Allometric equations for estimating biomass in agricultural landscapes: I. Aboveground biomass

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ABSTRACT

Meeting the reducing emissions from deforestation and degradation (REDD) framework demands stringent carbon measuring, reporting and verifying methods. In most cases, estimates of aboveground carbon stocks rely on allometric equations. Although generic and species-specific allometries have been developed for conventional areas such as forests, their use in agricultural landscapes is questionable as agricultural trees are typically managed and rarely mono-specific. Therefore, there is a need to develop a robust generic allometry that accounts for the heterogeneity of tree diversity throughout the landscape. Allometric equations were developed from empirical destructive sampling of 72 trees (diameter at breast height (dbh): 3–102 cm) from three 100 km^2 benchmark sites in Western Kenya. Diameter at breast height alone provided reliable prediction for aboveground biomass (17 ± 0.02 Mg C ha^{-1}) with >95% accuracy. Published equations overestimated landscape biomass due to errors in either smaller trees (dbh <10 cm) which dominate the landscape (66%) or the few larger trees (dbh >40 cm) which constitute 3% of all the trees but hold most of the biomass (48%). The apparently small differences in the equations for small trees could add up to a large amount of carbon when looking at a landscape. This study recommends diameter as the basis for assessing tree biomass in Western Kenyan agricultural mosaics. The equations developed are a useful tool for assessing the potential for carbon sequestration in agricultural landscapes and represent key information for scaling biomass estimates for entire landscapes.

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1. Introduction

Reducing emissions from all land uses (REALU or REDD++) has emerged as an important broad-based approach to climate change mitigation. By comparison to REDD, REDD++ targets a greater variety of emission sources, reduction of leakage (unintended consequences), and increased benefits for local people (Velarde et al., 2010). The success of REDD++ hinges upon robust, reliable and efficient procedures for evaluating carbon (C) stocks across entire landscapes, not only forested areas. The ubiquity of agricultural ecosystems complicates the task of estimating C stocks for REDD++. Woody vegetation in these land uses represents a significant carbon pool and has been identified to play a role in carbon sequestration in some systems (Albrecht and Kandji, 2003). In sub-Saharan Africa, about 87% of agriculturally dominated landscapes hold >10% tree cover (Zomer et al., 2009). Hence, accurate quantification of mitigation potential in these regions requires practical methods to assess the C in trees of agricultural landscapes. While significant success has been achieved in quantifying C stocks in forests, our knowledge of C stocks in agricultural landscapes is fairly poor, in part due to their high spatial and temporal heterogeneity. Complex agricultural landscapes rarely contain trees of only one species and thus differ in wood density and architecture (Chave et al., 2004). Efforts to quantify C stocks accurately in agricultural landscapes have therefore been hindered by lack of valid allometric equations allowing tree measurements to be converted into biomass and ultimately into C.

Allometric equations are a fundamental tool for non-destructive estimation of biomass in woody vegetation. These equations express tree biomass as a function of easy-to-measure parameters such as diameter, height, or wood density, or a combination of these (Brown, 2002; Chave et al., 2005). Equations generated from a small sample of trees are then used to estimate biomass at landscape

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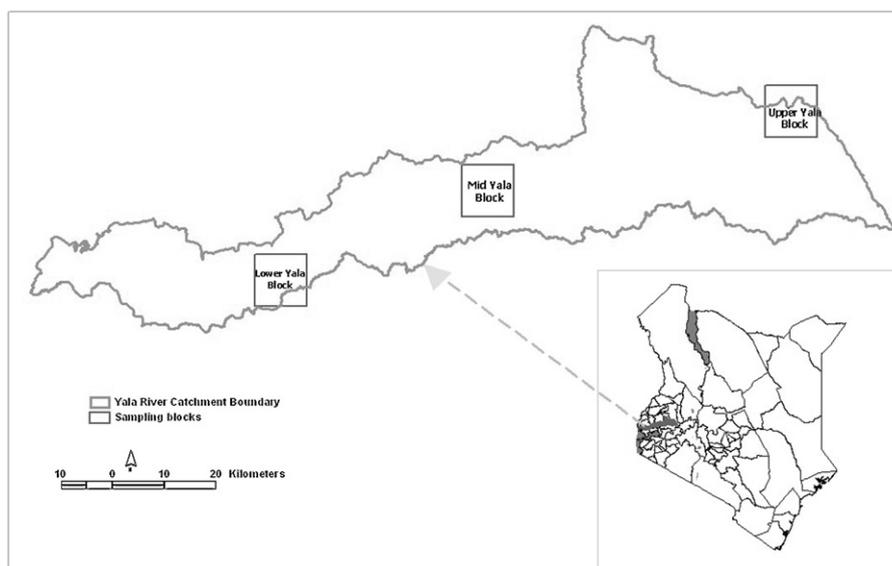
Fig. 1. The location of the three 10 km × 10 km study sites (Lower Yala, Middle Yala and Upper Yala) in the River Yala basin of Western Kenya; ranging in elevation from 1200 m in Lower Yala to 2200 m in Upper Yala.

scales. The value of the allometric equations depends on the empirical data used. Several allometric equations have been published for particular, rather homogenous systems such as coffee (Segura et al., 2006), forest plantation (Bastein-Henri et al., 2010) and various forest types (Brown, 1997) among other vegetation types. Biomass estimates from allometric equation can indicate the potential for C sequestration and can be used in assessing impacts of climate change (Eamus et al., 2000). Therefore, development of high quality and representative allometric equations cannot be overstated.

Existing allometric equations in East Africa are mainly developed for distinct land use systems such as forestry (Kiruki et al., 2009) and are species-specific (Okello et al., 2001). In addition, most existing equations have underrepresented certain vegetation types and tree size (Keith et al., 2000). Other equations developed for mixed tropical species (e.g. Brown, 1997; Chave et al., 2005) have not been validated for the region. Additional factors affecting the usefulness of equations produced in other contexts are the species mix, the fact that they are grown in stands that are often not closed and may include isolated trees, and that crowns may be cut during growth. Consequently, the use of equations developed elsewhere, using data from non-agricultural landscapes may greatly misjudge biomass in agricultural landscapes in East Africa.

Diameter at breast height is commonly used for aboveground biomass (AGB) estimation because it can easily be measured with high accuracy, repetitively and generally follows commonly acknowledged forestry conventions (Husch et al., 2003). Nevertheless, the relationship between biomass and tree dimensions differs among species and may also be affected by site characteristics and climatic conditions (Eamus et al., 2000). Management practices also influence biomass production and allocation within trees in the landscape (Keith et al., 2000; Ong and Huxley, 1996). For example, variation in pruning and coppicing may affect the rate of biomass accumulation after cutting (Droppelman and Berlier, 2000) and pruning can change biomass without changing dbh. As such, allometric equations based on dbh can be refined by including height, wood density, or crown area to improve accuracy (Ketterings et al., 2001; Chave et al., 2005).

We hypothesized that (i) dbh alone is a reliable parameter for prediction of AGB in agricultural landscapes and (ii) inclusion of height, wood density or crown area in allometric equations will usefully improve model fit. The aim of this study was to: (i) develop a generic allometry covering the tree diversity of the 300 km^2 region in Western Kenya through empirical, destructive measurements, (ii) validate the equation developed and (iii) estimate AGB held in standing trees in the landscape evaluated. We compare our results to existing, commonly employed allometries. We provide a robust generic equation based on a range of species with variable structural characteristics influenced by different management practices and climatic conditions.

2. Materials and methods

2.1. Study area

The study was conducted in three 100 km^2 sites (Lower Yala, Middle Yala and Upper Yala) along the Yala River basin in Western Kenya with contrasting vegetative cover (Fig. 1). The River Yala catchment covers an area of 3351 km^2 and drains into the Winam Gulf in Lake Victoria. The Lower Yala site (latitude 0°1′12.33″S; longitude 34°28′19.62″E) in Siaya and Kisumu Districts, hosts large portions of woody grassland that have been converted to agriculture with little thicket and woody cover remaining. The Middle Yala site (latitude 0°7′51.57″N; longitude 34°49′13.01″E) is located in Vihiga and partly in Kakamega Districts. The site hosts the Kaimosi forest and part of Kakamega forest reserve. The Upper Yala site (0°17′27.14″N; longitude 35°20′14.60″E) is located in Uasin Gishu District, toward the source of River Yala. The area is mainly under maize production with smaller portions of wheat and few shrubs and trees in the landscape. *Markhamia lutea*, *Eucalyptus* spp. and *Acacia mearnsii* are the dominant species in Lower, Middle and Upper Yala sites respectively. Rainfall follows a bimodal distribution through the year. There is a rainfall gradient across the blocks with the Lower, Middle and Upper Yala sites of the basin receiving a mean annual rainfall of 1479 mm, 1950 mm, and 1028 mm, respectively. The mean annual temperature is 21.9 °C in Lower Yala, 20.5 °C in Middle Yala 16.7 °C in Upper Yala. Dominant soil types along the Yala basin include Acrisols, Ferralsols and Nitisols (Jaetzold and Schmidt, 1982). The soils are characterized by a good physical structure, well drained, deep with variable fertility.

2.2. Sampling design and selection of trees

The sites chosen were established in Western Kenya Integrated Ecosystem Management Project (WKIEMP; Boye et al.,

2008) and build on the Land Degradation Surveillance Framework developed within the Africa Soil Information System (AfSIS, www.africasoils.net). Each site consists of 10 km × 10 km blocks, each divided into 16 sub-blocks (clusters, 2.5 km × 2.5 km) with 10 plots in each cluster. Vagen et al. (2010) provide information on the sentinel site approach and the sampling design. For this study, three plots of 30 m × 30 m each were randomly selected in each sub-block for biomass sampling. Randomly selecting the plots eliminated the likelihood of convenience sampling and allowed to capture the representative mix of tree species in the area. Sixty percent of the measurements were collected in the Middle Yala, which has high tree density while the Lower and Upper Yala sites contributed 20% of the harvested trees each. Sampling biomass across the three blocks ensured that a wider range of species and trees of identical species along an altitudinal gradient was captured. All trees with dbh >2.5 cm within each plot were identified and measured. Trees were stratified by size into 6 diameter classes of <10; 10.1–20; 20.1–30; 30.1–40; 40.1–60 and >60 cm. In each diameter class, 12 individual trees were randomly selected for harvesting resulting in a total of 72 trees harvested. An additional 879 trees were non-destructively measured on a 30 m × 30 m plot per sampled site across all the three blocks for estimation of representative AGB in the area.

2.3. Measurements and biomass sampling

Diameter at breast height was measured over-bark using diameter tapes. Crown edge was identified using clinometers and the crown diameter measured twice with a 50 m measuring tape, the largest diameter and the diameter perpendicular to it. Crown area (m^2) was calculated using the formula for an ellipse. Wood density was determined by coring about 50% deep into the stem at 1.3 m using a carpenter's awl and 2.5 cm bit (the bark at the cored section was removed prior to coring). Wood chips were collected from the hole with a spatula and their fresh weight determined using a top pan electronic scale 300 ± 0.1 g (TSA series, Avery Berkel Ltd). Wood density was then determined as the ratio of dry weight of the cored material to volume of the core, where volume was calculated from the radius (r) and depth (h) of the core using the formula: $v = \pi \times r^2 \times h$.

Each destructively sampled tree was cut at the lowest point possible using a chain saw for larger trees (dbh >10 cm) and machete for smaller trees. Total tree height of felled trees was measured with a 50 m measuring tape. Felled trees were separated into stem (main trunk of the tree from the base to the top), branches (lateral wood arising from the stem together with twigs) and foliage (leaves). The stem and larger branches were sectioned into weighable pieces <300 kg and weighed on an electronic bench scale (AWD120 Avery weight-tronix Ltd, USA) in the field (± 0.1 kg). The weight of the portion converted to wood scrapings and saw dust during partitioning of the stem was calculated from volume of the chain saw gap multiplied by the wood density calculated from the cored material as described above. Branches were bundled together, while leaves were put in tared sacks and weighed in the field. Subsamples were taken for fresh weight determination using a 3000 g scale (± 0.1 g). One to two discs of a freshly felled tree, 2 cm thick, were taken around (i.e. just above and below) the dbh while three discs, 2 cm thick, were taken along the lower, middle and upper end of the branch to account for variation in wood density along the branch. About 100–150 g of leaf subsample was collected in tared sample bags. Subsamples were oven dried at 105 °C for 24 h as no further weight loss occurred beyond that point. However, subsamples that showed a slight decrease in weight were returned into the oven for a further 12 h after which no further changes in weight occurred. Component biomass was calculated by multiplying subsample dry/fresh weight ratio with component fresh weight.

Total AGB was obtained by adding up the biomass of all components.

2.4. Allometric equations

Raw data were screened for outliers in scatter plots that assisted also in visually assessing the relationships between dependent variables and independent variables. Aboveground biomass and the biomass of components (leaves, branches and stem) were regressed on dbh alone, and dbh in combination with height, wood density and/or crown area to obtain allometric coefficients for estimating biomass. A generalized linear model with gamma distribution and log link function was used to avoid the problem of back transformation (Ketterings et al., 2001). All regression analyses were done in Genstat 12th Edition (VSN International Ltd) while graphs were prepared in SigmaPlot version 11. Allometric power function equations, $y = ax^b$ and their linear equivalents, $\ln(y) = a + b \times \ln(x)$ where y is the dependent variable, x is the independent variable, and a the intercept coefficient, b the scaling exponent, were used to predict biomass from independent variables. The following allometric relationships were tested.

$$\ln(y) = a + b \times \ln(\text{dbh}) \tag{1}$$

$$\ln(y) = a + b \times \ln(\text{dbh}) + c \times \ln(H) \tag{2}$$

$$\ln(y) = a + b \times \ln(\text{dbh}) + c \times \ln(\rho) \tag{3}$$

$$\ln(y) = a + b \times \ln(\text{dbh}) + c \times \ln(ca) \tag{4}$$

$$\ln(y) = a + b \times \ln(\text{dbh}) + c \times \ln(\rho) + d \times \ln(ca) \tag{5}$$

$$\ln(y) = a + b \times \ln(\text{dbh}) + c \times \ln(H) + d \times \ln(\rho) \tag{6}$$

$$\ln(y) = a + b \times \ln(\text{dbh}) + c \times \ln(H) + d \times \ln(ca) \tag{7}$$

$$\ln(y) = a + b \times \ln(\text{dbh}) + c \times \ln(H) + d \times \ln(\rho) + e \times \ln(ca) \tag{8}$$

where dbh is the diameter at breast height, H is the height, ρ is the wood density and ca the crown area.

The equations were fitted by including $ln(\text{dbh})$, $ln(H)$, $ln(\rho)$ and $ln(ca)$ as separate predictors, so that they each can be attributed their own scaling parameter. This is because the identical scaling rule inhibited a detailed assessment of the effect of additional explanatory variables for equations fitted with compound derivatives of dbh, height, wood density and crown area; for example $ln(y) = a + b \times ln(\text{dbh}^2 \times H)$ or $ln(y) = a + b \times ln(\text{dbh}^2 \times H \times \rho)$. Equations were developed using a sample size of 66 trees (training set) and additional 6 trees for validation. One tree was randomly selected from each of the six diameter classes for the validation set, while the remaining trees were used to develop the equation. The process was repeated 12 times with different selections such that each tree in the sample was used once also for validation. This approach was adopted because the holdout sample of six trees was considered too small for validation to adequately allow assessment of bias and prediction error per class.

2.5. Bias and error of allometric equations

We assessed the fit of the models in terms of error and bias. Bias is an important statistic for landscape-level application as it (bias) will not cancel out when making predictions for many trees in a landscape. For models that consistently over- or under-estimate the biomass within a diameter class, the expected value of the relative error is not zero; however, if on average across all trees in a diameter class the model does not over- or under-estimate biomass, then there is no bias. The quality of the estimate was determined by assessing the difference between the estimate and the true value
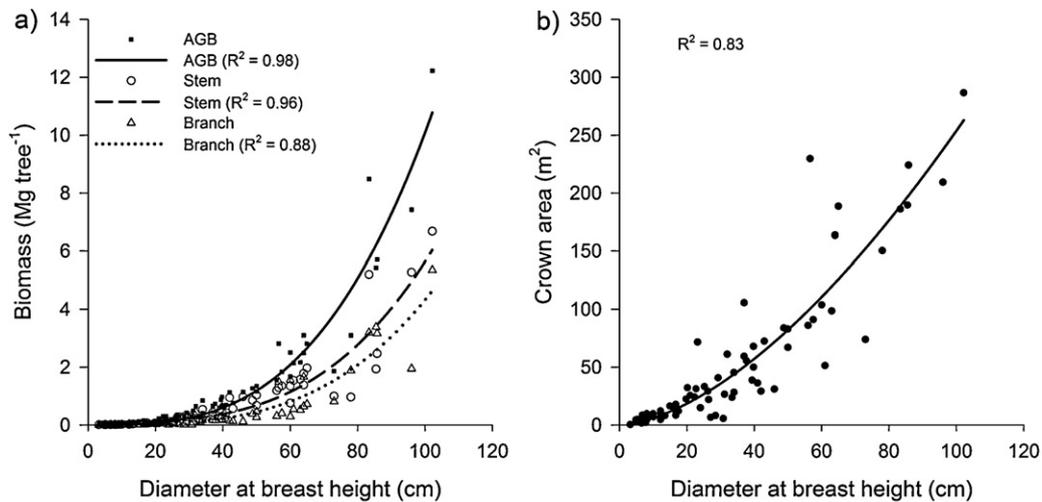
Fig. 2. Scatter plots showing: (a) the relationship between diameter at breast height (dbh) and the biomass of branches, stem and aboveground biomass (AGB), and (b) the relationship between diameter at breast height (dbh) and crown area. The description of corresponding equations for dbh is provided in Table 2.

and was expressed as a relative error as outlined by Chave et al. (2005):

$$\%\text{error} = \left(\frac{\text{AGB}_{\text{predicted}} - \text{AGB}_{\text{actual}}}{\text{AGB}_{\text{actual}}} \right) \times 100$$

When considering predictions for individual trees, the typical size of error is more important than the bias. This typical error of a single prediction was measured by root mean square error (rmse). Root mean square error helped to get the variability of bias, as zero bias might result when under- or over-estimates cancel out while predicting a lot of trees, but the prediction for an individual tree may be inaccurate. The coefficient of determination, determined as $R^2 = 1 - (\text{residual deviance}/\text{total deviance})$ from the general linear model fit and Akaike's Information Criterion (Akaike, 1981) were used to measure goodness of fit; however, bias and rmse were given much weight and used to compare and select the most suitable equation. The use of R^2 was limited to equations with a single explanatory variable while adjusted R^2 was used for models with two or more variables to reflect both the number of independent variables in the equation and the sample size.

The suitability of published equations commonly used for tropical forests and the equation of Henry et al. (2009) constructed from data collected in Western Kenya was also assessed. Equations developed in this study and selected published equations were used to estimate the biomass of 879 non-harvested trees measured in the landscape. Carbon concentration of biomass for individual harvested trees was determined by element analysis of representative samples from the stem. The 48% C concentration, biomass weighted average, was used to convert the calculated AGB into C (Mg C ha^{-1}). The standard error of the landscape level C per hectare was estimated from the plot-to-plot variation in estimated biomass.

3. Results

3.1. Distribution of dendrometric variables

Diameter at breast height was significantly correlated with AGB ($R^2 = 0.98$; $P < 0.001$) and stem biomass, $R^2 = 0.96$, $P < 0.001$ (Fig. 2a). The correlation between dbh and the biomass of branches ($R^2 = 0.88$) and leaves ($R^2 = 0.81$) was moderate but significant ($P < 0.001$). Similarly, there was a positive correlation between dbh and crown area (Fig. 2b: $R^2 = 0.83$, $P < 0.001$). The distribution for diameter, height and crown area was positively skewed with more

than half of all trees measured having dbh <10 cm while more than 75% of the crowns covered <15 m^2. The correlation between height and dbh ($R^2 = 0.57$) and height and biomass ($R^2 = 0.62$) was moderate for all trees from the three blocks evaluated; however, a highly significant correlation was observed between dbh and height for trees from the same block, Middle Yala ($R^2 = 0.73$) and Upper Yala ($R^2 = 0.84$) except the Lower Yala site ($R^2 = 0.50$). Variability in dbh and height relationship was greater in smaller trees (dbh <20 cm) for all three blocks ($R^2 = 0.38$ for Lower Yala, $R^2 = 0.42$ for Middle Yala and $R^2 = 0.04$ for Upper Yala) compared to larger trees ($R^2 = 0.61$ in Upper Yala and $R^2 = 0.62$ in Middle Yala); again, except for Lower Yala $R^2 = 0.11$. Trees in Lower Yala were generally short compared to those in Middle Yala and Upper Yala (Table 1).

Tree species that were dominant in harvested trees also occurred as the most frequent species in non-harvested trees measured across the three blocks evaluated. The most common species encountered were *M. lutea* (61.2%) in Lower Yala, *Eucalyptus* spp. (59.4%) in Middle Yala and *A. mearnsii* (62.8%) in Upper Yala. Wood density ranged from 0.28 g cm^{-3} in *Spathodea campanulata* to 0.78 g cm^{-3} in *Syzygium cordatum*. The overall median and mean ± standard error (SE) wood density for the sampled trees was 0.52 ± 0.02 g cm^{-3}. Whereas the mean wood densities between the three blocks were not significantly different (Lower Yala = 0.53 ± 0.03 g cm^{-3}, Middle Yala = 0.50 ± 0.02 g cm^{-3} and Upper Yala = 0.58 ± 0.03 g cm^{-3}), differences in mean wood density by tree size and species was statistically significant ($P < 0.001$). *A. mearnsii* and *Eucalyptus camaldulensis* (species dominant at altitude >1500 m) had high mean values (0.66 ± 0.03 g cm^{-3} and 0.55 ± 0.03 g cm^{-3} respectively) compared to *M. lutea* (0.41 ± 0.03 g cm^{-3}), a dominant species at 1200 m above sea level. A mean of 0.39 ± 0.03 g cm^{-3} was recorded for smaller trees (dbh <10 cm) compared to 0.61 ± 0.03 g cm^{-3} for larger trees (dbh >60 cm).

3.2. Accuracy of biomass estimation

Diameter at breast height predicted AGB of harvested trees with a small bias, 4.6%. Similarly high accuracy was observed in prediction of biomass for stem and branch components but not leaf biomass, which was overestimated (Table 2). Inclusion of wood density improved equation fit; crown area marginally improved the fit while height did not (Table 3). Although we present Eq. (1) as the most suitable and simple equation for estimating AGB in agricultural landscapes, we consider Eq. (3) as an alternative

Table 1
The range of plant characteristics measured for development of allometric equations (harvested) and for estimation of representative landscape biomass (non-harvested). Diameter at breast height (dbh), basal area (BA), height (H) and crown area (CA) was measured in the three sites evaluated. N describes the number of trees measured in each block while CV % and SE are the coefficient of variation and relative standard error, respectively.

Site	Category	N	dbh (cm)			BA (m² ha⁻¹)			H (m)			CA (m²)		
			Range	CV %	SE	Total	CV %	SE	Range	CV %	SE	Range	CV %	SE
Lower Yala	Harvested	16	3.2–78	74	5.78	0.7	128	0.04	4.2–15.4	41	1.00	0.4–150.2	98	10.29
	Non-harvested	152	2.3–55.6	89	0.81	1.1	198	0.00	3.3–16.8	36	0.22	0.2–95.5	145	1.27
Middle Yala	Harvested	38	5.3–102.2	69	4.09	2.3	121	0.03	6.6–44.5	52	1.83	2.2–286.5	125	11.35
	Non-harvested	650	2.5–89.5	98	0.39	4	284	0.00	2.4–45.6	59	0.23	0.9–272.5	175	0.72
Upper Yala	Harvested	18	6.6–85.8	72	5.99	1	126	0.04	5.8–24.7	45	1.50	1.5–229.6	108	18.16
	Non-harvested	48	2.7–68	88	1.56	1.1	206	0.01	3.8–22.5	46	0.46	0.6–186.5	140	3.70

Table 2
Regression equations for estimation of aboveground biomass and the biomass of the stem, branches and leaves. The allometric coefficients (a, b), standard error of the estimate (SE), coefficient of determination (R^2) and model bias (% error) are presented.

Component	a (SE)	b (SE)	R^2	% error
Eq. (1)	0.091 (0.131)	2.472 (0.039)	0.977	−4.63
Stem	0.059 (0.174)	2.442 (0.052)	0.960	−4.06
Branches	0.010 (0.351)	2.772 (0.104)	0.875	−1.55
Leaves	0.084 (0.282)	1.702 (0.084)	0.811	8.64

equation when additional explanatory variables such as height, wood density and crown area are available for use; mainly because Eq. (3) has lower AIC value, improved model fit and requires only two parameters.

Fig. 3 compares biomass estimation by Eq. (1), $AGB = 0.091 \times dbh^{2.472}$ to existing local and global equations. The equation of Chave et al. (2005) for dry forests, $AGB = \exp\{2.187 + 0.16 \times \ln(dbh^2 \times H \times \rho)\}$ underestimated biomass from 80 cm dbh while the equations of Brown (1997) for wet forests, $AGB = 21.297 - 6.53 \times dbh + 0.74 \times dbh^2$ and Henry et al. (2009) for Western Kenya, $AGB = 0.051 \times (dbh^2 \times H)^{0.930}$ underestimated biomass from 60 cm dbh. All equations showed patterns in bias across dbh classes (Fig. 4). Eq. (1) was the most optimal, comparing well with Chave et al. (2005) for dry forests. However, like most published models, Eq. (1) overestimated biomass for smaller trees (<20 cm) but was relatively consistent in biomass estimation across the dbh classes with a relative error of about 5%. Chave et al. (2005) equation for dry forest had a good spread of error across the dbh classes except for dbh <10 cm and dbh 60 cm which had relative error of 11% and 14%, respectively. The Brown (1997) equation for wet forest overestimated the biomass of trees with dbh >60 cm by an average of 12%, with greater errors encountered between dbh size 20–40 cm,
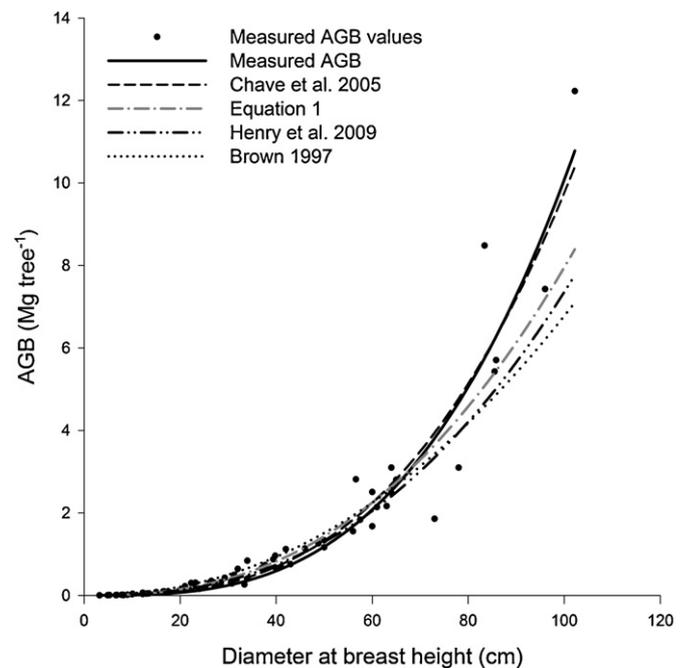

Fig. 3. Scatter plots of aboveground biomass (AGB) predicted by Eq. (1), $AGB = 0.091 \times dbh^{2.472}$ developed in this study, the equations of Chave et al. (2005) for dry forests $AGB = \exp\{2.187 + 0.16 \times \ln(dbh^2 \times H \times \rho)\}$; Brown (1997) for wet forests, $AGB = 21.297 - 6.53 \times dbh + 0.74 \times dbh^2$; and Henry et al. (2009) for agroforestry systems in Western Kenya, $AGB = 0.051 \times (dbh^2 \times H)^{0.930}$. A scatter of the actual AGB of the trees (measured AGB values) and its trend-line is plotted for comparison.

while it underestimated the biomass at dbh >60 cm by 16%. The pan-tropical equation by Chave et al. (2001) and the equation of Henry et al. (2009) had a total error of 15% and −11% respectively.

Table 3
Regression equations for estimating aboveground biomass using diameter at breast height (dbh) in combination with: height (Eq. (2)), wood density (Eq. (3)), crown area (Eq. (4)) and dbh in combination with height, wood density and/or crown area (Eqs. (5)–(8)) separately fitted in the model. The allometric coefficients (a, b, c, d), standard error of the estimate (SE), adjusted coefficient of determination (Adj. R^2), Akaike information criterion (AIC) and bias for each equation is given.

| Equation	a	b	c	d	e	Adj. R^2	AIC	% error
Eq. (2)	0.092	2.488	−0.028			0.977	99	−4.77
SE	0.149	0.065	0.089					
Eq. (3)	0.225	2.341	0.730			0.984	72	−5.26
SE	0.209	0.041	0.140					
Eq. (4)	0.107	2.318	0.101			0.979	95	−4.57
SE	0.161	0.098	0.059					
Eq. (5)	0.253	2.213	0.705	0.086		0.985	71	−5.06
SE	0.220	0.085	0.140	0.050				
Eq. (6)	0.221	2.301	0.062	0.755		0.984	73	−5.04
SE	0.211	0.064	0.076	0.143				
Eq. (7)	0.106	2.281	0.039	0.110		0.979	96	−4.46
SE	0.169	0.129	0.093	0.063				
Eq. (8)	0.319	2.097	0.119	0.743	0.112	0.985	70	20.34
SE	0.218	0.111	0.079	0.140	0.059			
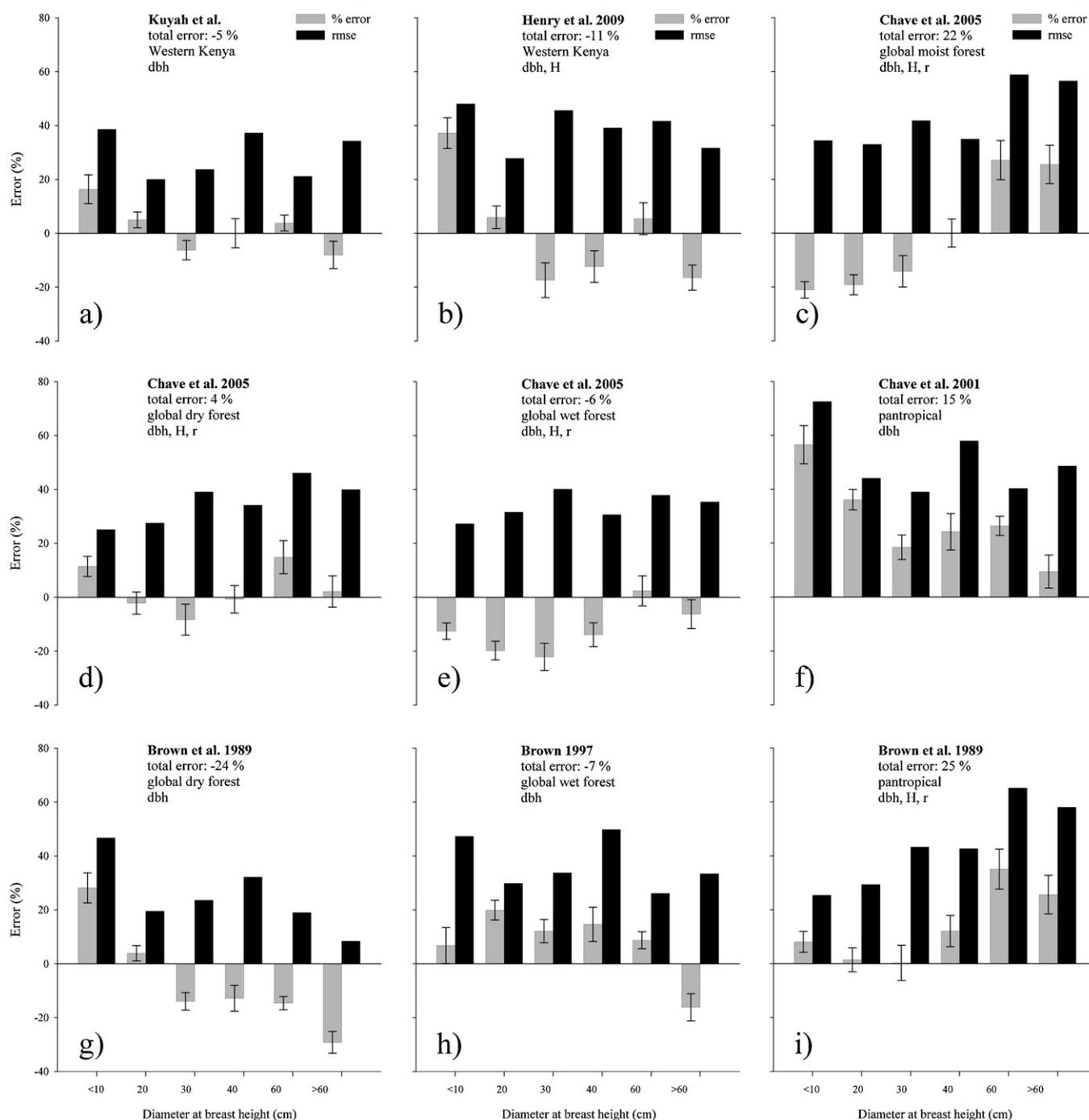
Fig. 4. Disaggregation of the relative error by tree size for Eq. (1) developed in this study (a) for application in agricultural landscapes, the equation of Henry et al. (2009) constructed from data collected from Western Kenya (b) and published equations recommended for tropical species (c–i). Parameters used as predictors are indicated as dbh for equations using diameter alone, dbh, *H* for equations using diameter and height, and dbh, *H*, ρ for equations using diameter in combination with height and wood density.

Additional globally renowned equations by Chave et al. (2005) for moist forests and Brown et al. (1989) pantropical equations overestimated by close to 25%. Other equations tested such as Djomo et al. (2010), Brown (1997) for moist forest, Brown et al. (1989) for moist forests and Chave et al. (2005) for moist forest had errors of >50% and are not shown. Root mean square error shows that the trend in prediction of single trees varied across size class for different equations (Fig. 4). For example, the equations of Brown et al. (1989) for pantropical forests gave poor estimates for larger trees while Brown et al. (1989) for dry forests gave better estimates for larger trees. The equation developed in this study

had about the same relative error across diameter classes which makes it superior to other tested equations.

3.3. Representative landscape biomass

The total AGB ± SE for harvested trees (basal area = 4 m^2 ha^{-1}) was 34.3 ± 0.16 Mg ha^{-1} with leaves, branches and trunks contributing 4, 39 and 57% respectively. Representative landscape AGB determined by Eq. (1) for the 789 non-harvested trees (basal area = 5.8 m^2 ha^{-1}) measured across the three sites evaluated was 36.2 ± 0.05 Mg ha^{-1}. Using the carbon concentration (48%)
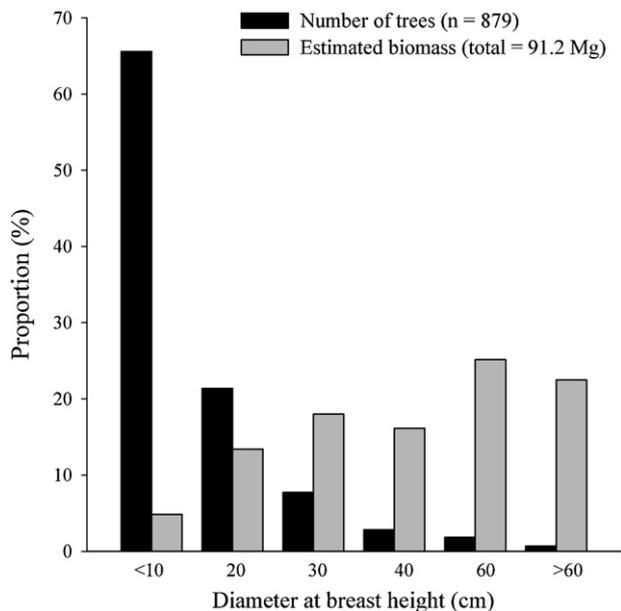
Fig. 5. Distribution of non-harvested trees measured per diameter class and their share of estimated biomass for the Yala basin in Western Kenya.

determined from analysis of C content of samples, trees in the landscape evaluated were estimated to hold about $17.4 \pm 0.02\,\text{Mg C ha}^{-1}$. Small trees, dbh <10 cm dominate the landscape (65.6%) though they accounted for only 4.8% of the estimated biomass (Fig. 5). In contrast, larger trees (dbh >40 cm) were very few (2.5%) but hold most of the biomass (47.6%). Estimated tree biomass for the 3 sites differed significantly ($P < 0.001$) with higher biomass estimated in Middle Yala (63%) compared to Upper (21%) and Lower (16%) blocks.

4. Discussion

Eq. (1) with dbh as the only explanatory variable provided a satisfactory estimation of biomass since the total variation explained by the relationship is high (R^2 >0.95) and the associated bias was small (<5%). The results indicate that dbh is a strong indicator of aboveground biomass, which implies that the variability of biomass of trees in agricultural landscapes is largely explained by the variability of dbh. This is neither surprising nor new. The importance of the results comes from assessment of how large the actual errors are, whether there is bias and how these depend on diameter, for the quality of landscape level measures will depend on this. Note also that the overall R^2 is as much a function of the diameter distribution of the sampled trees as of the fit of the model. The apparently small differences in the equations for small trees could add up to a large amount of carbon when looking at a landscape; this is an example of the bias problem. Our results agree with previous reports (Basuki et al., 2009; Zianis and Mencuccini, 2004; Brown et al., 1989) that dbh alone is a good predictor of biomass especially in terms of the multiple tradeoffs between accuracy, cost and practicability of measurements.

We found that including total tree height data did not substantially improve biomass predictions when compared to using dbh alone. These findings contrast with results from the Isthmus of Panama (Bastein-Henri et al., 2010), the humid lowlands of Costa Rica (Cole and Ewel, 2006) and Sumatra, Indonesia (Ketterings et al., 2001), which all report that height improves predictions. However, conclusions similar to our findings were drawn by Basuki et al. (2009) for Kalimantan, Indonesia, and by Nelson et al. (1999) for a mixed species equation in Brazilian Amazon. The weak relationship

between height and biomass may be attributed to the considerable variability in tree height of various species. It is also in line with the observation that trees of a particular species in a given location have a maximum height. The error associated with the equations of Chave et al. (2005) for global wet forests, $\ln(y) = a + b \times \ln(\text{dbh}^2 \times H)$ and $\ln(y) = a + b \times \ln(\text{dbh}^2 \times H \times \rho)$, supports our contention that height does not improve prediction in Western Kenya.

Our results show that wood density was affected by tree size. Smaller trees, dbh <10 had a low mean of $0.39\,\text{g cm}^{-3}$ while a high mean of $0.61\,\text{g cm}^{-3}$ was observed in larger trees, dbh >60. This observation is contrary to reports by Baker et al. (2004) and Basuki et al. (2009) who reported that increasing dbh is not followed by an increase in wood density. Similarly, wood density varied among species and within species but not between locations. This shows that wood density from a database could be used to improve precision of allometric equations rather than taking measurements for each location. Both mean and median wood densities ($0.52\,\text{g cm}^{-3}$) of tree species sampled varied considerably but were well within the range of tropical African forests ($0.3–0.9\,\text{g cm}^{-3}$; Brown, 1997). Our results also concur with previous reports that wood density data increases accuracy (Basuki et al., 2009; Chave et al., 2005). The effect of wood density can be demonstrated by comparing dbh, height, wood density and the biomass of larger trees: *S. cordatum* with dbh 83.4 cm, height 35.3 m and wood density $0.8\,\text{g cm}^{-3}$ had a total biomass of 8.5 Mg (actual biomass) compared to 7.4 Mg of *E. camaldulensis* with dbh 96 cm, height = 44.5 m and wood density $0.6\,\text{g cm}^{-3}$. Thus, although *S. cordatum* is shorter with a smaller dbh, the higher wood density results in a higher dry weight than *E. camaldulensis*.

The fairly significant correlation between dbh and crown area ($R^2 = 0.83$) corresponds to the relationship between crown area and AGB ($R^2 = 0.85$). Crown area marginally improved biomass prediction by dbh alone equations (Table 2). Since correlation between dbh and AGB is high, the addition of crown area is expected to only increase R^2 slightly. Difficulties or certain degrees of subjectivity associated with measuring crown area are frequently the reason for not including it as a parameter in equations. However, crown geometry in agricultural landscapes is highly heterogeneous due to interplant competition and management; hence incorporation of crown area would improve the accuracy of equations for trees in agricultural landscapes.

The relative error for Eq. (1) concurs closely with widely recognized global biomass equations, the wet forest equation of Brown (1997) and the dry forest equation of Chave et al. (2005). This indicates that most biomass equations are not necessarily site specific and may be applicable across broader conditions. However, mean annual rainfall and temperature for the study sites do not exactly match the criteria defining the forest type associated with the equation performing best, i.e. of dry forests by Chave et al. (2005) and wet forest by Brown et al. (1989). The average catchment rainfall can easily be interpreted as moist although the use of tropical moist forest equations of Chave et al. (2005) and Brown et al. (1989) would lead to a substantial overestimation of biomass compared to dry and wet forests equations by the same authors. This fact that a global tropical forest type classification does not seem to be intuitive underlines the importance of empirical validation as the choice of allometric equation has been reported to be the most important source of error in AGB estimation (Chave et al., 2004). The equations of Djomo et al. (2010), Brown (1997) for moist forest and Chave et al. (2005) for moist forest indicate the magnitude by which an equation can misjudge biomass when developed in one area and applied in another area without calibration. Using the published equations to predict landscape biomass for non-harvested trees, the equation of Henry et al. (2009) and Brown (1997) gave generous estimates of $36.1\,\text{Mg ha}^{-1}$ and $39.1\,\text{Mg ha}^{-1}$ respectively. These amounts are exaggerated although the two equations were

found to underestimate biomass by −11% and −7%. This discrepancy is explained by the disaggregation of the relative error by dbh class. Underrepresentation of larger diameter trees is a common problem in the development of allometric equations (Brown, 1997) which we overcame by sampling a consistent number of trees per dbh class. However, the landscape studied is dominated by small trees indicating a renewed effort in tree planting. The few larger trees account for most of the carbon stocks in the area, underlining the need to accurately estimate biomass for large trees.

5. Conclusion

Development of allometric equations applicable to agricultural landscapes is critical for accurate accounting of C stock for REDD++. Diameter at breast height was found to be a reliable proxy for estimation of AGB in complex agricultural landscapes of Western Kenya and its accuracy can be improved by adding data on wood density or crown area. The equations developed will be useful for programs assessing C stocks and storage potential by trees in agricultural landscapes. The equations are robust, derived from diverse species growing in a wide geographic range and influenced by management. Although the equations are generic, three species dominated the landscape, hence render these equations region or semi-species specific. Application of this equation to vegetation types with major differences in abiotic conditions may increase the error compared to our study. The equations presented need to be tested in other areas to determine their applicability across a wider range of agricultural landscapes.

Acknowledgements

Appendix.

See Table A.1.

Table A.1

Cross validation for Eq. (1). The average of the parameters from the twelve holdouts yields the equation, $AGB = 0.091 \times dbh^{2.472}$. Values of model coefficients (a and b), standard error of the estimate (SE), coefficient of determination (R^2) and model bias (% error) are presented.

Holdout	a	b	a (SE)	b (SE)	R^2	% error
1	0.081	2.497	0.129	0.038	0.985	−26.9
2	0.090	2.470	0.137	0.041	0.982	−4.1
3	0.089	2.478	0.134	0.040	0.983	−4.1
4	0.090	2.474	0.135	0.040	0.983	3.1
5	0.091	2.472	0.133	0.040	0.983	11.6
6	0.097	2.448	0.127	0.038	0.984	−34.9
7	0.095	2.458	0.135	0.040	0.983	−11.7
8	0.090	2.471	0.133	0.040	0.984	−13.5
9	0.096	2.455	0.123	0.037	0.986	−3.8
10	0.087	2.488	0.120	0.036	0.987	29.7
11	0.091	2.471	0.134	0.040	0.983	9.9
12	0.089	2.478	0.131	0.039	0.984	26.1

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