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Allometric models for estimating leaf biomass of sisal in a semi-arid environment in Kenya

Ilja Vuorinne [a,*], Janne Heiskanen [a,b], Marianne Maghenda [c], Lucas Mwangala [c], Petteri Muukkonen [a], Petri K.E. Pellikka [a]

[a] Department of Geosciences and Geography, University of Helsinki, Finland
[b] Institute for Atmospheric and Earth System Research, Faculty of Science, University of Helsinki, Finland
[c] School of Agricultural, Earth & Environmental Sciences, Taita Taveta University, Voi, Kenya

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ABSTRACT

Biomass is a key variable for crop monitoring and for assessing carbon stocks and bioenergy potential. This study aimed to develop an allometric model for predicting the dry leaf biomass of sisal, an agave plant with crassulacean acid metabolism grown for fibre production in the tropics and subtropics and whose biomass can be utilised as a feedstock to produce biogas through anaerobic digestion. The allometric model was used to estimate leaf biomass and productivity across different stand ages in a sisal plantation in semi-arid region in south-east Kenya (annual rainfall 611 mm and temperature 24.9 °C). Based on a sample of 38 leaves, the best predictor for biomass was leaf maximum width and plant height used as a combined variable in a log-log regression model (cross-validated R^2 = 0.96 and root-mean-square error = 7.69 g). The mean productivity in nine 26- to 36-month-old plots was 11.1 Mg ha^{-1} yr^{-1}, which could potentially yield approximately 3000 m^3 CH_4 ha^{-1} yr^{-1}. The leaf biomass in 55 field plots (400 m^2 in area) ranged from 2.7 to 42.7 Mg ha^{-1}, with mean at 13.5 Mg ha^{-1}, which equals to 6.3 Mg C ha^{-1}. The yielded allometric equations can be utilised for predicting the leaf biomass of sisal in similar agro-ecological zones. The estimates on plantation biomass can be used in assessing the role of sisal plantations as a regional carbon storage. In addition, the results provide reference on the productivity of agave and crassulacean acid metabolism in semi-arid regions of East Africa, where such reports are few.

1. Introduction

Sisal is a common name for the plant *Agave sisalana* and other varieties of *Agave* spp. (agave) grown in the tropics and subtropics for sisal fibre (or "sisal hemp") [1,2]. The largest producers of sisal are Brazil, Tanzania, Kenya, Madagascar, China, Haiti, and Mexico, where it is mostly cultivated in large commercial plantations [3]. Globally, the production was at its highest in the 1960s, until the introduction of synthetic fibres halved its demand. Recently, however, the demand for environmentally friendly natural fibres has seen a renewed increase [1,4]. In 1998–2018 the global annual production of sisal was 320 000 Mg on average, of which Kenya, the third largest producer, accounted for 23 000 Mg [3].

In Kenya, as well as in neighbouring Tanzania, the second largest producer of sisal, the economy is heavily reliant on agriculture, which provides most of the exports and employs majority of the workforce [5]. Sisal was introduced to East Africa in the early 20th century and although its production followed the decrease in demand after the 1960s, it remains an important cash crop for the area [5,6]. The global interest in environmentally friendly materials and the recent ban on plastic bags in Kenya indicate also a favourable future for both domestic and global demand [6,7]. The production processes, however, have mainly stayed the same since the crop was introduced to the area, and the opportunities to improve e.g. energy efficiency and residue utilisation have been acknowledged [5,8].

The main product from sisal is natural fibre extracted from its leaves and used globally in fibre industry [7]. Potentially, the plant could also be used in pharmaceutical and chemical industries [1,9]. The use of sisal and other agaves as a source of bioenergy has also gained attention recently, due the global need for sustainable and decentralised energy sources [10–13]. Furthermore, the good productivity and drought tolerance adaptions (such as crassulacean acid metabolism [CAM or CAM photosynthesis]) of agave species mean they can produce high yields in arid and semiarid environments [14]. This could create

* Corresponding author.
E-mail address: ilja.vuorinne@helsinki.fi (I. Vuorinne).

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opportunities to grow agaves for bioenergy production in marginal lands categorised unsuitable for agriculture and thus without competition from food production, but there is a lack of field studies in diverse geographical settings [15]. Due to their tolerance to heat and drought, some have also suggested that agaves and other CAM plants could help agriculture in semi-arid regions to adapt to warming and drying conditions [16,17] caused by climate change [18].

Reports on the biomass productivity of sisal are scarce, as such reports usually account only for the fibre yields [19]. The reported biomass productivities of other agaves range from 3.5 to 40 Mg ha^{-1} yr^{-1}, depending on the species and growing conditions [14,19–23]. Such yields are comparable to many bioenergy and food crops that use C3 or C4 photosynthesis [24], whereas CAM plants require 5- to 10-fold less water to produce the same amount of dry biomass [12,13,25]. The amount of ethanol produced from one Mg of dry agave biomass is up to 170 L [26,27]. Leaf residue from sisal fibre production has also been used as a feedstock to produce biogas through anaerobic digestion, with a yield of 0.3 m^3 CH_4/kg organic material [28,29]. With annual fibre production of 290 000 Mg globally (2009–2019 average) [3], there is a mostly unexploited potential in the sisal industry to utilize even the waste products of fibre production for bioenergy production, since the useable fibre comprises only approximately one third of the dry leaf biomass [5,30].

At present, no research has presented methods to non-destructively quantify the biomass of sisal. In agriculture, aboveground biomass (AGB) is a central parameter for monitoring crop growth and yield, and for estimating bioenergy potential and carbon stocks [28–31]. At the field level, allometric models that predict the mass of a plant from other dimensions, for instance diameter and height, are a convenient non-destructive method to predict biomass [35,36]. These dimensional relationships can be utilised for biomass prediction, since due to the similarity in individual ontogenetic development, the proportions between plant structure and mass are similar for certain plants growing under same conditions. These relationships can be determined by modelling biomass as a response variable and one or several plant dimensions as explanatory variables [37]. While the standard approach has been linear regression, non-linear methods have also been tested. Widely used predictors in allometric equations for both tropical and boreal trees are stem diameter and height [35,36,38], and for herbs and shrubs, stem and foliage diameter [39,40]. Allometric models based on stem diameter and length have also been developed for food and energy crops, such as soybean and perennial grasses [34,41]. The comparison of the established allometric equations have shown that accurate predictions require models that are specific to species or plant functional type [40,42]. Once the allometric relationships are formulated into equations, they provide a practical tool for predicting biomass [34]. On the whole, allometry advances our understanding of plant growth and structure and how plants allocate resources in response to environmental factors [43].

In this study, the allometric relationships of sisal leaves were examined in a semi-arid region in Kenya with the following objectives: (1) to formulate allometric models for predicting sisal leaf biomass, (2) to utilize the best model by assessing the biomass at different growing stages across a sisal plantation, and (3) to assess annual sisal biomass productivity. To clarify the role of sisal plantations in the regional aboveground carbon storage, the sisal biomass estimates were also compared to those of other land use and land cover types in the area.

2. Material and methods

2.1. Study area

The study was conducted next to the town of Mwatate at the 8850-ha Teita Sisal Estate (3°30′ S, 38°24′ E, 750-900 m.a.s.l), in Taita-Taveta County in the Coast Province of Kenya (Fig. 1). The Estate is one of the largest sisal plantations in the world and it is largest in Africa [6].

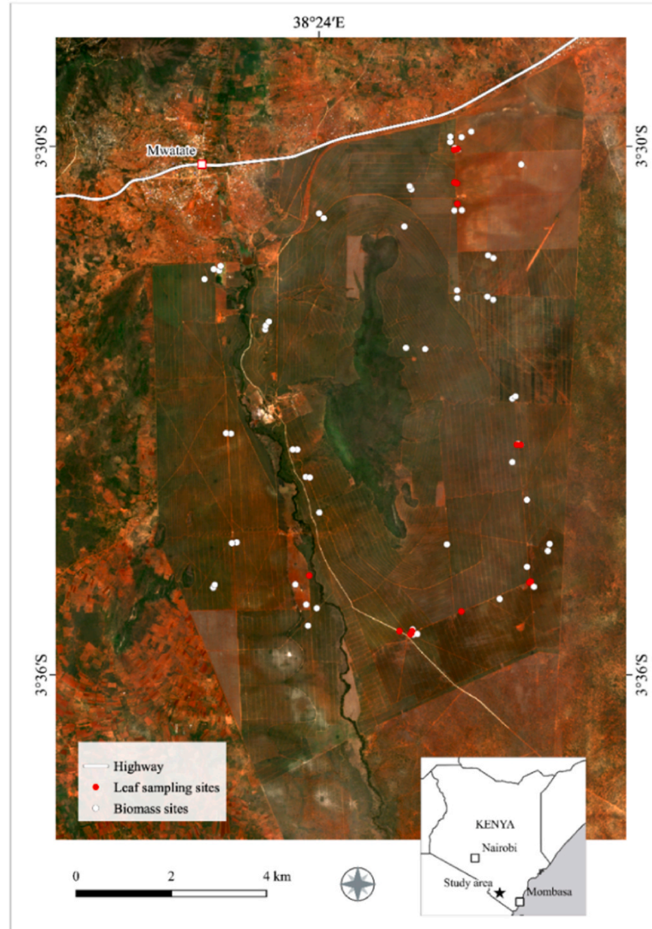

Fig. 1. Map of the study area in Taita Taveta, Kenya, with the leaf sampling sites and biomass assessment plots. European Space Agency's Sentinel-2 true color satellite image from 16 April 2019 as a basemap. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

The climate in the area is semi-arid. Two rainy seasons occur in March-June and October–December [44]. The long-term annual mean precipitation is 611 mm and temperature is 24.9 °C. Typical vegetation in the nearby lowland areas consists of bushlands, grasslands, thickets and riverine forests [45–47]. Farming is mostly small-scale, favouring seasonal crops such as maize, beans and cassava. Soil type (Ferralsols) is characterized by deep, acidic, dark red, sandy clay soil [46].

2.2. Description of sisal and its cultivation

Sisal is a perennial succulent with a lifespan of around 15 years [2]. Its morphology, like other agaves, is characterised by a rosette of leaves that forms around its stem [2,23]. New leaves unfold from a central spike in the middle of the rosette until the flowering stage begins. Sisal fibre is decorticated from the leaves, which also contain most of the plant's biomass (approximately 85% of agave AGB is in the leaves) [22,48]. The composition of the leaf is approximately 87.25% moisture, 4% fibre, and 8.75% other dry matter [49]. The carbon (C) content of leaf dry matter is generally 47% [50]. Leaf harvest begins at the age of 2–4 years when the oldest leaves, lowermost in the rosette, are cut manually. Leaves are harvested regularly up to approximately 15 years, when the plant grows a long flower stalk that is also harvested and can be used as a construction material [2]. The remaining plant is a leftover stump (also referred to as sisal ball), which consists of a stem, fragments of leaf bases, and the base of a flower stalk. The stump is traditionally used as a manure by burning and ploughing it when the field is prepared for a new rotation [5].

The two sisal cultivars primarily cultivated at the plantation are *Agave sisalana* 'Hildana' and *Agave* 'Hybrid 11648' (E. Mrombo, personal communication, 19 June 2019). The plant population density at the estate is 4995 plants per hectare. Plants are propagated vegetatively from bulbils or rhizomes of mature plants. The rhizomes are planted directly in the field, whereas the bulbils are kept in nurseries and subsequently planted in the field. Before planting, the fields are cleared and ploughed and around 40 t ha^{-1} of sisal waste (residue from the fibre production) is applied as a fertiliser. The crop is then planted in double rows, with a 3.75 m spacing between double rows, 0.7 m between single rows and 0.9 m between the plants. All the fields are rainfed and the management for subsequent years includes clearing of rhizomes and bushes and weed control with herbicides and mowing. Grazing (mainly cattle and goats) is also practiced all over the estate and occasionally wildlife such as elephants, giraffes, monkeys and zebras roam into the fields. The management is more intense in the younger fields and the older fields receive less attention and have a varying amount of weeds and bushes growing among sisal.

2.3. Leaf sampling

A sample of 38 leaves was harvested in August 2019 for development of allometric models for predicting leaf biomass a (Fig. 2A.). A sample of 30–50 individuals is a recommended minimum for species specific models for trees [38,40] and have been used for crops [34], which was used as a guidance to determine the sample size. Furthermore, stratified sampling is a recommended approach to increase the precision of modelling and to explore the variability in a study area [38]. Therefore, different aged field blocks were chosen for sampling to observe the whole range of plant sizes (Fig. 1). The fields were chosen based on satellite image data and prior knowledge of the planting year. The proximity of roads were avoided and the leaves were sampled from subjectively chosen representative plants in the selected field blocks. The heights of the plants were measured from topsoil to the central spike. All leaves were harvested from different plants approximately from the same position in the mid-canopy. The sample included sisal cultivars *Agave sisalana* 'Hildana' (n = 8) and *Agave* 'Hybrid 11648' (n = 30). The amounts represent roughly the prevalence of theses cultivars at the plantation.

Fig. 2. (A) The sampled leaves before they were subsampled and dried. (B) Sub-sampling procedure for leaf drying. The four 5 cm subsamples were cut and dried in the oven to determine the dry weight.

The measuring and drying of the leaves was done in a laboratory at the Taita Taveta University, Kenya. Some of the leaves were weighed immediately after they were cut and again at the laboratory to confirm that the leaves had not lost any weight via evaporation during transport. At the laboratory, all the leaves were cut along the narrowest width at the base to standardise the location of the cut before measurements. First, the leaves were weighed with a table scale (KERN PLE 4200-2 N, d = 0.01g) and measured for maximum width and length, both along the upper leaf surface. Then, to fit all samples into the oven (MEMMERT UF 450 PLUS), the leaves were subsampled. Subsampling was performed by dividing each leaf into four parts of equal length and by taking 5-cm samples from the middle of these parts (Fig. 2B). These leaf bits constituted the subsamples that were placed on dishes, weighed and put into the oven at 70 °C. A few of the samples were then weighed once a day until after 72 h a constant weight was reached and all samples were then measured for dry weight. Then, the dry weight to fresh weight ratio was calculated for every subsample and used to calculate the dry weights of the whole leaves.

2.4. Leaf modelling

To formalise the relationship between leaf mass and the other dimensions linear regression was used. This is a suggested approach when the aim of the allometric modelling is prediction [37]. Nine models were fitted in RStudio integrated development environment (version 1.2.5019) for R using the lm function and least squares method [51,52]. Dry leaf biomass (B, g) was used as a response variable and leaf length (L, cm), leaf maximum width (W, cm), and plant height (H, cm) were used as explanatory variables. Combining plant dimensions is commonly used in allometric modelling to enhance the prediction accuracy [38]. Hence, combined leaf variables ($L \times H$, W^2L, and W^2H) were also tested as predictors. Models were fitted both without transformation and with natural log-transformation for the response and explanatory variables. Such procedure can render the modelled relationship linear and tweak the error structure of the model to meet the assumptions of linear regression [38]. This is common approach for allometric models, because they often have a multiplicative error structure. Accordingly, the models were fitted as

$$B = \beta_o + \beta_1 X + \varepsilon \tag{1}$$

and the log-log linear models as

$$\log(B) = \beta_o + \beta_1 \log(X) + \varepsilon \tag{2}$$

where B is the response variable, X is the explanatory variable, β_o is the intercept of the regression line, β_1 is its slope, and ε is the error term.

The assumptions of linear regression (linearity, homoskedasticity, independence, normality) were tested in RStudio using gvlma-package [53]. Gvlma is a package for validating all the four assumptions of a linear model at once [53]. In addition, the models were cross-validated by the leave-one-out method [54] and by calculating the root mean square error (RMSE) and coefficient of determination (R^2) between the predictions and observations. In the leave-one-out cross validation, the model is trained with all the other observations expect one that is left aside to be used as a validation set. Then the process is repeated until all observations have been used for validation, which results in a prediction size equal to the sample size. RMSE was calculated as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \widehat{y}_i)}{n}} \tag{3}$$

where y is the observed value, $\widehat{y}$ is the predicted value, and n is the number of observations. R^2 was calculated as

$$R^2 = \sqrt{\frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2}} \tag{4}$$

where y is the predicted value of y and $\bar{y}$ is the mean value of y. Before the RMSE and R^2 were calculated for the log-log models, bias correction recommended by Baskerville [55] was used to transform the predicted values back original scale. This correction factor (CF) was calculated as

$$CF = (SE/2)^2 \tag{5}$$

where SE is the standard error of the regression.

2.5. Assessing biomass and productivity for the field plots

To assess the biomass at different stand ages, 55 field plots were measured in the study area between 22 and 29 August 2019. The field blocks were chosen subjectively all over the estate based on their age to observer the range of plant sizes (Fig. 1 and Fig. 3A–C). The 400 m^2 square-shaped plots were oriented with two opposite sides parallel to the crop rows, so that four double rows were inside the plot. Homogeneity inside the plot was preferred and proximity to roads was avoided when the plot locations were chosen.

Inside the plot, the number of the plants in the two midmost double-rows was counted and multiplied by 2 to assess the total number of the plants. Then plant height, number of leaves, and leaf length and maximum width were measured from one subjectively determined representative plant in both of the midmost rows. Measurements were performed the same way as in the leaf sampling (chapter 2.3). To constitute representative plot-specific plant metrics, the measurements from the two plants were averaged. If a notable variance in plant sizes was visually observed, the plants were divided into two size-class categories, which were measured separately. If the plots had rhizomes growing on the ground they were also measured if they were greater than 50 cm.

Plot biomass prediction was done in RStudio with the best performing allometric model. First, the biomass of representative leaf was predicted using plot-specific plant metrics (H and W) (details of model selection given in 4.1 below). The biomass of the leaf was multiplied the number of leaves in the plant and by the number of the plants in the plot to assess the total leaf biomass. Carbon stored in the leaf biomass was calculated assuming 47% carbon content [50].

The biomass productivity was estimated based on the plots where harvesting had not yet begun and thus the plants were intact. Plots younger than 1 year were also excluded as the exact date of planting was not available, and hence, estimation of productivity was considered uncertain for a short period. The cultivar at the remaining plots ($n = 9$) was *Agave* 'Hybrid 11648' and the age ranged from 26 to 36 months. Productivity (Mg ha^{-1} yr^{-1}) was assessed by annualising the predicted biomass at each of these plots.

3. Results

3.1. Leaf biomass and allometric models

A summary of the observed leaf and plant variables is shown in Table 1. The fresh weight of the leaves ranged from 7.0 to 839.2 g, while the dry weight ranged from 0.9 to 159.0 g. Leaf length ranged from 12.5 to 32.5 cm, maximum width 5.2–28.4 cm, and plant height 19–250 cm. The sample included plants aged <1–14 years. The water content of the leaves varied from 76% to 87% and showed a clear decreasing trend with plant age (Fig. 4).

Visualisation of the leaf variables showed that the non-transformed metrics had a non-linear relation to dry biomass, all with non-constant variance (Fig. 5A–C). Log transformation of the variables rendered the relations linear and variances close to constant (Fig. 5D–I).

All the tested models were significant ($p < 0.001$). Overall, the log-log models had better fit and validation metrics than the ones without transformations (Table 2). Furthermore, the log-log models with combined predictors (models 7–9) performed better than the log-log models with a single dimension as predictor (models 4–6). The model fit was almost the same for all the log-log models, but the validation metrics revealed some differences in prediction accuracy. Based on these differences, the best single dimension for predicting the mass was W (model 4), while the best combined predictor was W^2H (model 9). In particular, the best model (model 9) was set apart from the rest by the validation metrics. The tests for the assumptions of linear model showed that the models with non-transformed variables (models 1–3) and one of the log-log models (model 6) violated at least one of the assumptions, whereas the assumptions were suitably met for all the other models.

3.2. Field plot biomass and productivity

Leaf biomass for the field plots was predicted using the best performing model (model 9). Biomass ranged from 2.9 to 42.7 Mg ha^{-1} (mean 13.5 Mg ha^{-1} (Table 3). Stand age and harvesting status primarily controlled the biomass (Fig. 6). However, biomass did not increase linearly with age. During the first years after planting, biomass increased rapidly and reached maximum in 3–4 years. At this age, periodic leaf harvesting begins, which decreases the biomass and keeps it stable for the remainder of the plant's lifecycle. The observed productivities over 26–36 months ranged from 9.0 to 14.3 Mg ha^{-1} yr^{-1} (mean productivity 11.2 Mg ha^{-1} yr^{-1}). At the time, the unharvested 26 to 36-year-old plants had 84 to 150 unfolded leaves and 5.1–9.5 kg of leaf biomass, while all the observed plants had 23 to 150 unfolded leaves and 0.1–9.5 kg of leaf biomass.

4. Discussion

The relationships between plant structure and mass are an effective way to predict biomass once these relationships have been established [35,36]. The aim of this study was to build an allometric model for predicting the leaf biomass of sisal. We found that leaf length, maximum width, and plant height were all strongly related to biomass. A strong

Fig. 3. (A) Less than one-year-old stand, where the leaves had not yet been harvested. (B) Three-year-old stand, where the leaves had not yet been harvested. (C) 13-year-old stand at the end of the flowering stage, where the leaves had been harvested several times.

Table 1
Statistical summary of the measured leaves (n = 38). DW = dry weight, FW = fresh weight.

	Fresh weight (g)	Dry weight (g)	DW [% FW]	Length (cm)	Maximum width (cm)	Plant height (cm)	Plant age (years)
Minimum	7.0	0.9	12	12.5	2.5	19.0	<1
1st. Quantile	111.7	21.5	15	57.2	7.7	84.4	2
Median	272.3	53.8	17	81.2	9.9	140.0	8
Mean	330.8	56.3	17	79.2	9.6	139.1	7
3rd. Quantile	503.9	89.5	19	105.8	11.6	189.3	13
Maximum	839.2	159.0	24	132.5	13.9	250.0	14

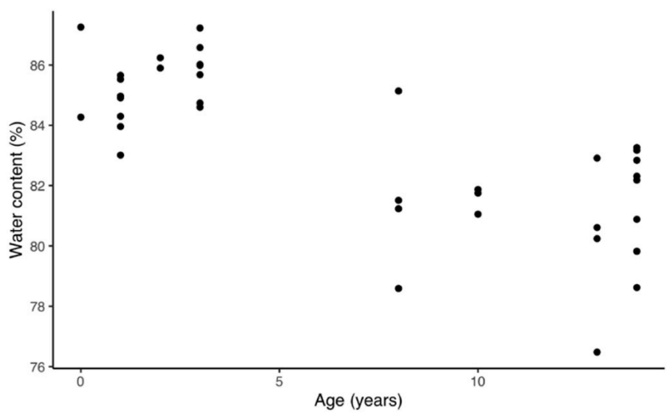

Fig. 4. The relationship of plant age and leaf water content.

linear log-log dependency was observed when the variables were combined and log-transformed. These relationships, which were stable for the whole range of the observed plant sizes, can be expressed with exponential allometric equations that can accurately predict leaf biomass. Potentially, they can be applied also to predict chemical compounds, such as sugars, when the chemical composition of the leaves is known [9,48]. Similar relationships linking combined variables and biomass have been observed for e.g. tropical trees [35]. For crops, combined variables are not commonly used, but linear log-log relationships between length and mass have been observed for soybean and tropical perennial grasses [34,41].

The best prediction accuracy was achieved when the plant height was combined with the maximum leaf width. Plant height was measured from ground to the central spike in the middle of the rosette, while leaf length was measured after the leaves had been cut along the narrowest width at the leaf base. This might have lead in minor inconsistencies, if the leaves were not cut at constant location along the leaf axis due to structural variation or difficulty of cutting leaves from the same position. This could explain why the use of plant height resulted in slightly more accurate predictions. On the other hand, the differences among the best models were minimal and could also be explained by natural variation. Nonetheless, the result showed that the best accuracies could be achieved by combining plant height and leaf maximum width as a log-log model. Leaf length and width, or plant height and leaf length could also be used, but this appeared to lead to slightly lower prediction accuracy. Log-log models with width or length as a single predictor were also observed to be satisfactory. While the advantage of these models is simplicity as they use only one dimension as a predictor, some accuracy is lost compared with the combined predictors.

The allometric models were formulated only for the leaves and to use these models to assess the total leaf biomass of a plant the leaves must be counted. Obviously, a model for the whole plant could be more practical and would also include stem biomass, which accounts for approximately 15% of the aboveground biomass [56,57]. However, leaves are the part of the plant that is harvested, although the whole plant could be utilised as bioenergy [5]. Furthermore, allometric equations for a whole plant are generally developed and used for intact plants [57]. The development of such model would have been problematic in this study setting, because harvesting of leaves alters the structure of the plant (e.g. diameter). However, accounting only for the leaves omits some parts of plant, mainly the stem. When the leaves were cut, also a small part leaf base was omitted. These omitted plant part, the stem and the remaining bits of leaves, is known as sisal ball. The dry weight of a mature sisal ball is approximately 5.8 kg [5]. Thus, in a mature field this would add up to 2.90 Mg/ha to the estimated biomass. Sisal balls are traditionally burned and used as manure when the field is prepared for the next rotation, but they could be used as a feedstock for bioenergy production. Future research should therefore be conducted to quantify their biomass and the biomass of the flower stalk. Furthermore, assessing the biomass of the root system would also be important from a soil carbon sequestration perspective [58,59].

The transferability of allometric models can be affected by growing conditions [43]. For crops, one such factor is management practices [60]. Leaf samples for the models had received roughly the same amount of fertilising (sisal waste), and therefore the impact of different fertilising practices was not evaluated in this study. Regional transferability is also worth noting, as climatic variables such as rainfall can affect allometric relationships [34]. On the other hand, Paul et al. [42] have argued in favour of models based on plant functional type and shown that they can be used instead of site-specific models to predict AGB across ecoregions. However, since sisal is grown in regions with varying climate and soil types [3] and regional transferability of the models should be investigated.

There was large variation in the observed biomass at the field plots, but the mean value was most likely stable at the plantation level, considering the long lifecycle of sisal and assuming the production rate remains steady. AGB and C storage at the plantation are therefore close to shrubland (5.5 Mg ha^{-1} woody AGB) and thicket (12.7 Mg ha^{-1} woody AGB) [45], which together constitute the so-called *Acacia-Commiphora* bushland, that is considered closest to a natural vegetation type in nearby (lowland) areas [61]. The woody AGB and C in the annual croplands are also lower (4.9 Mg ha^{-1}). Another study from the area reported 9 Mg ha^{-1} mean AGB for bushland, 5.8 Mg ha^{-1} for cropland, and 1.8 Mg/ha for grassland [62]. Higher mean AGB than at the plantation was found only from riverine forests (75.5 Mg ha^{-1}). Although these results revealed the C stored in the leaf biomass in a large-scale sisal plantation in Kenya, future research should quantify soil carbon sequestration [33] and plant carbon fluxes [46], for a comprehensive understanding of the carbon cycle at sisal plantations. So far only the soil CO_2 fluxes at a sisal plantation have been studied [6].

The observed biomass productivity of sisal was greater than previously observed for *A. Lechuguilla* (3.5 Mg ha^{-1} yr^{-1}) growing in natural environment in Mexico [32]. For cultivated agaves, such as *A. tequilana* (24.9 Mg ha^{-1} yr^{-1}) [56], *A. mapisaga*, and *A. salmiana* (40 Mg ha^{-1} yr^{-1}) [14], much higher productivities have been observed in Mexico. The observed productivity for another fibre yielding agave *A. fourcroyde* (Henequen) in Mexico is also slightly higher (16 Mg ha^{-1} yr^{-1}) [23]. In a field trial as bioenergy feedstock in southern US, a similar productivity to that observed here was noted by Davis et al. [31] for *A. americana* (9.3 Mg ha^{-1} yr^{-1}). These productivities were observed for whole plants, whereas here only the leaf productivity was assessed. Thus, based on the structural distribution of dry matter [56], the total productivity of

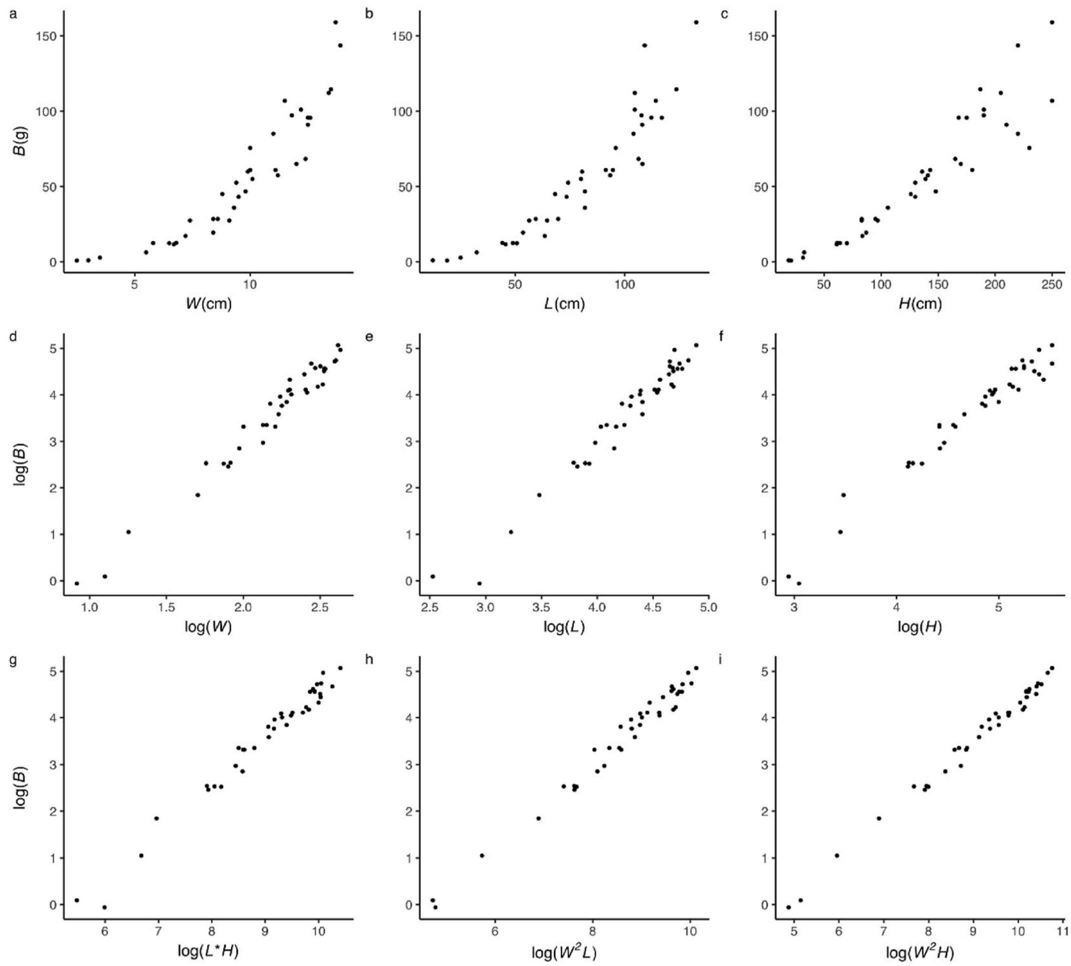

Fig. 5. The relationship between dry leaf biomass and leaf and plant dimensions. B = biomass (g). W = leaf maximum width (cm). L = leaf length (cm). H = plant height (cm).

Table 2
Allometric models for predicting sisal leaf biomass and validation metrics for these models.

		Coefficients			Cross-validation metrics		
id	Model	c	a	R^2	RMSE	MAE	R^2
1	$B = c + a\,W$	−62.26 ± 9.78	12.46 ± 0.99	0.81	19.19	14.60	0.78
2	$B = c + a\,L$	−41.56 ± 7.42	1.23 ± 0.09	0.84	17.09	12.21	0.82
3	$B = c + a\,H$	−22.25 ± 5.73	0.58 ± 0.04	0.86	16.07	12.05	0.84
4	$\log(B) = c + a \log(W)$	−2.96 ± 0.20	2.99 ± 0.09	0.96	12.74	9.29	0.90
5	$\log(B) = c + a \log(L)$	−6.24 ± 0.32	2.30 ± 0.07	0.96	13.31	8.79	0.89
6	$\log(B) = c + a \log(H)$	−5.12 ± 0.28	1.84 ± 0.05	0.96	17.18	10.83	0.84
7	$\log(B) = c + a \log(L{*}H)$	−5.74 ± 0.24	1.03 ± 0.03	0.98	11.51	8.01	0.92
8	$\log(B) = c + a \log(W^2L)$	−4.37 ± 0.19	0.92 ± 0.02	0.98	11.49	8.70	0.92
9	$\log(B) = c + a \log(W^2H)$	−4.11 ± 0.13	0.84 ± 0.14	0.99	7.38	5.27	0.97

B = biomass (g). W = leaf maximum width (cm). L = leaf length (cm). H = plant height (cm). R^2 = coefficient of determination. RMSE = root mean squared error (g). MAE = mean absolute error (g).

Table 3
Summary of the field plots. Stand age, number of leaves per plant, dry leaf biomass (B), leaf carbon (C), productivity, and their estimates.

	Min.	1st. Quantile	Median	Mean	3rd. Quantile	Max.
Stand age (years)	>1	3	7	7.5	13	17
B (Mg ha^{-1})	2.9	6.5	10.5	13.5	18.5	42.7
C (Mg ha^{-1})	1.4	3.1	4.9	6.3	8.7	20
B per plant (kg)	0.6	1.8	3.0	3.5	4.8	9.5
Leaves per plant	26	51	64	70	84	150
Productivity (Mg ha^{-1} yr^{-1})	9.0	10.6	11.3	11.2	11.9	14.2

the observed stands is likely to be approximately 15% higher. On the other hand, some of the stands were grown from bulbils that were kept in a nursery before planting, which may have resulted in overestimation of productivity.

Biomass productivities of trees and shrubs in a rehabilitated area in central Kenya measured over a 5-year period by Rosenschein et al. [63] provide a reference for native and introduced woody plants in a similar semi-arid environment. In Kenya, woody biomass provides most of the energy consumption for rural households [64]. The average productivity of the standing biomass (1.8 Mg ha^{-1} yr^{-1}) and the productivities of most of the tree and shrub species were lower than what was observed for sisal. The greatest productivities observed for introduced *Prosopis* spp. (11.5 Mg ha^{-1} yr^{-1}, with assumed spacing of 1000 trees per ha) were the same as the mean productivity observed for sisal. Similar

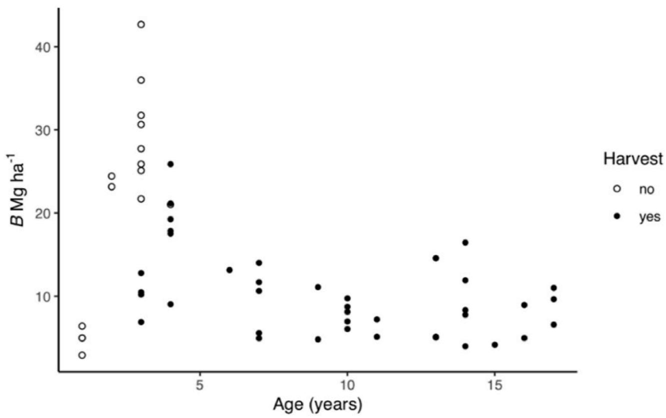

Fig. 6. Dry leaf biomass (B) against stand age. Colouring shows if the harvesting of the leaves had begun.

productivities have also been reported in Kenya for certain introduced shrub species (*Leucaena leucocephala* and *Senna siame*) [65]. Currently, there are not many CAM productivity reports from East Africa, but high productivities (7.5–24.5 Mg ha^{-1} yr^{-1}) were recently reported for two CAM plants, *Opuntia ficus-indica* and *Euphorbia tirucalli*, in a field trial for bioenergy production in Kenya [66]. At the same planting density, the productivity of these plants was comparable to sisal. However, when the density was substantially increased, the productivity also exceeded what was observed here.

Borland et al. [17] have proposed that CAM plants such as agaves should be considered for bioenergy production in the Global South as a means of stimulating sustainable economic growth. Their advantage is high water use efficiency, which allows them to be cultivated in marginal lands to avoid competition with food production [67]. Based on earlier studies on biofuel production from agaves [26] the estimated leaf biomass productivity for sisal would yield 1920 L of ethanol ha^{-1} yr^{-1} if all the leaves are harvested at once (plus additional yield from other plant parts). This corresponds to 3024 m^3 CH_4 ha^{-1} yr^{-1} through anaerobic digestion (assuming 90% of the plant material is organic) [28]. These estimates show the bioenergy potential of sisal if the plant is used for energy production only. Therefore, they are not directly translatable into energy potential in the current sisal fibre industry since the productivity does not equal to yield due to the periodic leaf harvesting and because some of the plant material is extracted for fibre production. There are, however, earlier assessments of the energy potential of sisal residues in Tanzania [5]. Although a lifecycle assessment by Broeren et al. [4] has shown that the energy use and greenhouse gas emissions from sisal fibre production are 75%–95% lower than from glass fibre production, the methane emissions from the residue disposal is a weak link in the sustainability of sisal fibre manufacturing. Producing biogas from the residues of existing sisal plantations would not cause land use to change and could also reduce the use of less sustainable energy sources [4]. Due to the fluctuating demand for sisal fibre [3], there are also abandoned plantations that could potentially be utilised for bioenergy production, which could reduce the pressure on natural ecosystems. For example, in Kenya, where fuelwood supplies most of the energy consumption in rural areas, the demand for energy is a driver of deforestation and land degradation [45,64]. However, to assess the potential of cultivating agaves and other CAM plants for bioenergy production in Kenya, system-level analyses are needed [68]. In addition to productivity, such analyses account for viability, economic consequences, and environmental impacts of agricultural production.

5. Conclusions

Sisal leaf biomass has a strong log-log linear relation to the other leaf and plant dimensions. Hence, the allometric equations described here can be used to predict the leaf biomass of sisal in similar agro-ecological zones to estimate productivity, carbon stocks and bioenergy potential. In this study, it was estimated that the mean carbon stock of leaf biomass at a large scale sisal plantation (6.3 C Mg ha-1) was close to aboveground carbon stock of thicket and bushland, which are the natural land cover types in the semi-arid study region in Kenya. The estimated productivity of sisal leaves (11.2 Mg ha^{-1} yr^{-1}) could potentially yield approximately 3000 m^3 CH_4 ha^{-1} yr^{-1} if used for biogas production. Further study is required on the allometry of the other plant parts, and on the impact of abiotic factors and management practices on the leaf allometry.

Data availability

Data openly available in (figshare repository will be publishes): https://figshare.com/articles/dataset/sisa_leaf_biomass_measurements/16834291.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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