baloloy *et al.* (2018); and Macedo *et al.*, (2018) showed a positive correlation between VI and AGB. However, other studies also showed a negative correlation.

Table 4. Correlation analysis results

Vegetation Indices		R
1	NDVI	-0.567**
2	SAVI	-0.586**
3	SRI	-0.585**
4	EVI	-0.594**

*** Correlation is significant at the 0.01 level (2-tailed).*

Although there are still problems of high value estimation in Above Ground Biomass field data gathered and low value estimation for vegetation index as shown in the graphs results leads to a trend negative correlation of the biomass to the vegetation indices. Yet, the results of the study were still reliable because the correlation of the Above Ground Biomass and the vegetation index are correlated to each other. The reasons why the results have a negative trend correlation was even the vegetation index is healthy based on the landsat8 image but when it comes to the diameter at breast height, the diameter of the trees present in the plots are small or big leads to overestimated or underestimated of Above Ground Biomass in forest stand. Vis versa, in the study of Moradi *et al.* (2022) as expected to be caused of the negative trend correlation of VI and AGB are the canopy shadowing of trees, canopy size, stand volume and density, and consequently, by a more complex vertical structure of the forest. They also mentioned in their study that FVC Fraction Vegetation Cover of the ground at the pixel level is another reason that affecting the radiation behaviour at the canopy level, particularly in taller stands.

The Table 5 shows the Developed model used to estimate Above Ground Biomass of forest stands at local scale by using high spatial resolution satellite images. The result shows that the four-vegetation indices are significant in correlation at the 0.01 level (2-tailed) which indicates a good correlation of

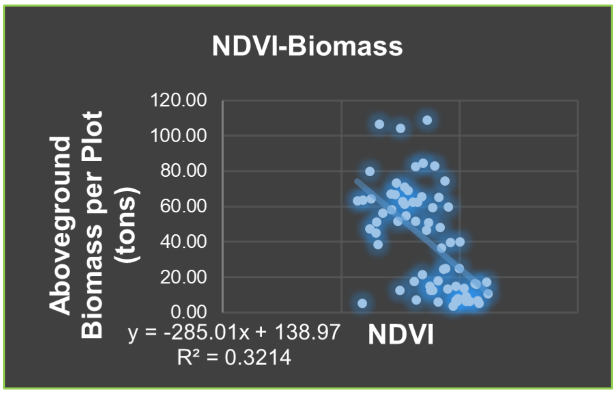

Figure 1. Normalized Difference Vegetation Index Biomass Scattered Plots

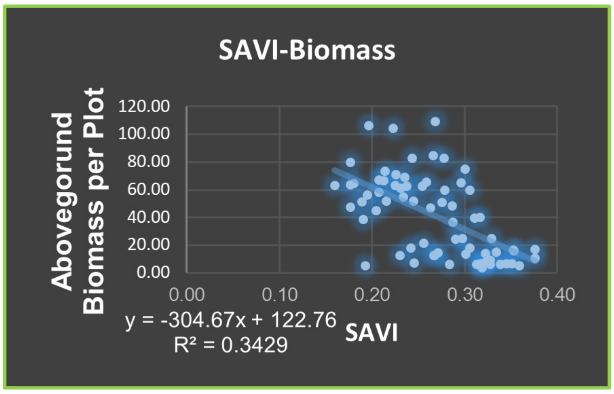

Figure 2. Soil Adjusted Vegetation Index Biomass Scattered plots

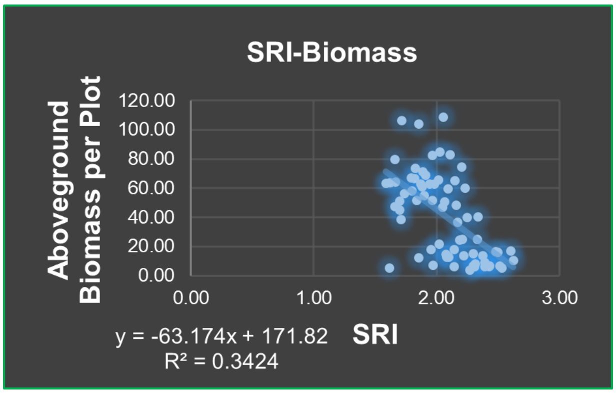

Figure 3. Simple Ratio Index Biomass Scattered Plots

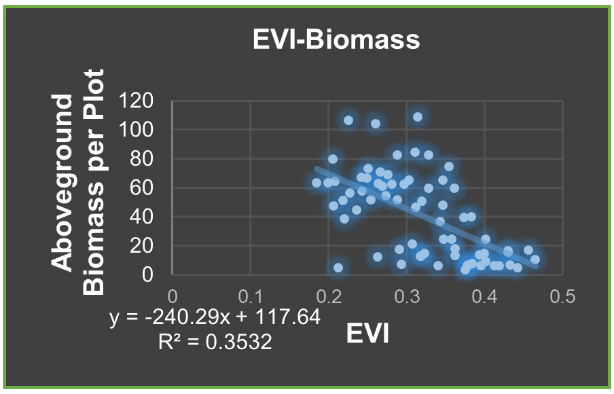

Figure 4. Enhance Vegetation Index Biomass Scattered Plots

the Vegetation Indices and the Above Ground Biomass of the Forests Stand. The results showing that the models are reliable in predicting the Above Ground Biomass of a Forest stand in Licuan Baay Abra. The NDVI R squared value is 0.321 and its RSME (Mg/ha^{-1}) value is 23.77; the SAVI R squared has a valued of 0.343 and the RMSE value is 23.39. The SRI indices R squared is the same with SAVI with a value of 0.343 and the RMSE (Mg/ha^{-1}) value is 23.40 which is the same with SAVI value, and while EVI R squared value is 0.353 and the RMSE (Mg/ha^{-1}) value is 23.20. In the study of Hamdan *et al.* (2014) as mentioned by Ismail *et al.* (2018) using NDVI and SAVI in mangrove forest they obtained RMSE = 43.77 Mg/ha^{-1} (r^2 = 0.59) and 68.21 Mg ha^{-1} (r^2 = 0.01) respectively. However, the correlation coefficients obtained in the study were lower than those reported by LIMA JÚNIOR *et al.* (2014) with Pearson's correlation coefficient of R = 0.84 as mentioned in the study of Luz (2022). This study also implies that the Rs range to 0.321 to 0.353 which lower than the Rs in the study of Luz (2022) with correlation coefficients (Rs) varying between 0.64 and 0.58. Nevertheless, it was shown in figure 1, 2, 3, 4 that the biomass obtained from the field data gathered and vegetation indices have a relationship. Therefore, the results of the study indicated that the four-vegetation model equation have a significant correlation of Above Ground Biomass and Vegetation Index in 0.01 level 2-tailed which shows that the four vegetation index model equations can be used to determined and analysed the biomass of a forest stand. with that, EVI vegetation index model is the most accurate model develop to use in estimating the Forest Stand Biomass, carbon and carbon dioxide based on its R squared which has the highest total value computed among the four Vegetation Index and has the lowest total value computed in the RSME (Mg/ha^{-1}). It also mentioned in the study of Askar *et al.* (2018) EVI is more reliable than NDVI to measure AGB on dense vegetation because of its ability to reduce the effect of atmosphere and canopy background. But the other model equations developed also be used as well to predict and estimate the AGB of Forest Stand because they have also a significant correlation at the 0.01 level (2 tailed) where the result showing the vegetation Index quantitative values and Biomass gathered from the field have a relationship.

In addition, EVI tends to be more sensitive to plant canopy differences like leaf area index (LAI), canopy structure, and plant phenology and stress than the other vegetation indices like NDVI which generally responds just to the amount of chlorophyll present, SAVI is a vegetation index that attempts to minimize soil brightness influences using a soil-brightness correction factor; This is often used in arid regions where vegetative cover is low, and SRI is a quick way to distinguish green leaves from other objects in the scene and estimate the relative biomass present in the image. EVI was developed as an alternative vegetation index to address some of the limitations of the NDVI where it was specifically developed to be more sensitive to changes in areas having high biomass, reduce the influence of atmospheric conditions on vegetation index values, and correct for canopy background signals.

Table 5. Model Summary

Model	Equation	R	R Squared	Adjusted R Squared	RSME
(Mg/ha-1)					
1 (NDVI)	-285.01*NDVI + 138.97	-0.567	0.321	0.311	23.77
2 (SAVI)	-304.67*SAVI + 122.76	-0.586	0.343	0.333	23.39
3 (SRI)	-63.174*SRI + 171.82	-0.585	0.343	0.333	23.40
4 (EVI)	-240.29*EVI + 117.64	-0.594	0.353	0.343	23.20

Table 5 shows the model equations developed based on the data gathered in the field and the vegetation indices which were derived from the Landsat8 images. This computed ABG and sequestered carbon of forests stand from the product of the developed equation model compared to estimate the Above Ground Biomass Forests stand of Licuan-Baay, Abra from the actual filed data gathered. The predicted Above Ground Biomass for NDVI model equation (-285.01*NDVI + 138.97) estimated a total value of 8,292,975.10 Mg/ha^{-1} of AGB and 3,731,838.80 Mg/ha^{-1} of C, the SAVI model equations (-304.67*SAVI + 122.76) also estimated a total value of 8,399.57.76 Mg/ha^{-1} of AGB and 3,779,796.49 of C, and SRI model equations (-63.174*SRI + 171.82) estimated a total value of 7,999,078.74 Mg/ha^{-1} of AGB and 3,599,585.43 of C, and in EVI model equation (-240.29*EVI + 117.64) estimated a total value of 8,228,374.73 Mg/ha^{-1} of AGB and 3,702,768.63 of C of the forest stand of Licuan-Baay, Abra with an area of 21,367.41 hectares. The estimated Above Ground Biomass using the actual data gathered in the field has a total value of 9,786,273.78 Mg/ha^{-1} and 4,403,823.20, showing that the estimated Above Ground Biomass from the four vegetation indices model equations developed shown in Table 6 was not over projected compared to the actual biomass from the field data. It also shown that the estimated value of Licuan-Baay, Abra forest stand biomass using the four models are reliable to estimate the Above Ground Biomass of the Forest Stands. The results also shown that they are not far from each other. In the study of Patriya *et al.* (2018) using the NDVI, SAVI, and ARVI showed the total biomass estimated was approximately 243.85 million kg in a forest stand mixed with Albizia saman, Pterocarpus indicus, Swietenia macrophylla, and Roystonea regia with an area of 50,149 km^2 which implies that the larger vegetation covers the biomass value increases.

Based on the results shown in the Table 6 it implies the different estimated Above Ground Biomass of Licuan-Baay, Abra using the four vegetation Indices Model Equations developed and the estimated value of Above Ground Biomass also be utilized by the people of Licuan-Baay. The developed model equations will be used not only for monitoring the Above Ground Biomass of the municipality, but it also used to monitor the vegetation cover of the forest stands of the municipality. With that, it is a big contribution for them to improve their records particularly in the forest stand biomass of the Municipality without going to the field. The model equations develop also be used by the leading agency DENR in monitoring the biomass and carbon sequestration of the forest stand particularly in Abra. With that, the Figure 8 shows the predicted Above Ground Biomass map of Licuan-Baay, Abra which was generated through the four-model equations develop.

Table 6. Estimated AGB, Carbon and Carbon Dioxide of Licuan-Baay Abra

VI	Estimated AGB	Carbon	Carbon dioxide
NDVI	8,292,975.10	3,731,838.80	13,695,848.38
SAVI	8,399,547.76	3,779,796.49	13,871,853.13
SRI	7,999,078.74	3,599,585.43	13,210,478.54
EVI	8,228,374.73	3,702,768.63	13,589,160.87
Field Data	9,786,273.78	4,403,823.20	16,162,031.15

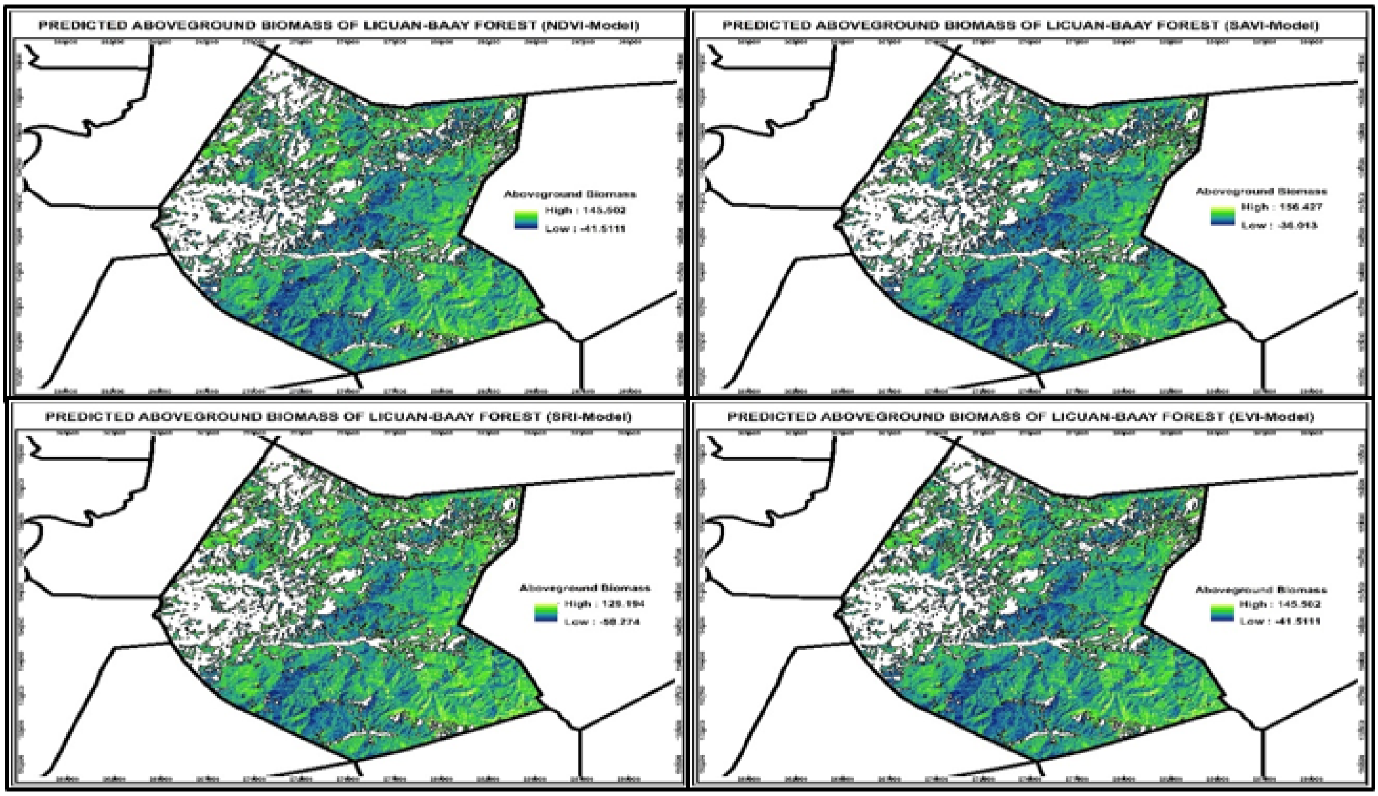

Figure. 5. Predicted above ground biomass maps of Licuan-Baay, Abra using vegetation indices

5. CONCLUSION

Based on the results of the study, the vegetation indices derived from Landsat8 images have the capability to estimate Above Ground Biomass of a Forest Stand since the vegetation indices above ground biomass values and the above ground biomass obtained from the field are correlated to each other. The vegetation indices acquired from the satellite image and above ground biomass of forest stand obtained from the field data have a relationship using linear regression. The results of the study in figure 1, 2, 3, & 4 showed a negative trend but then still the vegetation indices and above ground biomass values have a relationship. The above ground biomass values of forest stand computed using the vegetation indices model equation develop is low compared to the computed value of above ground biomass obtained from the field using the Brown's Model 1997. The carbon stock absorbs by the forest stand using the four-model equation develop are lower than the computed value of carbon stock obtained from the field. The Develop model to estimate above-ground biomass of forest stands at local scale by using high spatial resolution satellite images are the Normalized Vegetation Index, Soil Adjusted Vegetation Index, Soil Ratio Index, and Enhanced Vegetation Index model equations. Since, the vegetation indices and above ground biomass obtained from the field have a relationship or correlated to each other, the four model equations develop have the capability to estimate above ground biomass of forests stand.

RECOMMENDATIONS

To improve the results of the study, gathering of the data in the field needs more plots to establish. This is to improve the correlation of the above ground biomass from the field and the vegetation index. Furthermore, it is highly recommended to use other non-destructive equations to compute the Above Ground Biomass of the Forest stands. The four-models developed are still recommended to use in computing the Above Ground Biomass, carbon, carbon dioxide of forest stands because the biomass and the vegetation indices results are correlated. It still recommends a furthermore studies on estimation of Above Ground Biomass Forest stands using the four-vegetation indices. With that, the results of the study will be compared.

REFERENCES

Askar, Nuthammachot, N., Phairuang, W., Wicaksono, P., & Sayektiningsih, T. (2018). Estimating Aboveground Biomass on Private Forest Using Sentinel-2 Imagery. *Journal of Sensors, 2018*(1), 6745629. https://doi.org/10.1155/2018/6745629.

Baloloy, A. B., Blanco, A. C., Candido, C. G., Argamosa, R. J. L., Dumalag, J. B. L. C., Dimapilis, L. L. C., & Paringit, E. C. (2018). Estimation of mangrove forest aboveground biomass using multispectral bands, vegetation indices and biophysical variables derived from optical satellite imageries: Rapideye, planetscope and sentinel-2. *ISPRS annals of the photogrammetry, remote sensing and spatial information sciences, 4*, 29-36. https://doi.org/10.5194/isprs-annals-IV-3-29-2018

Beets, P. N., Kimberley, M. O., Oliver, G. R., Pearce, S. H., Graham, J. D., & Brandon, A. (2012). Allometric equations for estimating carbon stocks in natural forest in New Zealand. *Forests, 3*(3), 818-839. https://doi.org/10.3390/f3030818

Boelman, N. T., Stieglitz, M., Rueth, H. M., Sommerkorn, M., Griffin, K. L., Shaver, G. R., & Gamon, J. A. (2003). Response of NDVI, biomass, and ecosystem gas exchange to long-term warming and fertilization in wet sedge tundra. *Oecologia, 135*, 414-421. https://doi.org/10.1007/s00442-003-1198-3

Borges, E. R., Dexter, K. G., Pyles, M. V., Bueno, M. L., Dos Santos, R. M., Fontes, M. A. L., & Carvalho, F. A. (2021). The interaction of land-use history and tree species diversity in driving variation in the aboveground biomass of urban versus non-urban tropical forests. *Ecological Indicators, 129*, 107915. https://doi.org/10.1016/j.ecolind.2021.107915

Calders, K., Newnham, G., Burt, A., Murphy, S., Raumonen, P., Herold, M., ... & Kaasalainen, M. (2015). Nondestructive estimates of above-ground biomass using terrestrial laser scanning. *Methods in Ecology and Evolution, 6*(2), 198-208. https://doi.org/10.1111/2041-210X.12301

Chaturvedi, R. K., Raghubanshi, A. S., & Singh, J. S. (2010). Non-destructive estimation of tree biomass by using wood specific gravity in the estimator. *National Academy Science Letters, 33*(5-6), 133-138. https://www.researchgate.net/publication/225035042

Das, S., & Singh, T. P. (2012). Correlation analysis between biomass and spectral vegetation indices of forest ecosystem. *Int. J. Eng. Res. Technol, 1*(5), 1-13.

Fraser, R. H., Olthof, I., Carrière, M., Deschamps, A., & Pouliot, D. (2011). Detecting long-term changes to vegetation in northern Canada using the Landsat satellite image archive. *Environmental Research Letters, 6*(4), 045502. https://doi.org/10.1088/1748-9326/6/4/045502

Gizachew, B., Solberg, S., Næsset, E., Gobakken, T., Bollandsås, O. M., Breidenbach, J., ... & Mauya, E. W. (2016). Mapping and estimating the total living biomass and carbon in low-biomass woodlands using Landsat 8 CDR data. *Carbon balance and management, 11*, 1-14. https://doi.org/10.1186/s13021-016-0055-8

Goswami, S., Gamon, J., Vargas, S., & Tweedie, C. (2015). *Relationships of NDVI, Biomass, and Leaf Area Index (LAI) for six key plant species in Barrow, Alaska* (No. e913v1). PeerJ PrePrints. https://dx.doi.org/10.7287/peerj.preprints.913v1

Günlü, A., Ercanli, I., Başkent, E. Z., & Çakır, G. (2014). Estimating aboveground biomass using Landsat TM imagery: A case study of Anatolian Crimean pine forests in Turkey. *Annals of Forest Research, 57*(2), 289-298. https://www.afrjournal.org/index.php/afr/article/view/278

Gunawardena, A. R., Nissanka, S. P., Dayawansa, N. D. K., & Fernando, T. T. (2015). Estimation of above ground biomass in Horton Plains national park, Sri Lanka using optical, thermal and RADAR remote sensing data. *Tropical Agricultural Research, 26*(4), 608-623 https://doi.org/10.4038/tar.v26i4.8123

Hairiah, K., Sitompul, S. M., Noordwijk, M. V. & Cheryl Palm, C. (2001). Methods for sampling carbon stocks above and below ground. International Centre for Research in Agroforestry, Southeast Asian Regional Research Programme PO Box 161, Bogor, Indonesia. http://www.icraf.cgiar.org/sea

Hasmadi, M., Ismail, Omar, H., & Sarmin, N. S. (2018). Estimation aboveground biomass in mangrove forests using vegetation indices from SPOT-5 image. https://www.researchgate.net/publication/324758402

Hogrefe, K. R., Patil, V. P., Ruthrauff, D. R., Meixell, B. W., Budde, M. E., Hupp, J. W., & Ward, D. H. (2017). Normalized difference vegetation index as an estimator for abundance and quality of avian herbivore forage in Arctic Alaska. *Remote Sensing, 9*(12), 1234. https://doi.org/10.3390/rs9121234

Huy, B., Truong, N. Q., Khiem, N. Q., Poudel, K. P., & Temesgen, H. (2022). Deep learning models for improved reliability of tree aboveground biomass prediction in the tropical evergreen broadleaf forests. *Forest Ecology and Management, 508*, 120031. https://doi.org/10.1016/j.foreco.2022.120031

Ihlen, V., & Zanter, K. (2019). Landsat 8 (L8) data users handbook.

US Geological Survey, 54-55.

Karakoc, A., & Karabulut, M. (2019). Ratio-based vegetation indices for biomass estimation depending on grassland characteristics. Turkish Journal of Botany, 43(5), 619-633. https://doi.org/10.3906/bot-1902-50

Kumar, L., & Mutanga, O. (2017). Remote sensing of above-ground biomass. *Remote Sensing, 9*(9), 935. https://doi.org/10.3390/rs9090935

Lasco, R. D., MacDicken, G., Pulhin, F., Guillermo, I. Q., Sales, R. F., & Cruz, R. V. O. (2006). Carbon stocks assessment of a selectively logged dipterocarp forest and wood processing mill in the Philippines. *Journal of Tropical Forest Science, 18*(4), 212-221. http://www.jstor.org/stable/43594677

Lee, H. I., Seo, Y. O., Kim, H., Ali, A., Lee, C. B., & Chung, Y. (2022). Species evenness declines but specific functional strategy enhances aboveground biomass across strata in subtropical–Warm-temperate forests of South Korea. *Forest Ecology and Management, 512*, 120179. https://doi.org/10.1016/j.foreco.2022.120179

Lu, D., Chen, Q., Wang, G., Liu, L., Li, G., & Moran, E. (2016). A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems. *International Journal of Digital Earth, 9*(1), 63-105. https://doi.org/10.1080/17538947.2014.990526

Liu, S., Su, X., Dong, S., Cheng, F., Zhao, H., Wu, X., ... & Li, J. (2015). Modeling aboveground biomass of an alpine desert grassland with SPOT-VGT NDVI. *GIScience & Remote Sensing, 52*(6), 680-699. https://doi.org/10.1080/15481603.2015.1080143

Lumbierres, M., Méndez, P. F., Bustamante, J., Soriguer, R., & Santamaría, L. (2017). Modeling biomass production in seasonal wetlands using MODIS NDVI land surface phenology. *Remote Sensing, 9*(4), 392. https://doi.org/10.3390/rs9040392

Macedo, F. L., Sousa, A. M., Gonçalves, A. C., Marques da Silva, J. R., Mesquita, P. A., & Rodrigues, R. A. (2018). Above-ground biomass estimation for Quercus rotundifolia using vegetation indices derived from high spatial resolution satellite images. *European Journal of Remote Sensing, 51*(1), 932-944. https://doi.org/10.1080/22797254.2018.1521250

Moradi, F., Darvishsefat, A. A., Pourrahmati, M. R., Deljouei, A., & Borz, S. A. (2022). Estimating aboveground biomass in dense Hyrcanian forests by the use of Sentinel-2 data. *Forests, 13*(1), 104. https://doi.org/10.3390/f13010104

Pitriya, A., Rokhmatuloh, R., Wibowo, A., & Ash-Shidiq, I. P. (2018, October). Biomass estimation by combining field-sampling measurement and vegetation indices derived from SPOT-7 imagery in urban area: Case study in South Tangerang, Indonesia. In *AIP conference proceedings* (Vol. 2023, No. 1). AIP Publishing. https://doi.org/10.1063/1.5064185

Vashum, K. T., & Jayakumar, S. (2012). Methods to estimate above-ground biomass and carbon stock in natural forests-a review. *Journal of Ecosystem & Ecography, 2*(4), 1-7. http://dx.doi.org/10.4172/2157-7625.1000116

Wani, A. A., Joshi, P. K., & Singh, O. (2015). Estimating biomass and carbon mitigation of temperate coniferous forests using spectral modeling and field inventory data. Ecological informatics, 25, 63-70. https://doi.org/10.1016/j.ecoinf.2014.12.003

Wei, X., Sritharan, S. I., Kandiah, R., & Osterberg, J. (2012). Allometric Equations for Predicting Above-ground Biomass of Tamarix in the Lower Colorado River Basin. *Desert Plants, 28*(2) http://hdl.handle.net/10150/556805

Zhang, H., Wang, K., Zeng, Z., Du, H., & Zeng, F. (2017). Biomass and carbon sequestration by Juglans regia plantations in the Karst regions of Southwest China. *Forests, 8*(4), 103. https://doi.org/10.3390/f8040103