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Suitable Satellite Sensor for Elephant grass Above-Ground Biomass Estimation from Field Spectro-Radiometry Data

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Abstract: A satellite sensor is a key instrument that remotely collects data about an object or scene. However, since different sensors have varying spatial, temporal, spectral and radiometric properties, it is very necessary for vegetation cover mapping to identify and select suitable sensor for specific purposes. This study analyses seven of the most widely used satellite sensors for vegetation mapping; and evaluate their performance on elephant grass Above-Ground Biomass (AGB) estimation. Spectro-radiometry and AGB data of 40 grass samples were used for modelling and validation. The site for the experiment was Daware grazing land, Nigeria. The satellites analysed were Landsat products (OLI and ETM), Sentinel 2 MSI, MODIS 09Q1, IKONOS, Worldview and SPOT 5. The spectral window for each sensor was identified. Red and NIR reflectance were extracted from the Spectro-radiometric measurements. Variations in the distribution of the Red and NIR spectral responses for each satellite window was evaluated. A ratio of NIR and Red was calculated as Vegetation Index Number (VIN). The calculated VIN and the measured AGB were correlated. The result indicates that Sentinel 2 MSI has a good data distribution in the Red band and the NIR band. The level of correlation between the field AGB and the VIN was also good ($R^2 = 0.927$). The AGB calculated from Sentinel 2A MSI was validated at a good accuracy (RMSE = 0.326kg/pixel size and P value < 0.001) with the field measured AGB. The study concludes that Sentinel 2 MSI is the most suitable for estimating AGB for elephant grass. This provides a scientific contribution for accurate estimations of AGB specifically in grazing lands where grass information is vital.

1. Introduction
A remotely sensed sensor is a main device that remotely collects data about an object of interest [1]. As objects (such as grass) have specific spectral characteristics and can be classified according to their unique spectral characteristics from remote sensing imagery. Spectral radiances in the red and near-infrared regions are a clear example of vegetation mapping with the use of remote sensing technologies. Spectral vegetation indices (VI) that are directly linked to the captured fraction of photosynthetically active radiation may be integrated into the radiance in these areas [2 - 4]. The spectral characteristics of photosynthetically and non-photosynthetically active vegetation

demonstrated a great distinction and could be used to estimate the amount of grass and the quality of grazing land [5 - 7].

For decades, a number of airborne and space-borne sensors, from multispectral sensors to hyperspectral sensors with wavelengths ranging from visible to microwave, have acquired remote sensing imagery. Spatial resolutions varying from sub-meters to kilometres and with frequencies from 30 minutes to weeks or months in time. However, since different sensors have different temporal, spatial, and spectral characteristics, identifying and selecting suitable sensors is very important for vegetation cover mapping.

The most widely used successfully and consistently for production of remotely sensed data for vegetation studies include Landsat products (OLI and ETM). Landsat has been applied in vegetation mapping [8 - 9]. SPOT satellites have been used for mapping vegetation at different scales (large, medium, or small [10, 11]. MODIS applied to a larger scale mapping of vegetation changes and processes [12 - 14]. Sentinel 2 MSI has improved precision agriculture possibilities due to its high revisit time and spatial resolution [15 - 16]. IKONOS may be used to map vegetation cover from certain remote sensing images on a larger scale or verify vegetation cover [17]. Worldview with a fine spatial resolution of 2 m, as well as the strategically positioned red-edge waveband, offers better spatial information on vegetation mapping [18]. These satellite sensors have been more frequently used for vegetation studies from small scale to large. However, the sensors have different spectral, spatial, and temporal resolutions. Each sensor will provide an accurate information based on a particular application. Hence, the objective of this study is to investigate which satellite is the most suitable for elephant grass AGB estimation. This will provide a scientific contribution for accurate estimations of above-ground biomass specifically in grazing lands where grass information is vital. It will also add to the limited yet increasing number of studies showing good relationships with spectral measurements and above-ground biomass estimations.

2. Material and Method

2.1. Study Area
The experiment site was Daware grazing lands in Adamawa state, NE Nigeria (Figure 1.). It is situated approximately latitude 8° and 11° and longitude 11°.50 and 13°.50. The grazing land has an approximate area of 6349.76 hectares. The main grass specie in the area is the elephant grass (*Pennisetum purpureum*). In most grazing areas, the grass species is mainly used as feeding livestock. Hence, the samples collected from this site will address the objective of the study.
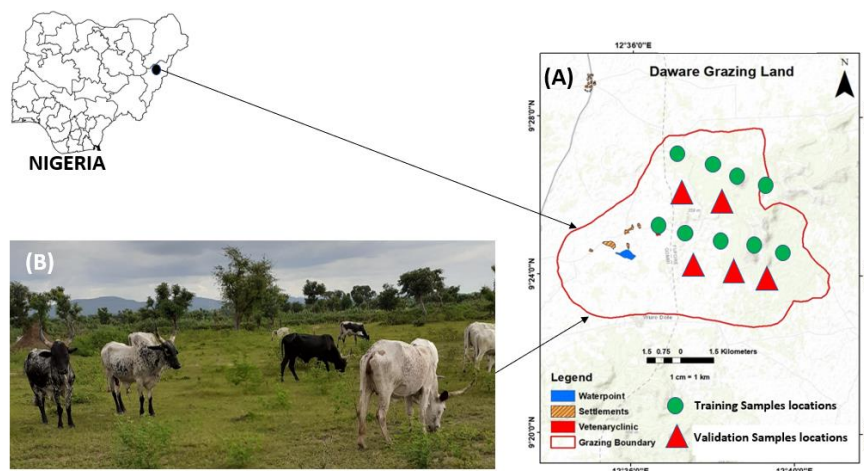

Figure 1. Nigeria in states (A) Daware grazing land (B) Cattle grazing on elephant grass.

2.2. Data Collection
The data collected in this study are the satellite data, field data and laboratory data. The field data collected include the spectral values of the grass samples with their locations, while the laboratory measurements is the biomasses of the harvested grass samples. The satellite data is Sentinel 2B MSI (L1C_T32PRR_A007455_20180810T094133) covering the study area. Spectral reflectance measurements for forty grass samples points (for training and validation) were collected between the hours of 10:00 and 14:00 (GMT) under a bright and clear sky during the early maturity stage in August 2018. The grass within each sample area of $0.15m^2$ were harvested, dried in oven for 24 hrs and weighed to get the dry biomass. The location of the grass samples was acquired using the Global Positioning System (GPS).

2.3. Methods
The Red and NIR data distribution for each satellite spectral window was analysed individually and tested for their accuracies in Elephant grass AGB estimation. Red and Near - Infrared (NIR) spectral bands were particularly suitable for vegetation studies, the ratio between red and near - infrared bands was shown to be a good predictor of the quantity of photosynthetically active green biomass [19]. Table 1. is the summary of the characteristics for satellite sensors under investigation.

Table 1. Satellite used for grass studies.

Sensor	Spectral Range (µm)		Spatial Resolution m)	Swath width	Average revisit	citation
	Red	NIR				
Landsat8 OLI	636-673	851-879	30	185km	16 days	Li *et al* (2015)
Landsat7 ETM	630-690	770-900	30	185km	16 days	Nazeer & Nichol, (2014); Yusuf et al., (2018)
Sentinel 2A MSI	650-670	727-957	10	290km	5 days	Shoko *et al* (2018)
MODIS 09 Q1	620-670	841-876	250	2,330km	1 to 2 days	Yang *et al* (2018), He *et al*., (2015), Li *et al* (2015)
World view	620-700	770-900	1.84	770km	1.1 days	Sibanda *et al* (2017), Moeckel *et al* (2017), Ramoelo . *et al* (2015)
SPOT5	610-680	780-890	20	60km	2 to 3 days	Goh et al., (2011)
IKONOS	630-690	760-900	3.28	12.2km	3 days	Zhu et al., (2019); Jorgenson et al., (2018)

The Red and NIR reflectance for each satellite category were extracted from the Spectro-radiometric measurements. They were extracted according to their spectral window. Box plot and whiskers was used in evaluating the variations in the distribution of the spectral responses for the seven sensors. Vegetation Index Number (VIN) was derived from Red and NIR value of the hyperspectral data and the satellite spectral window. A simple linear regression between the satellite derived VIN and the corresponding GAB was evaluated to get the most fitted model equation for the GAB estimation of the entire study area. The selected best model was validated with the validation GAB data set; and statistically tested using z-test.

3. Results

3.1. Variation Spectral Data Distribution
Landsat 8 OLI spectral data is not normally distributed. Landsat 7 ETM data is fairly distributed in both the Red and NIR bands. Sentinel 2A MSI is normally distributed in Red band. Little data tends to fall within the minimum values in the NIR. Both the Red and NIR in MODIS 09 Q1 has a higher variation with data below the 3rd quartile. Worldview and SPOT has a higher variation in the Red with more data above the 2nd quartile. The NIR band has a fairly normal distribution of data. IKONOS has a normal distribution in Red. However, higher values are within the 2nd quartile in the NIR band. The

distribution for the Red and NIR bands of the seven satellite sensors was summarized and presented from Figure 2 in such a form that is clearly understood.
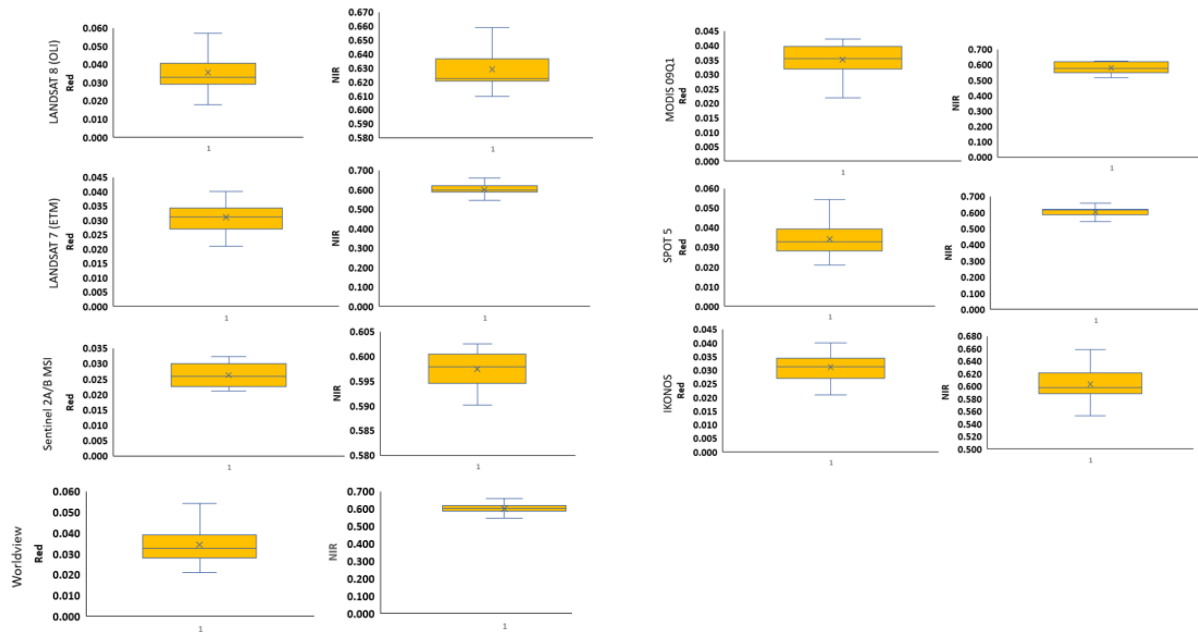

Figure 2. Spectral data distribution in Red and NIR

The probability function that describes how the Red and NIR values were distributed for the seven satellite sensors were presented in Figure 2. The distribution is the most important probability distribution because it gives a clue on the reliability of the results that were derived from these measurements. Table 2. is the summary of the satellite sensor spectral data distribution in the Red and NIR bands.

Table 2. Summary of the spectral reflectance distribution for Red and NIR bands.

Sensor	Band	Min.	Max.	Upper Q.	Lower Q.	Mean	Std. Dev.
LANDSAT 8 (OLI)	NIR	1.533	0.158	0.158	1.533	0.615	0.302
	Red	0.019	0.183	0.183	0.019	0.066	0.044
LANDSAT 7 (ETM)	NIR	0.155	1.553	1.553	0.155	0.622	0.306
	Red	0.019	0.292	0.292	0.019	0.075	0.061
Sentinel 2A MSI	NIR	0.142	1.320	1.320	0.142	0.545	0.267
	Red	0.018	0.288	0.288	0.018	0.072	0.060
MODIS 09Q1	NIR	0.158	1.533	1.533	0.158	0.615	0.302
	Red	0.019	0.287	0.287	0.019	0.074	0.059
WORLDVIEW	NIR	0.155	1.553	1.553	0.155	0.613	0.306
	Red	0.019	0.287	0.287	0.019	0.074	0.059
SPOT5	NIR	0.155	1.553	1.553	0.155	0.613	0.306
	Red	0.020	0.283	0.283	0.020	0.078	0.059
IKONOS	NIR	0.154	1.516	1.516	0.154	0.603	0.299
	Red	0.019	0.292	0.292	0.019	0.075	0.061

Landsat 7 ETM and Sentinel 2A MSI has a fairly normal distribution of reflectance values and can be suitable for vegetation studies specifically for elephant grass. However, the other factors that must be considered for the choice of a sensor for vegetation mapping includes (1) the sensor spatial resolution (2) standard deviation of the spectral reflectance from its mean; and (3) level of correlation between the corresponding data sets. To evaluate the correlation coefficients, Regression analysis was conducted between the sensors derived indices and their corresponding in-situ GAB.

3.2. Relationship of GAB with Vegetation Index Number (VIN)

To determine the best sensor for providing a suitable transformation model, a relationship between the derived satellite index (VIN) and the corresponding GAB was established. The best performing satellite was selected based on the level of correlation between the GAB and their corresponding index (Figure 3).
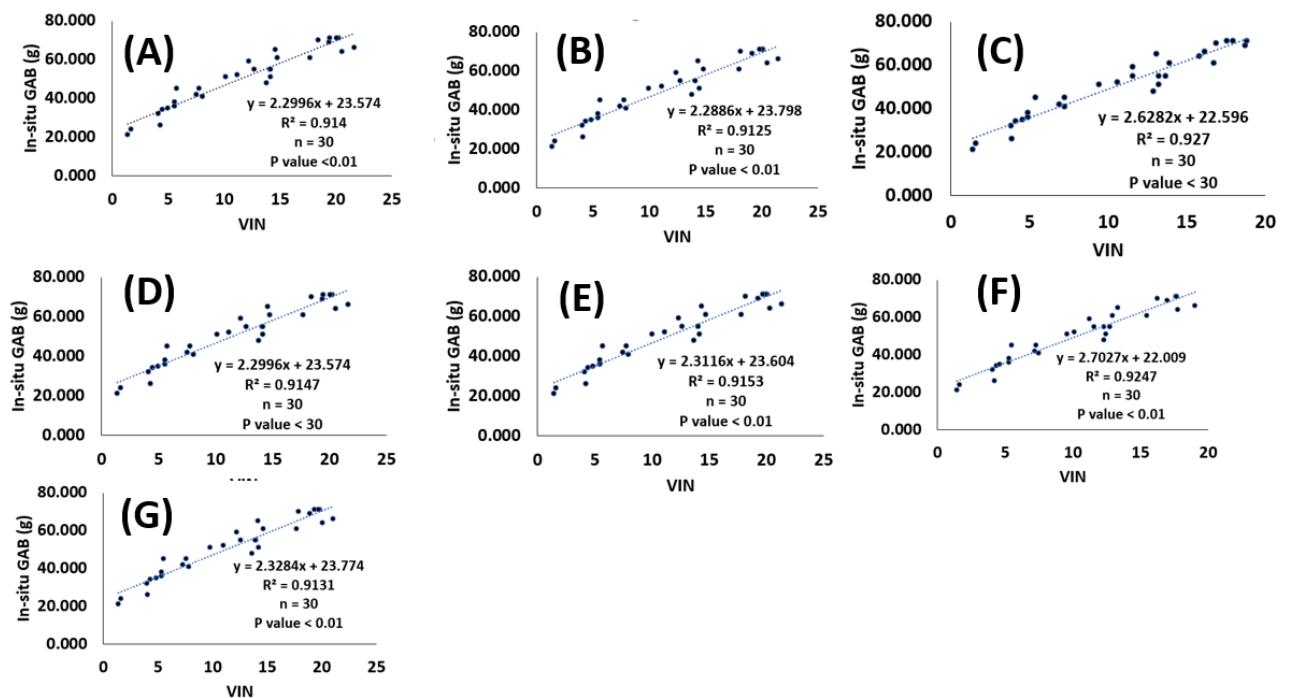

Figure 3. (A) Landsat 7 ETM (B) Landsat 8 OLI (C) Sentinel 2 MSI (D) MODIS (E) Worldview (F) SPOT 5 (G) IKONOS

Based on the results in Figure 3 and Table 2, all the satellites have a good correlation with GAB. However, Sentinel 2B MSI was found to be the best due to its data distribution in the Red band and NIR band. The level of correlation $R^2 = 0.927$ is adequate for yielding a better result. Its spatial resolution and revisit time make it good for time series analysis on grass growth. It was therefore recommended for used in the estimation of elephant grass above-ground biomass. Therefore, the model equation for elephant grass above-ground biomass estimation was using sentinel 2A MSI was:

$$Y = 2.628 * VIN + 22.596$$

Where Y = GAB. Table 3. is the summary of the satellite's sensor accuracies based on the level of corelation and data variation.

Table 3. Summary of sensor correlation and data distribution.

Sensor	R^2	Data Distribution
Landsat 8 (OLI)	0.914	Not normal in both Red and NIR
Landsat7 (ETM)	0.913	Fairly distributed
Sentinel	0.927	Normal in Red. Little variation in NIR.
MODIS 09 Q1	0.915	Higher variation below the 3rd quartile
World view	0.915	Higher variation in Red but fair distribution in NIR
SPOT 5	0.925	Higher variation in Red but fair distribution in NIR
IKONOS	0.913	Normal distribution in Red, but NIR has a higher value within the 2nd quartile.

3.3. Validation of Result and Significant Test

GPS coordinates were used to locate the sample points on the satellite image. Red and NIR values were extracted from the satellite data to get the VIN of the images for calculating GAB. The satellite calculated GAB was validated with the field measured GAB at a good accuracy (RMSE = 0.326kg/pixel size and P value < 0.001). This indicates that Sentinel 2 MSI has a higher accuracy for elephant grass biomass estimation. The relationships between the two set of data were statistically significant at the 99.5% confidence level. The result show that the calculated z value for one tail and two tail = 0.367 and 0.734, respectively. Since the values are within -1.96 <z< +1.96, the result was accepted. Hence, Sentinel 2A MSI was accepted as the best satellite sensor for elephant grass AGB estimation.

4. Discussion

Different considerations, procedures and techniques are involved in mapping vegetation by remotely sensed images. Growing remotely sensed image availability due to fast development of remote sensing technologies extends the scope of our selection of sources of imagery. Different imaging sources are noted for their variations in spectral, spatial, and temporal variability, making them ideal for various vegetation mapping purposes. The collection of images acquired by appropriate sensors is primarily determined by the purpose of mapping. The purpose of the mapping involves what is to be mapped and what accuracy is needed for the mapping. In particular, low-resolution images can only be taken if high-level vegetation classes are to be established, whereas comparatively higher-resolution images can only be used for fine-detailed vegetation classifications. The spectral variation in the distributions of spectral signatures in a specific band is another important factor for choosing a specific image. A correlation between spectral signatures as indices and a particular application can also provide insight into the suitability or non-suitability of such a sensor, depending on the specific application at hand. In the area of vegetation mapping, the most applied sensors include Landsat (TM and ETM+), SPOT, Worldview, MODIS, Sentinel 2 MSI, and IKONOS.

The use of statistical methods to detect anomalies that may be hidden in a set of reflectance values is used in spectral data analysis. The "box plot," which can be used to visually summarise and analyse groups of reflectance data within a given band, is one of these techniques. By using 25th, 50th and 75th percentiles, otherwise defined as the lower quartile (Q1), median (m or Q2) and upper quartile (Q3) and the interquartile range (IQR = Q3-Q1), that occupies the central fifty percent of the details, box plots describe a sample. In order to classify outlier data values, box plots can also be easily refined and can be easily created by hand. This study uses this technique to enhance understanding of distribution of reflectance values and make comparisons across different sensors.

The vegetation cover can be analysed and generally categorised on the basis of spectral data from satellite images and the related indices collected [20], complex analysis of the vegetation phases [21] as well as other matters of interest. Linear regression has been used to perform predictive models for biomass estimation based on known spectral values of satellite indices in view of the interdependence relations between chlorophyll material, satellite sensor indices and GAB, respectively. Such models were evaluated based on their performance of biomass prediction. Sensors likes sentinel 2A shows a good performance for AGB estimation.

The validation of satellite sensors for biomass estimation data requires reference field measurements from Spectro-radiometry data and the corresponding measured AGB. Errors in satellite sensor as compared with the field measurements will determine the accuracy of the selected for AGB estimation. Based on the seven satellite sensors evaluated in this study, Landsat 7 ETM and Sentinel 2A/B MSI has a shown a good accuracy in terms of R^2 and RMSE and can be suitable for vegetation studies specifically elephant grass. However, due to the spatial resolution of the sensors and revisit time sentinel 2 is preferable to be used for AGB estimation.

5. Conclusion

The choice of an appropriate satellite sensor is a critical step in reducing uncertainties in AGB estimates. This study provides a scientific contribution for selecting suitable sensors for accurate estimations of elephant grass above-ground biomass in Savannah grazing land. It also adds to the limited yet increasing number of studies showing good relationships between spectral indices and grass above-ground biomass. The selected sensors that were evaluated here provide an excellent opportunity for further work on the confirmation of robustness and accuracies for AGB estimation, leading to more realistic satellite sensor that can considered as the best for specific AGB estimation.

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