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Estimating above-ground biomass and carbon stocks of *Prosopis juliflora* using allometric equations in drylands of Magadi, Kenya

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Abstract

This research wanted to use *Prosopis juliflorae* weed for animal feed and climate change mitigation. Above-ground biomass and carbon stocks of *Prosopis juliflora* were estimated using allometric equations in floodplains and hillslopes landscapes of the drylands of Magadi in Kajiado, Kenya. Three hundred and twenty (320) *Prosopis* trees were sampled, out of which one hundred and twenty eight (128) were randomly selected and used for the development of the allometric equations. Basal diameter, diameter at breast height, crown width and tree heights were measured; and their fresh weights taken for the development of *Prosopis* biomass prediction models. Cubic and power models yielded better results than linear models in biomass prediction, with basal diameter being more reliable than diameter at breast height, crown width and height. Cubic curvilinear and power models for biomass prediction returned the better R^2 values (0.82 and 0.98) for single and multistemmed *Prosopis* trees respectively. Validation of models revealed significant correlation between predicted and measured tree biomass, suggesting effectiveness of the models in biomass predictions. The dense and managed plots in the hilllslopes had the highest *Prosopis* biomass (44.13tons/ha) followed by dense and unmanaged plots (43.68tons/ha). The dense and unmanaged plots of the floodplains had lower estimates (34.15tons/ha) followed by dense and managed (28.01tons/ha). The moderately and sparsely dense plots in both landscapes recorded lower biomass (18.75 and 3.47tons/ha in hillslopes and 12.72 and 5.09tons/ha in floodplains). The effects of management were not significant in both the hillslopes and floodplains. Further studies were recommended with longer time frames of observations to assess the effect of management on biomass production.

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Introduction

Introduced in Kenya for land rehabilitation during the 1970s and 1980s (Choge and Pasiecznik, 2006; Wahome *et al.,* 2008), *Prosopis juliflora* has become invasive through its superior aridity adaptive qualities and ubiquitous seed production. It is a threat to productivity of the drylands due to its invasive nature, but on the flip side it offers opportunity for the dryland communities to benefit from carbon credit trade, but there are barriers of initiating carbon credit schemes in the drylands, chief of them is methodological constraints. It is estimated that 2% of Kenya's landmass is now covered by *Prosopis* whose pod production potential has been estimated at about 60,000 tons per year (Choge and Pasiecznik, 2006).

Prosopis trees account for a significant amount of plant biomass and consequently, sequestered carbon worldwide. However, most of the previous studies on plant biomass estimation have focused on species from humid areas with little recognition of those adapted to dry environments. Tree species in arid and semi-arid zones are not currently considered when calculating carbon balances. There is yet an undiscovered value of *Prosopis* in the emerging global market for 'carbon credits'.

Plant biomass is the total amount of live material in a plant that includes water and other chemicals (Hoen and Solberg 1994; Husch, 2001). Carbon is an equivalent of charcoal from a tree when all the water is evaporated and it has been estimated at 50% of plant biomass (Losi *et al.,* 2003, IPCC, 2007 and IPCC, 2004). Modest improvements in *Prosopis* silvicutural management can raise biomass by as much as 0.5 tons C/ha/year in the drylands (Reid *et al.,* 2004; Galvin *et al.,* 2004). This is important since in the moisture stressed and degraded soils of the Kenya's rangelands, *P. juliflora* contributes an increasingly significant proportion of sequestered carbon (Steinfeld *et al.,* 2006) with the potential of offering pastoral communities an opportunity to benefit from *Prosopis* based carbon credit trade–off schemes.

Biomass has been estimated by ground physical measurements, otherwise known as allometric equations (Roy and Ravan, 1996), which are unique to particular tree species (Chave *et al.,* 2004). In the drylands, the methods are hampered in part by inadequate and underdeveloped methods of accounting for carbon stocks (Galvin *et al.,* 2004) and highly variable canopy cover among sites and species (Felker *et al.,* 1990; Geesing *et al.,* 1999).

The few allometric equations developed for *Prosopis* biomass estimation (Muturi *et al.,* 2011; Singh and Bilas Singh, 2011), cannot be easily replicated and are limited in their application and scaling-up potential (McMurtry *et al.,* 2006; Tennigkeit and Wilkes, 2008).There is need to build consensus around the more reliable parameter to use between basal diameter (BD) and diameter at breast height(DBH) and how to handle the multistemmed nature of *Prosopis* trees in estimating *Prosopis* biomass and carbon stocks (Sarmiento *et al.,* 2005; Montero and Montagnini, 2006; Redondo, 2007). This will contribute to the increased accuracy of the estimated above ground biomass (Chave *et al.,* 2004). This paper reports on the determination of an equation that enhances the accuracy of estimating *P. juliflora* AGB production and carbon stocks to model potential for trading in carbon credits.

Materials and Methods

Study area

The study was conducted in Olkiramatian location of Magadi division - Kajiado County. The area is located in south west of Kenya, bordering Tanzania to the south and Narok County to the west. It is situated at altitude of 600m within lat/long. – 1°40'S, 36°E, 2°S, 36°15'E (Fig. 1), under the inner lowland and lower midland agro-ecological zones (Jatzold and Schmidt, 1978). It has a bimodal rainfall pattern with a an annual total of 460mm and a mean of 50mm, mean temperatures of 32°C. The soil texture is very clay, clay and loam, with occasional sand. The clay types are montmorillonitic, kaolinitic and interstratified clay (Kenya soil survey, 1997). The landforms are composed of plains, plateaus, low gradient foot slopes, medium gradient hills and occasional high gradient hills (Gregorio and Latham, 2002). The slopes range from flat and wet slopes, gently undulating, rolling and steep slopes.

The vegetation is sparse, open bushland, with increasing presence of *Prosopis* (Gregorio and Latham, 2002).

Prosopis spread in Magadi division is mainly found in Olkiramatian location and the study is mainly concentrated in Ngurumani, Olchorro Olepo and Entasopia sublocations. These are the original sites where *Prosopis* was originally introduced. There are well established *Prosopis* stands, with adequate dense, moderate and sparse *Prosopis* clusters. Floodplains and hillslopes landscapes are well represented in these areas. The study sites were located in the *Ngurumani hillslopes* in Ngurumani and Entasopia sublocations and *Olkiramatian floodplains* in Olkiramatian sublocation (Fig. 2.1). These are the areas invaded by *Prosopis* with well-established *Prosopis* stands in the dense, moderate and sparse clusters. The *Olkiramatian floodplains* receive 400mm of rainfall annually, average temperatures of 35°C and vegetation cover of mainly shrubs, *Prosopis* and bare land. The *Ngurumani hillslopes* receives 600mm of rainfall annually with mean temperatures of 28°C and vegetation dominated by bushland, *Prosopis* and irrigated crop fields.

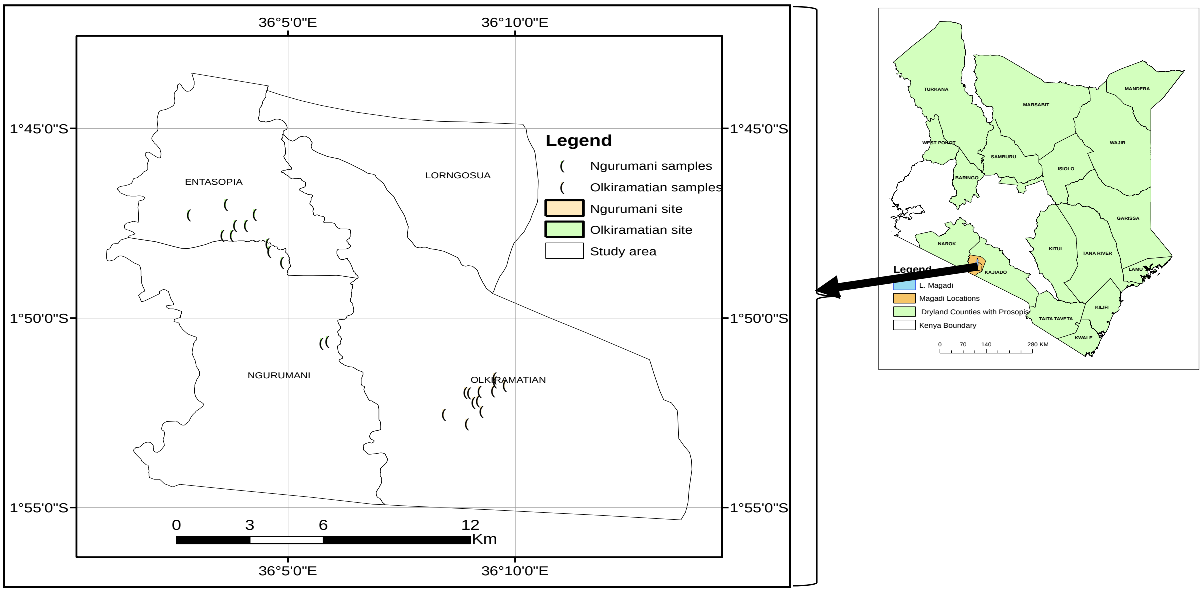

Fig. 1. Study area in Magadi of Kajiado County, Kenya.

Sampling design and delineating the Prosopis density sites

Two (2) *Prosopis* landscapes of hillslopes and floodplains were selected purposefully. Within each landscape, three (3) sites containing sparse density (less than 30% *Prosopis* cover), moderate *Prosopis* density of 50-70% cover and high *Prosopis* density (dense) of greater than 70% *Prosopis* cover were identified purposefully. The *Prosopis* density clusters were delineated using satellite images MODIS (250m), land use & land cover and validated using GPS data. These datasets were also used for ground truthing delineating *Prosopis* infested areas.

Each site had four (4) plots of 30mx30m randomly selected and fenced off to prevent interference from livestock, wildlife and humans.

The four (4) plots in each site had biomass estimation variables (basal diameter, breast height diameter, crown width, tree height) measured in the natural state. In the dense *Prosopis* sites (greater than 70% *Prosopis*), other four plots were selected randomly and management practices applied (pruning and 5m spacing between the *Prosopis* trees). The purpose of management was to reduce crowding, competition and increase production. The managed plots were only located in the high *Prosopis* density clusters (dense) due to fact that in the other sites of sparse and moderately dense areas, there was no need of management due to the occurrence of naturally spaced *Prosopis* stands. The total number of plots in the whole study area (in the 2 landscapes) was (2*(4+4+4+4)) = 32.

Using participatory resource mapping approach involving the local communities, the study sites were stratified into hillslopes and floodplains, which were further categorized depending on the density of *Prosopis* stands into sparse, moderate and dense *Prosopis* sites. The mapping was done on the area topographic map sheet with a scale of 1: 50,000. The identified *Prosopis* strata and sites was then be digitized in GIS software (ArcGIS) to create a GIS shapefiles of *Prosopis* density strata and sties.

In order to randomly select the sampling plots for data collection, the digitized *Prosopis* density shapefiles were then partitioned into 30m² grids and each grid assigned a unique number. MS Excel software was used to generate four (4) random numbers from the unique numbers in each of the four *Prosopis* density sites. The random numbers generated were used as the identifiers of the randomly sampled plots. The selected plots were then identified on the ground using GPS and fenced off to prevent interference from livestock, wildlife and humans and all the field observations taken on them.

In the dense *Prosopis* sites, two (2) 30m² plots were randomly selected and demarcated side by side. One of the two plots had management practices applied (pruning and spacing) and the other plot was left in the natural state as a control to enable comparison of the measured attributes.

Selection and management of Prosopis plots

Thirty two (32) plots were randomly selected in each of the two purposefully identified *Prosopis* landscapes of *Ngurumani hillslopes* and *Olkiramatian plains*. Four (4) plots were managed and twenty eight (28) were left in the natural state (unmanaged). The managed plots were placed adjacent to the unmanaged plots in the dense sites and demarcated as such. The management involved pruning (2-3 stems per plant) and thinning to space (5m apart) of the naturally occurring trees. Any vegetation undergrowth and re-growth was regularly removed in the managed plots.

The *Prosopis* plants (above 3m in height and producing pods) in each observation plot were identified and counted. Ten (10) *Prosopis* shrubs and trees in each plot were randomly selected (sampled) and basal diameter (m), breast height diameter (m), tree height (m) and crown diameter (m) measurements taken once every month for both managed and unmanaged plots.

Field data collection in the two *Prosopis* landscapes (*Ngurumani hillslopes* and *Olkiramatian floodplains*) was done once a month for ten (10) months in each of the 32 plots. In the managed plots, stems were thinned and pruned (2-3 stems per stump) and spaced at 5m. Measurements of base diameter and diameter at breast height (DBH), tree height and crown diameter, all in meters (m) were taken in the managed and unmanaged plots.

Development of allometric equation using groundtruthed data

A total of One hundred and twenty eight (128) *Prosopis* trees were randomly selected (four (4) each from the ten sample trees in the 32 plots). The measurements of basal diameter (BD), breast height diameter (DBH), tree height and crown diameter variables were taken in the managed and unmanaged plots for the development of the allometric equations.

All the 128 sampled trees were then cut down the actual weights (fresh weights) determined with a spring balance. To determine the whole tree weight, trees were cut into small sizes immediately after felling. Tree segments of weights that could be easily lifted were fastened together with a sisal twine and weighed with a spring balance until the entire tree materials were exhausted. Weights were then recorded separately for each tree.

SPSS software was used for the analysis. Exploratory analysis (variable and model evaluation) was done to find out the appropriate variables and models for estimating biomass. Stepwise regression analysis was carried out to compare diameter (DB and DBH) based biomass estimates with height and crown width based biomass estimates in *Olkiramatian floodplains* and *Ngurumani hillslopes*. Linear, Quadratic, cubic and Power regression models were applied to the one, two and three stemmed *Prosopis* basal diameter variables. Scatter plots were developed and coefficient of determination (R^2) evaluated for the relationships between the actual and estimated biomass.

Non-linear regression equations for estimating *Prosopis* biomass from previous studies (Equation .1, Equation 2 and Equation 3) were applied using FW and BD as the dependent and independent variables.

Ln(FW (Kg)) = 0.292DB + 0.59 (Muturi *et al.,* 2011) ....Equation 1

FW = λ*exp (p0 + p1 * ln(EDBH) + p2 * ln(H) + p3 * ln(SN) + p4 * ln(CW)) (Cienciala *et al.,* 2013).. Equation 2

FW = 0.1975 x1.1859DBH (Dabasso *et al.,* 2014)................................... Equation 3

(Muturi *et al.,* 2011; Cienciala *et al.,* 2013; Chave *et al.,* 2005; Dabasso *et al*, 2014, and Henry *et al.* 2011)

Where:

FW=Estimated biomass, BD=basal diameter, λ=correction factor, EDBH=tree equivalent diameter at breast height, H=tree height, SN=number of stems with diameter larger than 5cm, CW=crown width and p0–p4=fitted parameters, x= ratio of BD and DBH

These models (Equation 2.1, Equation 2.2 and Equation 2.3) either overestimated or underestimated the predicted biomass and did not show any correlations between the actual field weights measurements and the estimated biomass. Using the same principles, other models were developed, which were found to be working for this study.

The field *Prosopis* data variables from the 128 sampled trees was also used to develop allometric equations for estimating *Prosopis* above ground biomass (AGB) collected in *Olkiramatian* and *Ngurumani* for a period of 10 months. The data was divided into one stem, two stems and three stems *Prosopis* trees at the base (BD). Linear, quadratic, cubic and power regression equations, using fresh weight (FW) in kgs as the dependent variable and BD (cm) as the independent variable were developed for the one, two and three stemmed *Prosopis* trees. The following models were used:-

$Y = \beta_0 + (\beta_1 * t)$, ...Linear regression...........Equation 4

$Y = \beta_0 + (\beta_1 * t) + (\beta_2 * t^2)$, ...Quadratic models..........Equation 5

$Y = \beta 0 + (\beta 1 * t) + (\beta 2 * t^2) + (\beta 3 * t^3)$ ....Cubicmodels..............Equation 6

$Y = \beta 0 * (t^{\beta_1})$ or $\ln(Y) = \ln(\beta 0) + (\beta 1 * \ln(t)$ ....Power models.............Equation 7

Where:

Y = the estimated biomass (kg)

t = the basal diameter measured at a height of 30cm from the ground

$\beta_0, \beta_1 .... \beta_n$ are coefficients

To estimate *Prosopis* biomass and carbon stocks in *Olkiramatian* and *Ngurumani* landscapes, the above biomass estimation models were applied. The field *Prosopis* data was divided according to the sites (Olkiramatian plains and *Ngurumani hillslopes*). The data was further subdivided into one, two and three stemmed *Prosopis* biomass samples and the developed basal diameter and fresh weights relationship models applied to estimate biomass. Aggregations of biomass and carbon stocks (tons/ha) were done and averages calculated for each landscape type.

Scatter plots were developed for the single, two and three stemmed *Prosopis* trees to establish relationships between actual and estimated biomass (weights). The actual (measured weights) were plotted as the independent variables against the estimated weights as the dependent variables to determine the relationship of the measured and estimated weights. The R^2s were determined and the best models based on R^2 were selected for the single, two and three stemmed *Prosopis* trees based on the relationships between actual and estimated biomass (weights).

The least significant difference (LSD) was used to separate the means. To evaluate the effect of landscape type and season on the carbon level of various carbon pools, a general linear model (GLM) was used and significant difference accepted at 5% level of probability error, (Dabasso *et al,* 2014; Steel and Torrie, 1980; Mead and Curnow, 1990). Split-plot ANOVA were used to test for differences between the repeated measurements of biomass production in the managed and unmanaged plots.

Results

Equation 6 with R^2= 0.98 for the two stemmed trees and power models (Equation 7) with R^2=0.8; R^2=0.73 for the one and three stemmed trees respectively, showed significant relationships between the measured and the predicted biomass and were used in estimating *Prosopis* biomass in this study

$Y = ß0 + (ß1 * t) + (ß2 * t^2) + (ß3 * t^3)$ ....Cubicmodels ....Equation 6

$Y = ß0 * (t^{ß1})$ or $\ln(Y) = \ln(ß0) + (ß1 * \ln(t)$ ....Power models.............Equation 7

The results of the linear, quadratic, cubic and power regression models (Table 1 , table 2 and table 3) for the one stemmed, two stemmed and three stemmed basal diameter *Prosopis* trees showed that the power regression model was a better estimator (R^2=0.82) of the biomass in the one stemmed *Prosopis* trees (Table 1). The results also showed that the cubic regression model was a better estimator (R^2=0.98) of the biomass in the two stemmed *Prosopis* trees (Table 2). The results also showed that the power regression model was a better estimator (R^2= 0.73) of the biomass in the three stemmed *Prosopis* trees (Table 3).

Actual and estimated biomass relationships of the Prosopis biomass models

Scatterplot for the single stemmed *Prosopis* trees (Fig. 1a) showed very strong and positive relationships between actual and estimated biomass (R^2=0.8). Scatterplot for the two stemmed *Prosopis* trees (Fig. 1b) showed the strongest relationships between actual and estimated biomass (R^2=0.98) and the scatterplot for the three stemmed *Prosopis* trees (Fig. 1c) showed reasonable relationships between actual and estimated biomass (R^2=0.73).

Estimation of Prosopis biomass and carbon stocks

The *Prosopis* biomass estimates in the two landscapes of *Ngurumani* and *Olkiramatian* and in the four different density classes of dense managed, dense unmanaged, moderately dense and sparsely were compared. *Ngurumani hillslopes* landscape with higher rainfall amounts and lower temperatures had the highest *Prosopis* biomass (44.13tons/ha) in the dense managed category (Table 3.4). This was followed by dense unmanaged category (43.68tons/ha) also in the high rainfall and low temperature Ngurumani. The lowland plains of Olkiramatian had the third and fourth highest *Prosopis* biomass estimates in the dense unmanaged (34.15tons/ha) followed by dense managed category (28.01tons/ha) of the Olkiramatian plains. The moderately and sparsely dense categories in both landscapes recorded the lowest *Prosopis* biomass (18.75 and 3.47tons/ha in Ngurumani and 12.72 and 5.09tons/ha in Olkiramatian (Table 4).

Table 1. Regression results of one stemmed *Prosopis* basal diameter (cm).

Regression equation	R Square	Intercept /Constant	Coefficients		
			b1	b2	b3
Linear	0.76	-43.19	7.75		
Quadratic	0.79	3.30	0.40	0.20	
Cubic	0.79	30.13	-5.92	0.60	-0.01
Power	0.82	0.54	1.69		

Table 2. Regression results of two stemmed *Prosopis* basal diameter (cm).

Regression equation	R Square	Intercept /Constant	Coefficients		
			b1	b2	b3
Linear	0.75	-103.42	20.00		
Quadratic	0.94	90.69	-25.30	2.02	
Cubic	0.98	-76.66	35.95	-4.27	0.18
Power	0.85	0.67	1.92		

Table 3. Regression results of three stemmed *Prosopis* basal diameter (cm).

Regression equation	R Square	Intercept /Constant	Coefficients		
			b1	b2	b3
Linear	0.67	-28.99	9.72		
Quadratic	0.70	-114.36	19.64	-0.20	
Cubic	0.70	-120.97	20.96	-0.27	0.00
Power	0.73	0.94	1.62		

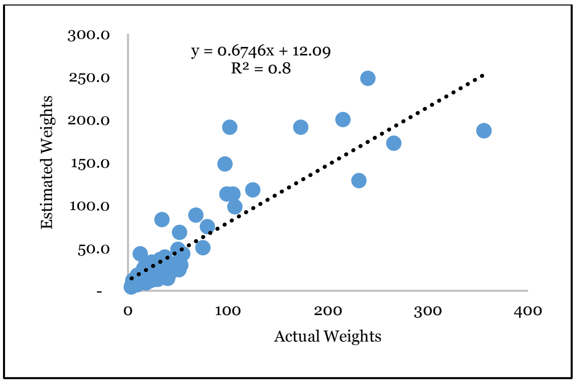

Fig. 1a. Single stem *Prosopis* basal diameter (actual vs estimated weights).

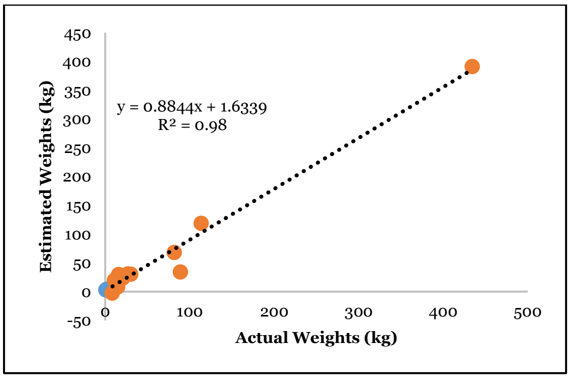

Fig. 1b. Two stem *Prosopis* basal diameter (actual vs estimated weights).

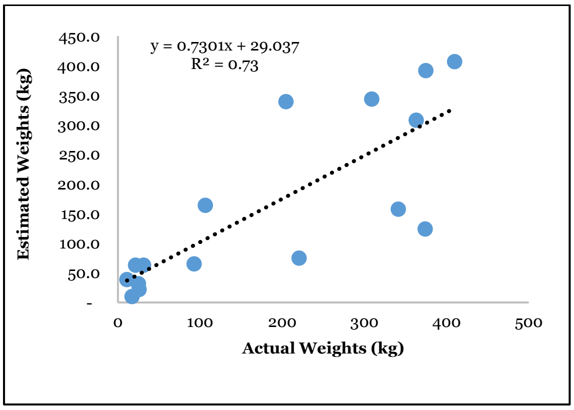

Fig. 1c. Three stem *Prosopis* basal diameter (actual vs estimated weights).

Carbon stocks were estimated at 50% of the biomass for the sparse, moderately dense and managed and unmanaged dense *Prosopis* plots in Ngurumani and Olkiramatian landscapes (Table 4).

Although the biomass values for the dense managed *Prosopis* plots were higher than the dense unmanaged *Prosopis* plots, the effects of management (spacing and pruning) were not noted in the Ngurumani landscape as the differences were insignicant (Table 4). However, the biomass values for the dense managed *Prosopis* plots were lower than the dense unmanaged *Prosopis* plots in the Olkiramatian plots, and again there was no effect of management in Olkiramatian landscape as the differences were insignicant (Table 4). A longer time of observations might be needed for the effect of management to the realized in biomass production.

The *Prosopis* biomass growth in the moderately and the sparsely dense clusters were significantly differently in Ngurumani but not in the Olkiramatian landscape. Possible reasons included greater competition for the available growth resources (water and light) with other vegetation types including other *Prosopis* plants outside the sample, leading to depressed and differentiated growth.

Table 4. Distribution of biomass and carbon stocks in different *Prosopis* densities in Ngurumani and Olkiramatian landscapes.

	Biomass and carbon Stocks (Averagetons/ha)			
	Ngurumani landscape		Olkiramatian landscape	
	Biomass	Carbon	Biomass	Carbon
Dense managed	44.13ᵃ	22.065	28.01ᵃ	14.005
Dense unmanaged	43.68ᵃ	21.84	34.15ᵃ	17.075
Moderately dense	18.75ᵇ	9.375	12.72ᵇ	6.36
Sparse	3.47ᶜ	1.735	5.09ᶜ	2.545

Means with different letter superscripts down each column are significantly different (*P<0.05)

Time series and trends analysis

Prosopis biomass time series trends in Olkiramatian and Ngurumani landscapes were plotted in charts with time (months) as X axis and *Prosopis* biomass as Y axis. The four lines (trends) for dense (managed and unmanaged), moderate and sparse densities were drawn and fitted with error bars (Fig. 2a).

The *Prosopis* biomass trends were developed for the dense and managed, dense and unmanaged, the moderately dense and the sparsely dense *Prosopis* clusters (Fig. 2a and Fig.2b). Although the biomass values for the dense managed *Prosopis* plots were consistently higher than the dense unmanaged *Prosopis* plots, the effects of management (spacing and pruning) were not noted in the Ngurumani landscape as the differences were insignicant (Fig. 2a). However, the biomass values for the dense managed *Prosopis* plots were consistently lower than the dense unmanaged *Prosopis* plots in the Olkiramatian plots, but again there was no effect of management in Olkiramatian landscape as the differences were insignicant (Fig. 2b). Possible reasons for the observed trends included less competition for plant growth resources (water and light) in the Ngurumani dense clusters as compared to the *Olkiramatian floodplains* with higher water stress. There was little effect of management on *Prosopis* productivity in both landscapes in the dense category of plots. A longer time frame for this type of experiment might be required to realize it.

The *Prosopis* biomass growth in the moderately and the sparsely dense clusters were significantly differently in Ngurumani but not in the Olkiramatian landscape over the study period (January to October, 2014). Possible reasons included greater competition for the available growth resources (water and light) with other vegetation types including other *Prosopis* plants outside the sample.

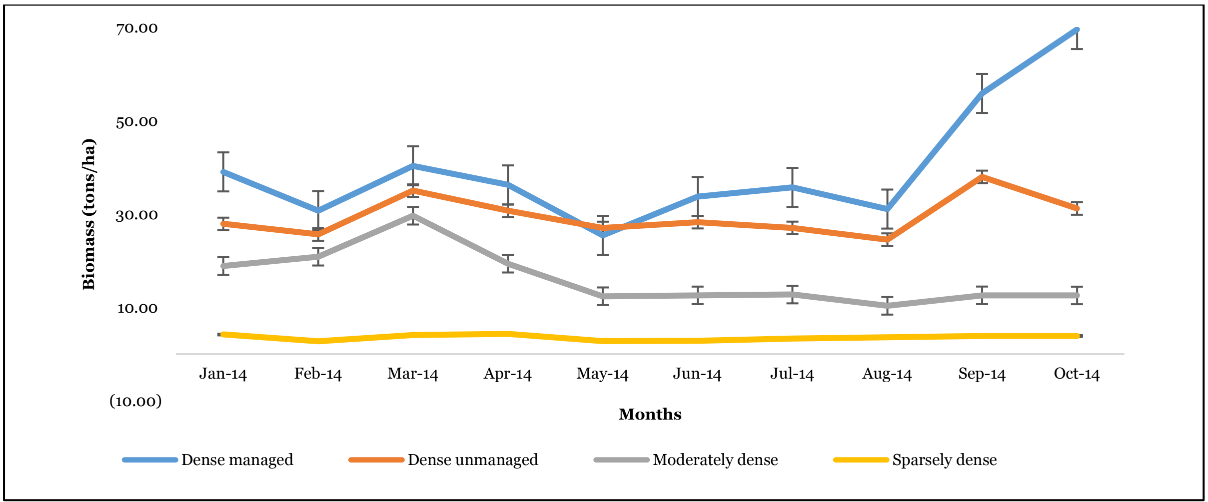

Fig. 2a. *Prosopis* biomass trends in Ngurumani landscape.

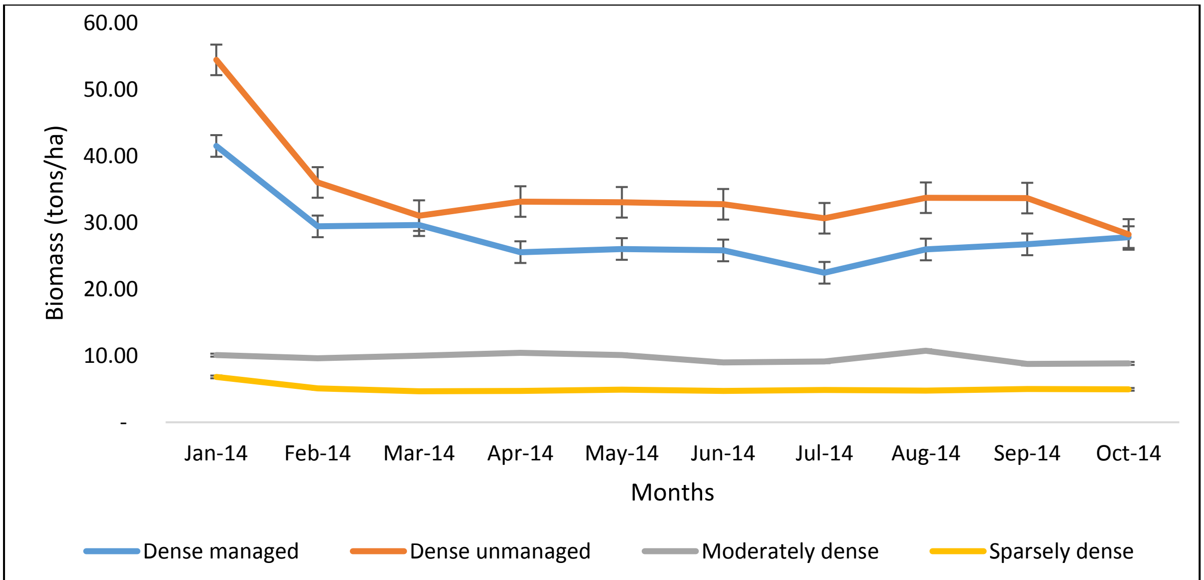

Fig. 2b. *Prosopis* biomass trends Olkiramatian landscape.

Discussion

One source of error in estimating carbon stocks in *Prosopis* forests is the lack of specific models for converting tree measurements to aboveground biomass (AGB) estimates. The two estimation approaches were applied to the field data in this study and the estimates compared with the ground truthed *Prosopis* biomass data. The models either over estimated or under estimated the biomass.

The variance of the *Prosopis* fresh weight biomass and the estimated biomass was too large for application in this study. However for multistemmed trees, only one stem was sampled and uniformity of tree characteristics assumed for the other stems. To estimate dry biomass, the results are multiplied by 60% and the carbon content taken as 50% of the dry biomass weight.

Prosopis juliflora is usually multiple stemmed plant, which the previous models did not address significantly. Therefore models were explored for estimating multiple stemmed *Prosopis* using multiple diameter biomass estimation methods. Curvilinear and power models were found to be promising models for estimating *Prosopis* biomass in the drylands of Kenya. In areas with substantial water resources in the drylands, management of the *Prosopis* clusters improves the rate of growth (productivity) as opposed to the drier areas.

Conclusion

This study found that curvilinear and power models improved the estimation of the above ground *Prosopis* biomass in the drylands. There were insignicant differences in biomass productivity between the dense managed *Prosopis* plots and the dense unmanaged *Prosopis* plots in the hillslope landscape, although the biomass in the dense managed plots were consistently higher than the unmanaged. In the floodplains landscape, however, the biomass for the dense managed *Prosopis* plots were consistently lower than the dense unmanaged *Prosopis* plots, but the differences were also insignificant. Further studies were recommended with longer time frames of observations to assess the effect of management on biomass production. More studies are also recommended for the development of allometric equations of estimating biomass of *Prosopis* plants whose height is less than 2 meters in height. Also the economics of *Prosopis* carbon stocks as *Prosopis* based carbon trade need further studies.

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