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A Critical Review of Allometric Models for above Ground Grass Biomass Estimation

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Abstract:
In identifying viable, suitable, reliable, and sustainable site for establishing grazing reserve, there is the need to first obtain the Above Ground Grass Biomass (AGGB) of the proposed site. This paper reviews the existing literatures dealing with above ground biomass estimation of plants. The aim is to get a model that can be used in adopting a systematic and reliable method for measuring, reporting and verifying quality and quantity of grasses, foliage and other vegetation for the purpose of cattle rearing and other agricultural activities. Most of the allometric models reviewed have a common objective but they differ in terms of theoretical assumptions. Correlations between biomass and morphological characters were closely scrutinized, model suitability or unsuitability over a specific specie, site or season was analysed and evaluated. This study will therefore provide scholars with the choices of an allometry model for AGGB estimation, thereby contributing to the sustainable livestock grazing and agriculture both at the local and global levels.

Keywords: *Grass, biomass estimation, Allometric models*

1. Background of Study

Above Ground Grass Biomass (AGGB), is defined as the total over-dry mass of the above ground portion of grasses ((Zumo et al., 2021; Lu et al., 2016)).Estimation of AGGB and aboveground productivity can be obtainedusing three maintechniques: (i) allometric equations;(ii) intensive biomass destructive sampling techniques; (Gao et al., 2018; Kuyah et al., 2016); and (iii) Remote Sensing method(Zumo et al., 2021; Zumo, & Hashim, 2020; Chabi et al., 2016). In grasslands, destructive techniques are possible, but they can also be very costly and logistically challenging due to remoteness and poor resources available to transport and process samples. In addition to cloud cover and fly-over frequency, remote sensing technique needs targeted field-based observations as control points to calibrate and validate images (Yang et al., 2017; Deery et al., 2014). Initially, allometric equations require a destructive sampling of biomass, but eventually they can be used to determine above ground biomass and productivity without destroying the biomass. Allometric equations were more often used for grass estimation both at small and larger scales. It is therefore often imperative to select an appropriate allometric model for AGGB estimation in order to minimize errors and increase accuracy (Kebede & Soromessa, 2018; Duncanson et al., 2017).

Allometric relationships, like stem area or diameter, stem mean height, leaf area index, volume, density, as well as biomass, is extremely useful for understanding plant growth processes and effects (Kuyah et al., 2016; Cornet et al., 2015). These variables can be utilized separately or in a single allometric model. Figure is a typical example of field measured parameters that can be used for modelling the AGGB of grass.

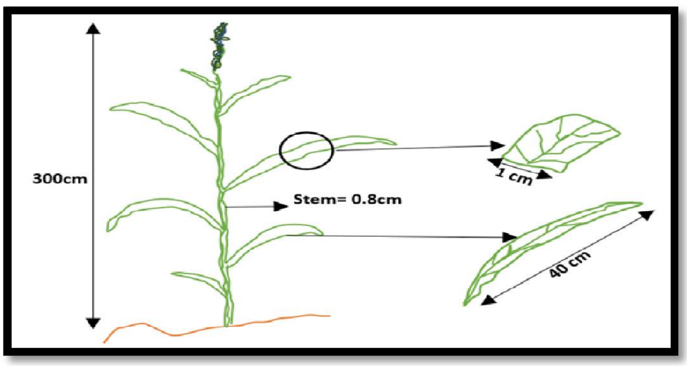

Figure 1: Measured Field Grass Parameters

The models could be used to calculate AGGB and, as a result, the duration of rotations, nutritional values, and economic benefits (Roxburgh et al., 2015; Cornet et al., 2015) as well as to calculate carbon storage (Ekoungoulou et al., 2014; Cornet et al., 2015). There were numerous reliable allometric formulae for various types of forest land (Yuen et al., 2016, He et al., 2018; Vargas-Larreta et al., 2017). However, just a few formulae for grasslands have been constructed (ref). The development of reliable allometric formulae for substantial grass lands, that could be used as a comprehensive means of measuring, providing information, and validating grass quantity and quality, is one of the initial steps toward an interrelated evaluation of AGGB in savannah ecosystems. Multispecies models, in this aspect, have a broader usage than species-specific equations, although their appropriateness is readily limited due to the inherent unpredictability incorporated in the models when multiple species are considered simultaneously.

Most of the allometric models have a common objective but they differ in terms of theoretical assumptions. Therefore, there is the need for a refined version of allometry model for AGGB estimation that can give a reliable result. The purpose of this paper is to critically review the existing allometric models and come with a suitable method for AGGB estimation that be used for grazing lands management. This will contribute in achieving sustainable agriculture by livestock grazing.

2. Methods

Allometric models can be linear or not linear regression depending on the measured grass variables used. However, both models involve the use of grass measured variables. Since allometry is the relationship between one part of a plant to another part, different dimensions of individual plants are statistically related to each other (Yang et al., 2017; Chave et al., 2014). The proportions between the height and the diameter of the plants, between the biomass and the density of the plants are all having and interrelationships among themselves. A typical regression analysis Correlation among plant variables is frequently used to estimate AGGB (Zumo et al., 2021; Stovall et al., 2018; Mganga, 2016). Physical qualities that include the stem diameter, grass maximum height, density, and volume are some of these measured variables.

2.1. Linear Regression Models

Linear regression is a linear approach for modelling the relationship between a dependent variable which is the AGGB and the independent variables known as predictors. Linear regression analysis is used when there is only one independent variable, and multiple linear regression is used when there are more than one.In estimating AGGB, the allometry linear models was given as:

$AGGB = a + bx$ - - - - (1) for single variable or

$AGGB = a + bx_1 + cx_2$ - - - (2) for multiple variables

Where a is the additive coefficient, b is the multiplying coefficient and x is the measured plant variable(s) as predictor(s).

Figure 2 is an example of a linear relationship between AGGB and independent variables (grass height and grass volume).

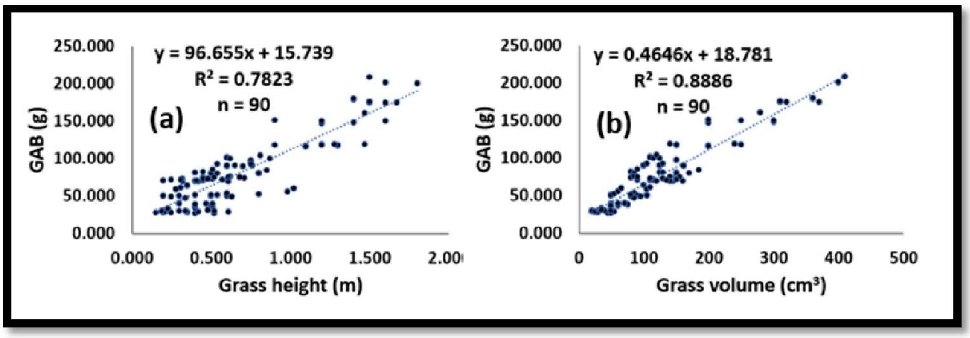

Figure 2: Linear Regression Equation for AGGB Estimation Using (A) Grass Height (B) Grass Volume

2.2. Non-linear Models

Nonlinear regression is a kind of data analysis whereby an observed data is represented by a functional that is a nonlinear combination of regression coefficients and depends on one or more independent variables. To fit the data, a method of successive approximations is applied. The relationships between AGGB and plant parameters may be non-linear equation according to the power function:

$AGGB = ax^b + \varepsilon$- - (3) for single variable or

$AGGB = ax_1^b x_2^c + \varepsilon$ - - (4)

$AGGB = ax_1^b x_2^c x_3^d + \varepsilon$ - (5) for multiple explanatory variables

Where x_i are the observed plant parameters, *a,b,c and d* are the constants and exponent approximated by non-linear equation analysis, and ε is the random error.

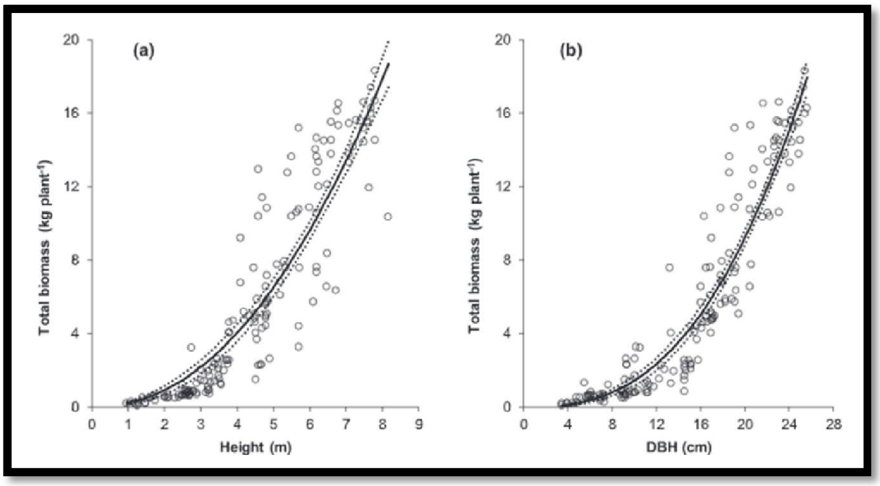

Figure 3: Nonlinear Regression Equation for Total Biomass Estimation Using (a) Plant Height (b) Plant Diameter at Breast Height (DBH)
Source: Laskar Et Al., 2020

In all the equations developed by previous researchers, equation that has more than one independent variable gives more precise result than a single independent variable. This assertion was revealed many scholars (Flade et al., 2020; Masota et al., 2014) who argued that using only one response variable in allometric models to estimate biomass will be less accurate.

3. Discussion

Allometric equations are equally known as Biomass estimation equations, or regression equations, that was used to calculate the biomass or volume of aboveground vegetation components based on the measured parameters (Prayogo et al., 2018; Maulana et al., 2016). The parameters can be plant height, stem diameter, plant density or volume. The use of biomass equations is a common and inexpensive method to estimate the biomass of plant species (Sinha et al., 2015; Qureshi et al., 2012). choosing an appropriate allometric model is a crucial step to reduce uncertainties in estimatingplant biomass stocks (Abdullahi &Aishetu 2015). Many factors can influence the growth rate of plants, but they do not influence the allocation of biomass to different structures for a given size.Because numerous morphological and biomass ratios change with plant size, scholars stressed the importance of utilizing allometric analysis to examine biomass allocation under varied stress conditions (Lu et al., 2019; Do et al., 2016). Depending on the plant factors and species, allometric equations can be linear or non-linear.

3.1. Linear Allometric Models

Estimating a straight line through the points in the plot, i.e., estimating the slope of the line and the intercept with the axis measured variable = 0, would be interesting because the connection between predicted biomass and measured grass characteristics can be linear (or affine).This principle was also used to evaluate the total biomass storage in the in plants (Nie XQ et al., 2018; Fang et al. 2014). The models were found to be the most suitable equation that gives a high coefficient of regression and a good significance of regression. Other models using height alone; diameter at breast height (DBH); height and DBH combine; height, DBH and wood density combine; with linear and logarithmic relations produced relatively poor coefficient of determination (Aabeyir et al., 2020). For shrubs and grasses, the Allometric linear model is the best for carbon stock estimate (Youkhana et al., 2017). the model gives a higher value of determination of coefficient and significance of regression coefficient.

3.2. Non-Linear Allometric Models.

Other studies (Youkhana et al., 2017; Oliveras et al 2014), use the power function for modelling relationships between the measured variables and AGGB.In most cases, the error variances for allometric nonlinear equations based on arithmetical units of measurement in vegetation biomass investigations are not constant over all data (Wirabuana et al., 2020). One of the most frequent approaches for removing the effects of heteroscedasticity is to utilize log-transformed data for linear regressions when estimating the parameters in nonlinear models.Hence, these equations need to be linearized using logarithms functions. Log-transformed linear regression has commonly been used for modelling plant biomass in many studies (Lai et al., 2013; Paine et al., 2012)

<u>3.2.1. Model Selection Criteria</u>

The best statistical models were selected base on the results of the coefficients of regression (R^2), root mean square error (RMSE)and standard error (SE),for each species for species specific models and for each site for site specific models.

R^2 is the model's ability to explain a percentage of the total variance in yield. It's an indicator for how near the values are to the linear regression line that was fitted. In multiple regression, it's also known as the coefficient of predicting or the coefficient of multiple regression analysis. All variation in the dependent variable is described by variation in the independent variable when $R^2 = 1$, but all variation in the dependent variable is explained by variation in the independent variable when $R^2 = 0$. The root-mean-square error (RMSE) is a metric for comparing predicted and observed values in a model. Because it is scale-dependent, it is only useful for comparing predicting errors of different models for a single variable, not between variables. It is preferable to use a model with a low RMSE.

The square root of the sum of squared errors divided by n2, or correspondingly, the standard deviation of the errors multiplied by the square root of (n-1)/(n-2), in which the other factor is a slightly higher value, is the standard error of a model (also indicated by the letter s).

$$s = \sqrt{\frac{1}{n-2}\sum_{t=1}^{n} e_t^2}$$

In this computation, the sum of squared errors is divided by n2 rather than n1 since predicting two variables (a slope and an intercept) instead of just one (the mean) in fitting the equation to the data has already used up an extra degree of freedom for error. The slope and intercept of each model parameter have their own standard error, which is the estimated standard deviation of the error in estimating it.

A p value is a measure of the likelihood that a particular result, especially one that is more severe than the observed result, might have happened by chance. In a nutshell, the p value is a measure of the null hypothesis's credibility (Nahm, 2017). A p - values would be a number between 0 and 1 that can be read as follows: A little p value (≤0.05) implies clear evidence of a model's statistical significance.

4. Conclusion

The models developed by scholars needs validation on different site with different species under investigation. Most of the models were centred on the biomass estimation of woody plants. Little or no attention that was given to Above Ground Grass Biomass (AGGB) estimation in the savannah grass regions. Savannas cover one eighth of worlds land surface, supporting a considerable portion of the global human population as well as the bulk of the world's grasslands and livestock (ref). Despite their own importance with regard to welfare as well as the economy, the origin, existence, and interactions of mostly grasses in savannas are poorly defined (ref). This becomes necessary to review the existing literatures dealing with AGGB that can be used in adopting a systematic and reliable method for measuring, reporting and verifying quality and quantity of grasses, foliage and other vegetation for the purpose of cattle rearing and other agricultural activities.

5. References

i. Aabeyir, R., Adu-Bredu, S., Agyare, W. A., & Weir, M. J. (2020). Allometric models for estimating aboveground biomass in the tropical woodlands of Ghana, West Africa. *Forest Ecosystems*, *7*(1), 1-23.

ii. Abdullahi Jibrin and Aishetu Abdulkadir (2015). Allometric Models for Biomass Estimation in Savanna Woodland Area, Niger State, Nigeria. International Scholarly and Scientific Research & Innovation 9(4)

iii. Chabi, A., Lautenbach, S., Oladokoun, V., Orekan, A., and Kyei-Baffour, N. (2016).

iv. Allometric models and aboveground biomass stocks of a West African Sudan Savannah watershed in Benin. Carbon Balance Manag. 11, 16. doi: 10.1186/s13021-016-0058-5

v. Cornet, D., Sierra, J., and Tournebize, R. (2015). Assessing allometric models to predict vegetative growth of yams in different environments. Agron. J. 107, 241–248. doi: 10.3732/ajb.1100249

vi. Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M. S., Delitti, W. B., ...

vii. & Vieilledent, G. (2014). Improved allometric models to estimate the aboveground biomass of tropical trees. *Global change biology*, *20*(10), 3177-3190.

viii. Deery, D., Jimenez-Berni, J., Jones, H., Sirault, X., & Furbank, R. (2014). Proximal remote sensing buggies and potential applications for field-based phenotyping. *Agronomy*, *4*(3), 349-379.

ix. Do, P. T., De Tar, J. R., Lee, H., Folta, M. K., & Zhang, Z. J. (2016). Expression of Zm GA

x. 20ox cDNA alters plant morphology and increases biomass production of switchgrass (Panicum virgatum L.). *Plant biotechnology journal*, *14*(7), 1532-1540.

xi. Duncanson, L., Huang, W., Johnson, K., Swatantran, A., McRoberts, R. E., & Dubayah, R.

xii. (2017). Implications of allometric model selection for county-level biomass mapping. *Carbon balance and management*, *12*(1), 1-11.

xiii. Ekoungoulou, R., Liu, X., Loumeto, J., and Ifo, S. A. (2014). Above-and belowground biomass allometrics for carbon stocks estimation in secondary forest of Congo. J. Environ. Sci. Toxicol. Food Technol. 8, 9–20.

xiv. Flade, L., Hopkinson, C., & Chasmer, L. (2020). Allometric equations for shrub and short-stature tree aboveground biomass within boreal ecosystems of northwestern Canada. *Forests*, *11*(11), 1207.

xv. Fang J, Kato T, Guo Z, et al. (2014) Evidence for environmentally enhanced forest growth.

xvi. Proceedings of the National Academy of Sciences 111: 9527-9532. https://doi. org/10.1073/pnas.1402333111

xvii. Gao, Y., Lu, D., Li, G., Wang, G., Chen, Q., Liu, L., & Li, D. (2018). Comparative analysis of modeling algorithms for forest aboveground biomass estimation in a subtropical region. *Remote Sensing*, *10*(4), 627.

xviii. He, H., Zhang, C., Zhao, X., Fousseni, F., Wang, J., Dai, H., ... & Zuo, Q. (2018). Allometric biomass equations for 12 tree species in coniferous and broadleaved mixed forests, Northeastern China. *PloS one*, *13*(1), e0186226.

xix. Kuyah, S., Sileshi, G. W., and Rosenstock, T. S. (2016). Allometric models based on Bayesian frameworks give better estimates of aboveground biomass in the Miombo Woodlands. Forests 7, 13. doi: 10.3390/f7020013

xx. Kebede, B., & Soromessa, T. (2018). Allometric equations for aboveground biomass estimation of Olea europaea L. subsp. cuspidata in Mana Angetu Forest. *Ecosystem Health and Sustainability*, *4*(1), 1-12.

xxi. Lai, J., Yang, B., Lin, D., Kerkhoff, A. J., & Ma, K. (2013). The allometry of coarse root biomass: log-transformed linear regression or nonlinear regression? *PloS one*, *8*(10), e77007.

xxii. Lu, M., Herbert, E. R., Langley, J. A., Kirwan, M. L., & Megonigal, J. P. (2019). Nitrogen status regulates morphological adaptation of marsh plants to elevated CO 2. *Nature Climate Change*, *9*(10), 764-768.

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

xxiv. Maulana, S. I., Wibisono, Y., & Utomo, S. (2016). Development of local allometric equation to estimate total aboveground biomass in Papua tropical forest. *Indonesian Journal of Forestry Research*, *3*(2), 107-118.

xxv. Mganga, N. D. (2016). Investigation of the desirable predictor variable in accounting above-ground carbon for Pseudolachnostylis maprouneifolia Pax. (Kudu-Berry). Int. J. Res. Agric. For. 3, 49–56.

xxvi. Masota, A. M., Zahabu, E., Malimbwi, R. E., Bollandsås, O. M., & Eid, T. H. (2014).

xxvii. Volume models for single trees in tropical rainforests in Tanzania.

xxviii. Nahm, F. S. (2017). What the P values really tell us. *The Korean journal of pain*, *30*(4), 241.

xxix. Nie XQ, Yang LC, Xiong F, et al. (2018) Aboveground biomass of the alpine shrub ecosystems in Three-River Source Region of the Tibetan Plateau. Journal of Mountain Science 15(2). https://doi.org/ 10.1007/s11629-016-4337-0

xxx. Oliveras, I., van der Eynden, M., Malhi, Y., Cahuana, N., Menor, C., Zamora, F., & Haugaasen,

xxxi. T. (2014). Grass allometry and estimation of above-ground biomass in tropical alpine tussock grasslands. *Austral ecology*, *39*(4), 408-415.

xxxii. Paine, C. T., Marthews, T. R., Vogt, D. R., Purves, D., Rees, M., Hector, A., & Turnbull, L. A.

xxxiii. (2012). How to fit nonlinear plant growth models and calculate growth rates: an update for ecologists. *Methods in Ecology and Evolution*, *3*(2), 245-256.

xxxiv. Prayogo, C., Sari, R. R., Asmara, D. H., Rahayu, S., & Hairiah, K. (2018). Allometric equation for pinang (Areca catechu) biomass and C stocks. *AGRIVITA, Journal of Agricultural Science*, *40*(3), 381-389.

xxxv. Qureshi, A., Badola, R., & Hussain, S. A. (2012). A review of protocols used for assessment of carbon stock in forested landscapes. *Environmental science & policy*, *16*, 81-89.

xxxvi. Roxburgh, S. H., Paul, K. I., Clifford, D., England, R. J., and Raison, R. J. (2015). Guidelines for constructing allometric models for the prediction of woody biomass: how many individuals to harvest? Ecosphere 6, 1–27. doi: 10.1890/ES14-00251.1

xxxvii. Sinha, S., Jeganathan, C., Sharma, L. K., & Nathawat, M. S. (2015). A review of radar remote sensing for biomass estimation. *International Journal of Environmental Science and Technology*, *12*(5), 1779-1792.

xxxviii. Stovall, A. E., Anderson-Teixeira, K. J., & Shugart, H. H. (2018). Assessing terrestrial laser scanning for developing non-destructive biomass allometry. *Forest Ecology and Management*, *427*, 217-229.

xxxix. Vargas-Larreta, B., López-Sánchez, C. A., Corral-Rivas, J. J., López-Martínez, J. O., Aguirre-

xl. Calderón, C. G., & Álvarez-González, J. G. (2017). Allometric equations for estimating biomass and carbon stocks in the temperate forests of North-Western Mexico. *Forests*, *8*(8), 269.

xli. Wirabuana, P., SETIAHADI, R., SADONO, R., LUKITO, M., MARTONO, D. S., &

xlii. Matatula, J. (2020). Allometric equations for estimating biomass of community forest tree species in Madiun, Indonesia. *Biodiversitas Journal of Biological Diversity*, *21*(9).

xliii. Youkhana AH, Ogoshi RM, Kiniry JR, Meki MN, Nakahata MH and Crow SE (2017)

xliv. Allometric Models for Predicting Aboveground Biomass and Carbon Stock of Tropical Perennial C4 Grasses in Hawaii. Front. Plant Sci. 8:650. doi: 10.3389/fpls.2017.00650

xlv. Yang, X., Blagodatsky, S., Liu, F., Beckschaefer, P., Xu, J., & Cadisch, G. (2017). Rubber tree allometry, biomass partitioning and carbon stocks in mountainous landscapes of sub-tropical China. *Forest Ecology and Management*, *404*, 84-99.

xlvi. Yuen, J. Q., Fung, T., & Ziegler, A. D. (2016). Review of allometric equations for major land covers in SE Asia: Uncertainty and implications for above-and below-ground carbon estimates. *Forest Ecology and Management*, *360*, 323-340.

xlvii. Yang, G., Liu, J., Zhao, C., Li, Z., Huang, Y., Yu, H., ... & Yang, H. (2017). Unmanned aerial vehicle remote sensing for field-based crop phenotyping: current status and perspectives. *Frontiers in plant science*, *8*, 1111.

xlviii. Zumo, I. M., Hashim, M., & Hassan, N. D. (2021). Mapping and Estimation of Above-ground Grass Biomass using Sentinel 2A Satellite Data. *International Journal of Built Environment and Sustainability*, *8*(3), 9-15.

xlix. Zumo, I. M., Hashim, M., & Hassan, N. (2021). Mapping grass above-ground biomass of grazing-lands using satellite remote sensing. *Geocarto International*, 1-14.

l. Zumo, I. M., & Hashim, M. (2020, July). Mapping Seasonal Variations of Grazing Land

li. Above-ground Biomass with Sentinel 2A Satellite Data. In *IOP Conference Series: Earth and Environmental Science* (Vol. 540, No. 1, p. 012061). IOP Publishing.