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Performance of ratio-based, soil adjusted and atmospheric corrected multispectral vegetation indices in predicting herbaceous above ground biomass in a Colophospermum mopane tree-shrub savanna

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Abstract

Accurate and near-real time estimation of herbaceous above ground biomass (AGB) at farm level is crucial for monitoring utilisation of pasture and proactive management of stock in semi-arid rangelands. Despite its importance, remote sensing has been rarely used by range ecologists and managers in Zimbabwe. This study aimed to assess the performance of multispectral vegetation indices (MVIs), either singly or combined with visible spectral bands in predicting herbaceous AGB in a *Colophospermum mopane* tree-shrub savanna. Field herbaceous AGB and corresponding Landsat 8 Operational Land Imager (OLI) visible spectral data were collected towards end of 2016-17 rainy season. Relationships between measured AGB, MVIs and spectral bands were analysed using bootstrapped simple and stepwise multiple linear regression functions. When MVIs were singly regressed with measured AGB, ratio based and SAVI yielded the highest r^2 values ranging between 0.61 and 0.64 ($p < 0.05$) followed by atmospheric corrected MVIs ($r^2 = 0.55$ to 0.58) whilst other soil adjusted indices did not significantly explain herbaceous AGB variation. A significant improvement in herbaceous AGB estimation was obtained by using a combination of visible spectral bands and the MVIs. Soil adjusted MVIs showed the greatest increase (44-46 %) in r^2whilst atmospheric corrected and ratio-based MVIs poorly improved (<5 %). The findings demonstrate that combining MVIs with Landsat 8 optical spectral bands, especial green band provides the best models for estimating AGB in *C. mopane* savanna rangelands. These findings emphasise the importance of testing band-MVI combinations when developing models for estimating herbaceous AGB.

Key words: herbaceous biomass, regression, multispectral vegetation indices, savanna, Landsat 8 OLI

Introduction

The southern African *Colophospermum mopane* woodland or tree-shrub savanna rangelands cover up to 90 % of total land cover predominantly in the south-central region (Mapaure 1994). Up to 18 % of this cover is spread in Zimbabwe where *C. mopane* woodland savanna occupies a quarter of rangelands that provide food and shelter to wildlife, livestock and people. These eutrophic rangelands support beef cattle production that contributes up to 8% of agricultural gross domestic product (GDP) (GoZ, 2013). Range managers are usually faced with the challenge of monitoring herbaceous above ground biomass (AGB) produced in the patchy vegetation community structure that evolve from long term, highly variable rainfall (Araujo et al, 2015). On ground, point-based measurements of AGB are accurate but they are usually destructive, labour-intensive, expensive and time-consuming. Selection of representative sampling areas is difficult since some closed *C. mopane* stands are inaccessible and such measurements are limited to local scale. The manager's capacity to tactically adjust stocking rates to match available herbaceous AGB at whole ranch level is thus constrained. In developing economies where long-term range experiments and research funding are limited, there is need to embrace alternative inexpensive approaches for near-real time monitoring of AGB that allows opportunistic management of the stock by managers at whole farm level.

In the past 40 years, remote sensing has gained much attention as an alternative, low cost technology for near-real time monitoring of biomass stocks at regional level in African savannas (Fuller & Prince, 1996; Wessels et al, 2004). Majority of the available studies on AGB are based on multispectral vegetation indices (MVIs) which provide information about visible electromagnetic spectrum absorbed or reflected by vegetation and its relationship with vegetation cover, density and biomass. Globally, MVIs have remained as the largest and most researched indices for herbaceous AGB estimation due to their simplicity (Price et al, 2002). However, most remotely sensed AGB literature in south central of southern Africa is based on low spatial resolution satellite products that usually do not satisfactorily meet management objectives of herbaceous AGB at vegetation community or paddock level. Hyper spectral VIs (HVIs) have been considerably used to estimate AGB using high spatial resolution products with emphasis on grass nutrient composition and total woody biomass (Zengeya et al, 2013; Gara et al, 2016). These HVIs have been however used with little progress due to cost and limited availability of high resolution satellite products and have remained appropriate at a localised scale (Dube et al, 2016). Multispectral VIs derived from free, medium resolution satellite products such as Landsat are thus likely to address the farm management needs. The

MVIs' utility to accurately predict herbaceous AGB in a specific landscape is affected by environmental factors such as vegetation type and density and atmospheric conditions.

Atmospheric contaminants such as water vapour present the biggest challenge to the utility of MVIs in herbaceous AGB estimation (Ali et al, 2016). Such contamination could be more pronounced in *C. mopane* savannas where peak biomass production is often reached during the wet season that is usually associated with overcast conditions. The saturation effect of the commonly used ratio-based MVIs such as simple ratio (SR) and normalised difference vegetation index (NDVI) in high density vegetation is another typical constrain to their use (Mutanga & Skidmore, 2004). Soil background effects are also very important to AGB estimation in sparsely covered and heterogeneous vegetation communities in arid and semi-arid rangelands (Jackson & Huete, 1991). Field spectral measurements and hyper spectral based approaches that overcome some of these problems are expensive and computationally intensive and thus have been slowly adopted by many range experts and managers in southern Africa. Broadband MVIs based on medium resolution products thus remain important for monitoring AGB at paddock level in savanna rangelands and the need to evaluate their performance under prevailing landscape features using improved and affordable satellite products remains a priority.

Evaluation of performance of MVI- based regression models for estimating herbaceous AGB have been done in other regions e.g Ren & Feng (2014) in Inner Mongolia and Price et al. (2002) in North America, but are limited to certain biomes in southern Africa (Dube et al, 2016). Where medium resolution products have been used, the reflectance information is based on Landsat 5 thematic mapper (TM) and 7 enhance TM plus (ETM+) sensors (Moleele et al, 2001; Samimi & Kraus, 2004) which are not calibrated for top of the atmosphere reflectance. Such difference in sensor response function between Landsat-7 ETM+ and Landsat-8 Operational Land Imager (OLI) are sufficient to warrant differences in accuracy of herbaceous AGB estimation by multispectral bands from these satellites (Flood, 2014; USGS, 2016). In addition, multispectral VIs' tendency of changing their properties at specific landscapes due to variability in soil and atmospheric conditions across rangelands warrants the need to evaluate these models under prevailing conditions in *C.mopane* savannas, southern Zimbabwe.

Landsat 8 OLI near-infra red band (5) width has been refinement to exclude water vapour absorbing features in its spectral domain. This together with the improved radiometric calibration of the sensor presents an opportunity to develop plausible optical reflectance models based on improved remotely sensed variables such as woody biomass (Dube & Mutanga, 2015) and grass leaf area index (LAI) (Masemola et al, 2016). When the remotely sensed herbaceous AGB data are available, they add value to on-farm herbaceous AGB measurements by enabling a quick, near real time assessment of forage availability by ranch managers to avoid under- or over-utilisation by cattle. The mapped products are important in providing ancillary variables that are important in selecting sites to ease labour-intensive on-farm measurements of herbaceous AGB in future and operationalisation of point, process-based pasture models. This study therefore seeks to examine the use of ratio- based, soil-adjusted and atmospherically-corrected VIs and environmental factors that interact with them when estimating herbaceous AGB production in *C. Mopane* savanna rangelands in southern Zimbabwe. This was achieved by developing empirical AGB estimation models based on various visible spectral bands and indices using Landsat 8OLI.

Materials and methods

Ecological characteristics of the study site

Nuanentsi Beef Cattle Ranch is located on a low plane (480 m.a.s.l) semi-arid region between Runde and Mwenezi river in the south lowveld of Zimbabwe (Figure 1). The plane landform is general undulating, covering 110 921 hectares (1109.21 km^2) of land. Annual rainfall that is received in summer between November and March is usually low with a mean of 480 mm and highly unpredictable (variability coefficient is 31.7%) (Fuller & Prince, 1996). Annual temperature range between 5 and 33°C and maximum daily temperature in summer are frequently above 40°C. Natural vegetation is predominantly a tree/bush savanna of the *Colophospermum-Grewia-Acacia-Combretum*-community format whilst other mono-dominant *C. mopane* stands are found in lightly disturbed areas. This vegetation portrays heterogeneous closed- and open-*Mopane-Grewia* canopies at vegetation community-level due to variation in features of soils associated with them. Herbaceous layer is dominated by palatable perennial C4 grasses such as *urochloa mosambisensis* and *panicum maximum* and forbs in heavily utilised areas. The soils are chromic luvisols formed from mafic gneiss (metamorphic) rocks (van Engelen et al, 2004). These soils have a dark brown colour and loamy sand texture. Extensive cattle ranching with heavy beef breeds in paddocks ranging from 300 to 1200 hectares has been the main land use since 1940s.

Data collection

Field measurement of herbaceous above ground biomass

A vegetation survey was conducted between 5 and 11 February 2017 through visits to the Nuanetsi cattle ranch section. The sampling plots within *C.mopane* stands were selected based on a two- stage sampling design of Morisette et al. (2006) for producing geo-referenced databases for integrating remote sensed- and ground- based vegetation information. Prior to field data collection, the extent of each vegetation community cover class was mapped using the FAO land cover classification system (LCCS) (Di Gregorio et al, 2016) to the represent sampling frame as shown in Figure 1. A stratified random sampling procedure was then objectively used to generate elementary (primary) sampling plots for ground measurements across the vegetation cover classes using the random point generator tool in ArcView 3.2 (ESRI, Redlands, CA, USA). On-ground, point measurements of total herbaceous AGB were done in forty 30 m x 30 m(900 m^2) elementary sampling plots that were 500 to 1000m apart depending on homogeneity and accessibility of the area. The plot size corresponds to the pixel resolution (30m) for Landsat 8OLI images that were used as observed vegetation reflectance data. The elementary sampling units were replicated at least 3 times in each vegetation cover type and were used to represent site variability of the dominant vegetation cover classes. The central position of the four corners of the plots was recorded using a Garmin Etex 20 Global Positioning System (GPS). Variability in herbaceous AGB within each elementary sampling unit was measured in second- stage sampling units (0.25m^2 quadrats) that were replicated 4 times. Herbaceous AGB in the randomly selected subplots were clipped to 5cm stubble above ground using shears, weighted to the nearest 0.01g and then pooled, and bagged for drying in a hot air oven. Herbaceous AGB dry matter measured in each quadrat was converted to $kgm^{-2}$and averaged at elementary sampling plot level.

Image acquisition and derivation of multispectral vegetation indices

A Landsat 8 OLI image (30m spatial resolution) that had been pre-processed and atmospherically corrected i.e. surface reflectance by the United States Geological Survey (USGS)'s data management unit was downloaded on a cloud-free day on 30 November 2016 from Earth explorer (path 169, row 075). The image was acquired before vegetation sampling was done and was used to study the utilities of MVIs and their interactions with visible spectral bands. The Landsat images has four bands in the visual domain of the spectra i.e, blue at 0.452-0.512 nm (band 2), green at 0.533-0.590 nm (band 3), red at 0.636-0.673 nm (band 4) and near infra-red at 0.851-0.879 nm (band 5). Layer staking of bands on the image was done using Environment for Visualizing Images (ENVI) software, version 5.2. Coordinates of the centre point of elementary sampling plots were geo-referenced on the imagery using an extraction tool nested in a computer-enabled Garmin® GPS map of ArcGIS® to accurately register the points on the satellite image.

Spectral band values corresponding to elementary sampling plots were extracted from the Landsat 8 OLI image and ten MVIs were computed using the conventional formulas shown in Table 1. The MVIs that were derived from spectral bands included: three ratio-based indices ((Simple Ratio (SR), Normalised Difference Vegetation Index (NDVI), Transformed Vegetation Index (TVI)); four soil adjusted indices ((Perpendicular Vegetation Index (PVI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI), Transformed Soil Adjusted Vegetation Index (TSAVI)) and, three atmospheric corrected MVIs ((Atmospherically Resistant Vegetation Index (ARVI), Soil and Atmospherically Resistant Vegetation Index (SARVI) and Enhanced Vegetation Index (EVI)).

Statistical analyses

Evaluation of vegetation indices for above ground herbaceous biomass estimation

Simple and stepwise multiple linear regression (SMLR) analyses were used to determine the appropriate model(s) for predicting herbaceous AGB measured in 40elementary sampling plots using ten MVIs and fourLandsat8 OLI bands (2- blue, 3- green, 4- red and 5- near infra-red) in the visible domain of the spectrum. Firstly, each of the ten MVIs was regressed with measured herbaceous AGB in kgm^{-2}. An r^2 was used to determine the amount of variation explained by the regression models. The appropriateness of each resultant regression function was assessed using an adjusted r^2 value which considers sample size and number of independent variables included in a model to compare different equations derived. The root mean square error (RMSE) of the estimate of each regression equation was used to determine the dispersion of values around the regression line. Forward SMLR was used to determine the most appropriate bands and indices to include in each multiple regression function. In this approach, each MVI was firstly combined with all 4 visible spectral bands (blue, green, red and near infrared) into a MLR model. In each successive step, spectral band(s) that do not significantly interact with the MVI to predict measured herbaceous AGB is removed. The procedure is repeated with relevant spectral bands until a satisfactory multilinear regression function is obtained or forward stepping is no longer possible.

Validation of optical reflectance models

Two common non-parametric re-sampling methods were used to estimate the accuracy (biases, variances) of transformed VI models (cross validation). The main advantage of these methods is that they can provide plausible results when limited sample sizes are available. Bootstrapping approach was used in combination with stepwise multi-linear regression to calibrate and validate optical reflectance models. The leave-one-out method, also known as the jack knife method was used to validate the models using R programming language. In this method, one sample is withheld, and the regression model is build using the data from the remaining samples. The process of removing one sample from the dataset was repeated until all samples had been withheld and model accuracy was examined by the root mean square error. The RMSE was calculated as follows:

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(y_1-y'_1)^2}{n}}$$

where $y_1$is the actual biomass of the field samples, $y'_1$is the estimated grass yield and n is the sample size.

Results

Prior to data analysis, descriptive statistics of the measured herbaceous AGB were estimated. Average herbaceous AGB was 0.324 kg m^{-2} and ranged from 0.134 to 0.753 kg m^{-2} (Table 2). Such a wide variation in herbaceous AGB was expected as typified by the adaptation of native pastures to uneven redistribution of water, nutrients and solar radiation in the range ecosystem. The sampling procedure used was therefore considered to have generated realistic herbaceous AGB data that could build realistic relationships with MVIs and visible spectral bands.

The elementary sampling plots provided adequate herbaceous AGB data for the development of relationships with MVIs and visible spectral bands. The performance of all MVIs and visible spectral bands for predicting herbaceous AGB is presented in Table 3. All linear regression models significantly estimated herbaceous AGB ($p < 0.05$) except for MSAVI. Ratio-based MVIs and SAVI outperformed other MVIs in simple linear estimation of herbaceous AGB (Figure 2 A - C and 3 A), explaining a maximum of 64 % variance in biomass at the highest accuracy (RMSE range between 0.089 and 0.094 kg m^{-2}). Atmospheric-corrected MVIs ranked second in accurately predicting herbaceous AGB with a coefficient of determination value between 55 and 58 % (Figure 4 A - C). Although significant relationships between most of the soil adjusted MVIs and herbaceous AGB were observed ($p < 0.05$), the relationships were generally weak (Figure 3 A - C) with an r^2 value ranging between 0.004 and 21 % and very sensitive (RMSE varied from 0.132 to 0.148 kg m^{-2}).

After forward SMLR, individual MVIs showed appropriate interactions with visible spectral bands for estimating herbaceous AGB with an r^2 ranging from 0.55 to 0.71 (Table 3).The accuracy of the regression models also improved as demonstrated by the general decrease in the RMSE. Soil adjusted MVIs, TSAVI and PVI, and SR accounted for 46, 44 and 7 % more of the variability in measured herbaceous AGB respectively. Despite a relatively smaller increase in accuracy of the SR, the MVI remained the most appropriate variable that interacts with bands 3, 4 and 5 ($p < 0.05$) (Figure 5 A - C). The model of TSAVI and its interactions with visible spectral bands was appropriate for bands 2, 3, and 4 ($p < 0.05$) whilst PVI significantly combined with bands 2 and 4. The rest of the MVIs (NDVI, TVI, SAVI, ARVI and SARVI) significantly interacted with the Landsat 8 OLI green (band 3) ($p < 0.05$) and their predictive performance improved by at least 3 % (Figure 6A - D and 7 A and B). Although TSAVI and PVI and their interactions with visible spectral bands portrayed plausible predictions of herbaceous AGB, these MVIs estimated AGB with the same accuracy as ratio-based MVIs, NDVI in particular with an RMSE of 0.091 kg m^{-2} and atmospheric corrected MVIs (ARVI, RMSE of 0.093 kg m^{-2}). Based on these findings, the following SMLR predictive model was chosen to produce a herbaceous AGB map for the Nuanetsi cattle ranch (Figure 8) and for validation:

$$AGB\ (kg\ m^{-2}) = 1.267985*SR + 0.00120*R - 0.00045*G - 0.00061*NIR - 1.70743;\ (r^2 = 0.71)$$

Where, AGB = herbaceous above ground biomass
SR = simple ratio
R = red band
G = green band
NIR = near infra-red band

Discussion

Ratio-based MVIs outperformed the other MVIs when singly regressed with measured herbaceous AGB in chromic luvisol soils (coefficient of determination ranged between 0.61 and 0.64).The findings concur with some previous studies which showed that soil adjusted MVIs did not improve green AGB estimation over ratio-based MVIs in semi-arid rangelands (Ren & Feng, 2014) and woody biomass in *C. mopane savanna* (Gara et al. 2016). The plausible performance of ratio-based MVIs could be due to enhanced model stability and their good relationships with grass biophysical parameters such as leaf area index (LAI) (Masemola et al, 2016). Despite the adjustment of background soil reflectance in their formula, atmospheric corrected MVIs yielded good accuracy in predicting herbaceous AGB (r^2 between 0.55 and 0.58, $p < 0.05$) that was comparable to ratio-based MVIs and far much better than soil adjusted MVIs. The refinement of the NIR band (band 5) in Landsat 8 OLI could have successfully excluded atmospheric features that absorb water vapour and enhanced sensor response to vegetation reflectance. Correction factors for atmospheric contaminants incorporated in hybrid MVIs could have resulted in their good predictive power of measured herbaceous AGB over soil adjusted MVIs.

The accuracy of the ratio-based MVIs for herbaceous AGB was however comparable to SAVI ($r^2 = 0.61$, $p < 0.05$) whilst the other soil adjusted MVIs poorly predicted herbaceous AGB. The inclusion of a soil line in the derivation of TSAVI and PVI could have greatly reduced their utility in predicting herbaceous AGB (Ren & Feng, 2014). The soil characteristics that affect soil reflectance of the visible spectrum are soil type, texture, organic matter content, moisture content, colour and the presence of iron oxide (Huete et al, 1985; Huete & Jackson, 1988). Soils at Nuanetsi cattle ranch are chromic luvisols formed from mafic gneiss (metamorphic) rocks that are rich in fero-magnesian minerals (van Engelen et al, 2004). The soils are fine to medium grained loamy sand and dark brown in colour (CSRI, 2007). Such soil properties are usually associated with low soil reflectance of the visible spectrum as observed by Ringrose (1987; 1989) in southern African savanna rangelands and Todd et al. (1998) in shortgrass steppe ecosystem or *in situ* (Huete & Jackson, 1987). This could also explain the failure of MSAVI to account for any variation in herbaceous AGB at the study site ($p > 0.05$).

In work based on hyper spectral VIs in *C. mopane* savanna rangelands, Ramoelo et al. (2012) also found ratio-based VIs to be able to provide accurate herbaceous AGB estimates in granite derived soils. The low soil reflectance background of chromic luvisols at the current study site explains the dominance of ratio-based MVIs over soil adjusted MVIs as explained by Todd & Hoffer (1998). In addition, since herbaceous AGB measurements were done during peak period of vegetation growth when herbaceous cover was maximum, soil adjusted MVIs could be insensitive to variation in herbaceous cover in the *C. mopane* savanna rangeland.

Visible spectral bands interacted with MVIs and improved their capacity for predicting observed herbaceous AGB (optimal MVIs and band combinations) as planned and observed in other studies (Fourty, 1997). Soil adjusted MVIs (PVI and TSAVI) and SR accounted for 44, 46 and 7 %more of the variability in measured herbaceous AGB respectively through their interactions with bands 2, 3, 4 and 5.Using Landsat 7 TM, Kraus & Samimi(2002) and Cohen et al. (2003) also found a similar trend in southern African savanna and temperate broadleaf ecosystems, respectively. However, as with any other remote sensing products (Teillet et al, 1997), difference in spectral bands width between Landsat 7 ETM+ and 8 OLI sensors makes it difficult to compare MVIs derived from these products. Most of the MVIs (NDVI, TVI, SAVI, ARVI and SARVI) significantly interacted with the green band (Landsat 8 OLI band 3) ($p < 0.05$) and improved their predictive performance by 3 %. The spectral reflectance measured by the green band (0.533-0.590 μm) of Landsat 8 OLI in the visible electromagnetic spectrum is reflected to a larger extend by leaf pigments, particularly chlorophyll of vegetation (Baret & Guyot, 1991; Bannari et al, 1995). The green band therefore improved the accuracy of ratio-based regression functions as the ratio MVIs have been shown to increase their utility in dark coloured, low reflecting soils (Huete & Jackson, 1987).

The positive interactions of the Landsat 8 green band with MVIs demonstrate the importance of including this band when predicting AGB in photosynthetically active herbage (peak biomass). In southern African savanna rangelands, Moleele et al. (2001) and Samimi & Kraus (2004) found high correlation coefficients between NDVI and Landsat TM spectral bands red (band 3) and green (band 4) whilst Calvão & Palmeirim (2004) found similar relationships in the Mediterranean scrub. In this study, the interaction between the Landsat 8 OLI green band with MVIs proved to be critical in herbaceous AGB estimation since soil adjusted MVIs (e.g TSAVI, r^2= 0.67) estimated AGB with the same accuracy as ratio-based MVIs (NDVI, r^2= 0.64) RMSE of 0.091 kg m^{-2} and atmospheric corrected MVIs (ARVI and SARVI).

This study add-value to the previous studies in that the appropriate regression models for herbaceous AGB estimation were selected from a wide range of MVIs including atmospheric corrected MVIs that have been rarely evaluated in southern Africa. Some of the models developed in this region did not successfully predict herbaceous AGB e.g Moleele et al. (2001). Other studies focused on using measured AGB in predicting other vegetation attributes such as grass nutrient quality in communal lands (Zengeya et al, 2013) and forest carbon biomass (Gara et al, 2016) which have relatively little relevance to livestock production. However, it would be more useful to apply these models to range sites that portray diverse soil types and herbaceous vegetation cover in southern African savannas to determine their consistency and further improvements. The study also identified the Landsat 8 OLI green band as the prominent band that produces plausible MVIs regression models, probably enhanced by a relatively narrow NIR spectral zone refined to avoid atmospheric absorption features and improve vegetation spectral response. These findings have important implications in monitoring and mapping herbaceous AGB production.

Conclusions and recommendations

This study examined the factors that determine the measurement accuracy of herbaceous AGB estimation by ratio- based, soil-adjusted and atmospheric corrected vegetation indices and visible spectral bands from Landsat 8 OLI sensor. Based on the linear regression analyses performed, ratio-based indices outperformed soil-adjusted and atmospheric corrected MVIs in single and multilinear relationships with measured herbaceous AGB. As expected, combining visible spectral bands and MVIs significantly improvement in herbaceous AGB estimation, irrespective of the type of MVI. Soil adjusted MVIs showed the greatest increase in coefficient of determination after SMLR though the relationships were not as accurate as atmospheric corrected and ratio-based MVIs. The green band of Landsat 8 OLI significantly improved the performance of most MVIs (NDVI, TVI, SAVI, ARVI and SARVI) that were evaluated for herbaceous AGB prediction. The findings demonstrate that the combination of MVIs and Landsat 8 optical spectral bands, especial the green band provides the best models for estimating AGB in *C. mopane* savanna rangelands.

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Table 1: Formula of vegetation indices evaluated for herbaceous AGB estimation utilities in the study

	Vegetation indices	**Formula**	**Reference**
Ratio-based	Simple Ratio (SR)	$SR = \frac{NIR}{Red}$	Jordan (1969)
	Normalised Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - Red}{NIR + Red}$	Tucker (1979)
	Transformed Vegetation Index (TVI)	$TVI = \sqrt{(NDVI + 0.5)}$	Tucker (1979)
Soil adjusted	Perpendicular Vegetation Index (PVI)	$PVI = \frac{(NIR - aRed - b)}{\sqrt{(a^2+1)}}$	Richardson & Wiegand (1977)
	Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(NIR - Red)(1+L^*)}{NIR + Red + L^*}$	Huete (1988)
	Modified Soil Adjusted Vegetation Index (MSAVI)	$MSAVI = NIR + 0.5\sqrt{((NIR + 0.5)^2 - 2(NIR - Red))}$	Qi et al.(1994)
	Transformed Soil Adjusted Vegetation Index (TSAVI)	$TSAVI = \frac{a(NIR - aRed - b)}{aNIR + Red + ab + X(1+a^2)}$	Baret & Guyot (1991)
Atmospheric corrected	Atmospherically Resistant Vegetation Index (ARVI)	$ARVI = \frac{NIR - RB}{NIR + RB}$ Where: $RB = Red - \gamma(Blue - Red)$	†Kaufman and Tanré (1992)
	Soil and Atmospherically Resistant Vegetation Index (SARVI)	$SARVI = \frac{(NIR - RB)(1+L)}{NIR + RB + L}$	†Kaufman and Tanré (1992)
	Enhanced Vegetation Index (EVI)	$EVI = \frac{NIR - Red}{NIR + C_1 Red - C_2 Blue + L}$	Huete et al. (2002)

NIR, R, B = near infra-red, red and blue band value, respectively; *a* = slope of soil line perpendicular to *NIR* and *Red*, *b* = intercept of the soil line on the x-axis; *X* = adjustment factor for reducing soil reflectance effects ; γ = atmospheric correction term; *L** = coefficient (0.2) for reducing background soil effects (Ramoelo et al. 2012); *L* = soil adjustment factor (1.0); C_1 = atmospheric correction term (6.0); C_2 = atmospheric correction term (7.5); †References were cited in Bannari et al. (1995).

Table: 2 Descriptive statistics of herbaceous above ground biomass (AGB) measured in this study

	N	**mean**	**minimum**	**maximum**	**range**	**Std. dev**	**†CV (%)**
Herbaceous AGB(kgm^{-2})	31	0.324	0.134	0.753	0.134-0.753	0.147	45%

†CV = coefficient of variation (%)

Table 3: Performance of VIs for herbaceous AGB estimation including independent variables, r^2, adjusted r^2, and RMSE (n=31)

VIs	Remote sensing variables	Regression model	r^2	Adj r^2	RMSE	P-value
Ratio-based	SR	AGB = 0.5201*SR – 0.6032	0.64	0.63	0.089	0.000
	NDVI	AGB = 2.0497*NDVI – 0.2435	0.61	0.60	0.093	0.000
	TVI	AGB= 3.6163*TVI – 2.8615	0.60	0.59	0.094	0.000
	SR and bands; B, G, R, NIR	AGB = 1.267985*SR + 0.00120*R -0.00045*G –0.00061*NIR–1.70743	0.71	0.67	0.084	0.035
	NDVI and bands; B, G, R, NIR	AGB = 1.740763*NDVI –0.000258*G + 0.073713	0.64	0.61	0.091	0.000
	TVI and bands; B, G, R, NIR	AGB = 3.05811*TVI–0.00026*G – 2.13496	0.63	0.61	0.092	0.000
Soil-adjusted	SAVI	AGB = 1.7082*SAVI – 0.2435	0.61	0.60	0.093	0.000
	TSAVI	AGB = 2.7649*TSAVI + 0.3251	0.21	0.18	0.132	0.009
	PVI	AGB = 0.0004*PVI + 0.3236	0.20	0.17	0.133	0.012
	MSAVI	AGB =3.3675E-5*MSAVI + 0.2019	0.004	--	0.148	0.725
	TSAVI and bands; B, G, R, NIR	AGB = 3.624089*TSAVI + 0.001181*B– 0.000294*R – 0.001124*G + 1.135	0.67	0.62	0.091	0.000
	SAVI and bands; B, G, R, NIR	AGB = 1.450720*SAVI–0.000258*G + 0.073719	0.64	0.61	0.091	0.000
	PVI and bands; B, G, R, NIR	AGB = 0.000423*PVI –0.000650*B –0.000278*R + 1.036335	0.64	0.60	0.093	0.000
	Bands; B, G, R, NIR	AGB = 0.000393*NIR – 0.000676*R + 0.304374	0.61	0.58	0.095	0.000
Atmospheric - corrected	ARVI	AGB = 1.843*ARVI + 0.0485	0.58	0.56	0.097	0.000
	SARVI	AGB = 1.5359*SARVI + 0.0485	0.58	0.56	0.097	0.000
	EVI	AGB = 1.4183*EVI - 0.1192	0.55	0.54	0.995	0.000
	ARVI and bands; B, G, R, NIR	AGB = 1.524115*ARVI–0.000311*G + 0.375345	0.63	0.60	0.093	0.000
	SARVI and bands; B, G, R, NIR	AGB = 1.270163*SARVI –0.000311*G +0.375346	0.63	0.60	0.093	0.000

VIs, vegetation indices; AGB, herbaceous above ground biomass (kgm^{-2}); Adj, adjusted; B, G, R and NIR, bands blue, green, red, near infrared; SR, Simple Ratio; NDVI, Normalised Difference Vegetation Index; TVI, Transformed Vegetation Index; PVI, Perpendicular Vegetation Index; SAVI, Soil Adjusted Vegetation Index; MSAVI, Modified Soil Adjusted Vegetation Index; TSAVI, Transformed Soil Adjusted Vegetation Index; ARVI, Atmospherically Resistant Vegetation Index; SARVI, Soil and Atmospherically Resistant Vegetation Index; EVI, Enhanced Vegetation Index.

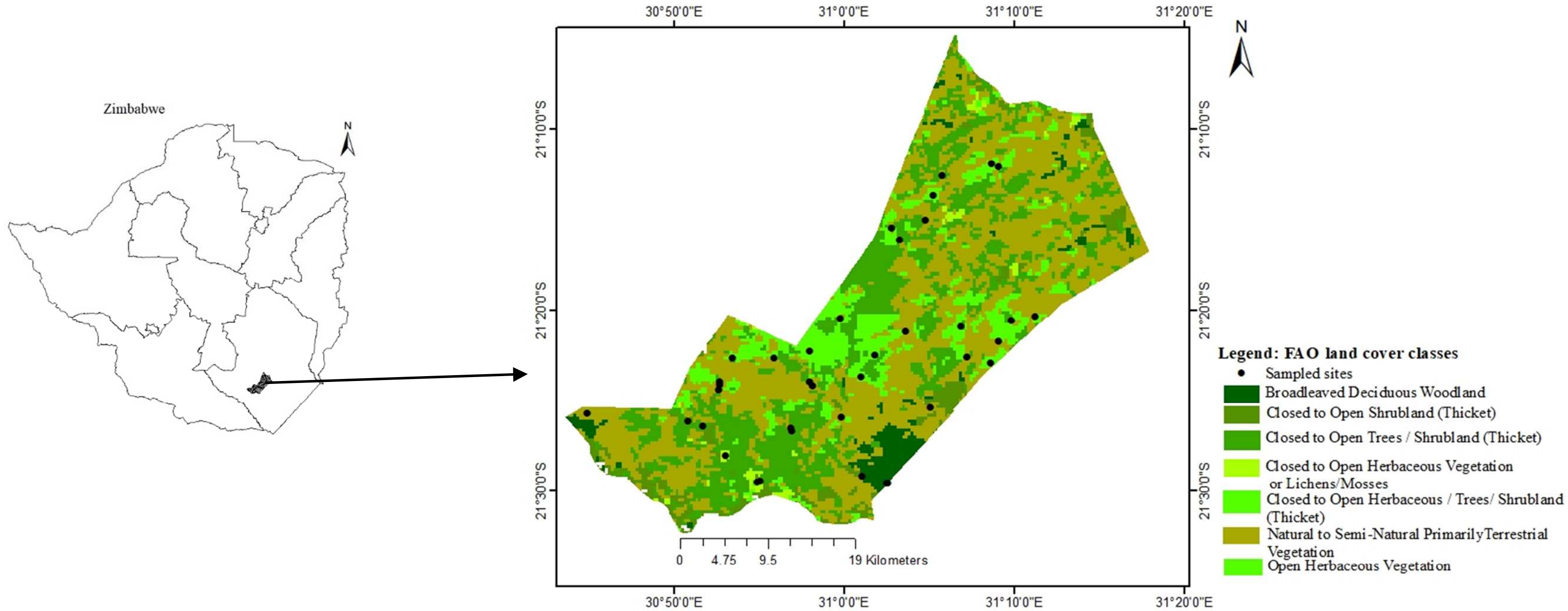

Fig: 1. Location of the study area in Nuanetsi sub-catchment, Zimbabwe.

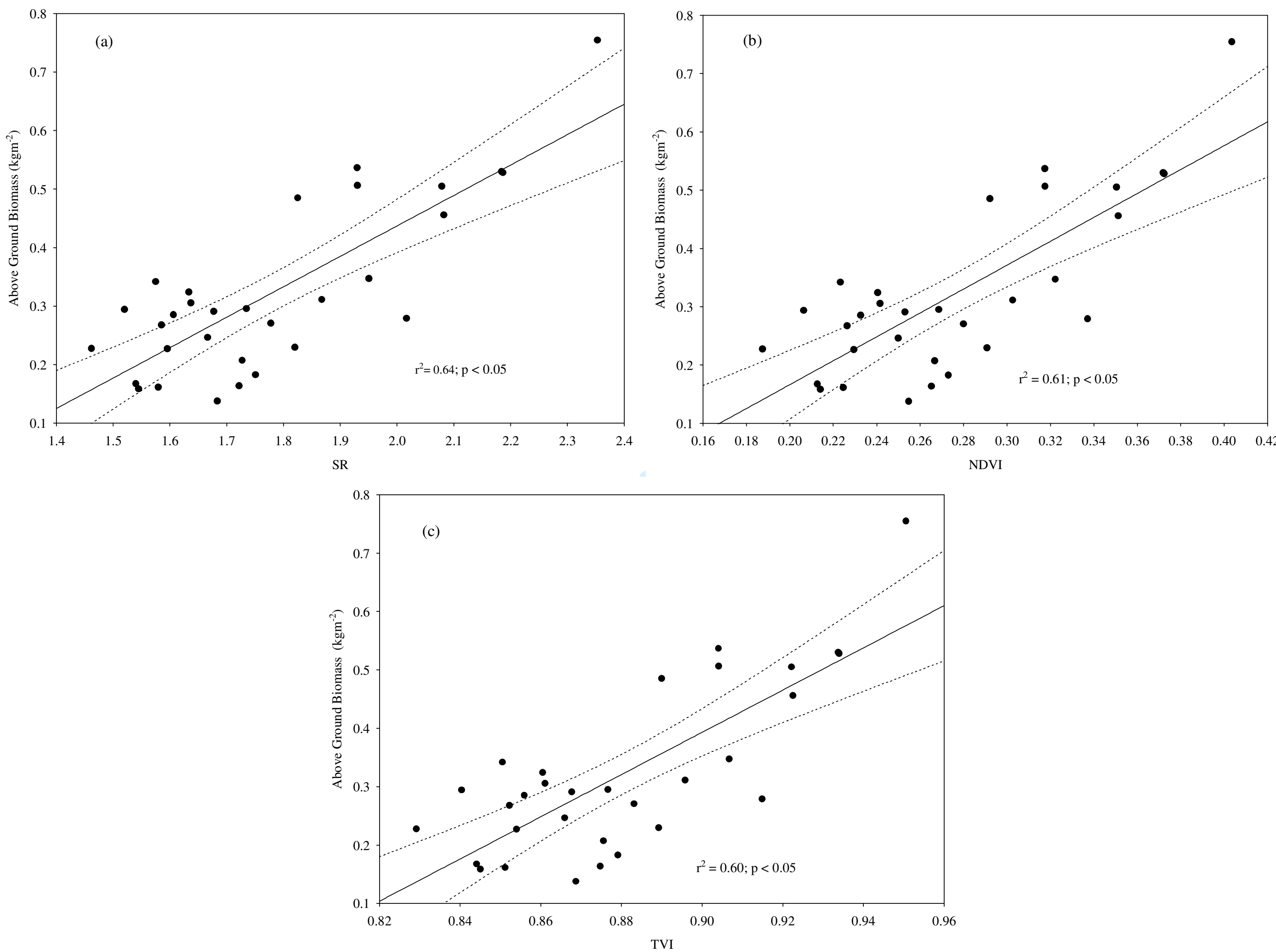

Figure 2: Performance of ratio-based vegetation indices; (a) SR, (b) NDVI (c) TVI in predicting aboveground biomass (AGB) production (n= 31).

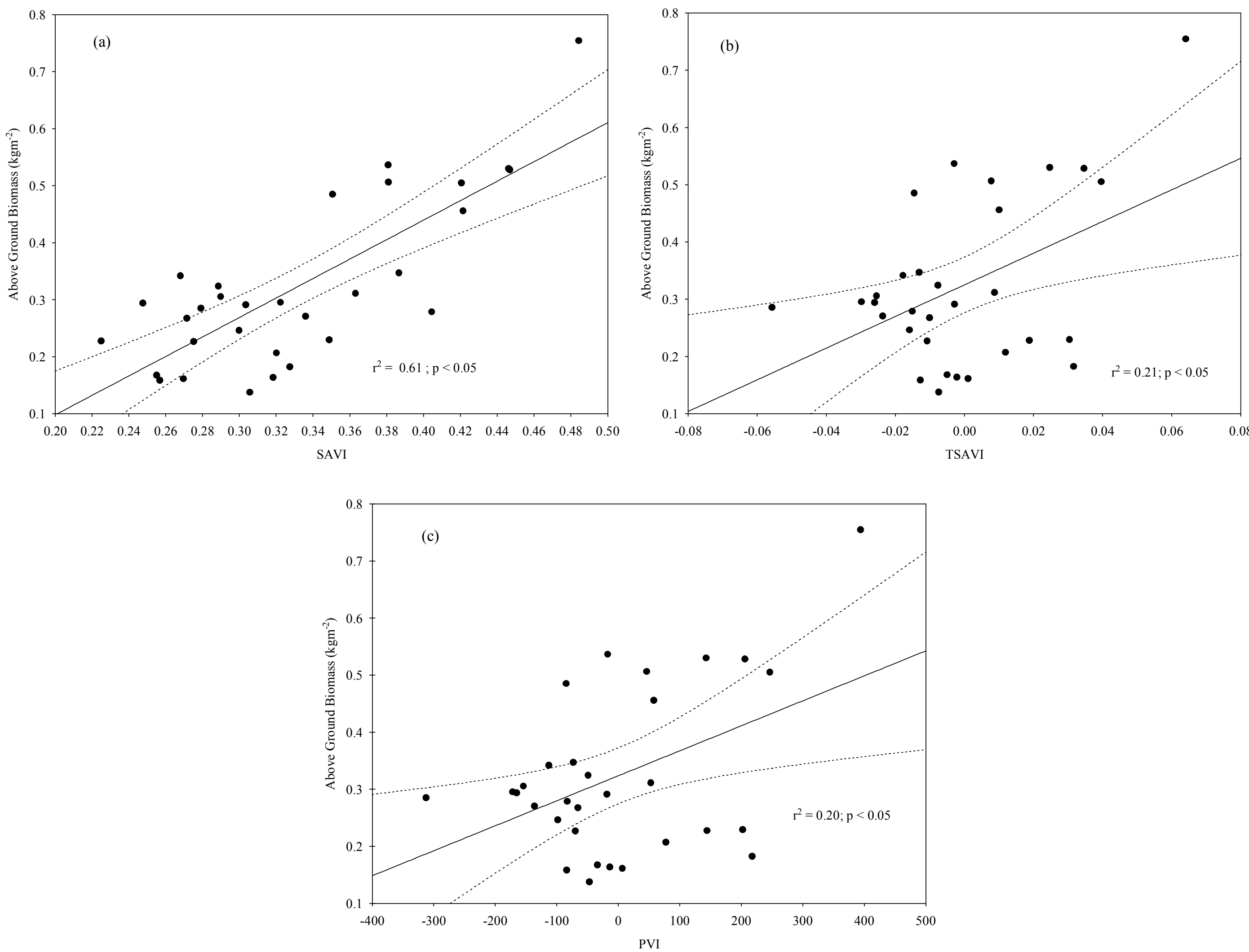

Figure 3: Performance of soil-adjusted vegetation indices; (a) SAVI (b) TSAVI (c) PVI

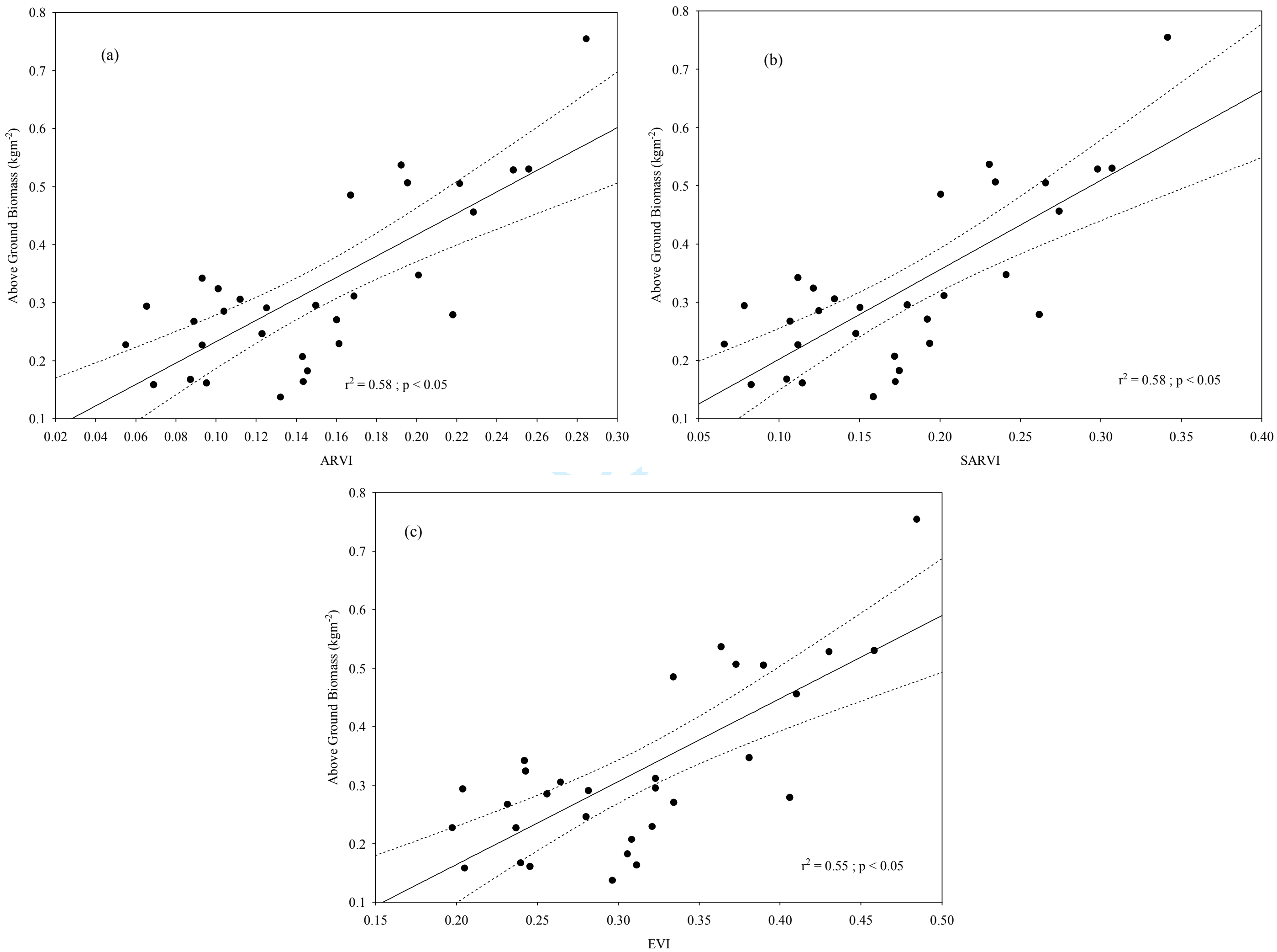

Figure 4: Performance of atmospherically corrected vegetation indices (a) ARVI; (b) SARVI and (c) EVI in predicting aboveground biomass (AGB) production (n= 31).

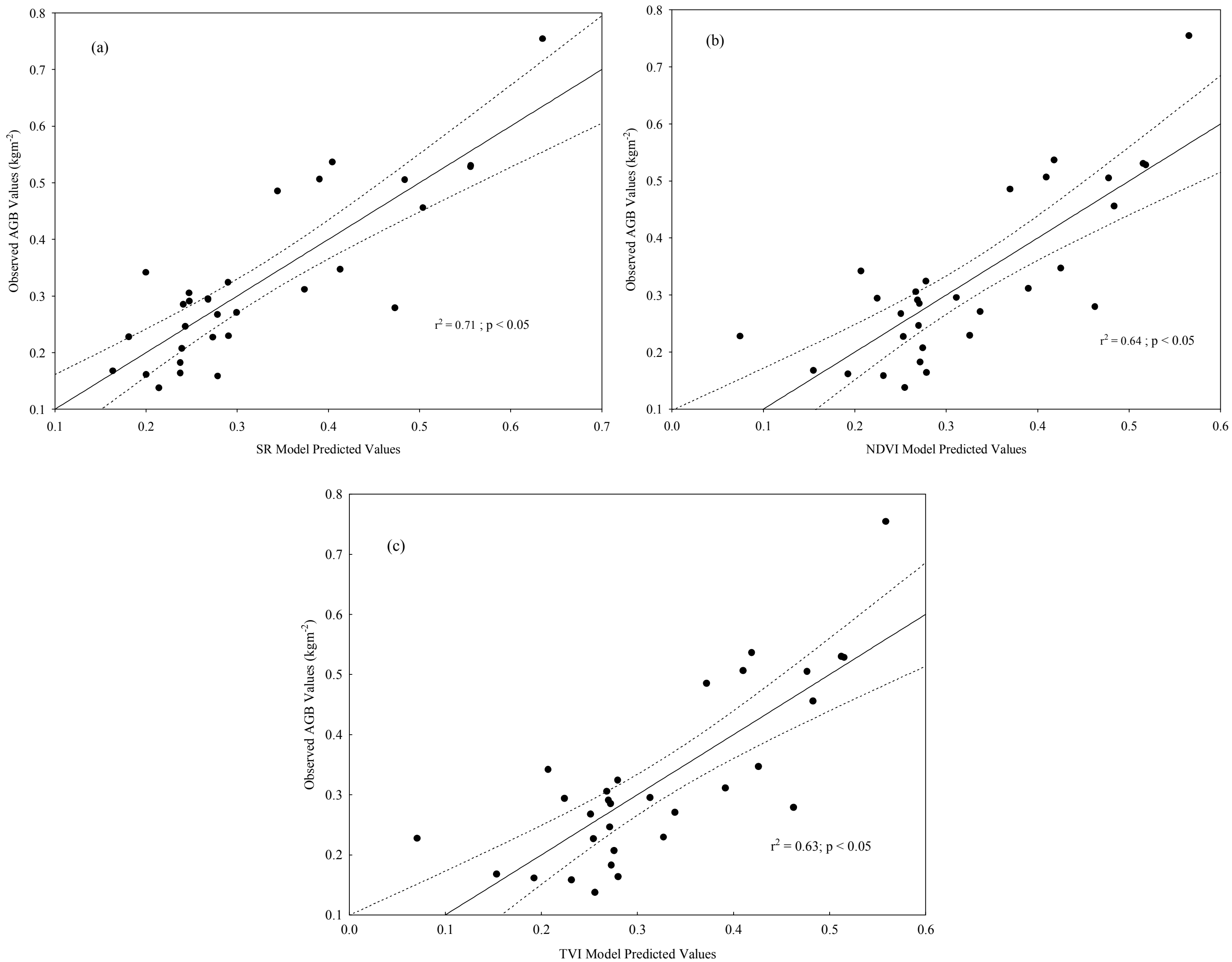

Figure 5: Comparison of measured and ratio-based VI*bands (Green, Red and NIR) model predicted values of aboveground biomass (AGB): (a) SR (b) NDVI (c) TVI

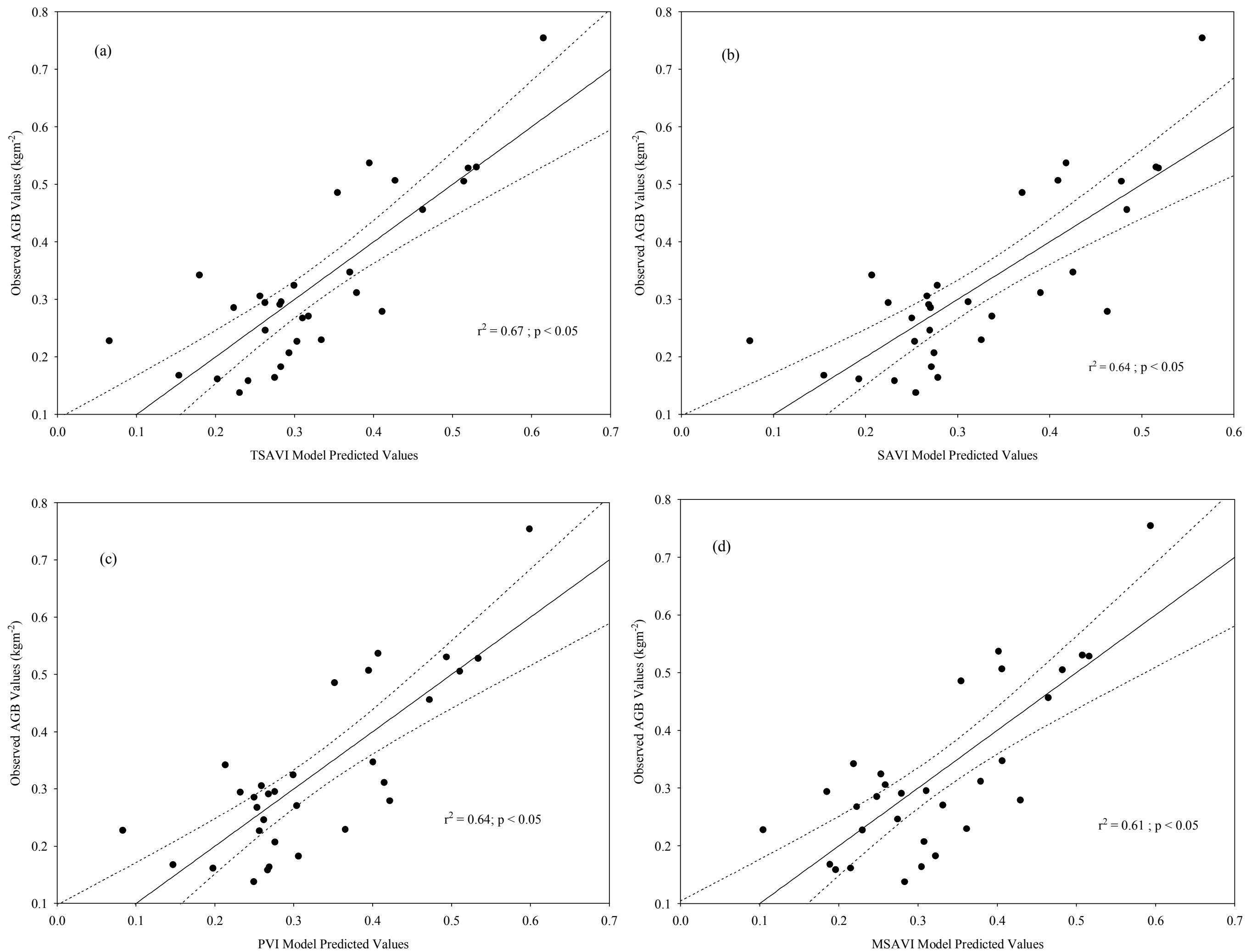

Figure 6: Comparison of measured and ratio-based VI*bands (Green, Red and NIR) model predicted values of aboveground biomass (AGB): (a) TSAVI (b) SAVI (c) PVI (d) MSAVI

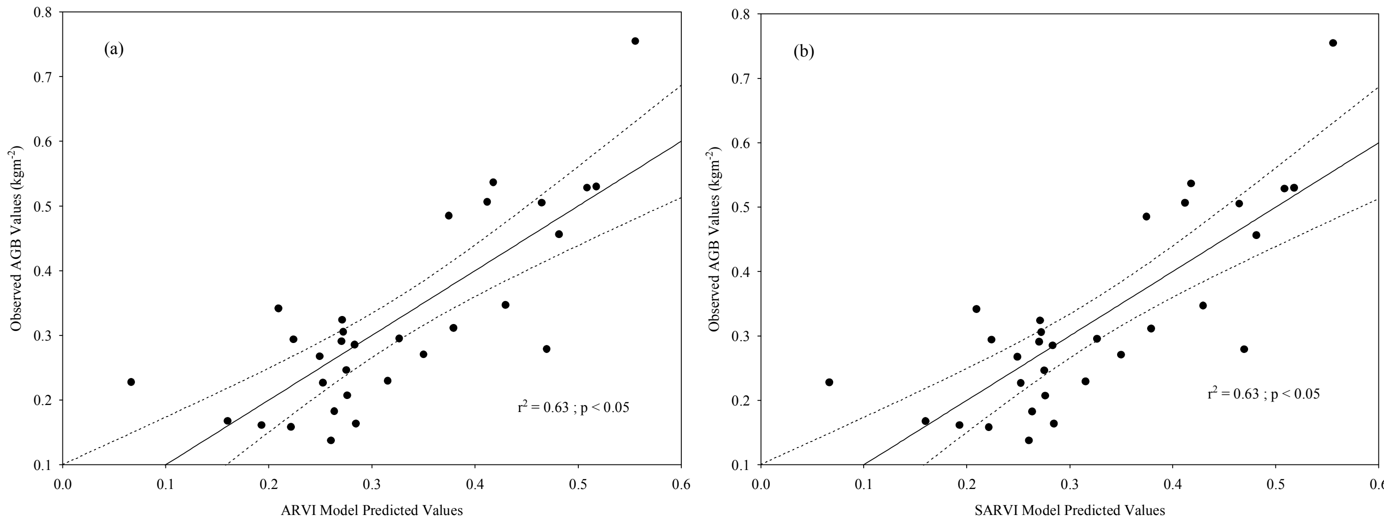

Figure 7: Comparison of measured and atmospheric corrected VI*bands (Green, Red and NIR) model predicted values of aboveground biomass (AGB): (a) ARVI (b) SAVI

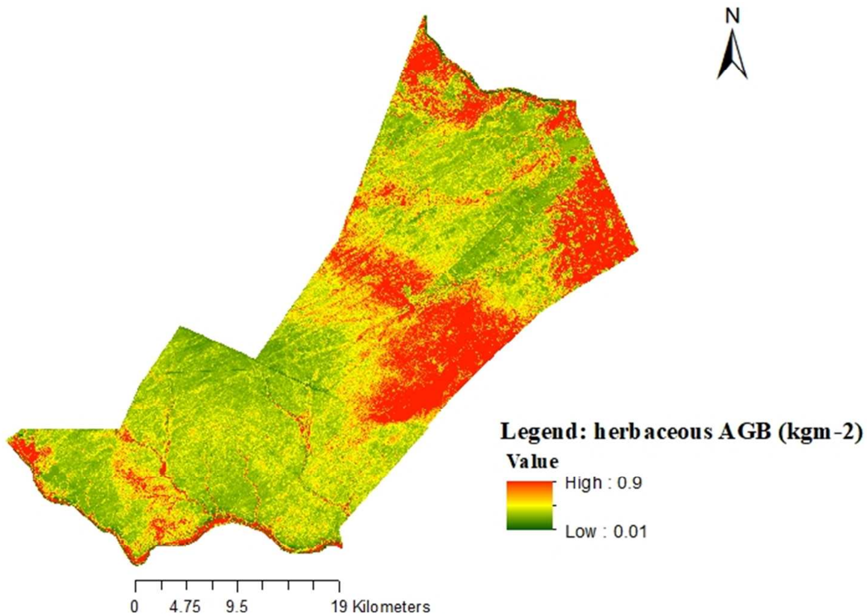

Figure 8: Herbaceous above ground biomass (AGB) map of Nuanetsi ranch