IOP Conf. Series: Earth and Environmental Science **540** (2020) 012061 doi:10.1088/1755-1315/540/1/012061

Mapping Seasonal Variations of Grazing Land Above-ground Biomass with Sentinel 2A Satellite Data

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Abstract. Seasonal variations have brought about significant changes in vegetation cover and spatial distribution in the past decade. Globally, grazing lands are experiencing a significant warming and drying process more especially the grazing lands in the Savannah and Sahel regions. This paper reports the study undertaken for mapping changes on the grass above ground biomass (GAB) due to these seasonal changes using Sentinel 2A Multispectral Instrument (MSI) data. Emphasising on the GAB, the main objective of this study is to map and model monthly GAB variations to their corresponding meteorological data. A set of selected widely used vegetation indices were applied to satellite data, and later were further regressed against corresponding in-situ GAB samples and weather data, hence, producing a predictor of GAB from satellite data. Sentinel 2A MSI data were acquired monthly from January to December 2018. Combined with precipitation and temperature data, the GAB variations on monthly scales were analysed. The results indicated that GAB determined and its seasonal variations shown good agreement ($r = 0.8$, $p < 0.001$) with corresponding in-situ verifications. Temperature was found inversely proportionally to GAB for the whole grazing calendar. Therefore, it was concluded that mapping GAB seasonal variations is achievable with Sentinel2 MSI, vast potential for input to grazing land management.

1. Introduction

The Grassland quantities are declining, mainly caused by human-induced changes along with agricultural production, substantial livestock grazing, as well as endangered species, and was further challenged by potential impact of seasonal changes [1]. Nomads need to adapt to seasonal change to ensure sustainable grazing ideas, but they also need assistance like obtaining information on the area's vegetation conditions and seasonal patterns [2]. Unless the grassland ecological system natural changes are recognized and are used as development policy guidelines, interventions are probably to be random tasks comprising guesswork development [3]. A systematic evaluation is required to explain the complexities of the grazing-lands in the Savannah as basis for the development of appropriate management policies [4].

Previous studies addressed the interaction between changes in vegetation and climate variations on annual basis and generally concluded that rainfall was most apparent to influence vegetation productivity [5]. Ibitola & Balogunb [6] utilize the 2005, 2010 and 2019 Moderate Resolution Spectro-

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radiometer (MODIS) datasets to investigate spatio-temporal drought variation in Northern Nigeria. Numerous methods were used in investigation the possible impacts of seasonal variations on grass productivity, e.g. vegetation index depending on remote sensing information to describe the possible relations between seasonal change and the corresponding changes in vegetation [7]. As such, the Vegetation Index was popularly used on broader spatial and temporal scales to describe the regional vegetation cover.

This paper reports the preliminary results on study of seasonal variations of GAB in grazing reserves using Sentinel 2A Multispectral Instrument (MSI) data, incorporated with corresponding meteorological data. These GAB derived information that can aid in restoring the reserves and increase livestock sustainability. The main objective of this study is to map and estimate monthly GAB variations and determines the impact of rainfall and temperature in Daware grazing land, north-eastern (NE) Nigeria. In addition, spatiotemporal dynamics of GAB within complete grazing calendar were also examined and analysed

2. Materials and Methods

2.1. Study Area

The study area is Daware grazing land in Adamawa state, north-eastern part of Nigeria (Figure 1); with approximate area of 7409.20 ha. Most regions in the NE-Nigeria are sparsely vegetated due to limited rainfall and the natural climate is fragile [8-10]. Daware grazing land's vegetation cover is essentially the grassland of Guinea Savanna with the grass interspersed with small, drought-resistant trees. The grass species was dominated by mixture elephant grass species and shrubs. The reserve soils are typically sandy-loam type except in very few areas where there are alluvial deposits [11, 12].

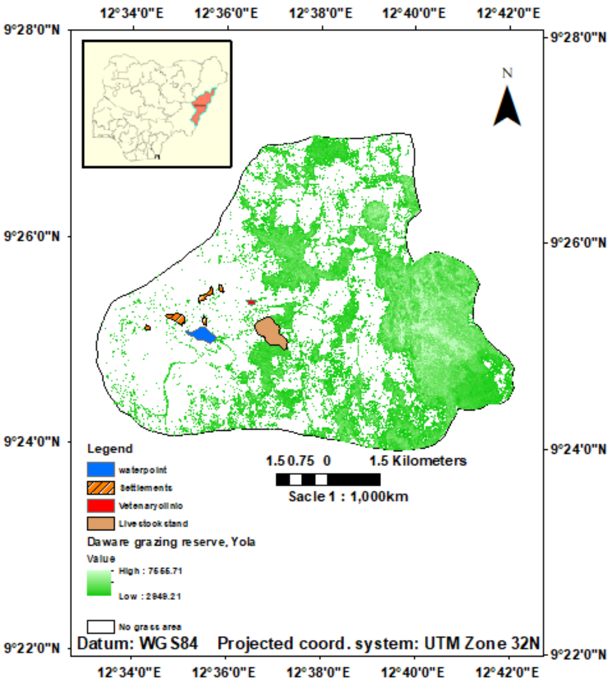

Figure 1. Daware grazing land, Yola, NE-Nigeria.

The study area's native people are mostly farmers who make up about 60% of the state's population. Agricultural production is the inhabitant's primary activity as they rear livestock in addition to crop production. Majority of the people are subsistence farmers in nature. The pastoralist is always on the move searching for grasses and water for their livestock.

2.2. Satellite and Ancillary Data

2.2.1. Field samplings. Systematic sampling was adopted for the collection of field GAB. The sampling was based on the Green House Gas Emission Guidelines [13] for above ground biomass field survey guide for baseline survey. The sampling quadrant 10x10 m quadrant was adopted for the sampling of grass measurement that represents the pixel size of the satellite imagery used. For each quadrant, five samples of 1m x 1m of grass was measured, harvested and weight for GAB estimation. The grass samples were later taken to the ovum in the laboratory for 72hrs at 40.6°C to dry. It was then weighed to get the biomass in grams. Total number of 300 samples was collected.

2.2.2. Satellite Data. Sentinel 2A MSI data spatial resolution is 10m, therefore a Satellite data of Sentinel 2A and 2B MSI for a complete season was acquired from the USGS explorer free data services (Table 1). A comparison was made between the monthly satellite images of the study area between 2017 and 2018; and has shown no significance difference.

Table 1. Sentinel 2A/2B MSI Data used in the study

Image data	Product level	Cloud cover	Date of acquisition
S2A_MSIL1C_20180127T093241_N0206_R136_T33PTL_20180127T132740	L1C	<10%	27 January 2018
S2B_MSIL1C_20180221T093029_N0206_R136_T33PTL_20180221T145848	L1C	<10%	21 February 2018
S2B_MSIL1C_20180303T093029_N0206_R136_T33PTL_20180303T113257	L1C	<10%	03 March 2018
S2A_MSIL1C_20180407T093031_N0206_R136_T33PTL_20180407T113929	L1C	<10%	04 April 2018
S2A_MSIL1C_20180517T093041_N0206_R136_T33PTL_20180517T114231	L1C	<10%	17 May 2018
S2A_MSIL1C_20170601T093041_N0205_R136_T33PTL_20170601T094458	L1C	<10%	01 June 2017
S2B_MSIL1C_20170716T093039_N0205_R136_T33PTL_20170716T093617	L1C	<10%	16 July 2017
S2B_MSIL1C_20180810T093029_N0206_R136_T33PTL_20180810T132651	L1C	<10%	10 August 2018
S2B_MSIL1C_20180929T093029_N0206_R136_T33PTL_20180929T132115	L1C	<10%	29 Sept. 2018
S2B_MSIL1C_20181019T093029_N0206_R136_T33PTL_20181019T113408	L1C	<10%	19 Oct. 2018
S2A_MSIL1C_20181123T093311_N0207_R136_T33PTL_20181123T112737	L1C	<10%	23 November 2018
S2A_MSIL1C_20181223T093411_N0207_R136_T33PTL_20181223T112232	L1C	<10%	23December 2018

2.2.3. Meteorological data. The climatic data was from the Nigeria Meteorological Survey Yola for 2018 grazing calendar (Figure 2.). Daware grazing reserve is very near to Yola, the capital of the Adamawa state; hence, they experience the same climatic conditions. The estimated annual temperature is 28.0 ° C. April is the warmest month with an average of 32.1 °C. December is normally the coldest month, having average temperatures of 25.9 °C. The average rainfall in a year is 933 mm. The precipitation ranges from the driest month to the wettest month to 211 mm. Temperatures usually vary by 6.2 °C throughout the year [14].

2.3. Methods

The methods involved in this study are data collection, data processing, and the presentation of the analyzed result as spatio-temporal information of the study area. These are summarized as a flowchart in Figure 2.

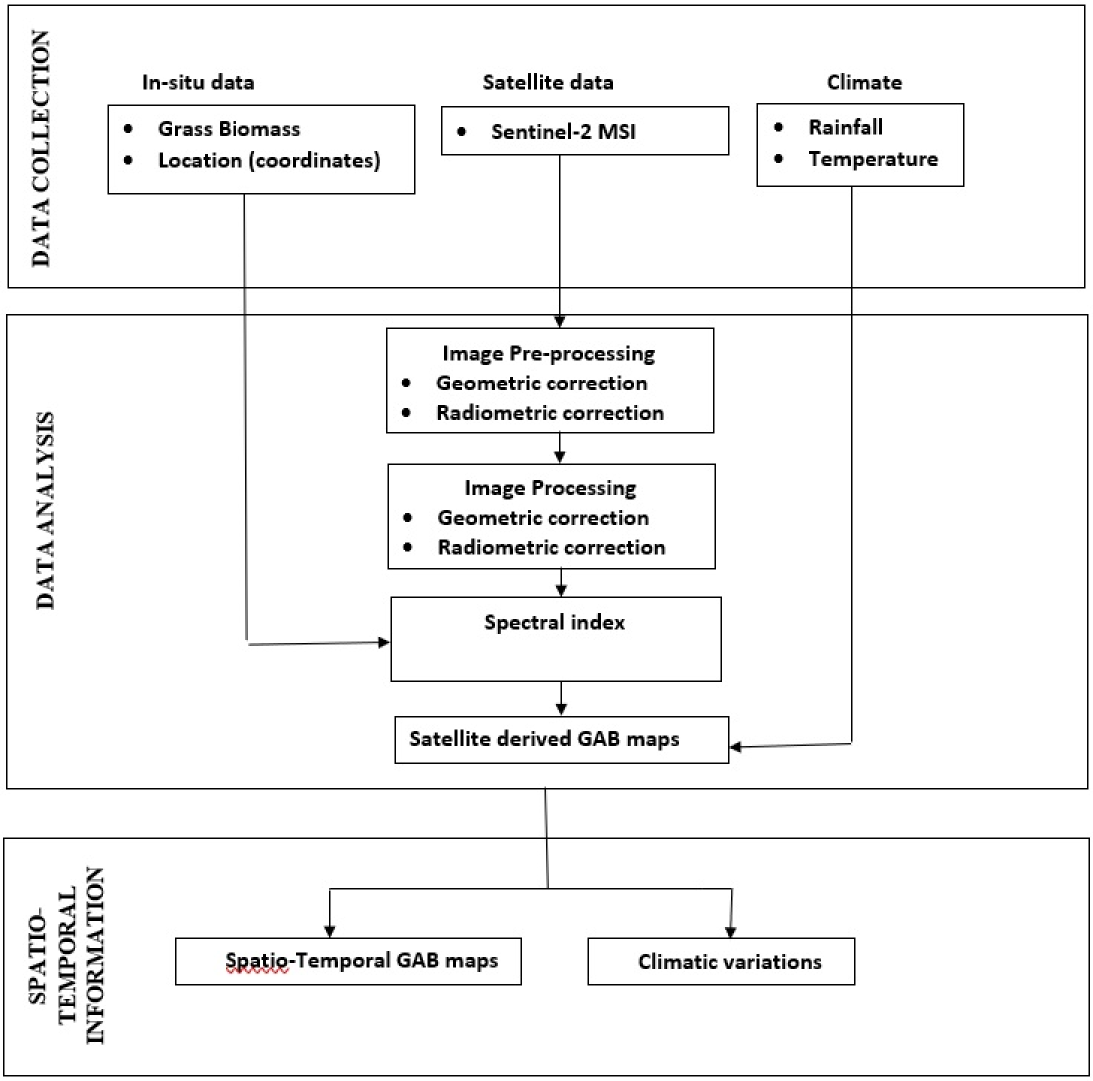

Figure 2. Flowchart of methodology.

A substantial number of vegetation indices were established tailored to vegetation analysis and mapping. These indices were sorted out and selected based on a threshold of $R^2 > 0.5$. The VIs were correlated with their corresponding induction GAB and were ranked from the best correlated to the worst. Four (4.) of these indices has a good correlation $R^2 > 0.5$ and they were chosen as the most relevant vegetation indices that will be used in the study. These are Normalized Distribution of Vegetation Index (NDVI), Vegetation Index Number (VIN), Normalized Difference Index (NDI) and Ratio Vegetation Index (RVI). They were determined based on variations between chlorophyll absorbing visible light (from 0.4 to 0.7 μm) and leaf cell structure reflecting near-infrared light (from 0.7 to 1.1 μm) which is the ratio between Near-infrared (NIR) and Red band. The pixel position was detected by the coordinates that was acquired by GPS during the capture of data samples. The linear regression was used in analyzing the correlation of this vegetation index with in-situ GAB to obtain the spectral transformation model. Using the transformation model, GAB estimates for the whole grazing calendar was obtained. Precipitation and temperature were correlated with the satellite derived GAB in order to determine its relationship.

3. Results

3.1. GAB Estimation using Spectral Transformation Model

Multiple regression was used to identify the relevant vegetation indices among the initially selected four and were also ranked in their performance in-terms of their correlation with GAB. This was chosen based on the threshold values R^2> 0.8000; P-value < 0.05 and validation at RMSE ±2.00g/m^2. Figure 3. Presents the relationship between the induction GAB and each of the four vegetation indices.

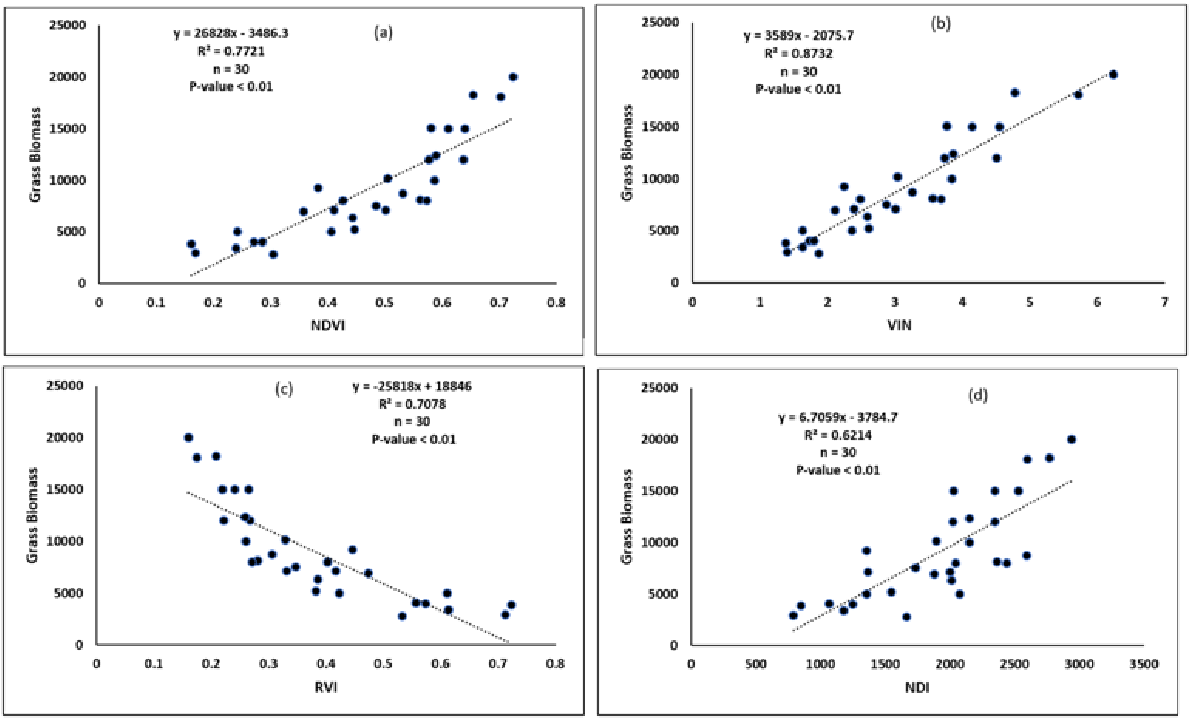

Figure 3. Map Biomass relationship with: (a) NDVI, (b)VIN, (c) RVI, (d)NDI.

The relationships of each of the VIs with in-situ GAB were indicated by R^2 and p-value. The result of the four of the VIs tested and validated was given in Table 2. Among the four vegetation indices, VIN is the most fitted vegetation index that can be used to modeled measured GAB to the satellite imagery. It has the highest degree of correlation and validated RMSE < 2.00g/m2.

Table 2. Summary of Spectral Models and Validation.

Vegetation Index	Model	R^2	F-Value	P-value	RMSE (g/m^2)
NDVI	GAB = 26828x - 3486.3	0.7721	192.88	<0.01	2.35
VIN	GAB = 3589x - 2075.7	0.8732	192.88	<0.01	1.75
NDI	GAB = 6.7059x - 3784.7	0.62	45.95	<0.0100	3.03
RVI	GAB = -25818x + 18846	0.71	67.83	<0.01	2.67

The VIN derived model was used to calculate the monthly GAB of the study area from satellite data. The calculated GAB in kg for 12 months was presented as maps in Figure 4 and Table 3.

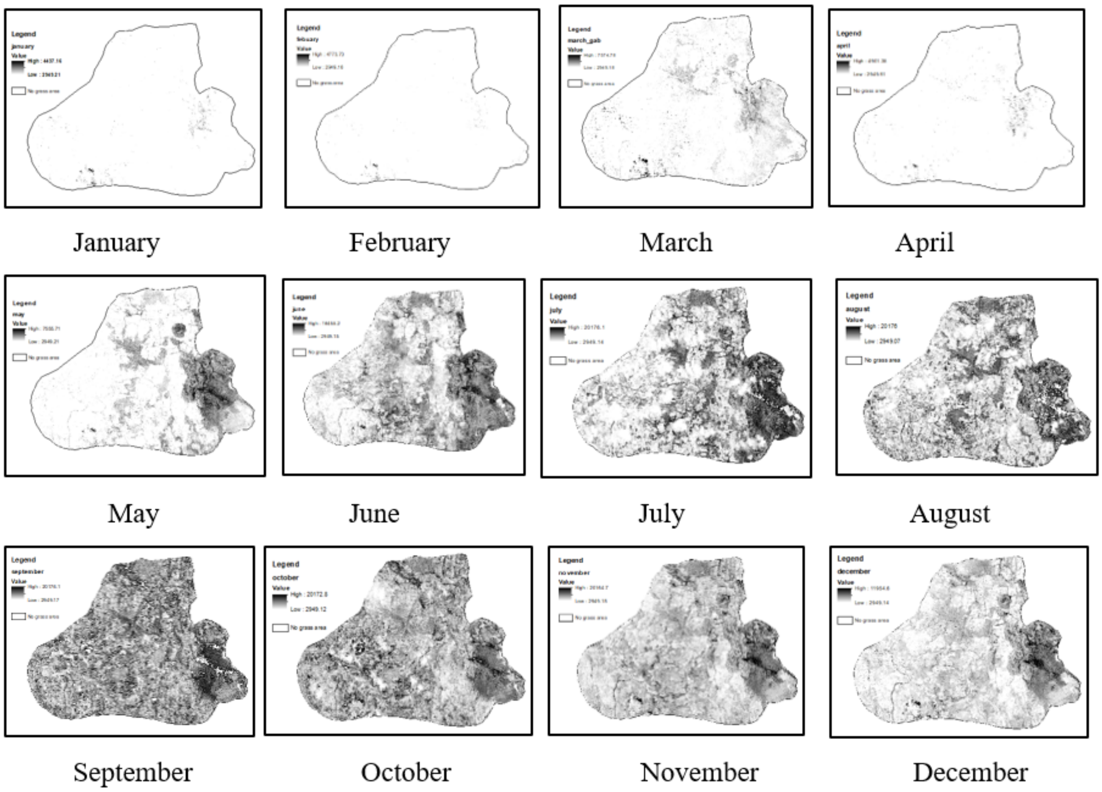

Figure 4. Monthly GAB derived from satellite data.

The reserve has a maximum GAB estimated at 7,353.55 tones of grass by the month of September, approximately, 1.02 $tn^{-1}ha$. The minimum grass availability is in the month of February estimated at 24.65 tones approximately 0.32$tn^{-1}ha$.

3.2. Relationship of GAB with Rainfall and Temperature

Over the years, grazing-lands in northern Nigeria were influence by changes in climate through temperature increase, protracted dry seasons, floods, and drought, that resulted to low grass productivity and spatial distribution. The result from this study revealed that in the wet season starting from April to September, there is an increase in GAB with rainfall amount ($R^2 > 0.8$) and ($P < 0.01$). This indicates there is a significant relationship between rainfall and GAB. However, temperature was negatively correlated with grass biomass in the wet season ($R^2 > -0.8$) and ($P < 0.01$) (Figure 5). This result will be used for future studies in predicting GAB availability within certain months using rainfall and temperature data as variables.

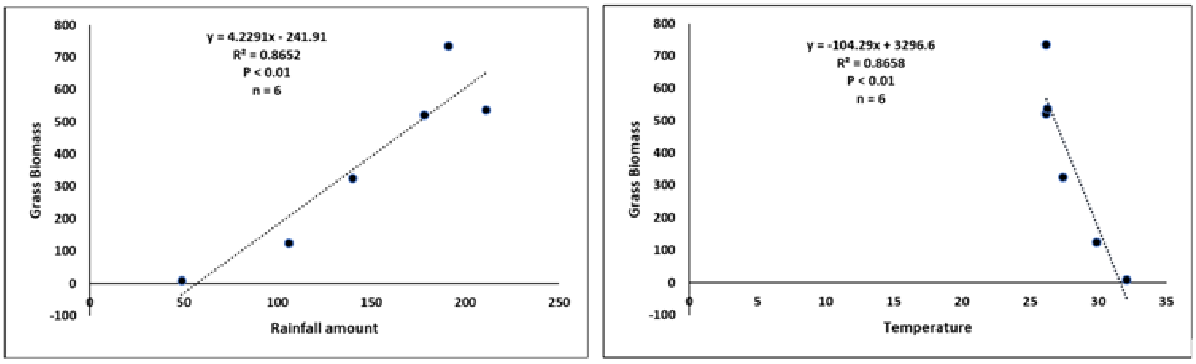

Figure 5. Effect of (LHS) rainfall (RHS) temperature on GAB in Daware grazing reserve.

Table 3 are the results of the monthly climatic conditions and the grass above-ground biomass in Daware grazing reserve situated in savannah zone.

Table 3. Result of the GAB and climate data in Daware grazing land.

Month	JAN	FEB	MARCH	APRIL	MAY	JUNE
GAB (kg)	46,067.65	24,647.67	737,975.15	69,031.07	1,236,422.23	3,249,077.53
Area (ha)	148.32	77.85	2,359.68	219.57	3,322.02	6,510.27
Rainfall (mm)	0	0	5	49	106	140
Temperature (°C)	26.5	28.6	31.3	32.1	29.9	27.4

Month	JULY	AUG	SEPT	OCT	NOV	DEC
GAB (kg)	5,219,687.05	5,365,059.38	7,353,546.42	5,889,869.13	3,471,028.57	2,380,951.93
Area (ha)	6,668.05	6,785.13	7,198.69	7,332.44	7,344.90	6,537.72
Rainfall (mm)	178	211	191	52	3	0
Temperature (°C)	26.2	26.3	26.2	27.7	27.4	25.9

4. Discussion

4.1. GAB Estimation using Satellite Data

The vegetation index serves as indicator in an equation, which transforms the measured in-situ biomass into satellite data [15]. As the spectral reflection of green vegetation is very low in the Red band and relatively much higher in the optical spectrum region of the NIR [16], the VIN value will be closer to 1 when the object has a similar reflectance in the Red and NIR regions, soil is a typical example. While, the green objects, the value will be greater than 1 [17]. Therefore, we expect highly densified grass area to have a high VIN value and the lower density to have a lower value near 1. The relationship between VIN and the in-situ GAB gives the transformation model with correlation coefficient = 0.8732, root mean square error (RMSE) = 1.75gm^{-1} and P value < 0.01.

Linear regression involves mapping from a training samples as independent variables to have and output vector [18]. Researchers choose this type of approach because of its simplicity and appealing data analysis incorporating vegetation index as input values (x) the response to which the satellite-derived GAB is predicted as (y), [19-22]. From the regression result, Daware grazing-land has the range of grass productivity from 1.02 Mg ha^{-1} to 0.32 Mg ha^{-1} for the two seasons.

4.2. Relationship of GAB with Seasonal Variations

Previous studies were able to determine the GAB estimate within a particular time frame [23]; [24, 25] and relate it to temperature and precipitation [26, 27]. However, they are silent on the spatio-temporal variations of GAB for the whole grazing calendar in a grazing land [28]. This study determining the relationship between monthly GAB availability and changes in temperature and rainfall (Figure 6).

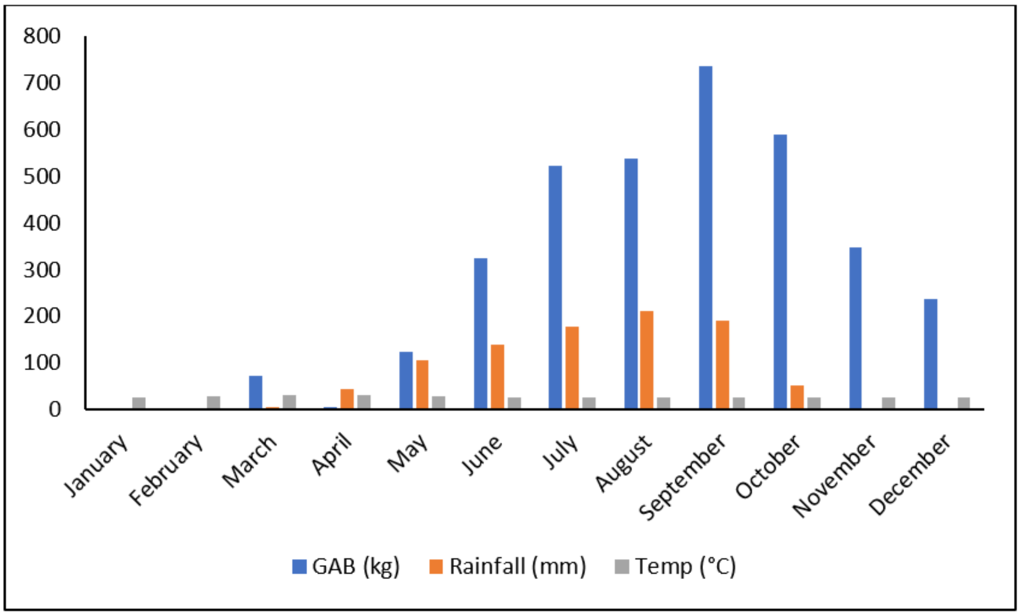

Figure 6. Relationship of GAB and climatic variations.

High rainfall is normally being experience in the months of June to September. During this period, plants take advantage of the available moisture. Grasses grow and multiply quickly and the grazing lands will have sufficient pasture for livestock feeds. The dry season starts from December to May. During this season, the grass dries out; the grazing land takes on a completely new appearance. From the month of May, there is an increase in grass productivity in relation to the rainfall amount up to September. Although there is no rain in the months of November and December, the soil is still wet and can support the grass for some weeks. Seasonal migration starts by the months of December when the grasses in the grazing reserves start drying out. The herds migrate to the tropical rainforest or the wetlands that are around the lakes for pasture and water [29]; and return to the grazing reserve around June.

5. Conclusion

Variation of GAB due to seasonal changes was successfully determined using Sentinel 2A MSI satellite data. Among the numerous vegetation indices, vegetation index number (VIN) was found to be the most relevant vegetation index that can be used for mapping and modeling GAB from in-situ GAB measurements at high accuracy and transforming the measured GAB to the satellite data. Combined with precipitation and temperature data, the GAB variations on monthly scales were analysed. The results indicated that GAB determined and its seasonal variations shown good agreement with corresponding in-situ verifications. Therefore, mapping GAB seasonal variations is achievable with Sentinel2 MSI. This can serve as a vast potential for input to grazing land management.

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