Table S1: A database of methodology, accuracy and average AGB value published in peer reviewed forty-four published articles (2004-2019) for forest AGB estimation and mapping using high-resolution satellite imagery

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **No** | **Reference** | **Model applied** | **Parameters** | **Number of samples for model formation** | **Equation** | **Model coefficient value (R2)** | **Number of samples for model validation** | **Validation coefficient value (R2)** | **Estimated biomass (Kg/ha or ton/ha or Mg/ha)** |
| 1 | Clark et al. (2004) | **Linear** | Plot basal area = (R2 = 0.779) and Above-ground Biomass from stem (EAGB) = (R2 = 0.786) | 18 | Y= 77.6 - 9.7X | 0.63 | 18 | 0.786 | **\_** |
| 2 | Thenkabail et al. (2004) | **Non-linear (Exponential)** | Ikonos NDVI43 Dry biomass = (R2 = 0.63)  Ikonos band 3 Dry biomass = (R2 = 0.65) | 208 | **\_** | Dry biomass = (R2 = 0.63) (R2= 0.65)  Oil palm biomass = (R2 = 0.50)  Wet biomass = (R2 = 0.72) | 77 | 0.64 and 0.72 | 29.5 and 29.88 ton/ha |
| 3 | Hyde et al. (2006) | **Non-linear (Multiple)** | Standard deviation canopy height (R2 = 0.64, RMSE = 3.2) Biomass (R² = 0.83, RMSE = 66.6 mg/ha) | 120 | **\_** | 0.77 | **\_** | 0.83 | **\_** |
| 4 | Ouma & Tateishi (2006) | **Linear** | For tea, the combination of NIR with homogeneity, entropy and second moment textures gave the best and equal results (R2 = 0.684). For the young pine trees, correlation texture gave the overall best results (R2 = 0.741), and for the older pine trees, contrast texture gave the best results (R2 = 0.753) as independent variables. | **\_** | **\_** | 0.684 | **\_** | **\_** | 6.502 kg for tea, 7.505 kg for young pine trees (3.5 years old) and 9.779 kg for the older pine trees (6 years old). |
| 5 | Leboeuf et al. (2007) | **Linear** | **\_** | 108 | **\_** | 0.85 to 0.87 | 32 | 0.84 | 163.5 t/ha |
| 6 | Proisy et al. (2007) | **Non-linear (Multiple)** | We estimated biomass from multiple linear regression models using the three textural indices (scores of the three main PCA axes) as independent variables. Results were compared according to the window size for both PA and NIR data . The best results were obtained from the prediction of AGB values from PA data, with R2 above 0.87 | **\_** | **\_** | 0.79 | **\_** | 0.87 | **\_** |
| 7 | St-Onge et al. (2008) | **Linear** | **\_** | 57 | **\_** | 0.79 | 25 | **\_** | **\_** |
| 8 | Fuchs et al. (2009) | **Linear** | k-NN | 7 | **\_** |  | **\_** | **\_** | **\_** |
| 9 | Y. Hirata et al. (2009) | **Non-linear (Exponential)** | The coefficients of determination of the non-linear regression analysis to investigate the relationship between the estimates of parameter aˆ and b ˆ of the allometric model and stand variables such as stand age, stand density, mean stand DBH, mean stand tree height and relative spacing, simultaneously, were 0.84 and 0.87 for C. japonica and C. obtusa, respectively | 26 | **\_** | 0.58-0.95 0.66 - 0.94 | 26 | 0.64 | **\_** |
| 10 | Castillo-Santiago et al. (2010) | **Linear (Multiple)** | The R2 of the final models were 0.58 for basal area, 0.70 for canopy height, 0.73 for bole volume, and 0.71 for biomass | 94 | **\_** | 0.737 | 87 | 0.71 | 59.3 ton/ha |
| 11 | Gonzalez et al. (2010) | **Non-linear (Multiple)** | Validation of QuickBird crown diameters against field measurements of the same trees showed significant correlation (R=0.82, P<0.05). Comparison of stand-level Lidar height metrics with field-derived Lorey's mean height showed significant correlation (Garcia–Mailliard r=0.94, P<0.0001; North Yuba R=0.89, P<0.0001). | 1) 38  2) 40 | **\_** | **\_** | **\_** | **\_** | 82±0.7 Mg/ha in Garcia–Mailliard and  140±0.9 Mg/ha in North Yuba |
| 12 | Mora et al. (2010) | **Non-linear (Machine learning)** | Regression tree | 175 | **\_** | **\_** | 30 | **\_** | **\_** |
| 13 | Soenen et al. (2010) | **Linear** | Regression parameters for crown surface area vs calculated individual tree biomass for lodgepole pine and trembling aspen with coefficient value (R2 = 0.63) and (R2 = 0.52) respectively | 36 | **\_** | **\_** | 36 | **\_** | For conifer plots 30 ton/ha (MFM: 23.0 ton/ha; SMA: 27.9 ton/ha; NDVI: 29.7 ton/ha). The average difference for deciduous using MFM was 43.8 ton/ha, more than both NDVI (41.7 ton/ha) and SMA (39.3 ton/ha) |
| 14 | Nichol & Sarker (2011) | **Linear (Multiple)** | These were the ratio of the texture parameters of AVNIR-2 (R2 = 0.899 and rmse = 32.04), the ratio of the texture parameters of SPOT-5 (R2 = 0.916 and rmse = 29.09), and the ratio of the texture parameters of both sensors together (R2 = 0.939 and rmse = 24.77) | 50 | **\_** | 0.93 | 50 | 0.911 | 500 ton/ha |
| 15 | Chen et al. (2012) | **Non-linear (Machine learning)** | **\_** | 96 | y = 0.0061\*d1.30 | 0.978 | 42 | 0.843 & 0.816 | **\_** |
| 16 | Mutanga et al (2012) | **Non-linear (Machine learning)** | The random forest regression produced the highest R2 (0.76) and the lowest root mean square error of prediction (RMSEP) (0.441 kg/m2) using the three NDVIs compared to the top NDVIs which produced R2 0.63 and RMSEP of 0.505.1 kg/m2 and the standard NDVI, which yielded an R2 of 0.31 and RMSEP of 0.858.1 kg/m2 | 82 | **\_** | **\_** | 25 | 0.76 | 3.4365 kg/m2 |
| 17 | Pierre Ploton et al. (2012) | **Linear (Multiple)** | Stand basal area (BA) and AGB estimates were also closely related to canopy texture indices, and these relationships remained fairly stable regardless of whether all trees were considered (R2 ¼ 0.74 and 0.78 for both parameters with GE and IKONOS, respectively) or only the largest trees (R2 ¼0.72 and 0.74–0.75 for both parameters with GE and IKONOS, respectively) | 15 | **\_** | **\_** | **\_** | 0.75 | **\_** |
| 18 | Jachowski et al. (2013) | **Non-linear (Machine learning)** | **\_** | 45 | AGB = 0.16\*[Elevation] + 0.27\*[Band 1] - 0.11\*[Band 2] + 0.41\*[Band 4] - 0.03 | **\_** | 45 | 0.66 | 345 ± 72.5 Mg ha¯¹ |
| 19 | Bastin et al. (2014) | **Linear (Multiple)** | **\_** | 26 | y= ax + b | **\_** | 26 | 0.85 | 26 Mg/ha to 460 Mg/ha |
| 20 | Yasumasa Hirata et al. (2014) | **Linear** | **\_** | 23 | y = pxq where x is the independent variable, y is the dependent variable, and p and q are regression parameters. | 0.65 | 23 | 0.72 | **\_** |
| 21 | Hussin et al. (2014) | **Linear** | The models were validated using coefficient of determination (linear regression) between calculated stocks through CPA and DBH relationship and predicted carbon stocks | 65 | For Shorea robusta = (y = 9.9773x - 88.303) For others = (y- 12.523x - 115.91) | Shorea robusta = 0.65 others = 0.62 | 20 | Shorea robusta = 0.60  others =0.82 | **\_** |
| 22 | Mbaabu et al. (2014) | **Linear** | Development of the relationship between crown projection area (CPA), height, and AGB resulted in accuracies of R2 range from 0.62 to 0.81, and RMSE range from 10 to 25 % for Shorea robusta and other species respectively. | 109 | **\_** | **\_** | 91 | Community forest (Shorea robusta) = 0.81 Community forest (other species) = 0.62 Government forest (Shorea Robusta) = 0.69 Government forest (other species) = 0.73 | 244 and 140 tonC/ha for community and government forests respectively |
| 23 | M.-H. Phua et al. (2014) | **Linear** | The field-measured above-ground biomass (AGB\_f) was highly correlated with DBH with R coefficients of 0.85. However, DBH has the highest correlation with CA\_I (R=0.82), followed by CD\_I (R=0.80) and CP\_I (R=0.77). In contrast, relatively low correlations (R coefficient ranges between 0.54 and 0.57) were found between field-measured Ht\_f and the satellite-based crown variables. | 50 | y = 0.7403x | 0.7197 | 50 | 0.7197 | 50 and 12,000 ton/ha |
| 24 | Singh et al. (2014) | **Linear (Multiple)** | Regression analysis was carried out for all land-use types, and the FOTOderived and field AGB values were strongly correlated (R2 = 0.9795, p = 0.000352) | 196 | All land use types (a) = y = 1.1677x ;  Heavily logged forest (b) = y = 0.7809x ;  Old growth forest (c) = y = 1.125 x ;  Lightly logged (d) = y = 0.945x | (a) = 0.97 (b) = 0.95  (c ) = 0.85 (d) = 0.96 | **\_** | 0.9795 | FOTO-derived biomass values indicated that Twice logged forest or LF have an AGB of 120–155 Mg/ha, while Oil Palm plantations have the lowest FOTO-derived AGB values, 0–80 Mg/ha; the lightly logged forests or the VJR showed very high values for FOTO-derived AGB (180–270 Mg/ha). Small patches of unlogged forest tracts have the highest FOTO-derived AGB values, ranging from 270 to 372 Mg/ha. |
| 25 | Sousa et al. (2015) | **Linear** | Crown horizontal projection vs above ground biomass per plot with inventory data (R2 = 0.965) | 17 | **\_** | Model 1 = 0.900 Model 2 = 0.999 | 17 | 0.965 | 23.2 ton/ha |
| 26 | Karna et al. (2015) | **Linear** | For this research, multi-resolution segmentation technique was applied to segment tree crown onto fused LiDAR and WorldView-2 data. | 72 | S. robusta: −0.877+0.597CPA+1.873CHM S. wallichii: −0.144+1.124CPA+0.883CHM L. parviflor: 0.205+0.370CPA+1.494CHM T. tomentosa: −0.126+0.45CPA+1.848CHM Othres: 0.044+0.616CPA+1.396CHM | 0.66 0.75 0.60 0.82 0.64 |  | 0.94 0.84 0.78 0.76 0.78 | 216.38 MgC/ha |
| 27 | Maack et al. (2015) | **Non-linear (Machine learning)** | Random Forest algorithm applied using solely spectral (S), textural (T) or photogrammetric (P) predictors as well as combinations of them, i.e. S+T, S+P, T+P and S+T+P. | 1) 98 2) 101 | **\_** | **\_** | **\_** |  |  |
| 28 | Kattenborn et al. (2015) | **Non-linear (Machine learning)** | Four semi- or non-parametric regression models in terms of their accuracy for biomass estimation: Random Forest, Generalized Additive Models and two boosted algorithms, Generalized Boosted Regression Models (GBM, Friedman, 2001) and the boosted version of the GAM (GAMB, Tutz and Binder, 2006). | 303 | **\_** | Best results random forest: 0.73 |  |  | 29.4 ton/ha |
| 29 | Zhu et al. (2015) | **Non-linear (Machine learning)** | A Back Propagation Artificial Neural Network (BP ANN) using B5 (red band), B7 (near-infrared-1 band) and B8 (near-infrared-2 band) of the Worldview-2 images were used to calculate six vegetation indices, including the normalized difference vegetation index (NDVI), the simple ratio index (SRI), and the difference vegetation index (DVI) | 91 | **\_** | **\_** | **\_** | **\_** | Mixed species: 72.26ton/ha Dummy species: 40.15ton/ha K. candel: 52.38ton/ha S. apetala: 24.32ton/ha |
| 30 | Clerici et al. (2016) | **Linear** | Normalized Difference Vegetation Index (NDVI) Vegetation index number (VIN) Ratio Vegetation Index (RVI) Normalized Difference Greenness Index (NDGI) Transformed Vegetation Index (TVI) | 8 | Best model log AGB = ‐3.208\*RVI + 2.185 | 0.582 | **\_** | **\_** | **\_** |
| 31 | P. Ploton et al. (2017) | **Linear (Multiple)** | We investigated from these simulated images the respective merits of the FOTO method and the lacunarity analysis in predicting AGB both locally (within sites) and globally (across sites). Combined FL Model (Combining FOTO and Lacunarity) | 279 | \_ | Best result (R2v= 0.69) | 230 | R2 = 0.47 | It is noteworthy that site-level MSDs seemed to decrease with the range of biomass encompassed across plots in a site: while plots in Yellapur (MSD =10.3%) and Paracou (MSD = −18.1%) are restricted to low and high biomass levels, respectively, in Uppangala (MSD = −5.3%) plots have been sampled along a biomass gradient spanning from c. 150 up to> 600 Mg ha−1. A practical application of the method to a mosaic of forest types in the Congo basin showed that forest AGB inferences could be made with reasonable precision (i.e. ≤ 25% of error) up to 600 Mg ha−1, without saturation. Average AGB over 49 field plots of 359 ± 98 Mg ha−1 |
| 32 | Dhanda et al. (2017) | **Non-linear (Machine learning)** | Estimation of aboveground biomass (AGB) at ICESat/GLAS footprint level was done by integrating data from multiple sensors using two regression algorithms, viz. random forest (RF) and support vector machine (SVM). Multiple linear regression (MLR) was also utilized to estimate AGB when number of variables were reduced using machin learning regression. | 40 | Biomass = 0.343 \* wdistance + 0.37 \* wextent + 0.008 \* Correlation2 - 0.0083 \* NIR2max - 6.5 \* IRGVI2max - 0.137 \* H75 + 47.125 Where  wdistance = top tree height  wextent = LiDAR spectral parameter Correlation2 = texture parameters NIR2max = Satellite image spectral parameter IRGVI2max = Satellite image spectral parameter H75 = Satellite image spectral parameter | SVM regression algorithm explained 88.7% of variation in AGB with an RMSE of 13.6 Mg ha–1 on the combined datasets while RF regression algorithm explained 83.5% of variation in AGB with an RMSE of 20.57 Mg ha–1. | \_ | \_ | It was found that SVM regression algorithm explained 88.7%of the variation of biomass and had an RMSE of 13.6 Mg ha–1 on the combined dataset while RF regression algorithm explained 83.5% of the variation of biomass and had an RMSE of 20.57 Mg ha–1. |
| 33 | M. H. Phua et al. (2017) | **Linear** | Normalized Difference Vegetation Index (NDVI) Pearson’s correlation was used to test which of these variables was most closely related to field-derived AGB. Least square regression for generating statistical model | 50 | Intact Forest: AGBT (intact forest )=exp(2.62⋅ln DBH−2.30) Degraded Forest: AGBT (degraded forest)=0.0829⋅DBH2.43 | Intact forest regression = 0.89 degraded forest regression = 0.87 | 25 | Intact forest regression R2= 0.812 degraded forest regression = 0.7142 | Average 1058kg for intact forest and 147kg for degraded forest |
| 34 | Suraj Reddy et al. (2017) | **Linear (Multiple)** | Fourier transform based textural ordination (FOTO) | 15 | **\_** | IKONOS R2 = 0.82 Carto-A R2 = 0.76 Carto-F R2=0.76 | \_ | \_ | The estimated AGB values from the 15 large (1 ha) plots covered a significant range of biomass varying from a minimum of 124 t ha-1 to a maximum of 684 t ha-1 with an average of 435 t ha-1. RMSE computed for predicted and field measured biomass using IKONOS and Carto-A imagery were 67.03 and 77.32 t ha-1 |
| 35 | Gonçalves et al. (2017) | **Linear** | Normalized Difference Vegetation Index (NDVI) | 57 | W = ww + wbr + wl wl = 0.09980 \* d ^ 1.39252 \* (h/d)^ 0.71962 wbr = 0.0308 \* d^2.75761\*(h/d)^-0.39381 ww = 0.0146\*d^1.94687\*h^1.106577 where d is the diameter at breast height, h the total height, W total above ground biomass, ww biomass of wood, wbr biomass of branches, wl biomass of leaves. W = b\*CHP  where b is the regression coefficient,Wabove ground biomass, CHP crown horizontal projection, | R2 = 0.719 | \_ | \_ | The above ground biomass estimated with M5 was 32.3 Mg ha-11 in 2004, 16.3 Mg ha-11 in 2007, and 10.8 Mg ha-11 in 2011. |
| 36 | Pargal et al. (2017) | **Linear (Multiple)** | Fourier transform based textural ordination (FOTO) | 21 | AGBtree = 0.0673 (ρ\*DBH^2\*H)^0.0976 | R2 = 0.82 | - | R2 = 0.76 | The predicted mean AGB values for the wet zone plots ranged between 141 Mg ha􀀀1 and 486 Mg ha􀀀1 A separate texture–AGB model was fitted for dry zone ground control plots which redicted low biomass values ranging between 159 Mg ha􀀀1 to 228 Mg ha􀀀1 |
| 37 | Mohd Zaki et al. (2018) | **Linear (Multiple)** | Oridnary Least Square (OLS) | 166 (No. of Trees out of 32, 2h Plots) | AGBest = 0.0673 (ρ\*DBH^2\*H)^0.0976 | R2 = 0.952 (Best Model) | 79 (No. of Trees out of 32, 2h Plots) | R2 = 0.914 (Best Model) | 655-12,300 kg/trees (Best Model) |
| 38 | Hlatshwayo et al. (2019) | **Linear (Multiple)** | The relationship between natural forests aboveground biomass and image texture variables was modelled using random forest (RF) algorithm and multiple linear regression (MLR). Raw band textures, Two band textures and Three band texture using Multiple Linear Regression and Random Forest Regression | 63 Plots | AGB = 0.112 × (ρD2H)0.916 Where AGB is total above-ground biomass, ρ is wood density, D is diameter at ground level and H is total tree height. | Multivariate analysis results for the three image processing techniques showed that single texture bands produced the lowest overall accuracy (R2=0.64 and RMSE=94.13 kg m−2) followed by some improvements using the two band texture combination (R2=0.85 and RMSE=60.65 kg m−2). However, the highest overall accuracy was obtained using three band texture combination (R2=0.88 and RMSE=54.54 kg m−2). | 27 | Three band texture models produced the highest overall predicted performance with an R2 of 0.88 and 0.77 compared to both the two band texture ratios (R2=0.85 and 0.67) and raw texture bands (R2=0.64 and 0.53) | 268.79 kg/m-2 |
| 39 | Koju et al. (2018) | **Linear** | Tree canopy cover (TCC) vs forest aboveground biomass (FAGB) model. A multivariate adaptive regression splines (MARS) machine learning algorithm was used to develop a model from the relationship between different predictor parameters from Landsat 8 bands and its vegetation indices with the FAGB of GEVHR virtual sample plots. | 30 plots | y=1.0865x-62.078 | (R2) of 0.76 | 20 | (R2) = 0.83 | The average forest aboveground carbon (FAGC) estimated was 260 tons ha-1, while in the field it was 249 tons ha-1 |
| 40 | Yasumasa Hirata et al. (2018) | **Linear (Multiple)** | Multiple Regression Analysis Digital canopy model (DCM) | 57 Plots | AGB = exp (􀀀2.134 + 2.530 ln (DBH)) AGBF = 0 + 1 hmax + 2 hmin + 3 hmean for LiDAR AGBL = 0+å5 k=1( kmk + ksk) for Satellite Data | R2 = 0.90 for LiDAR R2=0.73 for Satellite Data | \_ | \_ | RMSE = 38.7 Mg/ha from LiDAR RMSE = 42.8 Mg/ha from Satellite Data |
| 41 | Basso et al. (2019) | **Linear** | Simple Reason (SR) NDVI (Normalized Difference Vegetation Index) SAVI (Soil Adjusted Vegetation Index) | 29 | Bio = β0 + β1·DBH 14.4 0.86 -2901.85 96.3  Bio = β1·NDVI\_2 37.8 0.87 - 23168.7 Bio = β1·B1 38.8 0.87 - 51.8  Bio = β1·(NDVI) + β2·(SR) + β3·(SAVI) | 0.87 | \_ | \_ | \_ |
| 42 | Reyes-Palomeque et al. (2019) | **Linear (Multiple)** | Normalized Difference Vegetation Index (NDVI) Enhanced Vegetation Index (EVI) | 48 | \_ | Site-1 (LiDAR R2 = 0.82 & Orthophoto R2=0.70) Site-2 (LiDAR R2 = 0.88 & Orthophoto R2=0.91) Combined = 0.85 | . | Site-1 (LiDAR R2 = 0.62 & Orthophoto R2=0.52) Site-2 (LiDAR R2 = 0.85 & Orthophoto R2=0.86) Combined = 0.69 | Site-1 (LiDAR RMSE = 35.5 Mg Ha−1 & Orthophoto RMSE= 42.6 Mg Ha−1) Site-2 (LiDAR RMSE = 14.4 Mg Ha−1 & Orthophoto RMSE= 13.6 Mg Ha−1) Combined = 33.0 Mg Ha−1 |
| 43 | Hosseini et al. (2019) | **Linear** | DBH, Height, Crown Diameter and Stem Length | 48 | Bt=Bs+Bsb+Bb+Bt+Bf where Bt is the total aboveground biomass, Bs is the stem, Bsb is the stem bark, Bb is the branch, and Bt is the twig, Bf is the foliage biomass. All parts of trees were separated, followed by in situ measurement of total fresh weight of each part. | Total biomass R2=0.90 (RMSE=24.92 t ha-1)  Dry biomass R2=0.91(RMSE=12.74 t ha-1) | \_ | \_ | In this study, the highest amount of carbon sequestration was estimated for P. eldarica (4462.18 t ha-1), followed by C. arizonica (2103.37 t ha-1) plantations, whereas the lowest amount was estimated for M. alba (1009.09 t ha-1) and R. pseudoacacia (365.38 t ha-1) plantations. |
| 44 | Gascón et al. (2019) | **Linear** | Mean bands 1 to 5 Standard deviation bands 1 to 5 Ratio of mean to standard deviation for all bands Standard deviation. Ratios Red Vegetation Index Green Vegetation Index Green Red Vegetation Index Normalised Difference Vegetation Index Enhanced Vegetation Index Soil Adjusted Vegetation Index Shadow Index Modified Transverse Vegetation Index Modified Chlorophyll Absorption Reflectance Index Bare Soil Index Shadow to Soil Ratio GLCM Texture Features Bare Soil Shadow | 85% for training Random Forests (RF) - 435 plots out of 500 | AGB = D x ӯ Where D is the total study area and ӯ is the average AGB ha-1 of the sample areas | The best results were found using the random forests algorithm (R2 = 0.69) | 15% for training Random Forests (RF) - 77 plots out of 500 | RF with very high accuracies (i.e., RMSE~15, R2 = 0.93), | we find an average of 22.1 tons per ha of above ground biomass (AGB) |

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