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Estimating biomass of savanna grasslands as a proxy of carbon stock using multispectral remote sensing

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ABSTRACT

Limited research has been done to estimate the root biomass (belowground biomass) of savanna grasslands. The advent of remote sensing and related products have facilitated the estimation of biomass in terrestrial ecosystems, providing a synoptic overview on ecosystems biomass. Multispectral remote sensing was used in this study to estimate total biomass (belowground and aboveground) of selected tropical savanna grassland species. Total biomass was estimated by assessing the relationship between aboveground and belowground biomass, the Normalised Difference Vegetation Index (NDVI) and belowground biomass, and NDVI and total biomass. Results showed a positive significant relationship ($p = 0.005$) between belowground and aboveground biomass. NDVI was significantly correlated ($p = 0.0386$) to aboveground biomass and the Root Mean Square Error (RMSE) was 18.97 whilst the model BIAS was 0.019, values within acceptable ranges. A significant relationship ($p = 0$) was found between belowground biomass and NDVI and the RMSE was 5.53 and the model BIAS was 0.0041. More so, a significant relationship ($p = 0.054$) was observed between NDVI and total biomass. The positive relationships between NDVI and total grass biomass and the lack of bias in the model provides an opportunity to routinely monitor carbon stock and assess seasonal carbon storage fluctuations in grasslands. There is great potential in the ability of remote sensing to become an indispensable tool for assessing, monitoring and inventorying carbon stocks in grassland ecosystems under tropical savanna conditions.

1. Introduction

Present carbon dioxide (CO_2) emission trends are driving the globe towards exceeding the 2°C increase in warming, which has potential to trigger a plethora of social, economic and ecological challenges (Schellnhuber et al., 2012). Concerns over global warming have triggered research on methods to curb the increasing atmospheric accumulation of CO_2. Carbon dioxide is the principal greenhouse gas (GHG) that is causing accelerated climate variability and change as evidenced by the increase in the frequency and intensity of extreme weather events such as droughts, floods and heatwaves (Albrecht and Kandji, 2003; Brovkin et al., 2004; Schellnhuber et al., 2012). One of the methods used to curb CO_2 concentration is to increase storage in the terrestrial ecosystems (Sheikh et al., 2014; Walker et al., 2015). The capture and storage of atmospheric CO_2 in soils and vegetation is formally recognised as a means of curbing global climate change (Kimble and Follett, 2000; Ponce-Hernandez et al., 2004). Thus, photosynthetic assimilation of atmospheric CO_2 by plants offers an option for reducing atmospheric concentration of GHG, thereby reducing global warming and consequently climate change (Ponce-Hernandez et al., 2004; Smith, 2001). As a result, estimating vegetative biomass has emerged as a major international policy for climate change mitigation as knowledge of carbon stock is important in managing CO_2 (Bogaerts et al., 2017). However, there is limited knowledge of carbon stock of vegetative components of ecosystems like grasslands (Jones and Donnelly, 2004).

In southern Africa, in particular, there is lack of an inventory of carbon stocks of grass vegetation and their role in global warming (Ciais et al., 2014). Yet, the significance of grasslands biomass with regards to CO_2 storage and other ecological functions is widely recognised (Abberton et al., 2010; Stockmann et al., 2013). Lands dominated by

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grass vegetation, are among the largest ecosystems in the world, occupying approximately 26% of the earth's land surface (Sayre et al., 2017; Sterling and Ducharne, 2008). In Africa alone, savannah grasslands cover almost half the surface area of the continent (Adams et al., 1990). With vast terrains under grasslands, assessing grass carbon stocks becomes socially, environmentally and economically important in this era of increased global warming. Grass ecosystems significantly influence regional climates and global carbon cycle, as they contribute 10% of the globe's total biosphere carbon stock (Xia et al., 2014). Moreover, natural grassland ecosystems are estimated to contribute about 20% of total terrestrial biomass production, providing an annual carbon sink of about 0.5 *Pg* C. (Scurlock et al., 1999). Thus, grasslands are a carbon sink that can make a substantial contribution in reducing net atmospheric carbon (Lal, 2003, 2004).

Estimates of biomass are important indicators of carbon stock capacity as information on biomass provides the basic prerequisite for the estimation of carbon density and storage (Wang et al., 1999). Therefore, biomass estimates provide the means of calculating the amount of CO_2 that could be removed or fixed from the atmosphere by re-growing vegetation (Gunawardena et al., 2006). Previous studies have estimated vegetation biomass with existing forest inventories, which is the key method. Researchers have also developed other methods for quantifying biomass, as the traditional inventory of forest parameters based on fieldwork is difficult, costly and time consuming to conduct, particularly in large areas (Fan et al., 2008; Scurlock et al., 2002). However, remote sensing has allowed estimating grass biomass over large spatial areas timeously and in a cost effective manner (Ikeda et al., 1999; Schino et al., 2003). Advances in remote sensing like multi-sensor data fusion increase spatial and spectral resolution and integration with Geographical Information Systems (GIS) have made remotely sensed data the primary source for many forestry applications (Gunawardena et al., 2006). Some of the applications include, the extraction of forest stands parameters through correlation or regression analysis to examine relationship between spectral response and structural factors of forest such as basal area, biomass, canopy closure and vegetation density (Namayanga, 2002).

Recently, Landsat and Sentinel multispectral sensors have been very useful in providing remotely sensed data and products at moderate resolution (Li and Roy, 2017; Wulder et al., 2008). Data obtained from Landsat imagies (spatial resolution of 30 m) has been limited by the little texture information they offer as compared to the other more recent sensors like Sentinel-2 and WorldView-3. . Satellite images are useful for monitoring land cover and land use by means of vegetation indices. Vegetation indices such as the normalised difference vegetation index (NDVI) use specific reflectance properties of photo-synthetically-active vegetation (Tan et al., 2013). Multispectral remote sensing makes use of different spectral bands of the electromagnetic spectrum to determine the physical condition of landscapes based on the amount of reflectance in each band (Ashraf et al., 2011). Estimation of biomass as a proxy for carbon is based on absorption and reflectance of a vegetation canopy. Thus, biomass is a function of food produced through the process of photosynthesis, a process dependent on the amount of radiation absorbed and reflected. The intensity of absorption and reflectance is dependent on the wavelength and the three components of the vegetation canopy which include leaves, substrate and shadow (Pfitzner et al., 2006). The common remote sensing approach used in estimating biomass, particularly aboveground biomass (AGB), is to examine the possible association between ground measured biomass and NDVI (Sibanda et al., 2017; Timothy et al., 2016). NDVI quantifies vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs) (Bannari et al., 1995; Huete, 1986). This has been successful particularly in tropical and sub-tropical regions (Mutanga and Skidmore, 2004; Nichol and Sarker, 2011).

This study demonstrate a technique to estimate AGB of tropical grasslands using Landsat moderate resolution data. Although there are a lot of studies on the biomass of forest and agroforestry ecosystems, there is little that has been done on grass ecosystems (Jones and Donnelly, 2004). This has resulted in varied and unreliable statistics on carbon stocks, results that have influenced policy and decision making, yet policy is inadequate if it fails to cover the whole range of ecosystems. Estimates of aboveground (AGB) stocks exist for some ecosystems, however root biomass (belowground biomass) (BGB), especially of grasslands is less studied (Stockmann et al., 2013). In view of this gap, this study uses multi-spectral remote sensing to assess grass belowground biomass (BGB). NDVI derived from Landsat was used to estimate both AGB in grassland species over large areas. The relationships between AGB and BGB was determined, as estimated through NDVI. An assessment of the capability of remote sensing to inventory and quantify carbon stocks in grasslands was done, considering biomass as the basic unit of measurement.

2. Materials and methods

2.1. The study area

The study was done in Mashonaland Central Province (31°E, 17°S), located in north-eastern Zimbabwe (Fig. 1). The province is comprised of eight districts: Mazowe, Bindura, Shamva, Mt Darwin, Rushinga, Muzarabani, Guruve and Mbire with a population of about 1.2 million people. The study covered two districts Shamva and Bindura. The province has a Tropical Savannah Climate with hot, wet summer seasons and cold, dry winter seasons. Annual rainfall ranges between 750 and 1 000 mm and temperature ranges between 15°C and 32°C.

Most of Mashonaland Province lies in agro-ecological region II, characterised by intensive farming under rainfed agriculture with limited supplementary irrigation (Vincent et al., 1960). The province is known for its intensive livestock production based on pastures and pen-fattening using crop residues and grain (Patt and Gwata, 2002). Soils are of variable physiognomies that include granitic sands, sandy-loam soils (where intensive farming is practiced) and clay-loam soils. The diverse and generally rich soils favour the growth of grass, dominated by wide variety of graminae species (Table 1), as well as herbaceous, shrubs and woody tree species. Most of the vegetation is deciduous as they shed leaves or get dry during the dry and cold season (Mapanda and Mavengahama, 2011).

2.2. Field sampling and measurements

Field sampling was done in March 2015 and we also used a Landsat image of the same month and year that the sampled data be the same identified in the satellite image as well as the same landcover for NDVI analysis. Field measurements were done based on the nested non-aligned block sampling design (Liu and Taylor, 2002). The design allows an assessment of biomass at multi-scale level to facilitate the capture of variations over both small and large areas (Liu and Taylor, 2002). The initial process involved delineation of the village boundaries using a hand-held GPS receiver. Coordinates were later overlaid in ArcGIS to a Landsat TM image of the zone. A grid of 750×750 m was drawn for each village using the Integrated Land and Water Information System (ILWIS) (www.itc.nl/ilwis) (Fig. 2A). Next, each main cell of 750×750 m was divided into 25 sub-cells of 150×150 m, that were subsequently divided once again in 25 micro-cells of 30×30 m. All grids were later transferred to ArcView, where three sub-cells from each main cell and three micro-cells from each sub-cell were randomly selected. This yielded a cluster of nine micro-cells per main cell (Fig. 2B). Finally, the centroids of each selected micro-cells were estimated and the GPS was used to locate these points in the field (Fig. 2C). Plots that had 90% graminae species were considered for data collection, and those with less than 10% were discarded completely.

At each sampling point, three radial arms (Fig. 2C) were constructed within the 30 m^2, using a compass to establish the azimuth of the arms.

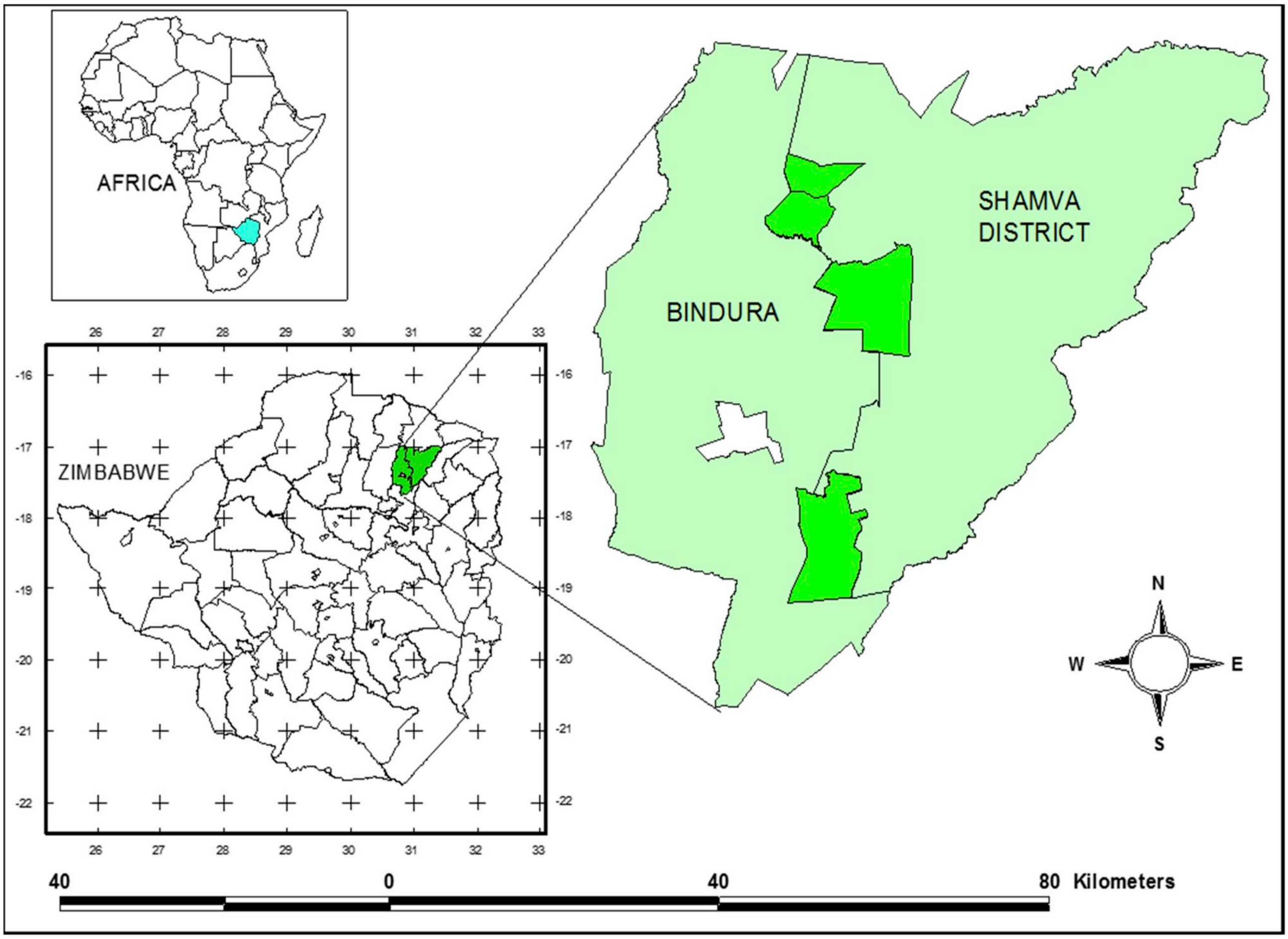

Fig. 1. Map showing the location Mashonaland Central Province in Zimbabwe.

The purpose of the radial arm was to facilitate the capture of variations within the 30-m^2 plot by considering four points: one from the centre, one from the north, one from the southwest and the other from the southeast. The angle between arms was 120° and their length was 12.2 m. At the end of each arm and at the centre, a 1 m^2 quadrat was designed and fully characterised, including aboveground and belowground biomass (Bray, 1963; Pilliod and Arkle, 2013).

2.3. Species identification

Graminae species were identified in both the sampling plots and quadrats with the help of a plant ecologist from the national herbarium of Zimbabwe. Species identification was meant to establish the dominant species to be considered when relating NDVI to AGB. This enabled establishing variations in carbon stock of the different species. Percentage cover was determined using the plant frequency per quadrant, as it is a more useful measure than density, as both the size and number of individual plants contribute to the area covered. Table 1 shows the identified species and their cover in percentage. The location of the villages and their districts is shown in Fig. 1.

2.4. Aboveground biomass sampling and estimation

Grass biomass is the sum of the mass of grass roots, stalks, leaves flowers and fruits (Fiala, 2010). The cutting quadrat method (Bray, 1963) was used to collect AGB data. Grass was cut to ground level within the 1 m^2 quadrant (Bray, 1963; Pilliod and Arkle, 2013). A digital scale was used to determine fresh weight of all the samples from the four quadrats in a plot. This was followed by taking a sub sample after mixing the grasses from all the quadrats. The final and fresh sub sample was weighed to enable the calculation of water content in the biomass and facilitate the extrapolation of dry weight to the 1 m^2 quadrat (Bray, 1963; Pilliod and Arkle, 2013). The collected samples from the homogenous vegetation plots were initially air-dried for two weeks. The samples were placed in an oven to dry for 12 h after weighing. Three samples were randomly selected and weighed. To ensure that the samples were adequately dry, replicated weighing of the same samples was done until no further loss of weight occurred (Schuman and Rauzi, 1981).

2.5. Belowground biomass sampling and estimation

The harvest method was used to collect root biomass data (Bray, 1963). Preliminary sampling was done to measure the percentage of BGB. Soil cubes to a depth of 20 cm were extracted. Other cubes from 20 to 40 cm depth were also extracted. The assumption was that grass roots do not grow beyond 40 cm depth under savanna climatic and edaphic conditions (Hipondoka et al., 2003). A previous study done in the humid African savanna also found out that grass roots in the region do not grow beyond 20 cm of the soil profile (Mordelet et al., 1997). Roots from both 0–20 and 20–40 cm profiles were separated from the soil using sieves, washed, dried at 55°C and weighed using a digital scale. To ensure that the samples were adequately dry, replicated weighing of samples was done until the weight was constant. The 0–20 cm layer contained about 88.23% ($n = 15$) of the total BGB. We, therefore, considered the 0–20 cm layer as the BGB. The assumption was that the remaining roots below 20 cm were not significant enough to affect the relationships between BGB and ABG.

Table 1
Identified graminae species in the tropical savanna grasslands of Mashonaland Province, Zimbabwe.

Village	Common name	Botanical name	Venacular name	% cover
Hereford	Cats tail grass	*Sporobulus pyramidalis*	Tsinde	60
	Thatch grass	*Hyparrhenia fillipendula*	Danfaruswa	30
	Wild sorghum	*Sorghum bicolor*	Mupfunde	1.5
	Couch grass	*Cynadon dactalon*	Shanje	1.5
	Shamva grass	*Roboellia exaltata*	Shamva grass	3
	Natal red top	*Rhychelytrum repens*	Bhurukwacha	0.5
	Herringborne grass	*Pogonanthria squarrosa*	Minyangwe	3.5
Chomutomora	Thatch grass	*Hyparrhenia fillipendula*	Danfaruswa	63
	Spear grass	*Heteropogon contortus*	Tsine	17
	[a]	*Steriochlaeca cameronii*	Shanje	12
	Guinea grass	*Panacium maximum*	Chivavane	2
	Crowfoot grass	*Dactylocterium aegyptium*	[a]	2
	Couch grass	*Cynadon dactalon*	Shanje	2
	Small silver	*Andropogon encomus*	[a]	2
Kanyera	Thatch grass	*Hyparrhenia fillipendula*	Tsinde	55
	Cats tail grass	*Sporobolous pyramidalis*	Tsinde	35
	Purple-spike perotis	*Perotis patterns*	Shava huru	8
	Love grass	*Eragrotis pseudosclerenthras*	Muswewedongi	4
	Natal red top	*Rhychelytrum repens*	Bhurukwacha	4
	[a]	*Sorghum arundinaceum*	Mupfunde	4

[a] Common *name unknown.*

2.6. Satellite image pre-processing and NDVI estimation of carbon stocks

Landsat TM imagery with spatial resolution of 30 m for March 17, 2015 was acquired from the online Landsat archive via GloVis web-link (http://glovis.usgs.gov/). March was chosen as it marks the end of the summer season when the maximum biomass content can be estimated. Grass biomass is expected to be high during this period. Thus, the selected year was not anomalous. The results obtained can be generalized as reflective of conditions that exist in a meteorologically normal year.

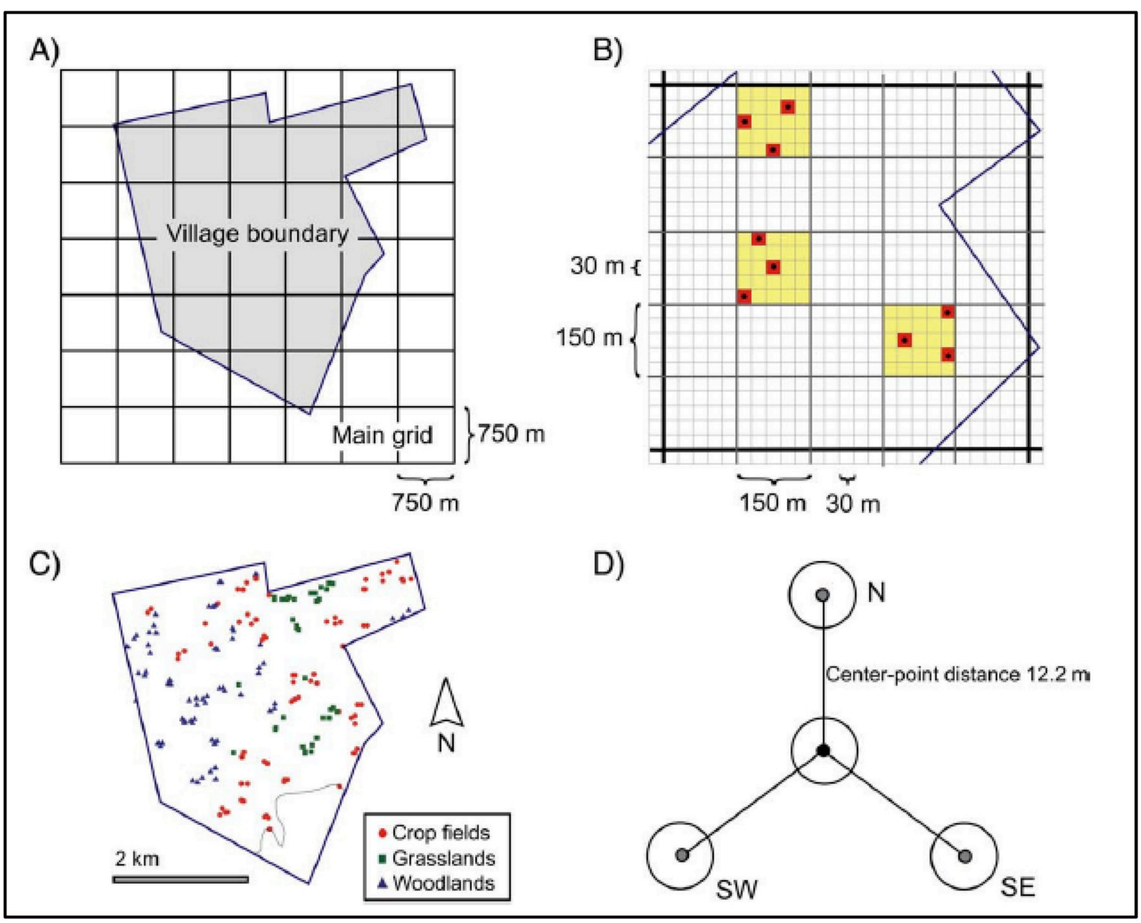

Fig. 2. The non-aligned block sampling design. Fig. 2A is an overlay of a village boundary with main grid of 750 × 750 m. Fig. 2B is a zoomed cell of 750 × 750 m where grids of 150 × 150 and 30 × 30 m, and selected sub-cells and micro-cells (with respective centroids) are shown. Fig. 2C is the final distribution of sampling points in the village. Fig. 2D is a schematic representation of the radial arm for each sampling point, where the central circle indicates the centroid of each micro-cell (N: north, SW: southwest; SE: southeast).

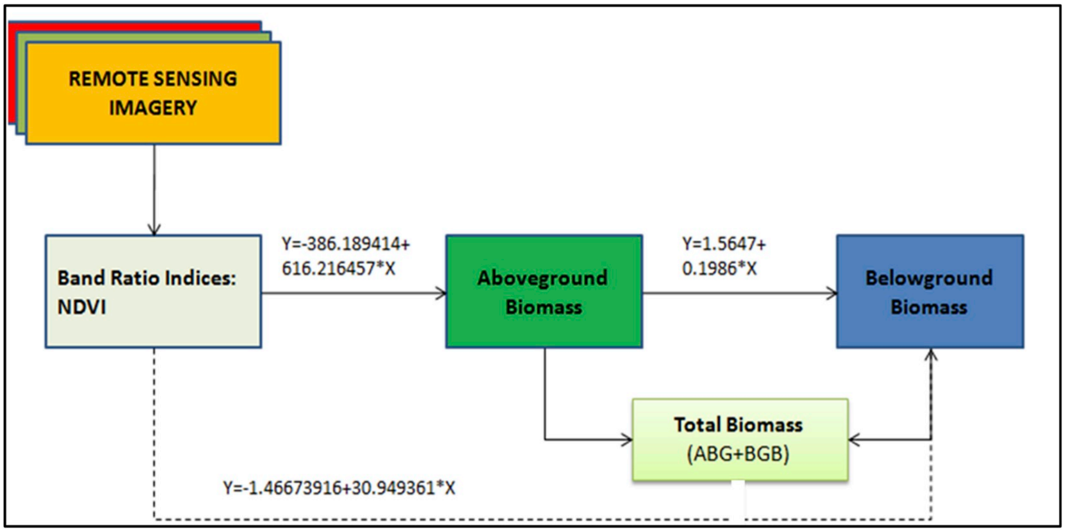

Fig. 3. The NDVI carbon estimation conceptual and methodological model.

Landsat image for the study area was acquired in digital number (DN) format and calibrated to spectral radiance units (W m–2 sr–1 μm–1). The conversion from DN to spectral radiance was done by using the algorithm developed by Chander et al. (2009) using the Environment for Visualizing Images (ENVI) software package. The algorithm calibrates Landsat images (Equation (1)).

$$L\lambda = \left(\frac{LMAX\lambda - LMIN\lambda}{Qcalmax - Qcalmin}\right)(Qcal - Qcalmin) + LMIN\lambda \tag{1}$$

where, $L\lambda$ is the spectral radiance at the sensor's aperture [W/(m^2 sr μm)], Qcal is the calibrated and quantized scaled radiance in units of digital numbers, LMAXλ is the spectral radiance at QCAL = QCALMAX, LMINλ is the spectral radiance at QCAL = QCAL = 0, and QCALMAX is the range of the rescaled radiance in digital numbers.

Only Landsat bands 3, 4 and 5 were used for both image classification and NDVI calculation, respectively. The three bands were atmospherically corrected using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) model [(Kaufman et al., 1997) which is applicable only to the 0.35–2.5 μm visible region of the electromagnetic spectrum. NDVI was calculated from the image using Equation (2):

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

where, NDVI is Normalised Difference Vegetation Index, NIR is reflection in the Near Infrared band and Red is reflection in the red band. Fig. 3 is the NDVI carbon estimation conceptual and methodological model.

NDVI was preferred as it is a numerical indicator that can be used as a proxy for plant biomass (Dube et al., 2014; Rulinda et al., 2010). Spectral reflectance is the ratio of the reflected over the incoming radiation in each spectral band individually; hence they take on values between 0.0 and 1.0, although NDVI range between −1 and +1. Thus, NDVI values range between −1.0 and + 1.0. It is correlated with green leaf biomass and green leaf area index. Chlorophylls, the primary photosynthetic pigments in green plants absorb light primarily from the red and blue portions of the spectrum, while a higher proportion of infrared is reflected or scattered. NDVI values increase with increased greenness of leaf biomass or leaf area index. NDVI detects vegetation presence and health and provides a strong vegetation signal and good spectral contrast from soils. It is an effective measure of photo-synthetically active biomass (Steininger, 2000). NDVI was used to correlate biomass (carbon content) obtained from ground sampling. Fig. 3 is an NDVI conceptual carbon estimation model that was followed to evaluate total grass biomass in grassland ecosystems. NDVI is thus, an indicator of vegetation quantity, the higher the NDVI value, the higher the AGB content. AGB is then used to estimate BGB through conversion factors (Ohsowski et al., 2016; Zhao et al., 2014) (Fig. 3).

2.7. Regression equation for estimating carbon stock through NDVI

A non-linear regression equation that has been successfully used in previous studies, was also applied in this study to estimate total carbon stock (ABG and BGB) (Nyamugama and Kakembo, 2015; Patenaude et al., 2005; Skowno, 2003). The non-linear regression equation was prefered instead of a simple linear regression equation because it produced higher correlations that were comparable with previous studies (Nyamugama and Kakembo, 2015), and also natural grassland conditions do not follow linear relationships (Bai et al., 2001). NDVI was used as the independent variable, while biomass was the dependent variable. The non-linear regression equation used to estimate carbon stocks was (Chave et al., 2004; Nyamugama and Kakembo, 2015),

$$CS = 108.2e^{(NDVI10.0184)} \tag{3}$$

where, CS is the total carbon stock (kg C/pixel) and NDVI is the Landsat NDVI value. After the model application, carbon stock estimates were up-scaled to t/ha.

2.8. Error modelling and model bias estimation

The Root Mean Square Error (RMSE) and the model Bias were calculated using Xlstat Statistical Software (www.xlstat.com/en). The RMSE was calculated to determine the deviation between BGB data and NDVI, ABG and NDVI. Equation (3) was used to calculate the RMSE as follows (Chai and Draxler, 2014), where P is the carbon predicted value by the model while O is the observed value and n is the number of observations.

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n}(Pi - Oi)}^{2}}{n} \tag{4}$$

Model Bias was calculated by subtracting modelled values from the actual observations and adding up the errors and divide by the total number of estimates. Equation (4) was used to calculate the model Bias (Peri and Sparber, 2011), where E is the expected value of the estimator H and θ are the values being estimated.

$$Bias = E(H) - \theta \tag{5}$$

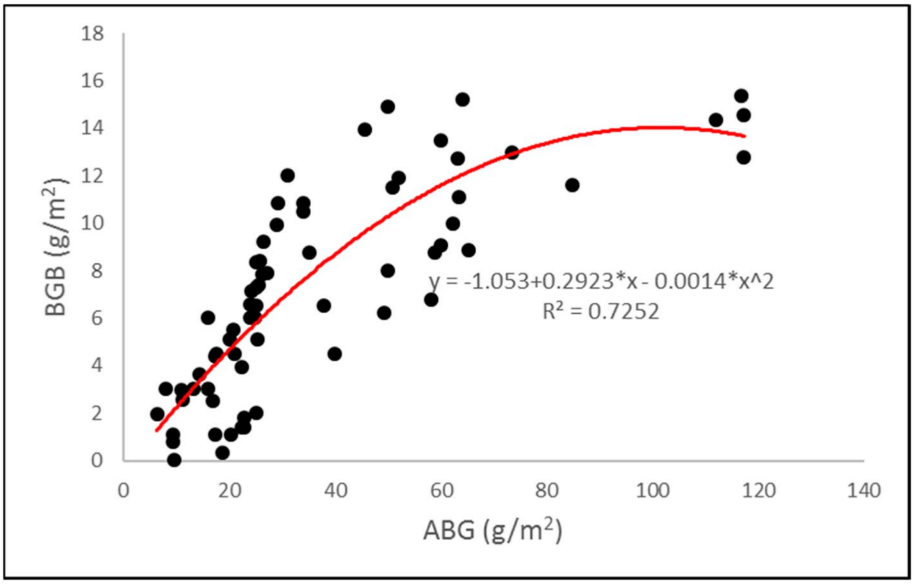

Fig. 4. Relationship between aboveground (AGB) and below ground (BGB) biomass of tropical savanna grasslands.

3. Results and discussion

3.1. Relationship between aboveground and belowground biomass

Results show a positive significant ($P<0.05$) nonlinear relationship between BGB and AGB (Fig. 4). The relationship is based on data collected directly through harvesting and weighing BGB and AGB. The results show that BGB can be estimated statistically using AGB ($R^2 = 0.7252$). The relationship between RGB and AGB is even stronger ($r = 0.7934$) and linear when AGB is below 100g/m^2, but the relationship becomes asymptotic when AGB increases beyond 100 g/m^2.

Further observations indicate that under the non-rainfall limitation zones and ferralistic soil characteristics, BGB can be estimated as long as it is possible to quantify AGB. The relationship is stronger in undisturbed grassland ecosystems dominated by cattail grass (*Sporobolus pyramidalis*). Although grassland management activities like grazing, cutting, and treading affect the relationship between belowground and aboveground graminae species biomass, it was noted that grass always maintain the ratio between BGB and AGB whether disturbed or not. This confirms similar results from a study by Zhengxi and Lai (Tan and Lal, 2005), in Ohio, USA. Nevertheless, this relationship is not always positive in other grassland ecosystems as the ratios vary from ecosystem to ecosystems (Fan et al., 2008). In their study in China, Fan et al. (2008) demonstrate that the ratios between AGB and BGB are greatly influenced by climatic and edaphic factors. However, for tropical grasslands this study has shown a consistent positive relationship, implying that total biomass and carbon in vegetation in tropical grasslands can be estimated by quantifying AGB.

It should be noted that Fig. 4 represents the relationship between below and above ground biomass based on data obtained from all land uses including those present even after disturbances. Thus, the number of points shown in Fig. 4 will not tally with those presented in later analyses where only data from undisturbed grasses was considered. The assumption was that undisturbed grasses provide a better picture of the relationship between NDVI and belowground biomass.

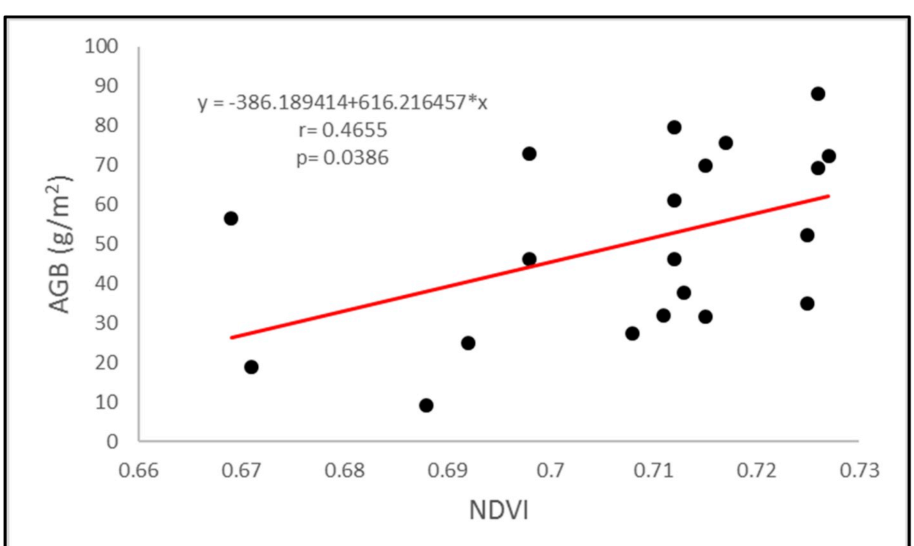

Fig. 5. Relationship between AGB and NDVI under tropical savanna climate.

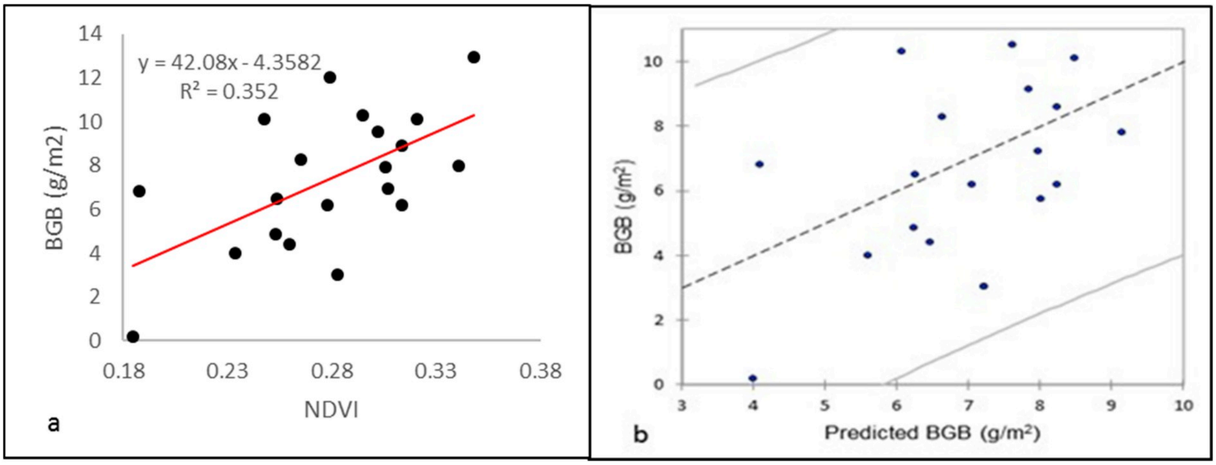

Fig. 6. Relationship between (a) BGB and NDVI, (b) BGB and modeled BGB. *Source.*

3.2. Signifcance of NDVI in estimating aboveground biomas

Measured grass biomass showed a significant correlation with NDVI ($r = 0.4655$, $r^2 = 0.35$, $p<0.05$) (Fig. 5). The AGB for *Sporobolus pyramidalis* was more dominant in this assessment. Thus, NDVI is significantly correlated with biomass content as the RMSE was calculated at 19.97 and the model Bias at 0.019. However, the predictive value found in this study is lower than predictive values established in other studies (Ikeda et al., 1999; Mašková et al., 2008; Schino et al., 2003; Vicharnakorn et al., 2014). The calculated RMSE shows a greater magnitude of deviation of the predicted values from the observed values, but the model BIAS shows that the model prediction is not far off from the actual values of the training data. The accuracy of satellite estimates could have been affected by the presence of photo-synthetically inactive dry biomass. Thus, we suggest the best time to assess biomass using remote sensing is when the ratio of dry to green biomass is low, during the spring or summer in savanna regions.

Thus, remote sensing has great potential to be an effective tool in estimating AGB of savanna grass ecosystems. An improvement on the timing of assessments and resolution of the imagery is highly likely to provide better predictive power of the models. The use of remote sensing to quantify AGB is time and cost effective, as it allows the process of carbon accounting over large spatial areas within a short space of time.

3.3. Signifcance of NDVI in estimating belowground NDVI

BGB data measured directly from the ground was correlated with NDVI. Estimating BGB through NDVI was done indirectly through quantifying AGB and then correlating the AGB with BGB. Spearman's correlation coefficient tests (McDonald, 2009) show that there is a positively significant ($p = 0.0485$; $r = 0.4582$; $R^2 = 0.352$) correlation between BGB and NDVI (Fig. 6). The RMSE of the fit is 2.66 whilst the model Bias is −0.00036.

The RMSE is close to 0, showing that the model is not far off from the estimated BGB. More so, the model Bias shows that the model predictions are not far off from the actual values. The relationships are a further indication of the potential and importance of remote sensing in indirectly estimating BGB of grass ecosystems.

3.4. Significance of NDVI in estimating total biomass

The results show a positive correlation ($r = 0.452$) and a significant relationship ($P = 0.037$, $\alpha = 0.05$, $R^2 = 0.22$) between NDVI and total biomass (aboveground + belowground biomass) (Fig. 7). This agrees with the positively significant linear relationship between NDVI and grassland biomass shown in previous studies (Ikeda et al., 1999; Mašková et al., 2008; Schino et al., 2003; Vicharnakorn et al., 2014).

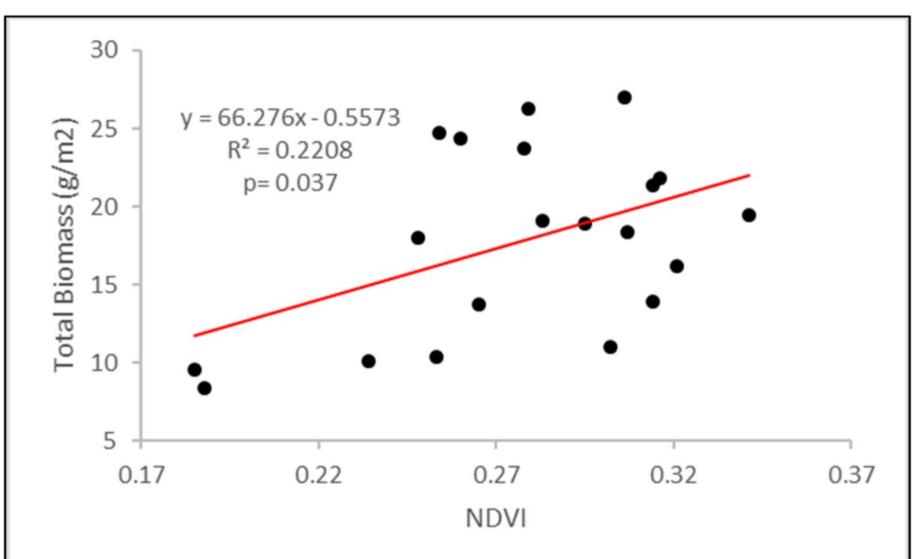

Fig. 7. Relationship between NDVI and total biomass showing a significant relationship of $p = 0.037$.

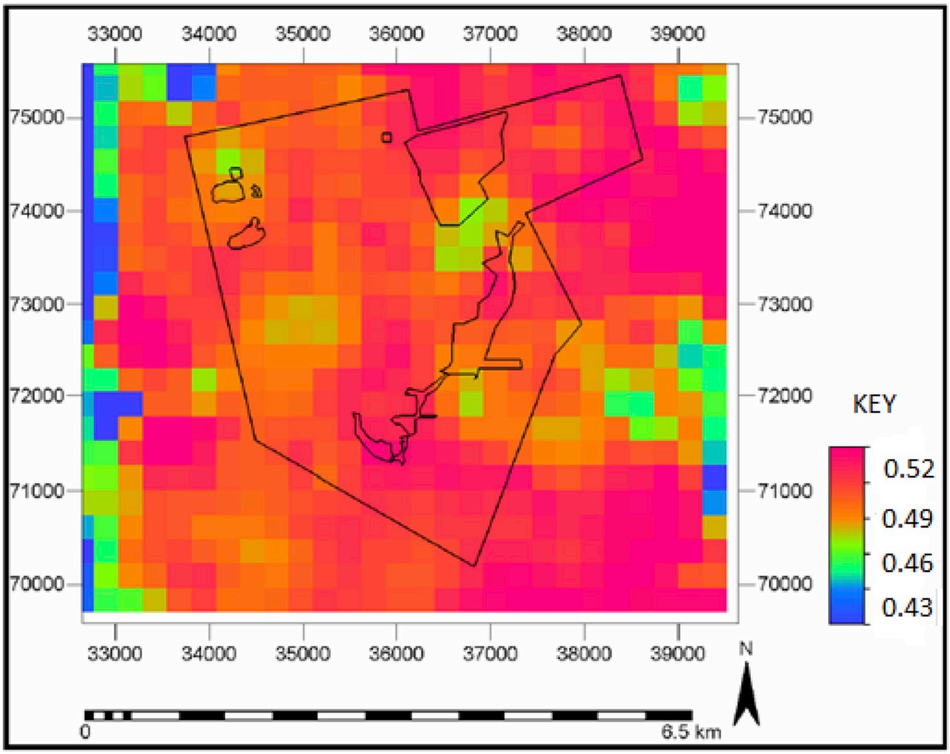

Fig. 8. NDVI based model estimates of carbon stocks of a savanna (in tons) grassland at a study site in Bindura district.

The RMSE for the fit is 5.53 whilst the model BIAS is 0.0041. The RMSE is quite big but the Bias shows that the model is not far off from observed values. The use of high resolution imagery could reduce the error of the model in predicting the actual values. Proper timing of assessments could also contribute to increased predictive power of the model.

Total carbon stock was calculated using a non-linear regression equation (Equation (3)), which established the quantitative relationship between NDVI and direct measures of biomass used to produce the map on Fig. 8. The NDVI algorithms for estimating carbon stock produced values oscillating between 0.43 and 0.52 tons (Fig. 8). The total carbon stock derived from the NDVI model at the study site averaged 0.47tons/ha.

As NDVI values were strongly correlated with AGM, remote sensing products can be used to measure total biomass, as a proxy for carbon stock in tropical grass ecosystems. Different relationships can be observed if similar studies are carried in different regions with different climatic and edaphic characteristics. The most important parameter in biomass conversion is the carbon fraction. Values varied from 0.43 to 0.52 tons depending on conversion factors, which include the ratio between oven-dry weight and given volume of species and the ratio between biomass in tonnes and growing stock in m^3. The significant relationship between BGB and AGB with NDVI enables the estimation and inventorying of biomass, as well as carbon stock through remote sensing. The use of higher resolution satellites like Sentinel has the potential to improve the statistical relationship between NDVI and BGB. If the error margin is reduced, the predictive accuracy may also increase (Hu et al., 2017; Schulze, 2012).

4. Conclusions

This study used remote sensing to estimate aboveground and belowground biomass, demonstrating the significant relationship between AGB and BGB for tropical savannah grass ecosystems dominated by the species *Sporobolus pyramidalis*. There was also a significant correlation between NDVI and AGB in the same ecosystems. The RMSE and model BIAS values were also within acceptable ranges to validate the importance of remote sensing in estimating grass biomass of tropical savannah ecosystems. These positive relationships provide the basis for using remote sensing products to estimate carbon storage in grassland ecosystems, biomass being the proxy indicator. The ability to estimate BGB through remote sensing, and the resultant positive relationships have provided a less labour intensive method of quantifying biomass, which is a basic measurement of carbon stocks of ecosystems. Remote sensing has become indispensable for estimating vegetative carbon in tropical grass ecosystems. The continued availability of free and low cost satellite images with high spatial resolution facilitates the possibility of routinely producing accurate and frequently updated maps of carbon density in grass ecosystems. Future research efforts should focus on improving the accuracy of satellite estimates and to investigate the possibilities offered by the more recently launched satellites characterised by higher spatial, temporal and spectral resolutions. Further research is also need to use an approach based on the relationship between the amount of dry matter and green foliage. The advent of a new generation of multispectral sensors, such as the Sentinel 2 multispectral imager and WorldView-3, offers an opportunity to improve the accuracy of aboveground grass biomass estimation as these sensors have finer spectral resolution in regions like the red-edge, which are crucial for vegetation mapping, as well as having high spatial resolution. However, it should be emphasised that the regression equations applied in this study are only applicable in areas with similar climatic and edaphic characteristics of tropical grasslands.

Ethical statement

The study does not deal with human beings, animals, genetically modified organisms, nor does it modify any environment. The article preserve all ethical issues.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2019.100275.

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