

Mapping and Estimation of Above-ground Grass Biomass using Sentinel 2A Satellite Data

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ABSTRACT

Above-Ground Grass Biomass (AGGB) mapping and estimation is one of the important parameters for environmental ecosystem and grazing-lands management, particularly for livestock farming. However, previous models for estimation of AGGB with satellite imagery has some difficulty in choosing a particular satellite and vegetation index that can build a good estimation model at a higher accuracy. This study explores the potentiality of Sentinel 2A data to derive a satellite-based model for AGGB mapping and estimation. The study area was Skudai, Johor in Malaysia Peninsular. Grass parameters of forty grass sample units were measured in the field and their corresponding AGGB was later measured in the laboratory. The samples were used for modelling and assessment. Four indices were tested for their fitness in modelling AGGB from the satellite data. The result from the grass allometric analysis indicates that grass height and volume demonstrate good relationship with the measured AGGB ($R^2 = 0.852$ and 0.837 respectively). Vegetation Index Number (VIN) has the best fit for modeling AGGB ($R^2 = 0.840$) compared to other vegetation indices. The derived satellite AGGB estimate was validated with the assessment field and allometry derived AGGB at RMSE = 15.89g and 44.45g, respectively. This study demonstrate that VIN derived from Sentinel 2A MSI satellite data can be used to model AGGB estimation at a good accuracy. Therefore, it will contribute to providing reliable information on AGGB of grazing lands for sustainable livestock farming.

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1. Introduction

Grasslands are among the most popular types of covered vegetation, covering over 31.5% of the world's land mass (Latham et al. 2014). It is one of the sustainable resources and provides a significant portion of livestock with the food source (Herrero et al, 2013), however, previous models for estimation of AGGB with satellite imagery has some difficulty in choosing a particular satellite and vegetation index that can build a good estimation model at a higher accuracy. Many studies have used remote

sensing data such as Landsat (Powell et al 2010, De et al, 2012, Hansen and Loveland 2012), world view, thematic mapper and MODIS data product to examine the mapping and estimation of AGGB. In addition to vegetation indices, spectral bands, image transformation algorithms are often used to identify AGGB modeling variables (Zang and Kovacs 2012, Mutanga et al 2012). Because different remote sensing data are available with different spectral and spatial resolutions, a large number of potential variables can be used (Myint et al, 2011). However, the correct identification of key variables is critical to the accurate mapping

and estimation of above-ground biomass and the selected variables can vary considerably depending on the grass species, the time of investigation, the location of the study and the remotely sensed data themselves (Karlson et al, 2015; Dube et al 2014). Another key problem for investigating grass studies is the use of a proper modelling algorithm (Yuyun et al 2019).

Understanding variations in AGGB at various scales is becoming extremely critical among interested parties, like farmers, ecologists and scholars (Sibanda et al 2017). Remote sensing researchers have accumulated experiences on the assessment of vegetation/physiognomic types and their ecological state (Mucina, 2019). Recently, the usefulness of earth observation (EO) data has become much more popular and viable with an increase in available sensors as well as innovations to obtain robust quantitative information on grass biomass. (Bastin et al, 2014). Knowing that different EO methodologies were evaluated in aboveground biomass quantification, no study showed a consistent, accurate and repeatability operational method for estimating biomass at smaller to larger scales (Sibanda et al 2017). This is due to the variations in vegetation's biophysical, environmental and topographical characteristics in space and time

(Popescu et al 2009, Montesano et al 2013). Previous studies have reported even higher correlations between grass biomass and vegetation indexes (e.g., Mutanga, et al 2012). Most of them, however, investigated 'simpler' vegetation communities (often monospecific) on relatively flat ground and uniform soil.

In this study, Sentinel 2A MSI was used to estimate the AGGB in Skudai, Johor, Malaysia Peninsula. The satellite derived AGGB was later validated with the grass allometry derived and the assessment field AGGB. Therefore, the objective of this paper is to derive a satellite transformation model for AGGB estimation from ground sample points to Sentinel 2A MSI satellite data. Four grass species were identified (Figure 1) in the study area, although they belong to one of the largest and most economically and ecologically important families of plants, they exist as minor components next to forest of the plant community in the area. The grasses are *Pennisetum purpureum* (elephant grass), *Ottochloragraccillima* (creeping grass), Genus *stipa* (needle grass) and *Poacea* grass.

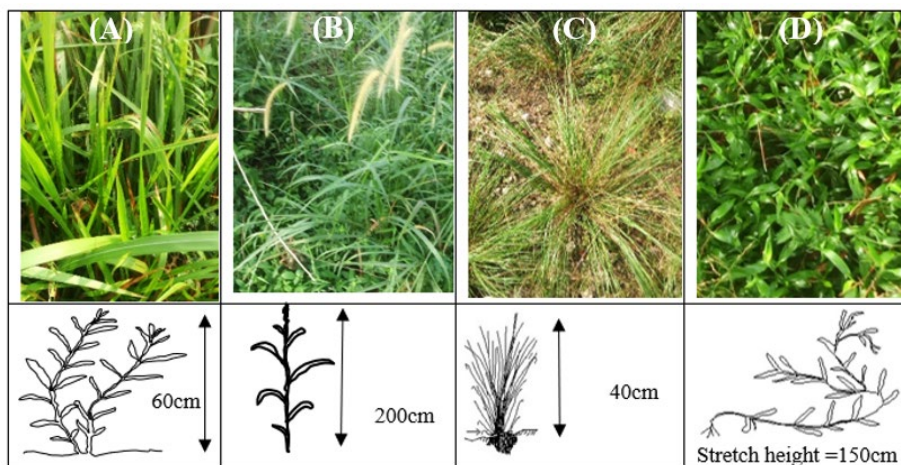


Figure 1. Dominant grass in the study area (A)Elephant grass (B) Poacea grass (C) Needle grass (D) Creeping grass

2. Material and Method

2.1 Description of Study Area

The study area was Universiti Teknologi Malaysia (UTM) campus, Skudai in the State of Johor Bahru, Peninsular Malaysia. The total area was 1,222 hectares. It lies between 170000mN to

172500mN and 346000mE to 351000mE (Figure 2.). The average yearly rainfall is 250 mm, the wettest month is in November with an average of 320 mm. June and July are overall the driest months with an average of 130 mm. Temperatures rise above 30°C (86°F) throughout the day and drop rarely below 20°C (68°F) during the night. Temperature is 27°C at an average. (Country data and statistics (2019))

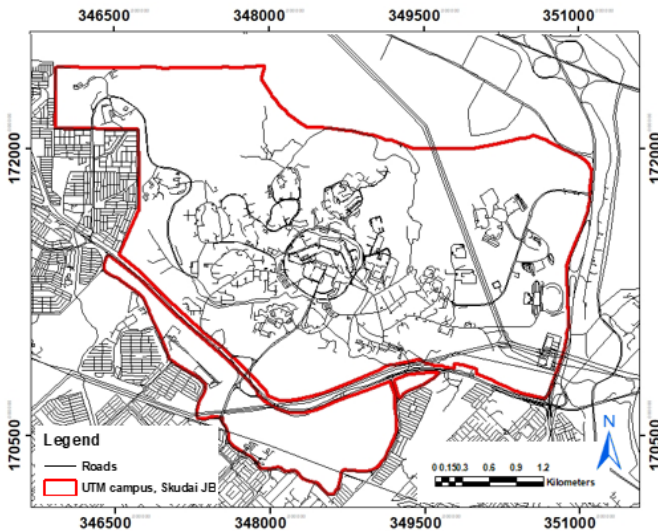


Figure 2. Study area
Source: INSTeG UTM

2.2 Material

The materials used for this study are the field data and Satellite data. The remotely sensed data were derived from the Sentinel 2A imagery. It has thirteen bands and a spatial resolution of 10m. Two bands were used in this study; the red band (central λ of 665nm) and a near-infrared band (central λ of 842nm) as was investigated by many scholars (Yuyung, 2019, Rongrong 2018, Li et al 2016, Zumo et al 2021, Ali et al 2017). The data was downloaded on 18th July 2018 at the period when grasses were fully saturated. In-situ data are the grass allometry and the measured GAB of some selected sample points. Ground control and validation sample points were measured using the quadrant method. Forty samples for each of the four different dominant grass species were harvested at 1m² grids for both the controls and assessment. Five samples' points were measured in each plot. This was done in order to avoid degradation/destruction of the environment by minimising the sample size and meeting up with the required specification. The mean and the standard deviation of the measured biomass for samples in each plot was computed (see Table 1)

Table 1 Statistics of collected samples

	No. of samples/plots	Range of AGGB	Mean	Std. dev.
Total No. of samples	40	38.21 - 197.32	118.63	9.87
Samples collected modelling	20	41.21 - 195.00	117.88	9.84
Sample collected for assessment	20	38.21 - 197.32	109.23	8.97

2.3 Method

The method used in this study were grass allometry modelling, satellite transformation modelling and validation of results. This demonstrated as flowchart in Figure 3

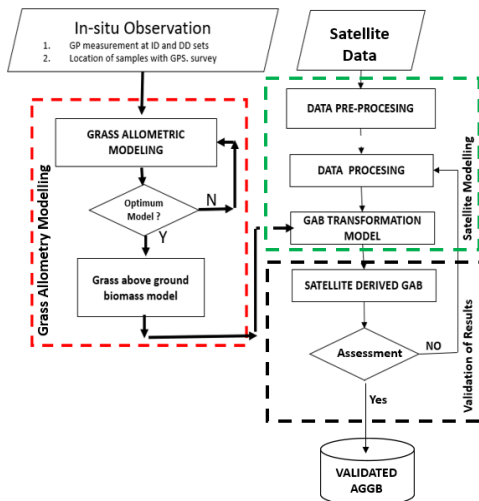


Figure 3. Flowchart of methodology

Maximum grass height, stem diameter, grass volume and leaf area were measured from the field as in-situ observation. (Figure 1). Grass volume was measured using displacement method, and density of each grass was calculated from its measured mass and volume. The clipped vegetation was dried at 40.6°C for 72 h in an air forced oven. The vegetation was then weighed when dried to get the mass per sample and eventually calculate the biomass production in tons per hectare. Location of the grass samples were acquired using the Global Positioning System (GPS) for easy location of the sample points in the image. This study considers the use of the most common Vegetation indices as Normalized Distribution of Vegetation Index (NDVI), Vegetation Index Number (VIN), Ratio Vegetation Index (RVI) and Normalized Difference Index (NDI) for the modelling of AGGB estimation.

2.3.1 Grass Allometry Modelling

Linear regression between the five measured grass variables and the field AGGB was carried out. Grass height and volume was found to have a good level of fitness for AGGB estimation. The relationship between the stem diameter, leaf area and grass density were poor. Therefore, grass height and grass volume were used for modelling the AGGB estimation.

2.3.2 Satellite Transformation Modelling

Reflectance values of band 4 (Red) and band 8 (NIR) were extracted from the pixel of each respective band of the sample points. The pixel location was identified by the GPS acquired coordinates during the sample data acquisition. The four vegetation indices were calculated using their respective formular (Table 2.)

Table 2. VIs and equations

VI	Equation
NDVI	$(NIR-R)/(NIR+R)$
VIN	NIR/R
NDI	$(NIR-R)$
RVI	R/NIR

A linear regression between the calculated indices and the in-situ AGGB was conducted in order to determine which of these indices that will be best for modelling AGGB of the entire study area. The relationship of each of the VIs was indicated by R².

3. Result

3.1. Allometry Result

The result for grass allometry indicates that stem diameter, leaf area index and grass densities have a poor fitness for AGGB estimation. Their R² = 0.256, 0.182 and 0.312, respectively. This indicates that they are not suitable predictors for AGGB estimation. Grass height and grass volume has a good level of fitness at R² = 0.852 and 0.837, respectively. They were used for allometry AGGB modelling to derive 5 allometry models for this study. Level of performance for each derived allometry model was in Table 3.

Table 3 Model Summary

Model	Model Equation	a	b	c	R ²	Std. Error.
1	AGGB = a + b(ht.)	25.131	2.644		0.798	38.638
2	AGGB = a + b(vol.)	76.973	0.480		0.885	31.790
3	AGGB = ae ^{b*ht.}	93.922	0.011		0.801	31.400
4	AGGB = ae ^{b*vol.}	116.150	0.002		0.884	27.280
5	AGGB = a + b(ht.) + c(vol.)	28.266	1.301	0.315	0.987	13.760

Model 5 has the best result of R² and least standard error. Thus, it was considered as the most suitable model to use in the study for AGGB estimation, taking grass height and grass volume as the most suitable predictors. Average height and volume of grass samples were identified and measured. AGGB was later determined for each sample using the created allometric model 5.

3.2 Spectral Result

The four indices namely NDVI, VIN, RVI and NDI has a good level of fitness (R² = 0.828, 0.840, 0.818, and 0.742 respectively (Figure 4A - 4D). Among the four, VIN has the best fitness and was selected for the AGGB modelling.

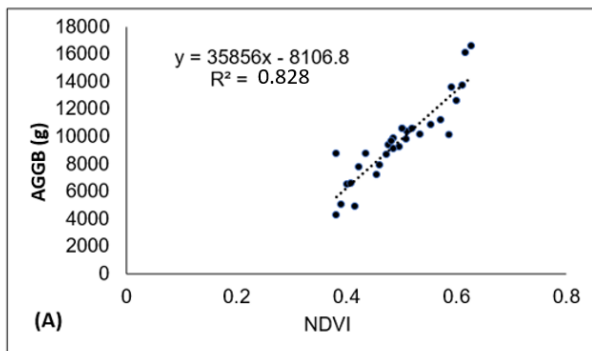


Figure 4A Biomass and NDVI relationship

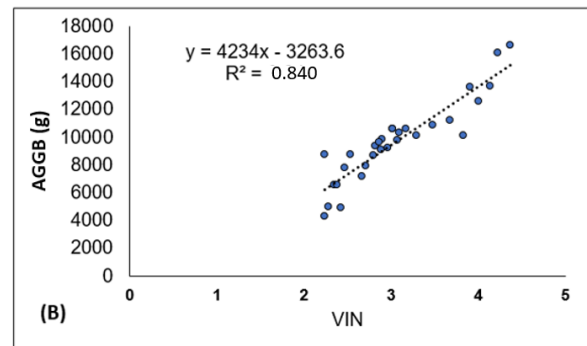


Figure 4B Biomass and VIN relationship

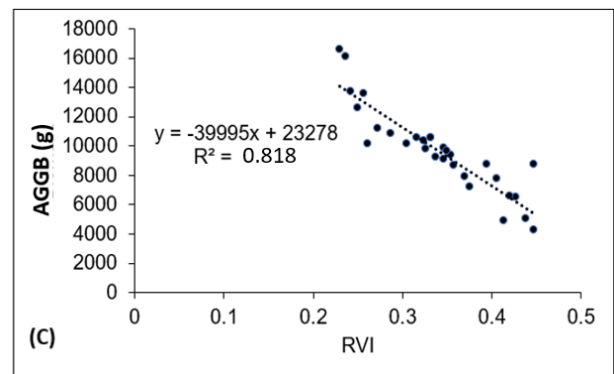


Figure 4C AGGB and RVI relationship

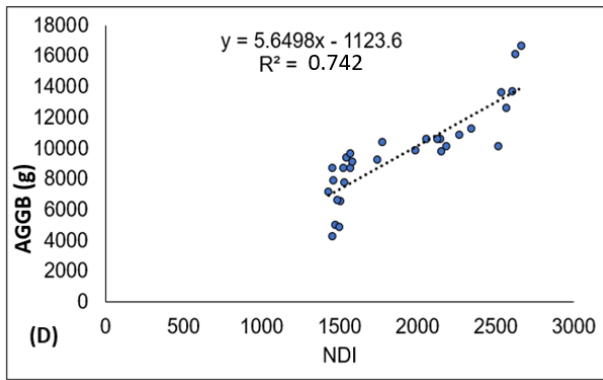


Figure 4D Biomass and NDI relationship

Using VIN model equation, Pixel-based sampling of AGGB was calculated for all grasses on the grid equivalent to the pixel size of the image.

$$AGGB = 4234x - 3263.6 \quad (1)$$

Where, AGGB is the grass biomass in grammes of a pixel of interest and x is the VIN image.

The VIN map calculated for the entire study area has a range of 0 to 10, but VIN of the grass sample points calculated from the image is within the range of 2 to 4. Areas covered by grasses were extracted from the satellite imagery using Boolean operation (Figure 5A). 1 represents areas all values from 2 – 4 (grass areas) while 0 represent any other values (non-grass areas). The Boolean map was multiplied by the VIN map to get the VIN grass map (Figure 5B). the VIN grass map was substituted in eqn 1 to get 1 to get the total AGGB of the study area. The AGGB map was presented in Figure 5C.

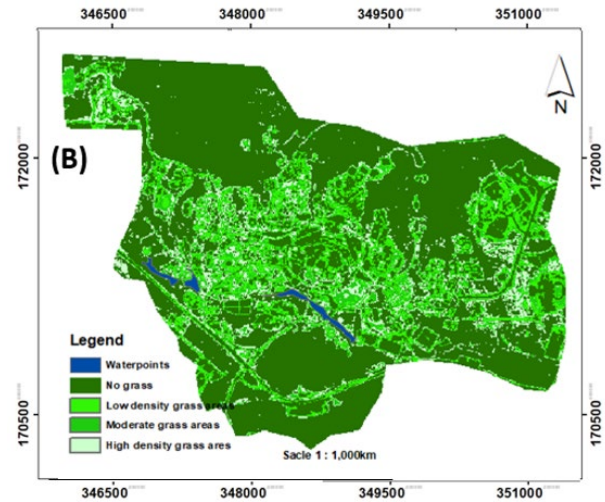


Figure 5B Grass VIN map

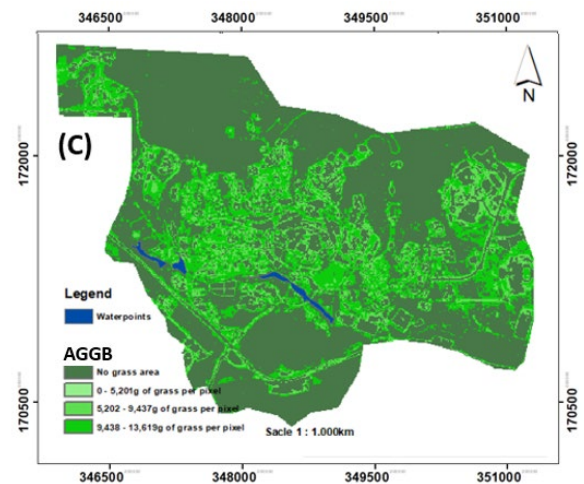


Figure 5C AGGB map

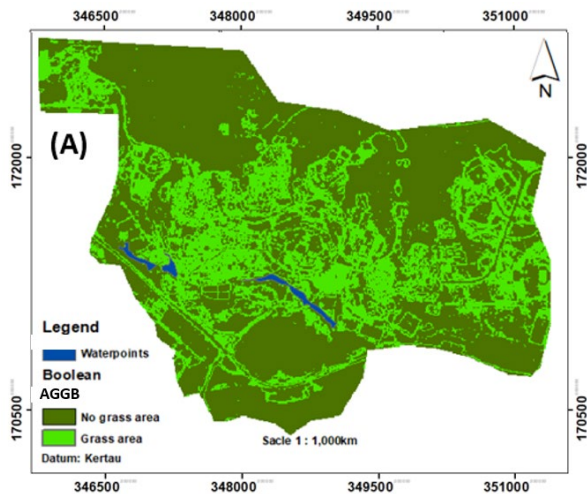


Figure 5A Boolean grass map

3.3 Assessment of Result

Independent evaluations of the spectral derived AGGB were verified by validation field samples and allometric calculated AGGB. From the assessment, the model developed meets the assumption of a linear models (Figure 6A and Figure 6B).

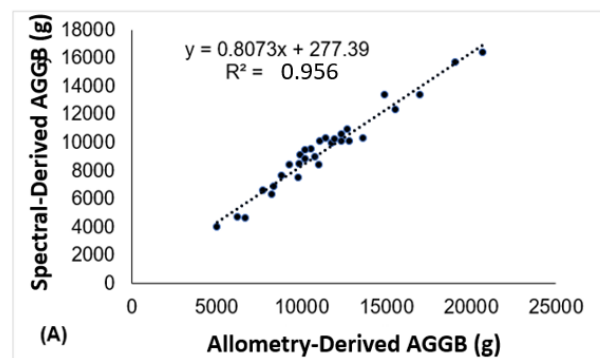


Figure 6 A. Model validation with Allometry Derived AGGB

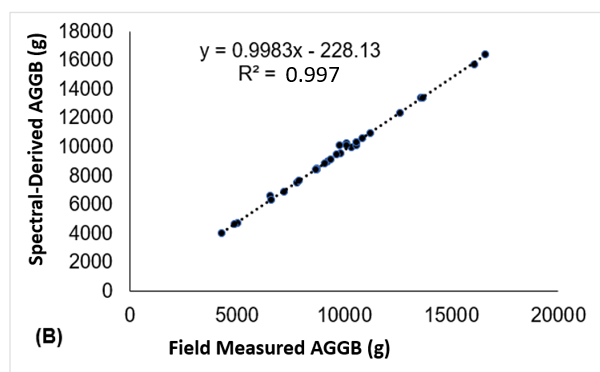


Figure 6B Model validations with field AGGB

The satellite derived AGGB has a level of fitness with the allometry and the field measured AGGB ($R^2 = 0.956$, $R^2 = 0.997$) and a good accuracy at $RMSE = 15.90$. and $RMSE = 44.45$ respectively

4. Discussion

Grass allometry model used in this study found out that grass height and grass volume are the most suitable predictors for estimating AGGB. This agrees with Oliveras (2014) where he finds out that plant height was the best predictor of biomass estimation. In this paper, stem diameter, density and leaf area show no relationship with AGGB. This contradicts the AGB estimation of woody plants where DBH is one of the best predictors of AGGB as was documented by many scholars (Ubay et al (2018).

NDVI and RVI have been popularly used in recent decades to estimate biomass at a regional level (Jiang et al., 2015). They were criticized, however, for problems with saturation at high density vegetation levels (Li et al., 2014). Our study tested four of the most frequently used VIs for modelling AGGB estimation in a densely vegetated region. These are NDVI, RVI, VIN and NDI. VIN was found to be the most suitable VI for the modelling the estimation of AGGB using Sentinel 2A data. However, this may be verified by further studies using different satellite data with different vegetation species. VIN shows a significant relationship with grass biomass where $R^2=0.84$.

The grass distribution in the study area covers 221.8 hectares out 1,222. The study area is a forested region with few grass species. Most grasses were found by the roadside, behind buildings and in playing fields. Very little grasses that was meant for grazing of livestock. The maximum AGGB within 10m² was 13,672.08g and the minimum was 3,014.12g. The total estimated AGGB was 323,183,164.70g equivalent to 1.46 tons per hectare. This result was similar to Cisneros et al., (2020) with 1.8 tons per hectare in a similar tropical region likes Skudai; when he used Sentinel 2 MSI data. Result from other studies that use MODIS was 0.5 tons per hectare (He et al., 2014), HJ satellite was 1.22 tons per hectare (Zhou et al., 2016).

5. Conclusion

AGGB mapping and estimation is crucial for evaluating the health and of grassland eco system including grazing areas. Despite some sources of error, satellite data constituted a sufficiently accurate indicator of grass biomass and allowed biomass estimation and production of maps at a local and regional levels. This study confirmed that Sentinel 2A MSI as the best satellite data for AGGB estimation. Among the vegetation indices analyzed, Vegetation Index Number (VIN) derived from satellite data estimates AGGB at a good accuracy compared to other indices. The result obtained in this study will be beneficent in the decision-making processes regarding the expanding of grazing livestock in the study area, hence, contributing in the sustainable agriculture and food security.

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