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Spatial variability of herbage yield, grazing capacity and plant diversity in a tropical savannah rangeland ecosystem

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To improve ruminant livestock production, evaluation of rangelands must be a routine. Rangeland evaluation gives information about the vegetation structure, biomass yield and quality. The Guinea savannah rangelands of Ghana lack research that characterises the spatial variability of herbage yield and quality. It was hypothesised that there is spatial heterogeneity in herbage yield, grazing capacity and plant diversity in the Guinea savannah rangelands of Ghana. The objective was to evaluate the spatial structure of herbage production and grazing capacity in the Guinea savannah rangelands of Ghana for sustainable livestock production. Data were collected from 105 sampling sites and integrated into geo-statistics, using ordinary kriging interpolation to generate herbage yield and grazing capacity estimates. Herbage yield and grazing capacity ranged from 0.63 t ha^{-1} to 13.43 t ha^{-1} and 0.18 LU ha^{-1} to 3.79 LU ha^{-1} respectively. The root mean square error and the average standard error values were close (2.38 and 2.51 respectively for herbage yield and 0.67 and 0.71 respectively for grazing capacity). Species diversity using the Shannon's index ranged from 1.13 to 2.40. There was spatial heterogeneity in herbage yield, grazing capacity and species diversity in Ghana's Guinea savannah rangelands with some parts needing effective site-specific improvement strategies for sustainable livestock production.

Keywords: dry matter yield, dominant grass species, Guinea savannah, Kriging

Introduction

Rangeland ecosystems worldwide provide many vital ecosystem services and resources critical for sustainable ruminant livestock production, viz. water and forage (Constanza et al. 1997). As a result of their importance, rangeland ecosystems need regular evaluation. Monitoring and evaluation of rangelands can provide information on the types of vegetation present, their abundance and diversity. Regular monitoring also identifies changes in vegetation cover and rangeland condition (Holechek et al. 2004). Vegetation condition is the relative physiognomy (structure and composition) and health of any given vegetation, as compared to similar vegetation that has had no disturbance (Zerger et al. 2008). Information derived from rangeland monitoring can therefore be used to better understand rangelands and to track the progress of any management practice put in place to ensure greater forage production (Godínez-Alvarez et al. 2009).

Rangeland monitoring facilitates good planning for sustainable use. Traditional rangeland monitoring and evaluation methods involve actual field sampling methods. These methods are time consuming and labour intensive, especially for large tracts of land. Modern methods of assessing rangeland parameters that complement conventional methods are currently available and widely being used (West 2003). They are reported to improve accuracy, reduce labour costs and encourage a higher frequency of monitoring and evaluation (Booth and Tueller 2003).

Remotely based range monitoring methods have been widely adopted. Remote sensing provides a way of efficiently and effectively detecting vegetation cover with an acceptable level of error (Hunt et al. 2003; Booth et al. 2006; Booth and Cox 2011). This modern method improves data collection by reducing the labour required for monitoring and reduces errors or biases associated with human measurements. Records obtained from such techniques can easily be stored and retrieved for further analysis if need be (Booth et al. 2006).

The use of satellite remote sensing measurements of vegetation reflectance using aerial photography has provided useful data for vegetation studies (Hudak and Wessman 1998). The use of satellite image indices and ratios, and relating them to above-ground biomass has also been carried out by numerous authors (Timpong-Jones 2000; Mutanga et al. 2003; Mutanga and Skidmore, 2007; Sousa et al. 2017). Accordingly, some relations for above-ground total biomass, herbaceous biomass and biomass of woody species have been established. However, the established relations from the satellite data are done with regression methods that do not make full use of the provided information because they do not factor in any autocorrelation and or cross-correlation present. The use of autocorrelation improves interpolation accuracy (Mutanga et al. 2003). Regression methods used on satellite data also calculate the ground biomass only from a pixel and ignore data from neighbouring pixels and thus sometimes produce worthless estimates due to the non-use of autocorrelation and cross-correlation (Atkinson et al. 1994; Said 2003).

One technique that can act as an improvement over regression methods is Geostatistics. The latter describe a collection of statistical methods used in various spatial models because there is no need in avoiding autocorrelations, and sampling is less restrictive and thus, changes the emphasis from average estimation to spatially distributed population mapping (Sharov 1996). As such, it uses the spatial correlation between close points or observations to predict that of unvisited locations (Ryu 2002). This provides a more accurate estimation of vegetation information needed to boost livestock production.

Livestock production in West Africa is an important contributor to millions of livelihoods, particularly to the rural dwellers and also to the national economies of the various countries. According to Ilu et al. (2016), more than 50% of West Africans own livestock. It is estimated that over 100 million people, including women, rely on livestock production as their main or secondary means of livelihood (Nyberg et al. 2015). Improving the livelihoods of those hugely dependent on livestock production will require improvement in the livestock industry, which is strongly dependent on the provision of adequate forage for livestock maintenance and growth by available rangelands.

A major agro-ecological zone important for livestock production in Ghana is the Guinea savannah. The Guinea savannah rangelands of Ghana is home for about 75% of the cattle population in Ghana. However, because of the expanse of this resource and the cost involved, the regular monitoring and evaluation of this valuable resource has not been given the needed attention. Additionally, the estimation of forage yield has been done by some researchers and range managers at various locations and results generalised for the entire expansive region. Although the average biomass yield value of a given rangeland is useful in estimating the general productivity of the ecosystem, information about the spatial distribution of biomass is more relevant (Correll et al. 2003). This aids in identifying specific areas where herbaceous plant growth is persistently poor and allows for the introduction of more functional grazing management decisions to that specific site (Timpong-Jones et al. 2013).

To improve forage yield to meet the increasing demand for livestock and livestock products, there is a need to provide information on the spatial variability of forage production in the Guinea savannah zone of Ghana. This will enhance the introduction of effective site-specific rangeland improvement strategies for the sustainable management of this valuable resource. It will also provide more accurate and reliable information on the biomass production potential of the Guinea savannah rangeland to boost ruminant livestock production.

It was hypothesised that there is spatial heterogeneity in herbage yield, grazing capacity and plant diversity in the Guinea savannah rangelands of Ghana. The objectives of this study were to: (1) evaluate the spatial structure of herbage production and grazing capacity in the Guinea savannah rangelands of Ghana for sustainable livestock production; (2) determine the nutritive value (crude protein content) of herbage at peak vegetation cover; (3) determine the dominant grass species in various parts of the Guinea savannah rangeland of Ghana; (4) determine the diversity of herbage species in various parts of the Guinea savannah rangelands of Ghana.

Materials and methods

Study area

The study was conducted in the Northern Region of Ghana. The Region falls within the Guinea savannah agro-ecological zone of the country (Figure 1) and is located at 9°29′59.99″ N, 1°00′0.00″ W (Abbam et al. 2018). The Northern Region is made up of 15 districts, namely; Kumbumgu, Savelugu Nanton, Sagnerigu, Tamale Metro, Karaga, Gushiegu, Tolon, Saboba, Yendi Municipal, Mion, Nanumba North, Nanumba South, Zabzugu, Tatale and Kpandai districts respectively (GODI 2019).

Fieldwork preparation

Prior to data collection, a reconnaissance survey was conducted in the study area to understand the physiography, topography and vegetation structure. This was to ensure effective planning of the field work and identify appropriate access routes to survey sites. Subsequently, input maps of the Northern Region showing vegetation cover and district boundaries were obtained, digitised and input in ArcGIS (version 10.4.1) using the World Geographic System 1984 (WGS) Zone 30 N coordinate system. One hundred and twenty sample points were randomly generated using the Create Random Point function of the Sampling functionality in the ArcGIS (version 10.4.1) toolbox. The coordinates of the created sample points were obtained from the reference layer. The map with the sample points was overlaid onto the district and vegetation maps and printed for fieldwork. Sample points were reduced to 105 due to anticipated accessibility challenges. Relevé sheets were also prepared to record field data.

Fieldwork

With the printed map and coordinates of the sample plots, and a handheld Garmin GPS, all the 105 sample points were accessed, and data collected. At each sample point, (1) a site of 30 m × 30 m was demarcated (Timpong-Jones et al. 2013). The data recorded in the measured plot were the Aerial Cover Percentage of both woody and non-woody vegetation cover using visual estimates. The aerial cover was estimated as the vertical projection of the perimeter of plant canopies onto the ground (Fehmi 2010; FAO/LADA 2011), (2) the Ranked Set Sampling method (RSS) was used to create three random plots, each 3 m × 1 m in size within the site of 30 m × 30 m. The Ranked Set Sampling method was used because it is very efficient in forage yield estimations (Wolfe 2012; Chen et al. 2013). These three plots were then each subdivided further into three 1 m × 1 m subplots. A subplot of 1 m × 1 m was used because it is the best size suited for herbaceous measurements (FAO/LADA 2011; Baxter 2014). The 1 m × 1 m subplots of each of the 3 m × 1 m plots were ranked in order of magnitude from high, medium to low with regards to basal cover

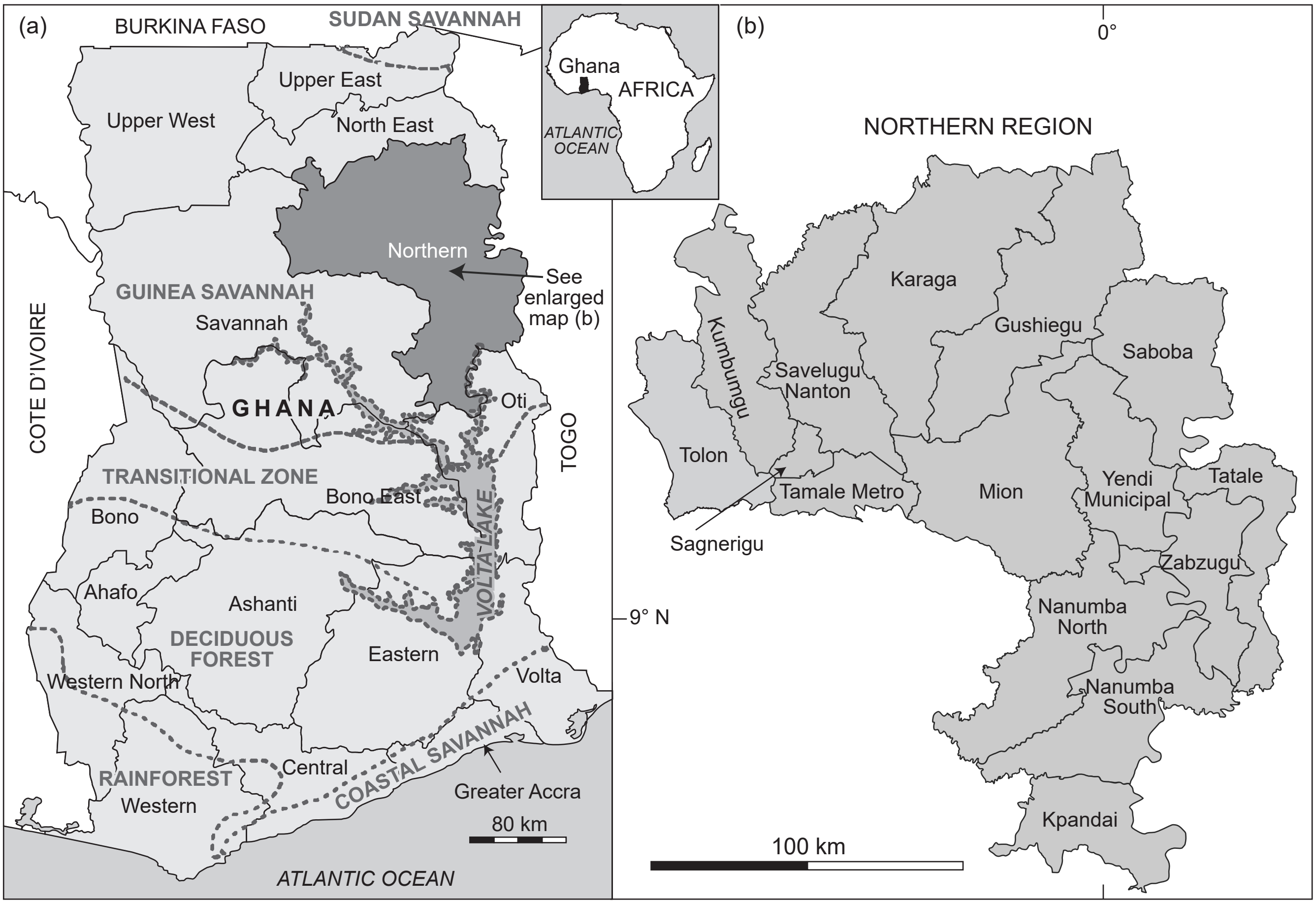

Figure 1: Map of the study area as part of the Guinea savannah agroecological zone of Ghana

percentage of herbaceous species (Figure 2). Basal cover was used because it is a parameter that is generally more stable from year to year and has fewer changes due to climatic fluctuation, or utilisation by grazing animals whilst providing an estimate of how much a plant dominates an ecosystem (Timpong-Jones et al. 2013). The subplot with high basal cover from the first plot, the subplot with medium basal cover from the second plot and the subplot with low basal cover from the third plot were selected for detailed measurements (Figure 2). Detailed data taken from the selected subplots included: species types and number, dominant grass species, basal cover percentage of herbaceous species and herbaceous biomass (FAO/LADA 2011; Mganga et al. 2016).

Clipping of herbaceous biomass in the subplots were done at 5 cm from the base of the plants and put in labelled sample bags and weighed using a handheld digital scale. This was done for all the 315 subplots of the 105 sample sites. Values of the three subplots per sample site were averaged into one as a good unbiased representative of the sample site. Sampling was done at the peak of the raining season when vegetation cover was also at its peak in harmony with a report by Jensen (2000). At peak vegetation cover, there is optimum biomass production that ruminant livestock depend on for the rest of the year.

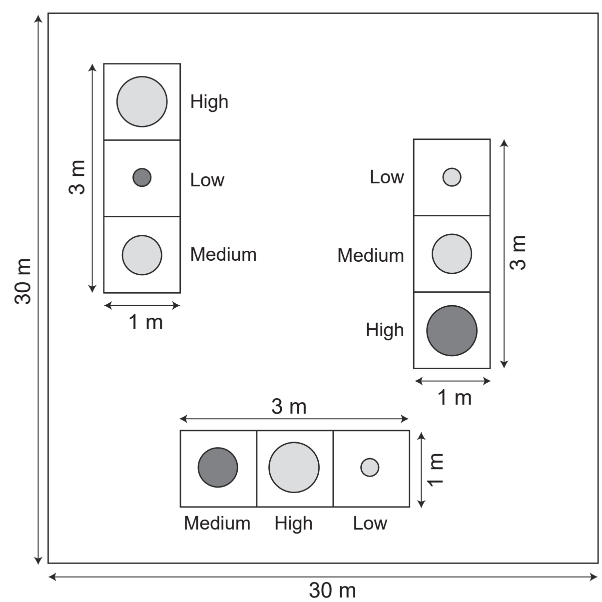

Figure 2: Diagram illustrating how field data were obtained using Ranked Set Sampling Method (samples were taken from subplots ranked low, medium and high with regards to basal cover as shown by dark grey circles)

Data analyses

Dry matter yield prediction

Weighed fresh forage samples were put in labelled envelopes and dried in an oven at 65 °C till constant weight (AOAC 2016). The 315 dried samples were then weighed and the weights expressed as dry matter yield (DMY) values in tonnes per hectare. The three values of each site were averaged into one value, thus resulting in a total of 105 values. The resulting DMY values were added to the attributes table of the map of the study area in ArcGIS to create a dry matter yield field.

Geostatistics (descriptive statistics and test for normality)

The Geostatistics analyst extension tool in ArcGIS version 10.4 was used in predicting DMY. First, the analyst tool was applied to the DMY values to examine the structure of the data. Parameters examined were the shape (the kurtosis as a measure of the peakedness of the distribution or how thick the distribution tails were and the skewness as a measure of the normal distribution symmetry or lack thereof), the dispersion (deviation from the mean) and the central values (ESRI 2016; Gupta et al. 2019).

The Shapiro–Wilk test for data normality was used to provide the best power for a given significance, and thus the best estimator of variance to the corrected sum of squares estimator of the variance (Razali and Wah 2011). Data were log transformed to fit normality (Hengl 2007) before ordinary Kriging interpolation was performed.

Kriging

Kriging is a quick and flexible interpolator that allows one to investigate graphs of spatial autocorrelation, thus warranting its use in this study (ESRI 2001). Ordinary Kriging was the particular Kriging method used. It is the most general and widely used of the Kriging methods because of its good performance in several vegetation studies (Lefohn et al. 2005; Wackernagel 2003). Furthermore, it is simple and robust and is unbiased because it minimises variance of errors and maintains the mean error, thus reducing estimates that are consistently above or below the true values (minimises mean square prediction errors) (SAS 1999). Ordinary Kriging uses semi-variograms to express autocorrelation, allows transformations and error measurement (ESRI 2019). Variograms that determine the measure of spatial variability was used to assess autocorrelation and to plot semivariance (γ) as a function of lag distance (h), which is the distance between sample points (ESRI 2001).

Data anisotropy

Anisotropy is a property of a spatial process or data in which spatial dependence (autocorrelation) changes with both the distance and the direction between two locations (ESRI 2019). Anisotropy was assessed on the calculated DMY data using the semivariogram cloud tool. The semivariogram values were calculated and the output rasterised to visually assess any possible anisotropy in the said data, and to determine the direction of anisotropy axis if present. The trend analysis tool was also used to further validate the above procedure.

Validation test

The calculated DMY map was used as the input layer and training, and test datasets were obtained for validation. The 75% training and 25% test datasets were used as it gives more weight to data for building a model (Skidmore 1999). The validation tool was used evaluate prediction accuracy (ESRI 2001) afterwards, the Root Mean Square Error (RMSE) value between the predicted and test data was used to ascertain the prediction accuracy. The equation below expresses the RMSE calculation:

$$RMSE = \sqrt{-\sum \left(f_i - o_i\right)} \qquad (1)$$

where: n = number of samples, f = predicted values, and o = observed values.

The full cross validation automatically done at the end of the Geostatistical Wizard was further used to validate this result.

Predicting grazing capacity

Grazing capacity is explained as the number of animals that may graze on a unit of land without injury to the land, for a specified length of time or indefinitely (Galt et al. 2000). Grazing capacity was expressed as follows (FAO 1991):

$$G = \frac{F}{R} \times g \qquad (2)$$

where: G = grazing capacity in livestock units (LU) per unit area for the specified grazing season, expressed as LU ha^{-1}, F = weight of herbage produced per given unit area during the season in kg ha^{-1}, R = dry matter requirement per livestock unit during the season in kg LU^{-1}. Daily dry matter intake was assumed to be 2.5% of live weight, and g = grazing efficiency of 45% was used (Van Winjngarrden 1985; Timpong-Jones et al. 2013). The specified grazing season was the rainy season and was estimated to be 255 days (end of February to mid-November) (MSD 2020) and one tropical livestock unit was 250 kg (LEAD 2010).

With the above assumptions, the corresponding grazing capacities were calculated for all the 105 sample points and the resulting values were input into the attributes table of the study area map in ArcGIS.

Crude protein yield

The Kjeldahl method of nitrogen determination was used according to AOAC (2001). The derived crude protein values for all the 105 sample points were input into the attributes table of the study area map in ArcGIS.

Estimating dominant grass species

In each of the 315 quadrats (subplots) in the 105 sites, herbaceous species were identified and counted. The three most dominant grass species in each of the 315 quadrats sampled in the 105 sample sites were recorded and evaluated per district, namely, Kumbumgu, Savelugu Nanton, Sagnerigu, Tamale Metro, Karaga, Gushiegu, Tolon, Saboba, Yendi Municipal, Mion, Nanumba North, Nanumba South, Zabzugu, Tatale and Kpandai districts. The herbaceous species regarded as dominant in a district were those present in at least 45% of the quadrats in that particular district (Timpong-Jones et al. 2013).

Rank Abundance for herbaceous species was evaluated using GenStat 12th edition (Matthews and Whitaker 2015). The Rank Abundance was calculated for each location, but grouped per district.

Species diversity and richness indices

Diversity indices provide more information about community composition than simply species richness, as they also take the relative abundances of different species into account (Kiernan 2020). Diversity indices provide important information about commonness and the rarity of species in a community, thus giving more insight into the community plant structure (Beals et al. 2000). Three diversity indices were used to study the vegetation structure.

Shannon–Wiener's Diversity Index (H') was used to evaluate uncertainty, where low uncertainty represents communities with low diversity and high uncertainty representing communities with high diversity (Shannon 1948). Shannon–Wiener's Diversity index is represented mathematically as:

$$H' = \frac{N \bullet \ln N - \sum\left(n_i \ln n_i\right)}{N} \tag{3}$$

where: N = total number of species, and n_i = number of individuals of species i.

The Shannon's Evenness Index (SEI) (or the Shannon's Equitability Index) was also used to calculate how close in number species in the community are to each other to provide information on species composition and richness. It was calculated by dividing the Shannon–Wiener Diversity Index by its maximum (Beals et al. 2000). This provided values between 0 and 1 with 1 being complete evenness.

The Simpson's Index measures the degree of concentration when individuals are classified into types. It is based on the probability of any two individuals of the same species drawn at random from a community (Simpson 1949). It is represented mathematically as:

$$D = \frac{\sum n\left(n-1\right)}{N\left(N-1\right)} \tag{4}$$

where: n = total number of organisms of a particular species, and N = total number of organisms of all species.

The D values range from 0 to 1, with 0 representing infinite diversity and 1 no diversity, thus the larger the value of D, the lower the diversity. However, since this is counter-intuitive, D is often subtracted from 1 to give a more intuitive assessment. Thus, with 1–D which still is between 0 and 1, the greater the value, the greater the diversity.

Species Richness is a measure of the number of species per sample/sample area; thus, the more the species present in an area, the richer the area, i.e. the higher the richness value (Colwell 2009).

All the species and their respective counts at all the 105 sample points were grouped into their various districts and the Diversity Indices tool in GenStat run to obtain results for the various index measurements.

Results

Dry matter yield estimation

The DMY in the Eastern part of the Guinea savannah rangelands of Ghana ranges between 0.63 t ha^{-1} to 13.43 t ha^{-1}, with the average DMY being 3.09 t ha^{-1} during the peak of the raining season.

The standard deviation, skewness, and kurtosis were 2.20, 2.36 and 9.57 t ha^{-1}, respectively. The DMY dataset without transformation was not normally distributed (Figure 3). However, the standard deviation, skewness, and kurtosis were 0.59, 0.26 and 3.45 t ha^{-1}, respectively, after log transformation. The resultant Normal QQ Plot after log transformation (Figure 4) indicated that the DMY dataset was close to forming a straight line, making the data distribution close to a normal distribution (ESRI 2019).

The Shapiro–Wilk test for normality also showed that the DMY dataset assumed a normal distribution after Log transformation (Table 1).

Grazing capacity estimation

Grazing capacity ranged between 0.18 LU ha^{-1} to 3.79 LU ha^{-1}, with the average grazing capacity of 0.87 LU ha^{-1} during the peak of the rainy season.

The standard deviation, skewness and kurtosis were 0.62, 2.35 and 9.52 LU ha^{-1}, respectively. The Log transformed grazing capacity dataset (Figures 5 and 6) had the standard deviation, skewness, and kurtosis to be 0.59, 0.27 and 3.40 LU ha^{-1}, respectively.

The Shapiro Wilk test for normality also showed that the grazing capacity dataset assumed a normal distribution after Log transformation with a significant value of 0.243 (which is greater than 0.05) (Table 2).

Anisotropy in data

Investigating anisotropy in the DMY and grazing capacity datasets by using variograms, showed that there was a gradual increase in the semivariogram values from the origin into all directions (Figures 7 and 8), indicating there was no anisotropy. Thus, datasets were fairly isotropic. Trend analysis evaluation also showed that there was no significant trend in both datasets (Figure 9).

Accuracy of predicted surface

Validating the 79 training samples using the 26 test samples showed that the choice of model was appropriate. For a good model, root mean square standardised error should be close to one (1) and the root mean square error should be close to the average standard error, and as small as possible (ESRI 2019; GISGeography 2020). For the DMY dataset, the root mean square prediction error was 2.38 and the average standard error was 2.51. These figures were deemed close. The root mean square standardised error was 1.22 which is close to one (1).

The resulting prediction equation for validation is represented as: $-0.018x + 2.979$.

For the grazing capacity dataset, the resulting root mean square prediction error was 0.67 with the average standard error being 0.71. These figures were deemed close. The root mean square standardised error was 1.22 which is close to 1.0.

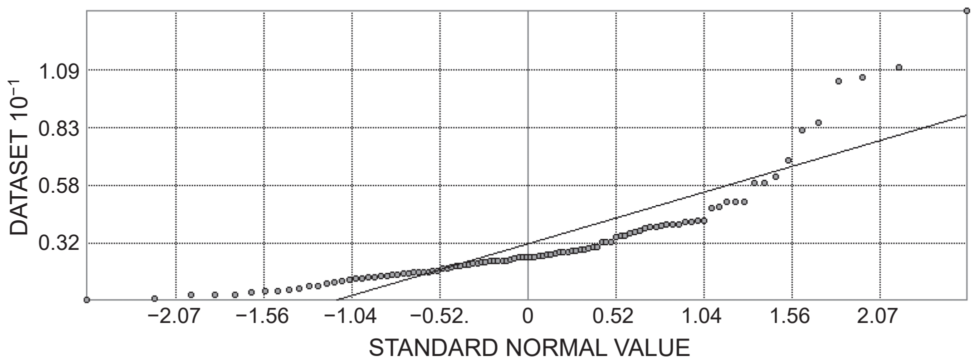

Figure 3: Normality graph of dry matter yield dataset

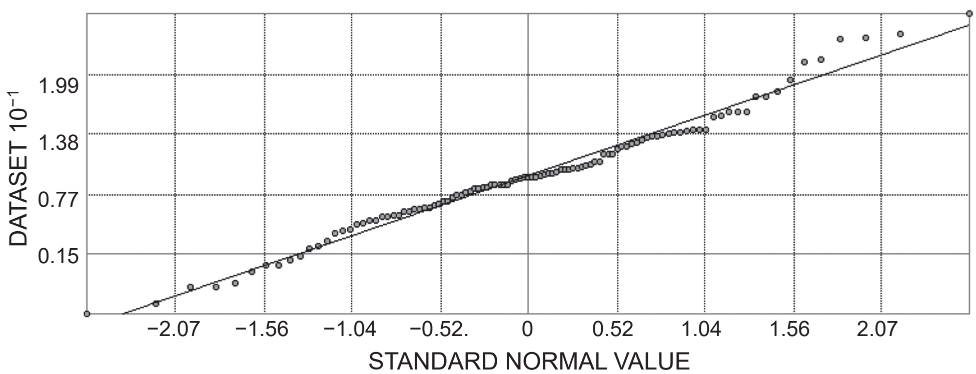

Figure 4: Normality graph of transformed dry matter yield dataset

Table 1: Shapiro–Wilk's test for normality for dry matter yield

Variable	Statistic	df	Signif.	α
Dry matter yield	0.759	105	0.000	0.05
Log transformed dry matter yield	0.984	105	0.243	0.05

The resulting prediction equation for validation is represented as: $-0.018x + 0.841$.

A summary of the various parameters selected for the prediction of the DMY and grazing capacity can be found tabularised (Table 3).

District level ranges of dry matter yield and grazing capacity

Generally, the DMY and grazing capacity values were lower in the Western half of the study area and higher in the Eastern half of the study area (Figures 10 and 11). The lowest DMY in all the districts was estimated to be 0.6 t ha^{-1} and the highest was 13.4 t ha^{-1} (Table 4). The lowest and highest grazing capacity estimated in all the districts were 0.1 LU ha^{-1} and 3.7 LU ha^{-1}, respectively (Table 4).

Crude protein estimates

The general trend of crude protein estimates showed significantly high values towards the western parts of the study area followed by values in the eastern parts (Figure 12). The northern part of the study area recorded the lowest levels of crude protein (%) with the southern part having moderately low values.

The Tolon district recorded an overall crude protein estimate of about 6.7 to 9.3%, with just a small portion being between 6.73 to 7.56%. The neighbouring districts, Kumbumgu, Savelugu Nanton, Sagnerigu and Tamale Sub-Metro recorded crude protein ranges of about 4.91 to 11.23%. The Karaga and Gushiegu districts recorded crude protein estimates within the ranges of 3.06 to 9.37%, with about 30–40% of each district having values within 7.14 to 9.37%. Mion and Nanumba North districts had crude protein estimates between 3.06 and 11.23. The Saboba and Yendi Municipal districts also reported crude protein values between 4.92 and 11.23%. The Zabzugu and Tatale districts had the highest and almost evenly spread crude protein values, with a range of 7.14 to 11.23%. The Nanumba South district had the widest and most diverse crude protein range of 3.06 to 14.29%, with about half of it being between 6.05 to 9.37%. Crude protein estimates for Kpandai were between 4.92 to 9.37%.

Vegetation cover estimates

The aerial cover percentage of woody species in the study area ranged from 0 to 90% with an average 14.51% in the 15 districts. Of the sampled sites 76.2% had aerial cover of woody species between 0 and 20% with 18.1% of them between 21–40% and 5.9% above 40% (Table 5). On the

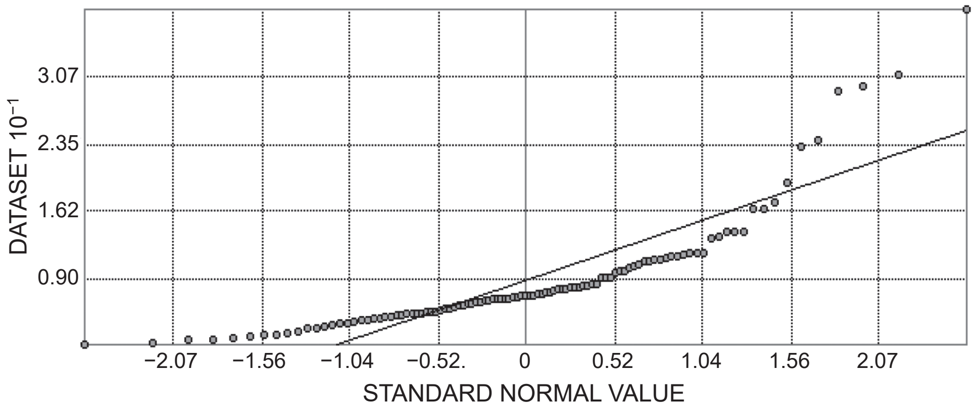

Figure 5: Normality graph of grazing capacity dataset

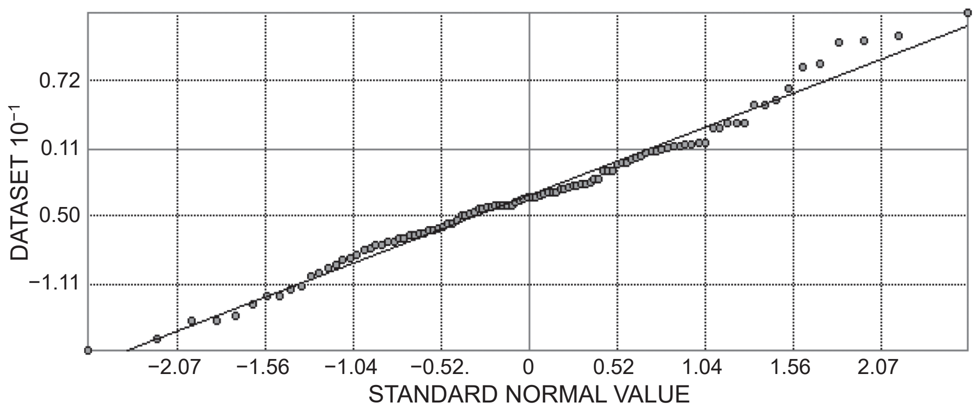

Figure 6: Normality graph of transformed grazing capacity dataset

Table 2: Shapiro–Wilk's test for normality for grazing capacity dataset

Variable	Statistic	df	Signif.	α
Grazing capacity	0.759	105	0.000	0.05
Grazing capacity (Log transformed)	0.984	105	0.243	0.05

other hand, herbaceous cover percentage ranged between 5 and 95% (with only 16% of the sites recording under 40%).

Dominant species

About 96 different herbaceous species were recorded in the study area, among these, 23 different grass species were recorded as dominant species in the 315 sub-plots sampled. Out of the 23 dominant grass species, 12 were perennials and 11 were annuals (Table 6).

Species diversity indices at the district level

Districts in the north-western parts of the study area generally had lower species richness. The Sagnerigu, Kumbumgu and Tamale Metro districts had 7, 11 and 16 different species, respectively (Table 7). On the other hand, districts located in the Central parts of the study area recorded high species richness. Gushiegu, Mion, Nanumba North, Nanumba South and Yendi Municipal recorded 39, 37, 36, 31 and 31 different species respectively (Table 7).

The highest species diversity was recorded at the Kpandai district using the Shannon–Weiner *H′* (2.40), Shannon–Weiner *J* (0.76) and Simpsons *1–D* (0.89) diversity indices (Table 8). Species richness was however highest in the Gushiegu district. Apart from the Shannon–Weiner *J* species diversity index that recorded the lowest diversity in the Nanumba North district (0.49), the Sagnerigu district recorded the lowest species diversity for the Shannon–Weiner *H′* (1.13) and Simpsons *1–D* (0.62) indices with low species richness 7 (Table 8).

Discussion

Accuracy of models

The results of this study show that clipped biomass data incorporated into Geostatistics and Geographic Information Systems is a reliable means to predict DMY and grazing capacity. In both DMY and grazing capacity models, the root mean square error and average standard errors were very close (2.38 and 2.51, 0.67 and 0.71 respectively). The root-mean square standardised error for DMY and grazing capacity predictions were also close to one (both being 1.22). For a good model, root

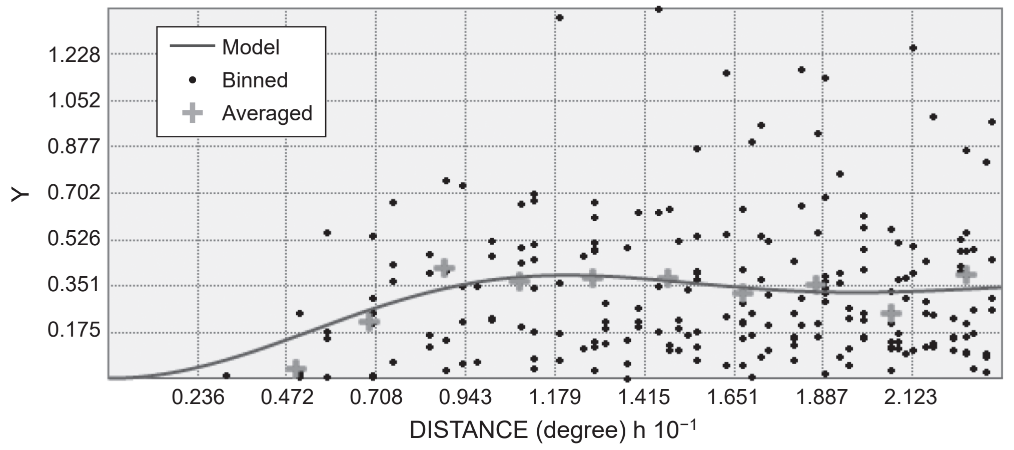

Figure 7: Semivariogram for dry matter yield

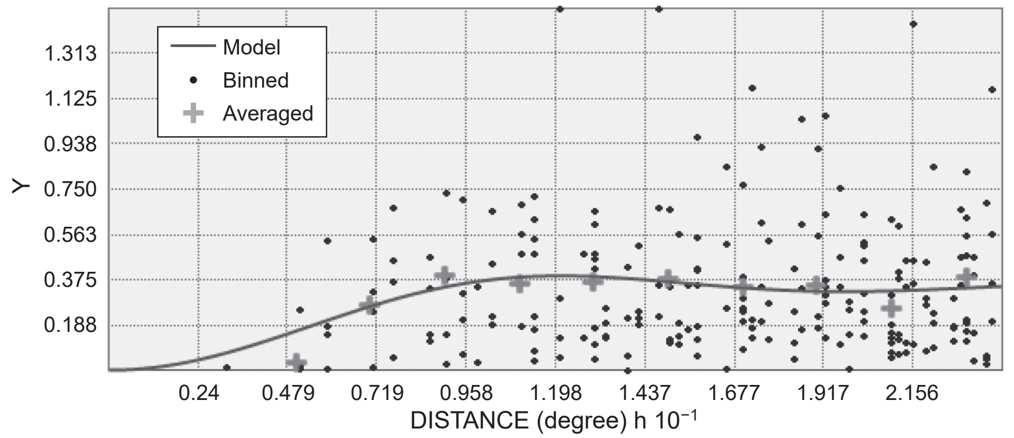

Figure 8: Semivariogram for grazing capacity

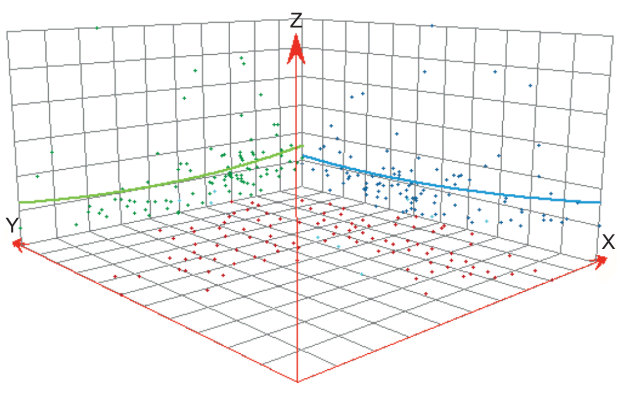

Figure 9: Trend analysis of datasets (the blue line shows trend in the north-south direction whilst the green line shows trend in the east-west direction)

mean square standardised error should be close to one (Diodato 2005) and the root mean square error should be close to the average standard error (ESRI 2019; GISGeography 2020).

The root mean square error and the average standard error are indices that represent the goodness of prediction (precision), while the root mean squared standardised error compares the error variance with a theoretical variance. The results obtained indicate that the decision criteria for predicting the models were valid (Table 3).

The root-mean square error obtained for DMY in this study (1.22 t ha^{-1}) was slightly higher than that obtained by Timpong-Jones et al. (2013) and Mutanga and Rugege (2006). Using the ordinary Kriging interpolator for herbaceous biomass estimation, Timpong-Jones et al. (2013) obtained a root mean square error of 0.9764 t ha^{-1} whilst Mutanga and Rugege (2006) obtained 1.008 t ha^{-1} both in tropical rangelands. The spatial information contained in both datasets through spatial autocorrelation, can be said to explain the variance in DMY and grazing capacity estimations as seen by the results of this study.

In Geostatistics interpolations (unlike the use of various regression analyses), the semivariogram allows the examination of the spatial autocorrelation between measured sample points with the assumption that points close together are more alike than those farther apart

(Isaaks and Srivastava 1989; ESRI 2019). This contributes to their accuracy (Mutanga and Rugege 2006).

Dry matter yield and grazing capacity and observed trend

Dry matter yield

The DMY of the Guinea savannah rangeland ranging between 0.63 and 13.43 t ha⁻¹, with a mean value of 3.09 t ha⁻¹, is a clear indication of spatial variability in DMY. The western part of the study area had lower values while higher values were obtained in the north-eastern and south-eastern parts. Fosu et al. (2004) reported DMY of the Guinea savannah to be between 5 to 15 t ha⁻¹. These values are close to the values obtained in this study. The difference between the two results however is attributable to the different locations sampled and the detail in sampling methods. This study surveyed far more sampling locations than that of Fosu et al. (2004). Additionally, the varying levels of soil quality at the sampled locations could cause variations in DMY, as higher quality soil promotes plant growth as a result of increased nutrients and water absorption (Brown et al. 2016). Avornyo (2014) indicated that although soils in the districts of the Guinea savannah are reported to have been formed from the same parent material, significant differences in soil characteristics are found at different locations within the agroecological zone. Behnke and Scoones (1992) reported that African rangelands are ecologically heterogeneous and may be expressed in terms of a patchy distribution of pockets of high and low range productivity. Scoones (1999) further clarified that the heterogeneity of rangelands is often forgotten, with simplistic categorisations made to describe situations over wide areas.

Grazing capacity estimates

Grazing capacity ranged between 0.18 LU ha⁻¹ and 3.79 LU ha⁻¹, with a mean value of 0.87 LU ha⁻¹. This is close to results obtained by Timpong-Jones et al. (2013)

Table 3: Decision ‘protocol’ used for predicting dry matter yield and grazing capacity in geostatistics

Decision	Method	Type	Others
Interpolation	Kriging	Ordinary	Output: prediction
Transformation		Log	
Searching neighbourhood		Standard	Neighbours to include: 5 At least: 4 Sector type: Full
Variogram		Semi-variogram	
Model		J Bessel	Partial Sill

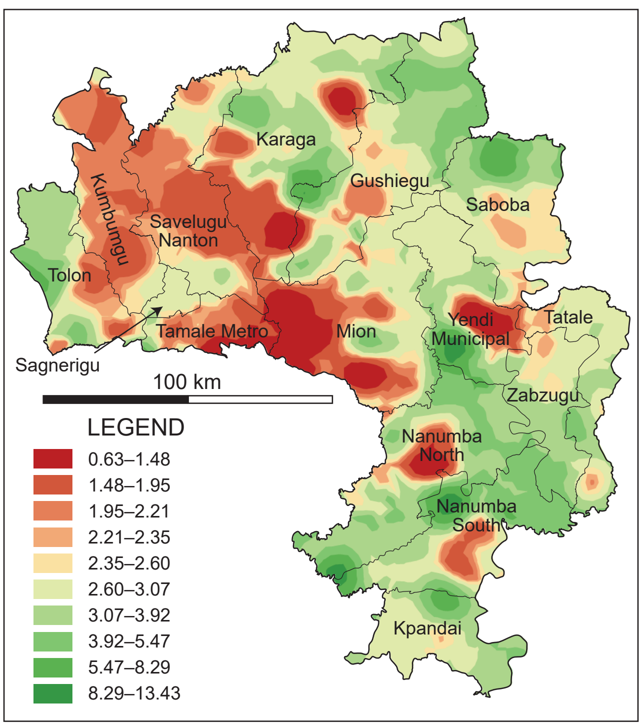

Figure 10: Dry matter yield map of study area (t ha⁻¹) showing the districts

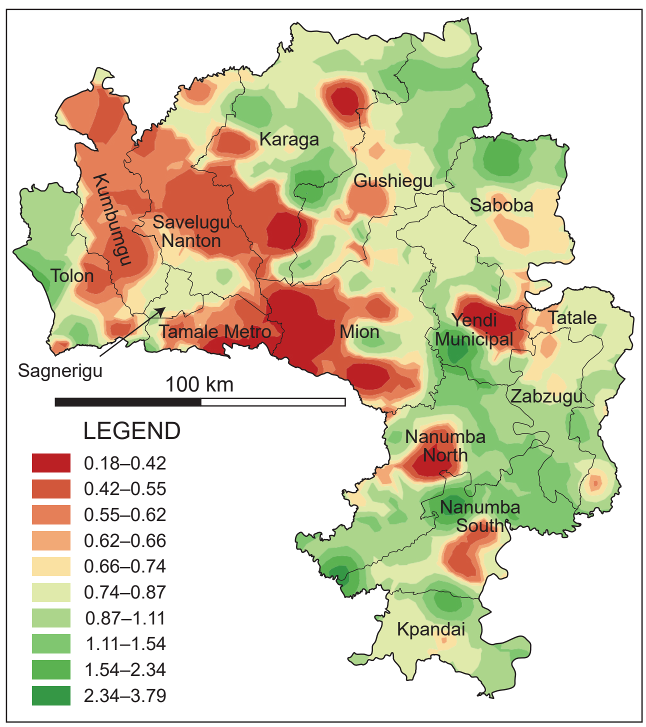

Figure 11: Grazing capacity map of study area (LU ha−1) showing the districts

Table 4: District level ranges of dry matter yield and grazing capacity

District	Dry matter yield (t ha^{-1})	Grazing capacity (LU ha^{-1})	Important observation
Tolon	1.4–8.2	0.4–2.3	
Kumbumgu	1.4–3.0	0.4–0.8	
Sagnerigu	1.9–3.9	0.6–1.1	90% of DMY fell within the range of 2.6–3.0 t ha^{-1}
Savelugu Nanton	0.6–5.4	0.1–1.5	
Karaga	0.6–8.2	0.1–2.3	
Mion	0.6–5.4	0.1–1.5	
Tamale Sub-Metro	0.6–8.2	0.1–2.3	80% of DMY fell within the range of 0.6–2.3 t ha^{-1}
Gushiegu	1.4–5.4	0.4–1.5	
Saboba	1.5–8.2	0.5–2.3	Majority of DMY values ranged between 2.3–5.7 t ha^{-1}
Nanumba North	0.6–8.2	0.1–2.3	
Nanumba South	1.4–13.4	0.4–3.7	
Kpandai	2.2–8.2	0.7–2.3	
Zabzugu	1.9–5.4	0.6–1.5	
Tatale	1.4–3.9	0.4–1.1	
Yendi	0.6–13.4	0.1–3.7	50% of DMY fell between 2.6–3.9 t ha^{-1}

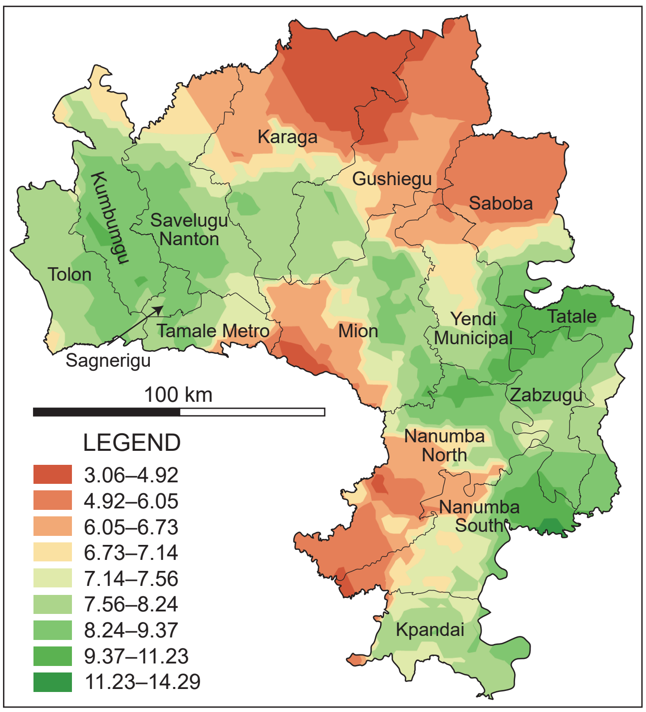

Figure 12: Map of predicted crude protein percentage of study area

in the Coastal Savannah rangelands of Ghana. They reported a range between 0.4 and 4.94 LU ha^{-1} with a mean value of 2.16 LU ha^{-1}. Since the same proper use factor was used in both studies, any differences obtained in the grazing capacity values could be attributed to the different environmental conditions (such as weather and soil types) at the sampled locations. The values obtained for grazing capacity are strongly influenced by the DMY values (Timpong-Jones et al. 2013) since DMY values are used in the computation of the grazing capacity values.

Table 5: Aerial cover percentage of shrubs in the eastern part of the Guinea savannah rangeland

Cover class (%)	Number of sites	Percentage of the total number of sites (%)		
0–10	60	57.1	76.1	98
11–20	20	19.0		
21–30	10	9.5	18.1	
31–41	9	8.6		
41–50	3	2.8	3.8	
51–60	1	1		
61–70	0	0	1	2
71–80	1	1		
81–90	1	1	1	
91–100	0	0		
Total	105		100	

Observed trends

The observed trend of lower DMY and grazing capacity values in the western part of the study area and higher values in the north-eastern and south-eastern parts of the study area (Figures 9 and Figure 10), which could be attributed to factors such as population size and level of urbanisation. Population data from the GSS (2014) indicate that there has been a consistent increase in the population of people living in urban settlements in Ghana. The population in the Western parts with lower DMY and grazing capacity values such as Mion and Tamale districts is reported to be high (GSS 2014), compared to other districts such as the Tatale and Kpandai districts in the north-eastern and south-eastern parts of the study area. Additionally, GSS (2021) indicated that, Tamale is 100% urbanised while Tatale and Kpandai districts are 14.2% and 15% urbanised respectively. As such, it can be concluded that anthropogenic activities associated with high population and urbanisation has led to relatively lower DMY and grazing capacity values in the western part of the study area when compared to the north-eastern and south-eastern parts.

Crude protein content

The varying crude protein content of forages recorded across the study area can be attributed to the different species identified and their growth stage at harvest. Districts such as Karaga, Gushiegu and Saboba were dominated by *Hyparrhenia rufa*, which has been reported to have good to fair nutritive value. *Hyparrhenia rufa* is palatable only when young and immature as the plant becomes lignified with age (Roodt 2011). Similarly, the Tatale and Sagnerigu districts reported higher crude protein contents as they were dominated by *Pennisetum pedicellatum*, which has relatively high crude protein levels (Zailan et al. 2018). The districts with high DMY recorded low crude protein contents due to the fact that, the more forages mature, the higher the DMY but the lower the crude protein content (Figure 10 and Figure 12). Some parts of the Mion district however had both low DMY and low crude protein contents. This can be attributed to anthropogenic activities such as excessive grazing and constant land clearing. These activities exert pressure on the rangelands, making their recovery difficult (Hilker et al. 2014).

Table 6: Dominant grass species grouped into perennials and annuals

Perennial species	Annual species
Andropogon gayanus	*Brachiaria lata*
Andropogon tectorum	*Chloris pilosa*
*Digitaria longiflora**	*Digitaria horizontalis*
*Eragrostis ciliaris**	*Digitaria nuda*
*Eragrostis tremula**	*Echinochloa colona*
Heteropogon contortus	*Leptochloa caerulescens*
*Hyparrhenia involucrata**	*Oryza barthii*
*Hyparrhenia rufa**	*Pennisetum pedicellatum*
Imperata cylindrica	*Pennisetum polystachion**
Paspalum orbiculare	*Rottboellia cochinchinensis*
Rhynchelytrum repens	*Setaria pallide-fusca*
Sporobolus pyramidalis	

*Grass species considered as annuals or short-term perennials.

Dominant plant species in the Guinea savannah rangeland

The most dominant species in the Guinea savannah rangeland of Ghana in decreasing order are *Hyparrhenia rufa, Pennisetum pedicellatum, Eragrostis tremula* and *Andropogon gayanus*. Areas to the west and north-west of the study area (Tolon, Kumbumgu, Tamale Metro, Karaga, Gushiegu and Mion) were dominated by *Hyparrhenia rufa* whilst areas to the east and south-east

Table 7: Dominant grass and sub-dominant grass species in the districts of the study area

District	Dominant grass species	Subdominant herbaceous species
Kumbumgu	*Hyparrhenia rufa*	*Andropogon gayanus, Eragrostis ciliaris, Eragrostis tremula*
Savelugu Nanton		*Hyparrhenia rufa, Pennisetum pedicelatum, Heteropogon contortus*
Sagnerigu	*Pennisetum pedicellatum, Paspalum orbiculare*	
Tamale Metro	*Hyparrhenia rufa, Eragrostis tremula*	*Heteropogon contortus*
Karaga	*Hyparrhenis rufa*	*Pennisetum pedicellatum*
Gushiegu	*Hyparrhenia rufa*	*Pennisetum pedicellatum, Eragrostis tremula*
Tolon	*Hyparrhenia rufa*	*Andropogon gayanus*
Saboba	*Andropogon gayanus, Hyparrhenia rufa, Pennisetum pedicellatum*	*Eragrostis tremula*
Yendi	*Pennisetum pedicellatum, Hyparrhenia rufa*	*Eragrostis tremula, Oryza barthii*
Mion	*Hyparrhenia rufa*	*Andropogon gayanus, Eragrostis tremula, Pennisetum pedicellatum*
Nanumba North	*Pennisetum pedicellatum*	*Eragrostis tremula*
Nanumba South	*Pennisetum pedicellatum*	*Eragrostis tremula, Hyparrhenia rufa*
Zabzugu	*Eragrostis tremula, Hyparrhenia rufa*	*Pennisetum pedicellatum, Andropogon gayanus*
Tatale	*Pennisetum pedicellatum, Rottboeilia cochinchinensis*	*Eragrostis tremula, Hyparrhenia rufa*
Kpandai		*Pennisetum pedicellatum, Hyparrhenia rufa, Eragrostis tremula, Andropogon tectorum*

Table 8: Species diversity indices per district within the Guinea savannah rangeland

Locations	Species diversity indices			
	Shannon–Weiner, *H*	Shannon–Weiner, *J*	Simpsons, *1–D*	Species richness
Gushiegu	2.20	0.60	0.82	39.00
Karaga	1.67	0.53	0.66	23.00
Kpandai	2.40	0.76	0.89	24.00
Kumbumgu	1.39	0.58	0.66	11.00
Mion	2.20	0.61	0.82	37.00
Nanumba North	1.74	0.49	0.65	36.00
Nanumba South	2.13	0.62	0.80	31.00
Saboba	2.24	0.69	0.86	26.00
Sagnerigu	1.13	0.58	0.62	7.00
Savelugu Nanton	2.13	0.68	0.82	23.00
Tamale Sub-Metro	1.51	0.54	0.63	16.00
Tatale	2.19	0.72	0.84	21.00
Tolon	1.76	0.57	0.73	22.00
Yendi	2.23	0.65	0.84	31.00
Zabzugu	1.72	0.55	0.71	23.00
Total	2.71	0.59	0.86	96.00

(Nanumba North, Nanumba South and Tatale) were dominated by *Pennisetum pedicellatum*. Tamale Metro and Zabzugu showed presence of *Eragrostis tremula* as well as *Hyparrhenia rufa*. The Saboba district showed the dominance of *Andropogon gayanus, Hyparrhenia rufa* and *Pennisetum pedicellatum*.

Grass species from the Andropogonae tribe (*Andropogon gayanus* and *Hyparrhenia rufa*) as well as the Paniceae tribe (*Pennisetum pedicellatum*) are described as mostly abundant in tropical savannahs of Africa, India and South America (Skerman and Riveros 1990). Due to the general classification of *Andropogon gayanus, Hyparrhenia rufa* and *Pennisetum pedicellatum* as having moderately high nutritive value and palatability (Skerman and Riveros 1990), their presence in the Guinea savannah is an indication of a fairly good range condition. However, these species are very palatable and highly nutritious when young but their quality and palatability decline when mature (Roodt 2011). As a result, the presence of mature plants at the time of sampling, is indicative of a deteriorating range condition.

Rank abundance plot and diversity indices

The general diversity trend as indicated by the rank abundance plot and calculated diversity indices (Shannon–Wiener's Diversity Index and Simpson's Index of Diversity) show that the districts at the western part of the study area have low plant diversity, while the districts to the south have relatively high plant species diversities and the districts to the north-eastern part having comparatively higher plant species diversity (Table 8). A similar trend was obtained for the calculated species evenness among the districts (Table 8). Generally, the districts to the north-western part of the study area had lower species richness whilst those toward the central parts of the study area had the highest levels of species richness, with Kpandai, Saboba, Yendi and Tatale being the most diverse with regards to their species. The area with least diversity is the Tamale Metro district.

In community ecology, much premium is placed on the relationship between live, aboveground herbaceous biomass, and species richness and diversity (Bai et al. 2007; Prtel et al. 2007). However, these relationships have not been well studied and documented in many tropical rangelands in sub-saharan Africa. Some studies however have found the relationship between plant biomass and species diversity/richness to be weak, negative, positive or not detectable (Osem et al. 2002). The decline in species richness at high productivity levels is however attributable to plant extinction due to competition (Jacobs and Naiman 2008). Rapidly growing tall grass species outcompete smaller ones for resources such as water, nutrients and space, leading to loss of vigour and their eventual death.

Conclusions

The integration of Geostatistics into Geographical Information Systems is a modern and reliable method of estimating DMY and grazing capacity of rangelands. The study has shown the clear spatial variability of DMY in the Guinea savannah rangelands of Ghana, with lower values in the western parts and higher values in the north-eastern and south-eastern parts. It was concluded that there is spatial variation in herbage yield, grazing capacity and species diversity in the Guinea savannah rangelands of Ghana supporting our hypothesis. Some areas need effective site-specific improvement strategies for sustainable livestock production.

Additionally, the presence of *Hyparrhenia rufa, Pennisetum pedicellatum, Eragrostis tremula* and *Andropogon gayanus* as dominant species in the Guinea savannah of Ghana is indicative of potential good range condition, if the range resource is well managed and utilised. A larger range of diverse plant species could be found in the north-eastern part of the Guinea savannah, with the lowest diversity being in the western parts, and the southern part having relatively higher plant species diversities than the north- eastern parts.

Recommendations

A similar study should be carried out in the western part of the Guinea savannah and the Sudan Savannah areas to provide a comprehensive overview of the present condition of the rangelands of Ghana. This will give a holistic overview of the health, production and condition of the forages for ruminant livestock production. It is also recommended that a study on actual stocking rates of the Guinea savannah rangelands be carried out. There is also the need for studies into the relationship between herbaceous biomass and species richness and diversity.

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