Use of remote sensing in native grass biomass modelling to estimate range productivity and animal performance in a tree-shrub savanna in southern Zimbabwe

by

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Animal Production Management

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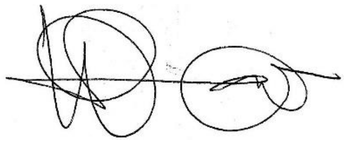
(2020 August 21)

Declaration

I, **Walter Svinurai** declare that the thesis/dissertation, which I hereby submit for the degree

PhD Animal Production Management

at the University of Pretoria is my own work and has not been previously submitted by me for a degree at this or any other tertiary institution.



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Preface

This thesis is based on the following chapters, which have been published, presented or are to be submitted for publication.

Peer reviewed journal articles:

1. **Svinurai W.**, Hassen A., Tesfamariam E., Ramoelo A. (2018). Performance of ratio-based, soil-adjusted and atmospherically corrected multispectral vegetation indices in predicting herbaceous aboveground biomass in a *Colophospermum mopane* tree - shrub savanna. (Published in *Grass and Forage Science. 73:727–739*).
2. **Svinurai W.**, Ramoelo A., Hassen A., Tesfamariam E., Malherbe J. (2020). Response of remotely sensed herbaceous aboveground biomass to rainfall variability and droughts in a south-central African savanna (Submitted to *Rangeland Ecology and Management* journal, Ref: REMA-D-20-00067).
3. **Svinurai W.**, Hassen A., Tesfamariam E., Ramoelo A., Cullen B. (2020). Calibration and evaluation of the Sustainable Grazing Systems pasture simulation model for predicting grass aboveground biomass in a southern African savanna (Submitted to *African Journal of Range and Forage Science*, Ref: TARF-2020-0103).
4. **Svinurai W.**, Hassen A., Tesfamariam E., Ramoelo A. (2020). Modelled effects of grazing strategies on native grass production, animal intake and growth in Brahman steers (Submitted to *African Journal of Range and Forage Science*, Ref: TARF-2020-0104).

Conference presentations:

1. **Svinurai W.**, Hassen A., Tesfamariam E., Ramoelo A. (2018). Performance of ratio-based, soil-adjusted and atmospherically corrected multispectral vegetation indices in predicting herbaceous aboveground biomass in a *Colophospermum mopane* tree - shrub savanna. In: *Proceedings of the 53rd Annual Congress of Grassland Society for Southern Africa.* ARC Training Centre, Roodeplaat, Pretoria, South Africa, 22 - 27 July 2018.
2. **Svinurai W.**, Hassen A., Tesfamariam E., Ramoelo A. (2019). Parameterisation and evaluation of the Sustainable Grazing Systems pasture simulation model for predicting native grass growth in a southern African savanna. In: *Proceedings of the 54th Annual Congress of Grassland Society for Southern Africa*. Upington, Northern Cape, South Africa, 30 June - 04 July 2019.

The complexity of interactions between climate variability and grazing pressure is the major challenge to effective monitoring of herbage and animal productivity in semi-arid regions. This thesis comprises of eight chapters including introduction and general discussion (Figure 1.1). The chapters were aimed at increasing our understanding of two main issues concerning the monitoring of rangeland productivity in order (i) to determine the ranch-scale impacts of rainfall variability and drought on herbaceous aboveground biomass (AGB) using optical remote sensing; and (ii) to parameterise, evaluate and apply a systems model, the Sustainable Grazing Systems (SGS) whole farm model to complement grazing experiments in assessing the effects of grazing strategies at management unit level. To analyse and prescribe sound grazing management guidelines, information about how the rangeland system works is required at the appropriate spatial and temporal scale. General introduction chapter provides an overview of the knowledge gaps in monitoring herbage and animal production in a data limited environment and proposes a systematic monitoring approach of using remotely sensed inputs and variables in simulation modelling to close these gaps. ***Chapter 2*** provides a review of literature about the ecological factors that determine management of sweetveld and the status and prospects of using remote sensing and systems modelling in monitoring herbage and animal production. Each of the remaining chapters was meant to address one or two of the objectives outlined in Chapter 1. Finally, chapter eight provides an overall discussion and synthesis of the findings of this study and their implications to grazing management in semi-arid rangelands of southern Africa.

Chapter 3 evaluates factors that determine the accuracy of estimating herbaceous AGB under site conditions using cheaply available, medium resolution satellite product. This is necessary because accuracy of empirical remote sensing models depends on site conditions of soil, vegetation and atmosphere. These models enable biophysical drivers of herbaceous AGB production to be identified and development of local forage maps, and management decision making in areas sensitive to degradation.

Chapter 4 aimed to develop and validate a statistical model of herbaceous AGB and rainfall and, use this model to estimate the temporal variability AGB production in herbaceous communities at landscape level. This was achieved by using herbaceous AGB modelled from medium spatial resolution satellite images and daily satellite rainfall estimates (SREs) that were corrected for bias. Landscape scale assessments of spatial and temporal variation of herbaceous AGB production enable effective allocation of cattle to paddocks on near-real time basis. Spatial extend of herbaceous community cover determined from classification of satellite images was used to delineate woody community cover in sites selected for SGS model evaluation and application. Seasonal estimates of remotely sensed herbaceous AGB were used as independent data for evaluating performance of the simulation model.

Chapter 5 introduces the approach that was used to parameterise and calibrate the SGS model for simulating grass production in a semi-arid rangeland of southern Africa. Soil physical parameters obtained from soil surveys that were conducted previously at the study site and, ancillary landscape attributes derived from a digital elevation model and regional databases were used. Plant canopy and growth parameters were obtained from an extensive review of published experiments. A dataset of bias corrected daily SREs and solar radiation together with measured temperature were used as inputs. An iterative procedure was used to obtain the best fit between simulated outputs and measured herbaceous biomass production. The integrated workflow for parameterising and calibrating a process-based pasture-simulation model developed in this study can benefit model users in data-constrained environments.

Chapter 6 aimed at evaluating the adequacy of the SGS model in the predicting long-term herbaceous biomass production using two model evaluation techniques. Firstly, parameter sensitivity analysis was performed to determine behavioural responses of model to prevailing climatic conditions. Simulation outputs were then compared with remotely sensed herbaceous AGB estimates derived across land types. Model evaluation is required to build model user confidence when a simulation model is applied to different seasons and locations where field measurements of parameters used to calibrate the models are unavailable.

Chapter 7 applies the SGS model to analyse the effects of grazing management practices on herbaceous grass production, intake, and growth of beef steers. The analyses were not possible before this study but could now be conducted using the evaluated model. Information about impacts of management decisions such as varying stocking rate and paddock systems on sustainability of herbage and animal production is needed to come up with sound management guidelines.

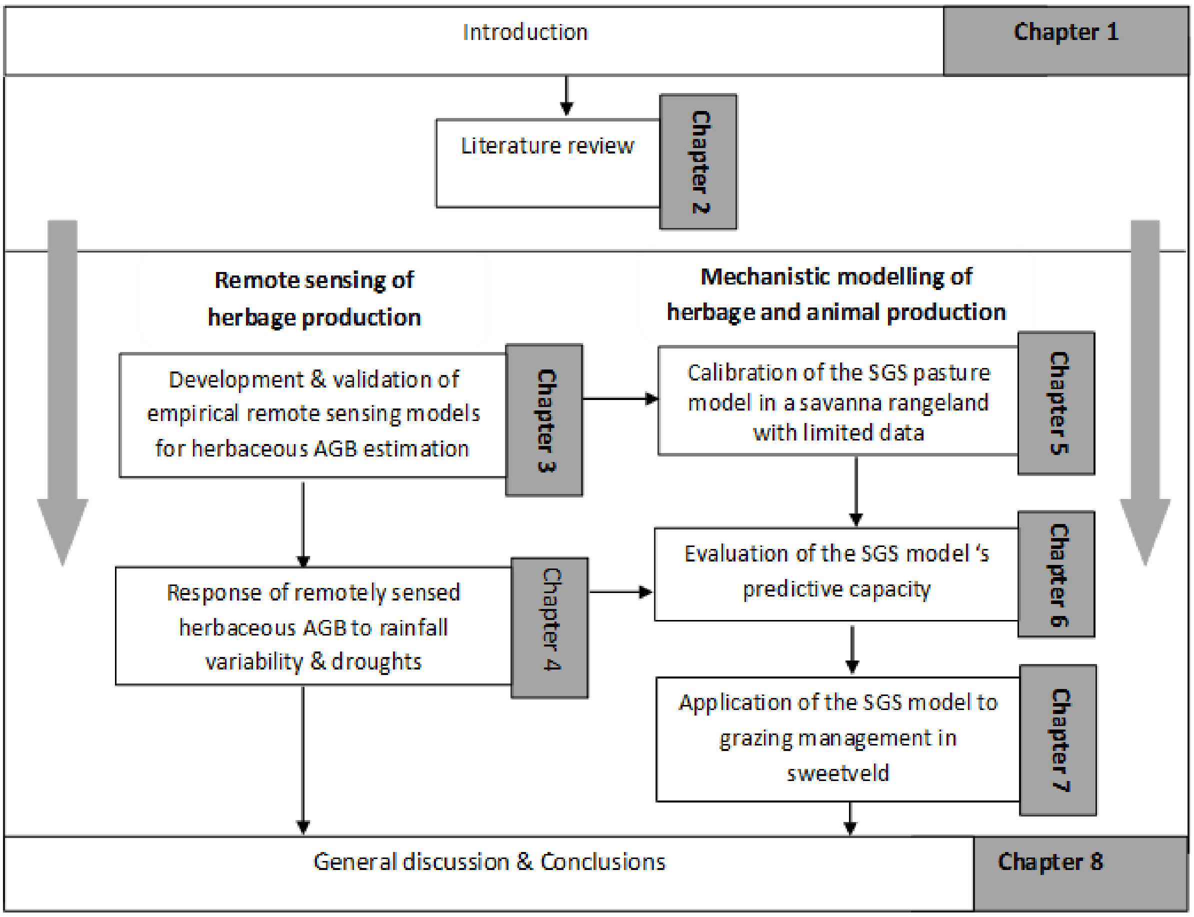

Figure 1. 1: Outline of the thesis

Acknowledgements

First, I would like to thank Prof A. Hassen, my main supervisor for his willingness to engage with me in my studies. Prof Hassen is greatly appreciated for his guidance during the conceptualisation, implementation, and completion of this research program. I would also like to thank him for introducing me to key resource experts who assisted me in gathering various data required for the integrated modelling framework adopted in this study. I am very grateful to Prof E. H. Tesfamariam and Dr A. Ramoelo for serving as my co-supervisors during the entire time of my study. Prof E. H. Tesfamariam introduced me to simulation modelling and, his guidance and support from the model review and selection stage to the model calibration and validation is greatly appreciated. My sincere gratitude goes to Dr A. Ramoelo who introduced me to geographic information systems and remote sensing in my studies. His patience, encouragement and motivation provided me with a new perspective on use of remote sensing in rangeland management.

The Department of Research and Innovation Support of the University of Pretoria is hereby greatly appreciated for providing the postgraduate research bursary to this research programme. The National Research Foundation of South Africa is also acknowledged for partly funding the research. Avery special gratitude goes to the management personnel at Nuanetsi cattle ranch for their willingness to allow me to conduct my research at their property. The cattle manager, Mr T. Madhongo and his co-workers assisted me during fieldwork and provided accommodation and food during my stay at the ranch. Without their support, this programme would have not been successful. I am indebted to Mr “OB” O. Busu, the field taxonomist who made this study a success through his tireless assistance in vegetation surveys. The Chemistry and Soil Research Institute (CSRI) of the Department of Research and Specialist Services of Zimbabwe is greatly appreciated for providing soil survey reports for Nuanetsi sub catchment. Data from these reports served as the basis for parameterisation of the SGS model and without the CSRI’s support, this research would not have been possible.

The Zimbabwe Sugar Association Experiment Station is acknowledged for providing long-term weather data that was used in downscaling global climate datasets. In this regard, the Mwenezi District Agritex office is also thanked for providing long-term daily rainfall data. The Earth Observation, Natural Resources and Environment team at the Council for Scientific and Industrial Research (CSIR) in Pretoria is acknowledged for granting me the permission to use infrastructure for processing satellite data. I would like to also thank Dr J. Malherbe of the Climate Studies, Modelling and Environmental Health department at CSIR who provided valuable expertise and assistance in acquisition, processing and analysis of climate data. His co-worker from the Agricultural Research Council Soil, Water and Climate institute in Pretoria, Ms P. Maluleke is greatly appreciated for assisting with interpolation of temperature data. I am also indebted to W. Gumindoga of the University of Zimbabwe for assisting with the bias correction algorithm for satellite rainfall data. A very special thanks goes to Dr B. Cullen from Melbourne University, Australia for providing access and assistance with running the SGS pasture model. His efforts are greatly acknowledged.

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List of abbreviations

AGB	Aboveground Biomass
ARVI	Atmospheric Resistant Vegetation Index
CAMS SODA	Copernicus Atmospheric Monitoring Service Solar Radiation Data
CSRI	Chemistry and Soil Research Institute, Zimbabwe
CSIR	Council for Scientific and Industrial Research, South Africa
DEM	Digital Elevation Model
DMI	Dry Matter Intake
ENVI	Environment for Visualizing Images software
ETM+	Enhanced Thematic Mapper plus
EVI	Enhanced Vegetation Index
FAO	Food and Agricultural Organisation of the United Nations
FLAASH	Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube
GDP	Gross Domestic Product
GPFARM	Great Plains Framework for Agricultural Resource Management model
GPS	Global Positioning System
GRASP	Grass Production model
HVIs	Hyperspectral Vegetation Indices
IFSM	Integrated Farming Systems Model
LAI	Leaf Area Index
LCCS	Land Cover Classification System
LWG	Live Weight Gain
MDA	Mwenezi District Agritex office
MLC	Maximum Likelihood Classifier
MODIS	Moderate Resolution Image Spectroradiometer
MSAVI	Modified Soil-Adjusted Vegetation Index
MVIs	Multispectral Vegetation Indices
NDVI	Normalised Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
NOAA AVHRR	NOAA Advanced Very High-Resolution Radiometer
NOAA CPC	NOAA Climate Prediction Centre
NOAA CPC ARC2	NOAA CPC African Rainfall Climatology
OLI	Operational Land Imager
PaSIM	Pasture Simulation Model
RMSE	Root Mean Square Error
SAVI	Soil-Adjusted Vegetation Index
SGS	Sustainable Grazing Systems model
SOTERSAF	Soil and Terrain of Southern Africa database
SPI	Standardised Precipitation Index
SR	Simple Ratio
SRE	Satellite Rainfall Estimate
TM	Thematic Mapper
TSAVI	Transformed Soil-Adjusted Vegetation Index
TVI	Transformed Vegetation Index
USGS	United States Geological Survey
WFM	Whole Farm Model
ZSAES	Zimbabwe Sugar Association Experiment Station

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Abstract

Herbage and cattle production in semi-arid regions are primarily controlled by climate variation particularly rainfall variability and secondarily by disturbances such as drought, grazing and fire. These factors interact at different spatial and temporal scales in a complex manner difficult to observe or comprehend and, reduce availability and quality of herbage and cattle productivity. Variables for quantifying rangeland productivity are thus rarely available and unreliable yet options for sustainable management are limited. Grazing experiments have provided useful insight about ecological and management factors involved in rangeland functioning, but they have limited scope to deal with high environmental variation. This highlights the need for a systems approach for monitoring rangeland and cattle productivity at the appropriate spatial and temporal scales to enable productivity to be maximised whilst risk to climate variation is minimised. This study explored two broad objectives: to determine the ranch-scale impacts of rainfall variability and drought on herbaceous aboveground biomass (AGB) using optical remote sensing; and to parameterise, evaluate and apply a systems model, the Sustainable Grazing Systems (SGS) whole farm model to complement grazing experiments in assessing the effects of grazing strategies on beef cattle production.

To determine rainfall variability impacts, twenty regression models were firstly developed between measured herbaceous AGB and, classical and extended multispectral vegetation indices (MVIs) derived from a Landsat 8 image. End-of-season herbaceous AGB was predicted with high accuracy (r^2 range = 0.55 to 0.71; RMSE range = 840 to 1480 kgha^{-1}). The most accurate model was used to construct a regression between rainfall and AGB derived from peak-season Landsat images available between 1992 and 2017. Standardised precipitation index and standardised anomalies of herbaceous AGB production were then used in a convergence of evidence approach to determine the response of AGB to rainfall variability and drought intensity. Total wet season rainfall revealed high variability (33 to 41 % CV) and subsequent herbaceous AGB production were 18 to 35 % more variable. Spatial heterogeneity of AGB production across herbaceous communities were high and deviated from mean AGB by 51 to 69 %. Landscape-level temporal variation of AGB production remained stable despite the increase of climate variability experienced in the region in the past 50 years.

Climate inputs and parameter sets for upper-, mid- and foot- slope land types and key grass species, *Urochloa mosambicensis* and *Eragrostis curvula* were developed by integrating spatial data with previous soil surveys and extensive reviews of published experiments. A simulation experiment was conducted between 1992 and 2017 for all combinations of land types and grass species to analyse the extent of improvement resulting from parameter adjustments. The SGS model predicted the growth pattern known for grasses native to dry regions of southern Africa. The model represented measured herbaceous biomass moderately well ($r^2 = 0.57$), at low average error (RMSE, 820 kg DM ha^{-1}) despite huge discrepancies in summary statistics for measured (mean, 3877 kg DM ha^{-1}) and simulated (mean, 3071 kg DM ha^{-1}) biomass and residuals. Model predictions were also significantly correlated with remotely sensed AGB ($r^2 = 0.46$) at reasonable overall performance error (RMSE, 981 kg DM ha^{-1}). The integrated workflow developed for parameterising and calibrating the SGS pasture-simulation model can benefit model users in data-constrained environments. Animal growth parameters specific to Brahman weaner steers were defined in the SGS model to enable evaluation of impacts of recommended (10 haLU^{-1}) and other three stocking rates (7, 15 and 20 haLU^{-1}) and multi-paddock grazing systems (2-, 3- and 4- paddocks per herd) on rangeland productivity. Overall, there were no observable differences in herbage production and dry matter intake irrespective of stocking rate and multi-paddock grazing system. But stocking rate effects on animal production were more pronounced compared to multi-paddock grazing systems. To maximise cattle productivity in semi-arid rangelands, management should be emphasised on manipulation of stocking rates over multi-paddock grazing systems.

Keywords

Rangeland monitoring, climate risk, sustainability, animal productivity, grazing strategies

CHAPTER 1

General introduction

Semi-arid regions occupy 15 % of global land area, 54 % of which are rangelands and provide shelter and food to 855 million people and half of the global livestock (Stafford Smith et al., 2009). By 2050 the current global population (6.8 billion people) is expected to increase by 34 %, with most of the growth occurring in developing countries (FAO, 2009). Meat production should increase to over 200 million tonnes per year to feed the growing population. The management of grazing systems has been intensified to meet the emerging demands for food (Godde et al., 2017). However, the potential for intensifying management in semi-arid rangelands is limited given their dependence on seasonally variable rain that is associated with episodic droughts and, low and variable forage supply and quality. Extensive ruminant production systems are highly vulnerable to increasing climate variability and, ruminant meat production may decrease by 17 % by mid-century (Havlík et al., 2015). Range managers face the challenge of sustainably increasing meat production to meet the expected food demand whilst maintaining the rangeland's capability to produce useful forage. Thus, understanding the dynamics of rangeland functioning in face of global environmental change would enhance our ability to predict the responses of range and animal production to anticipated climatic changes, for effective management planning.

Tropical rangelands have evolved from broad-scale, long term changes in climate and localised, short term disturbance events such as drought, grazing and fire (Hempson et al., 2007; Mberego et al., 2013). These abiotic and biotic factors have interacted over time to create complex landscapes that portray a high degree of spatial and temporal variation in herbaceous community production (Scoones, 1995). Advances in rangeland ecology and management concepts have led to new monitoring approaches aimed at improving our understanding of the drivers of rangeland function at multiple scales (Stuth and Maraschin, 2000). On one hand, a new concept in landscape ecology theory depicts that spatial variability of local communities influences the temporal stability in aboveground biomass (AGB) production in spatially heterogenous landscapes (McGranahan et al., 2016). On the other hand, grazing management theories are indecisive about the viability of grazing strategies such as multi-paddock grazing systems and stocking rate (SR*)* (Teague et al., 2013). Both theories rely on experimental knowledge acquired at plot-scale at which there is low variability of herbaceous AGB production resulting from environmental variation. Recently, research emphasis has shifted to the overriding interactive influence of climate variation and SRs on herbage and animal production (Heitschmidt et al., 2005; Reeves et al., 2014). This emphasises the need for developing systematic monitoring approaches at appropriate spatial and temporal scales to provide ranch managers with reliable and actionable information about range and cattle productivity.

Current improvements in remote sensing and computer modelling provide opportunities for establishing proper systems' framework for monitoring variation of rangeland productivity across spatial and temporal scales (Angerer, 2012; Ewert et al., 2011). Given its large area coverage and high temporal frequencies of data collection, remote sensing provides continuous observations required for assessing the response of herbaceous AGB production to rainfall variability and droughts (Chamaillé-Jammes and Fritz, 2009). At the same time, simulation models effectively use soil, plant and animal inputs to explicitly represent interactions among system components at paddock level and analyse the implications of stock management decisions (Fang et al., 2014). Thus, the integrated use of these tools is important in strategic management of broad-scale changes in herbage production and, provides better understanding of the localised effects of these changes and stock management to inform planning of tactical decisions. Despite these benefits, the combined use of remote sensing and simulation modelling in assessing range and animal productivity in southern Africa has been limited (Scanlon et al., 2005), yet opportunities do exist.

Instead, previous studies used remote sensing solely to assess herbaceous AGB production response to climate variation (Brown, 2008). Most of these assessments used low spatial resolution satellites (Brown, 2008) at regional (Chamaillé-Jammes and Fritz, 2009; Wessels et al., 2006) and continental scales (Winkler et al., 2017). However, low spatial resolution satellites do not provide spatially explicit representation of AGB production in savanna rangelands owing to high plant diversity among local vegetation communities (Assal et al., 2016). More so, the spatial coverage of many grazing lands in southern Africa is too small to allow application of low spatial resolution satellite products for effective decision-making. Medium spatial resolution remote sensing products have the potential to provide detailed spatial representation of AGB production at multiple scales and at long timeframes sufficient for assessment of heterogeneity in herbaceous communities. For example, Sentinel imagery has demonstrated the intra-seasonal spatial and temporal variability of herbaceous AGB in tropical southern Africa (Shoko et al., 2019). Whilst remote sensing is important in strategic planning for climate variation, it does not represent the interaction effects of climate with grazing strategies on animal performance, justifying the need for integrating systems modelling.

Systems modelling provides invaluable information about the long-term impacts of stock management practices on herbage and animal production under prevailing climate conditions. In the past two decades, empirical and mechanistic modelling gained huge attention globally in predicting herbage and animal production (Snow et al., 2014). However, in semi-arid rangelands of southern Africa, simulation modelling has been limitedly applied to empirical models for plant growth (Oomen et al., 2016; Wiegand et al., 1998) and a few deterministic and stochastic models for herbage and animal production (Illius et al., 1998; Kazembe, 2010; Richardson et al., 2000). Empirical models give spurious results if they are applied to regions that lack the experimental data used to develop them. Dynamic models, commonly known as process-based biophysical models, are more realistic than empirical models as they are capable of simulating soil, plant and animal processes at a high level of detail and contain default parameters adjustable across regions (Johnson, 2011). But other than the inherent errors of model structure, their application has been limited due to errors associated with system input variables and data measured for deriving parameters (Andrade et al., 2016). In developing countries, climate data is rarely available at ranch level due to sparse distribution of national meteorological stations. Also, system parameters and state variables are unknown as they cannot be fully included in experiments.

The increasing availability of environmental variables from remote sensing and geographic information systems (GIS) at high temporal- and spatial- resolution provide means for retrieving climate inputs (Ovando et al., 2018) and explanatory variables for WFMs. These ancillary data are useful in model calibration yet they have been rarely explored in southern Africa. If proper systems for rangeland monitoring using remote sensing and systems models are established at the appropriate spatial and temporal scales, our understanding of the effects of climate variation on herbage and cattle production can be improved. Such systems enable comparison of the potential of different grazing strategies for sustaining high rangeland productivity. When used to forecast future events, simulation modelling enables early deviations in forage production to be detected thereby minimising risk associated with climate variability. In this study, the landscape scale impacts of rainfall variability and drought disturbances on the spatial and temporal variation of herbaceous AGB were assessed using remote sensing. Then, a systems model was parametrised, evaluated, and applied to analyse the localised effects of grazing strategies on herbage and animal production at management unit level.

1.1 Objectives of the study

To assess whole-ranch herbaceous aboveground biomass production, intake and animal growth in a *C. mopane* tree/shrub savanna, in order to compare the potential of grazing management strategies for maximising long-term rangeland and cattle productivity.

The specific objectives of this study were to:

- identify factors that determine the measurement accuracy of herbaceous aboveground biomass estimation (Chapter 3).
- assess the response of herbaceous aboveground biomass to rainfall variability and drought using satellite-based estimates of herbaceous vegetation and rainfall (Chapter 4).
- parameterise and calibrate the SGS pasture model for estimation of herbaceous biomass production using data derived from independent experiments (Chapter 5).
- test the performance of the SGS pasture model in simulating long term herbaceous biomass production across land types (Chapter 6).
- apply a newly parameterised SGS whole model to analyse effects of grazing management practices on herbaceous biomass production, intake and weight gain in Brahman steers (Chapter 7).

CHAPTER 2

Literature review

2.1 Introduction

Rangelands are important to the ecology and economy of sub Saharan Africa as they occupy 62 % of the land area, provide shelter and food to 38 % of Africa's population and support 56 % of livestock in the region (Liniger and Mekdaschi Studer, 2019). These savannas present unique management problems due to high climate variation and subsequent inconsistent availability of herbage to cattle, in space and over time (Stuth and Maraschin, 2000). The variations occur at large scale, on a long-term basis which make it difficult to observe or understand them. As a result, appropriate and accurate variables for monitoring rangeland production are rarely available to enable a timely decision making (Karl et al., 2017). Grazing experiments have provided important but abstractive information about the environmental variation of these systems (Briske et al. 2008). There is need to embrace a collection of information and tools in a systems approach to enhance our understanding of complexity in these systems and, to provide ranch managers with reliable and actionable information.

This chapter aims to provide a critical analysis of opportunities in using remoting sensing and systems modelling, either singly or combined in systematic rangeland monitoring. Firstly, an appraisal of the status and challenges of the beef industry in Zimbabwe is given. Then, an overview of the ecological considerations for managing semi-arid rangelands to maximise productivity and the factors that influence herbage and animal productivity is provided. In the third component of the review, the current status of *in situ* observations in rangeland monitoring is discussed and the need for integrating remote sensing and systems modelling in a systematic framework for rangeland monitoring is highlighted. The fourth and fifth section separately outlines the characteristics, procedures, current status and areas for improvement for remote sensing and systems modelling whilst the last section identifies opportunities for integrating remote sensing and systems modelling in monitoring herbage and animal production.

2.2 Status of the beef industry in Zimbabwe

Since the past three decades, the herd of beef and dual-purpose cattle in Zimbabwe has remained at approximately 5 million heads despite the huge shift in ownership from large white commercial to black commercial and small-scale farmers following the fast-track resettlement programme that occurred in the early 2000s (Mavedzenge et al., 2006). About 75 % of this herd is raised under extensive management in the low rainfall southern region of the country that comprise of Midlands, Masvingo and Matebeleland provinces which have comparative advantages for commercial beef production. The commercial herd dropped from 1.5 million in 1999 to fewer than 10 % of the national herd by 2006 (Scoones et al., 2010). In 2000, cattle density at province level varied from 7.3 to 33.9 heads km^{-2} in Matebeleland north and Mashonaland east, respectively (Figure 2.1). By 2013, the highest cattle densities of up to 18 heads/km^2 were recorded in Mashonaland East and Central and Masvingo provinces. The increase in cattle density in northern provinces was due to the shift of beef production to the highveld as the lowveld region was zoned in the foot and mouth zone. Though Mashonaland East province has retained the highest cattle density compared to other provinces in the past 20 years, its cattle density has declined by half. Between 2000 and 2013, the highest increase in cattle density of 26 % occurred in Masvingo province, implying a reduction in grazing land due to land use changes.

The beef industry contributes up to 10 % of agricultural gross domestic product and has thrived between economic viability and equity. Offtake has decreased from 25 % to 6 % due to shift in players from large scale commercial to new A2 entrants (small-scale commercial) after 2000 (Mavedzenge et al., 2006). Like other sectors of the economy, Zimbabwe's beef sector faces severe challenges of high inflation and lack of foreign currency. Capacity utilisation of beef processing has continued to declined due to shortage of forage and water during winter due to increased drought occurrence and uncertainty and volatility in prices (LMAC, 2019). Prospects of returning to high value beef exports are very challenging due to the outbreak of foot and mouth disease which occurred in 2003 and is endemic in cattle populations across the country. Therefore, the deteriorating conditions of operations in the local beef industry prompts the need for re-examining the sector's potential to enable its rehabilitation.

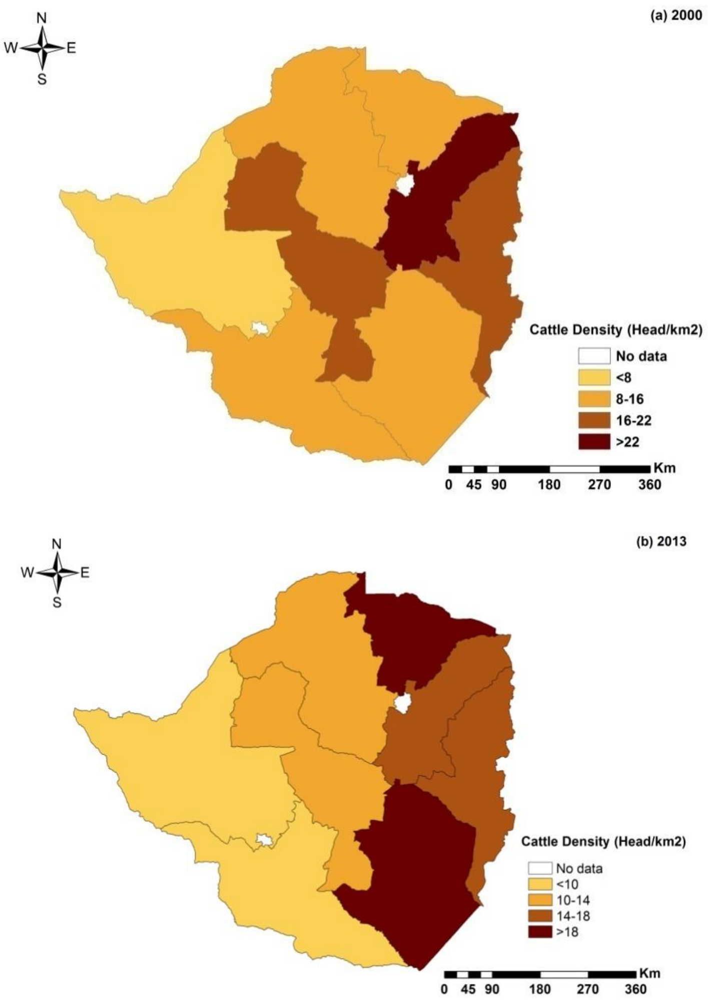

Figure 2. 1: Zimbabwe's cattle population density in 2000 and 2013

2.3 Ecological considerations for management of semi-arid rangelands

Rangeland systems and associated problems of sustainable management are typically complex. Rangeland systems are composed of many subsystems and components operating together for the sole purpose of converting specific inputs e.g. climate and soil moisture and nutrients into outputs such as meat and milk (Rickert et al., 2000). Each component has its own unique characteristics and contributes to the structure and function of the whole rangeland system. Backward and forward interactions occur between different components in a chaotic manner leading to complex dynamics in these systems and, change in one component affect other components (Jones and Luyten, 1998). Soil water, plant growth and animal responses to variable climate, topography and herbivory depend on the complexity generated by these interactions (Scholes et al., 2003).

Depending on the problem, rangelands can be viewed as different levels of hierarchy of organisation which range from the cell to individual organism (plant or animal), the field or management unit and the farm or ranch ecosystem, the landscape and region up to the continental and global levels (Ewert et al., 2011). Responses at the rangeland ecosystem and higher levels are determined by socio-economic and other factors whilst responses at the field and lower levels are mainly determined by biophysical relationships (Ewert et al., 2011). The individual organism and the ecosystem levels have the major impacts on overall performance of semi-arid rangeland systems (Richardson et al., 2010) and are the focus of this study. The plant/animal interphase is one of the key subsystems in grazed rangelands which impact soils, nutrient cycling, plant community structure and composition (Gordon, 2000) (see Figure 2.2).

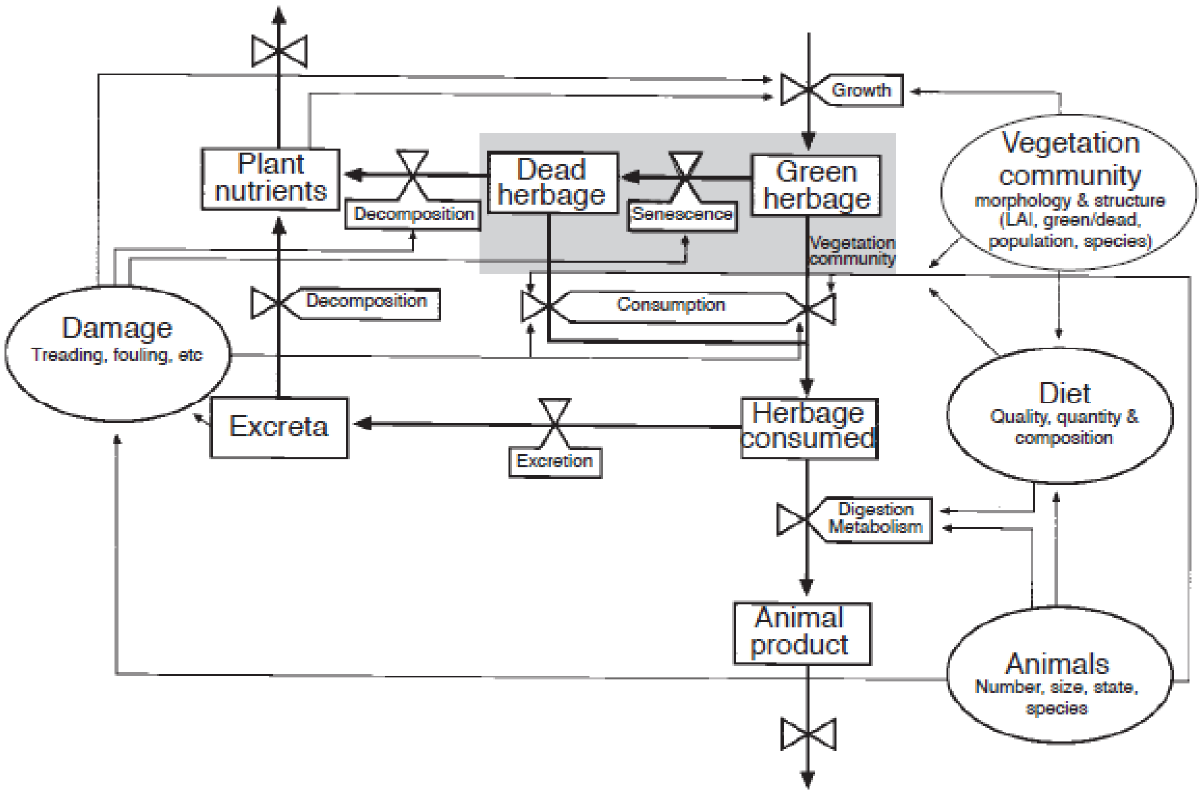

Figure 2. 2: Plant and animal interrelationships in grazing systems (Gordon, 2000)

Management of southern African rangelands is difficult as decisions must be adapted to large spatial and temporal variation of climate and persistent droughts which occur during ENZO events. Prediction of herbage production is problematic as production can fluctuate up to five-fold (Barnes, 1979) and making timely informed decisions is also challenging due to unavailability or unreliability of climate and herbaceous vegetation condition information. The confounding effects of ecological factors and grazing are thus important as they reduce availability and quality of forage and cattle productivity and, options for managing the range sustainably. The best way to maximise productivity in such systems is to adopt long-term carrying capacities during below average-rain seasons whilst increasing SRs to match available forage during above average seasons (Derner and Augustine, 2016; Oin et al., 2014; Shrum et al., 2018). The latter can be enabled by better monitoring, data forecasts and analytical capacity. Light SRs applied in the lowveld regions enable controlled selective grazing and a high plane of nutrition to be maintained by favouring palatable and productive perennial grasses (Clatworthy, 1998). More understanding about factors affecting herbage and animal production is required to enable sound decisions to be made by range managers.

2.3.1 Factors affecting herbage and animal production in semi-arid rangelands

Different factors affect herbage and animal production at individual organism and ranch ecosystem levels (Richardson et al., 2010). Herbage growth at individual plant level is a function of climate variables, i.e. rainfall, energy (radiation and temperature), atmospheric CO_2 and, plant-available soil water and nutrients (Jones et al., 2017a). Soil water and nutrient availability, particularly N and P are the primary determinants of seasonal herbage production and quality in Mopane savannas (Hempson et al., 2007). Soil water controls growth duration while soil nutrients and temperature influence growth rate. High irradiance, temperatures and low humidity in semi-arid regions create high daily evaporative demand. This causes soil moisture to deplete below the wilting point of grasses and discontinued growth for several weeks during growing season (Scholes and Walker, 1993) which lead to reduced availability of herbage to cattle.

At ecosystem level, the influence of the climate factors on total herbaceous AGB production is modified by species composition, competition with other vegetation components for soil water and nutrients and, impacts of fire and grazing (Richardson et al., 2010). Dry conditions and high grazing pressure lead to discontinued herbage growth, reduced leaf area and vigour of grasses to regrow after defoliation. During a seven-month dry season, energy and protein supply of herbage fall below the critical threshold level for efficient digestion, eventually leading to reduced animal growth and production. These variations often occur at huge spatial scales difficult to observe, measure or comprehend. Given the complexity of interactions of biophysical and management factors affecting forage and animal production, there is need for systematic collection and analysis of rangeland variables to enable early detection of forage shortages and decision making.

2.4 Monitoring herbage and animal production for sustainable rangeland management

To understand herbaceous vegetation dynamics and the influence of grazing, proper monitoring systems should be established at the appropriate scale and time frames (Stuth and Maraschin, 2000). Management strategies should also be designed based on the understanding of growth patterns of herbaceous vegetation relative to weather events and, drivers of intake and growth of animals. Rangeland productivity variables include below and aboveground biomass, herbage quality (CP content and digestibility), animal intake and live weight gain. These should be observed within and between seasons for tactical and strategic planning of grazing management (Stuth and Maraschin, 2000). The main challenge is the unavailability of accurate appropriate variables for monitoring rangeland production on a timely basis for effective decision making (Karl et al., 2017). Field experiments, remote sensing and systems modelling have provided productivity variables but at different timescales and levels of accuracy.

Grazing experiments provide the basis for many grazing management theories (Briske et al., 2008; Teague et al., 2013, 2008). They improve our understanding about the short-term effects of management strategies. Also, field trials have been useful in strategic planning for drought and high rainfall variability in developing regions (O´Connor et al., 2001). Despite these benefits, reductionist studies have been criticised for their incapability to produce consistent results for effects of grazing systems and SRs on herbage and animal production across locations. Field data do not enable spatially or temporally explicit analysis of droughts due to inconsistent availability and scarcity of observation stations (Wardlow et al., 2017). Many field data are available at long lags between when the data are collected and when management decisions are made because of the huge resources required (Antle et al., 2017). To provide valuable information to ranch managers, *in situ* observations must be designed with potential for application in a systems framework to study and make predictions about complex processes in rangelands (Teague et al., 2008).

Goals for sustainable management can be achieved by monitoring and assessing components of the rangeland system using a suite of techniques at different spatial and temporal scales (Antle et al., 2017; Teague et al., 2013). Current improvements in remote sensing and computer modelling provide opportunities for establishing proper frameworks for systematic monitoring of rangeland productivity across spatial and temporal scales (Ewert et al., 2011; Tedeschi et al., 2017). Given the huge spatial coverage and cheap availability of some satellite products for research purposes, remote sensing has provided information valuable in the strategic planning for rainfall variability and droughts (Angerer, 2012). On the other hand, systems modelling allows comparison of grazing management practises at whole-farm scale and how these practises and biophysical processes interact and evolve over time (Ma et al., 2019). When properly used, these tools enable the development of near-real time monitoring systems in developing regions where resources are scarce. This bottom-up approach requires researchers to work and communicate closely with ranch managers to understand their goals and plans for adaptive management (Tedeschi et al., 2017). The background characteristics, procedures, current challenges and opportunities for improving remote sensing and systems modelling in rangeland monitoring are discussed below. Prospects for combining these tools to analyse the impacts of both large- and small-scale changes on rangeland and cattle productivity are also discussed.

2.5 Rangeland monitoring using remote sensing

Remote sensing is defined by ESRI (2019) as ‘collecting and interpreting information about the environment and the earth’s surface from a distance, primarily by sensing radiation that is naturally emitted or reflected by the earth's surface or from the atmosphere, or by sensing signals transmitted from a device and reflected back to it’. The definition encompasses different sources of energy and mechanisms through which radiation or signals are measured. Passive remote sensing measures electromagnetic radiation from the sun reflected or transmitted across the electromagnetic spectrum (EMS), while in active remote sensing, a sensor measures a pulse of synthetic (non-solar) energy that is sent from a device and returned to it (Panda et al., 2016). In both cases, the sensors can be mounted on aircraft or satellite. Thus, the major type of energy used in remote sensing is light or radiant flux in the form of electromagnetic energy, which includes visible light, infrared, radio waves, heat, ultraviolet- and x-rays.

The image produced by each sensor portray different characteristics related to the sensor’s spatial, spectral, radiometric and temporal resolution. Spectral information forms the basis for mapping and modelling the biophysical properties of vegetation. For remote sensing to effectively estimate herbaceous AGB, LAI or cover, spectral information should differentiate vegetation from soil features (Todd et al., 1998), and the vegetation and soils should have different reflectance patterns. The typical spectral reflectance curve of green vegetation shows that leaf pigments strongly absorb the visible portion of the EMS (Figure 2.3). Green vegetation absorbs EMR heavily in the red portion at about 0.68 µm but strongly reflects the EMR in the near infra-red portion infrared between 0.76 and 0.90 µm. Water and protein content and other variables affect the reflectance from the near-IR to the middle-IR portion of the EMS (Liang, 2004). Most of the characteristic features of green vegetation are lost during senescence of leaves due to loss of pigments, cell structure and moisture content. Further detail about grass species features that influence remote sensing measurements are discussed by Shoko et al. (2016).

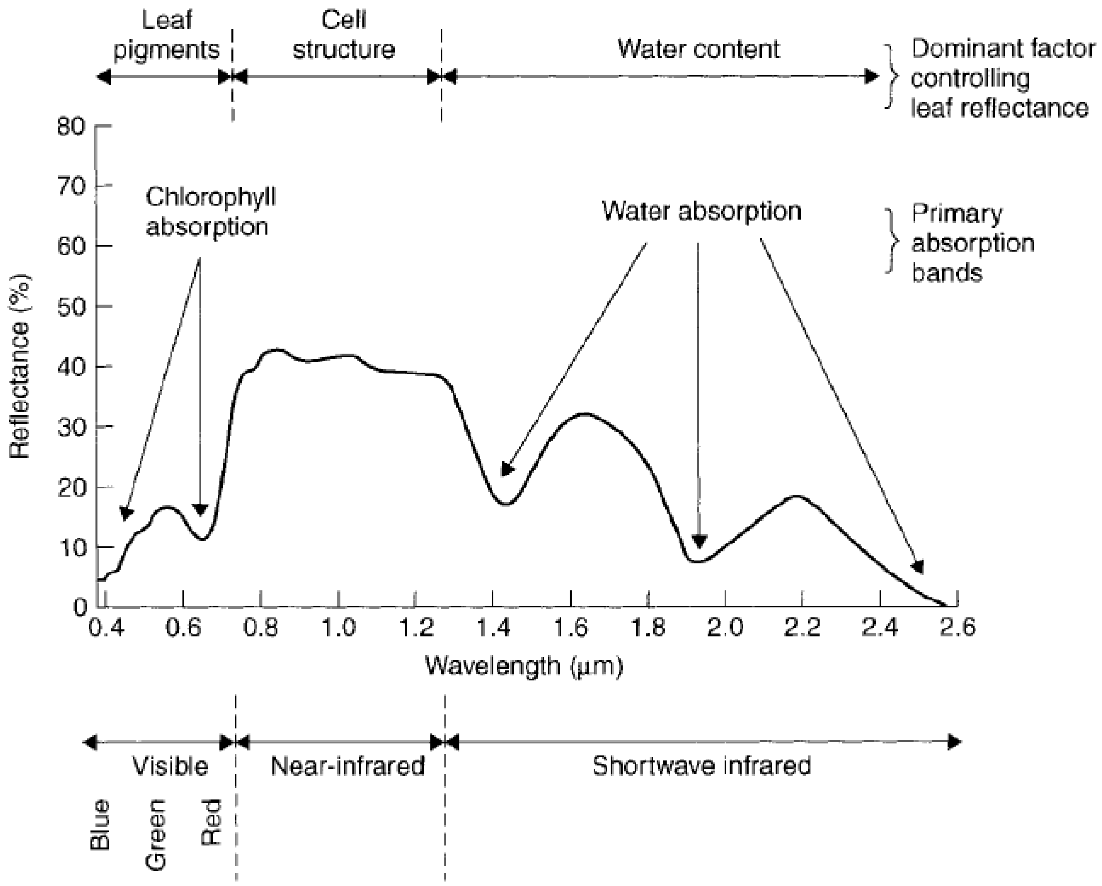

Figure 2. 3: Typical spectral response characteristics of green vegetation (Liang, 2004).

In addition to the classification of sensors using energy source and data collection mode described above, earth observing satellite systems are further classified into optical, radar, and microwave based on their operational principles within the EMS (Panda et al., 2016). Optical remote sensing is the widely used system which operate in the visible (0.4-0.7 μm) and infrared (0.7-1000 μm) portions of the EMS. Microwave sensors measure EMR in the microwave (0.3 mm -1 m) region of the EMS and have been widely applied to provide reliable estimates of soil moisture (Wang and Qu, 2009). Because radar and microwave satellite information are rarely used for remote sensing of herbaceous vegetation, optical remote sensors are the focus of this study and are discussed further.

2.5.1 Characteristics of optical remote sensing satellites

Optical remote sensing systems are classified into panchromatic, multispectral, and hyperspectral imaging systems depending on the number of spectral bands used in processing the image (Panda et al., 2016) (Table 2.1). The panchromatic (i.e., grayscale) imaging system uses a sensor with a single detector that is sensitive to radiation within a broad wavelength e.g. the broad bandwidth (0.45-0.9 µm) in IKONOS PAN images (Panda et al., 2016). Multispectral sensors such as Landsat and QuickBird have few broad spectral bands like B, G, R and NIR which combines tens to hundreds of nanometres into one band but leaving gaps between different bands. Contrary, hyperspectral sensors such as Moderate Resolution Imaging Spectrometer (MODIS) and Hyperion comprise of hundreds of spectral bands of narrow width (e.g. 0.1 µm) that allows a continuous spectrum to be generated for each pixel. Thus, hyperspectral remote sensing holds more potential in accurately mapping different vegetation features compared to multispectral remote sensing.

While hyperspectral remote sensing applications to estimate herbage production and quality have been made in southern African rangelands (Ramoelo et al., 2012), it is still uncommon to researchers. Hyperspectral remote sensing is technically challenging due to high computational demands and, its application is limited to small geographical coverage due to high image acquisition costs (Lu et al., 2019). In addition, the need for advanced planning prior to data acquisition makes their application a challenge in resource-constrained areas. Therefore, multispectral remote sensing remains as the widely used tool for operational monitoring and assessment of rangeland productivity because of their greater availability. The choice of multispectral remote sensing product to use depends on the monitoring objectives. There is a clear trade-off between spatial and temporal resolution (Jensen, 2014) with low spatial resolution (1 km) satellites products such as NOAA having high temporal revisit frequency (daily) often used for vegetation assessments at regional level.

Table 2. 1: Characteristics of optical remote sensing satellites

Sensor type	Satellite sensor	Spectral band information	Spatial resolution (m)	Revisit period (days)
Panchromatic	Landsat 7 Enhanced TM (ETM+)	0.52 - 0.9 µm	15	16
	SPOT 4 HRV	0.51 - 0.73 µm	10	pointable
	Space Imaging IKONOS	0.45 - 0.9 µm	1	
	Digital Globe QuickBird	0.45 - 0.9 µm	0.61	
Multispectral	NOAA-9 AVHRR LAC	R, NIR, 3TIR	1100	14.5/day
	NOAA- K, L, M	R, NIR, 2SWIR, 2TIR	1100	14.5/day
	Landsat Multispectral Scanner (MSS)	G, R, 2NIR	79	16-18
	Landsat 4 and 5 Thematic Mappers (TM)	B, G, R NIR,2SWIR, TIR	30 and 120	16
	Landsat 7 Enhanced TM plus (ETM+)	B, G, R NIR,2SWIR, TIR	30 and 60	16
	Space Imaging IKONOS	G, R NIR, SWIR	4	pointable
	SPOT 4 HRV	G, R, NIR	20	pointable
	Digital Globe QuickBird	G, R NIR, SWIR	2.4	pointable
Hyperspectral	ASTER - Advanced Spaceborne Thermal Emission and Reflection Radiometer	0.52 - 0.86 µm (3 bands)	15	5
		1.6 - 2.43 µm (6 bands)	30	16
		8.12 - 11.6 µm (5 bands)	90	16
	MODIS - Moderate Resolution Imaging Spectrometer	0.405 - 14.385 µm (36 bands)	250, 500, 1000	1 - 2
	MERIS/Envisat	VIS - NIR (18 selectable bands)	230 x 300	3
	Hyperion/EO-1	VIS - TIR (36 bands)	250-1000	16

2.5.2 Remote sensing process

The remote sensing process are systematic procedures for collecting and analysing data used in both scientific and technological applications for generating new knowledge (Jensen, 2014). The procedures comprise of four phases namely; the statement of the problem, data collection, conversion of data to information and information representation (Figure 2.4). Firstly, the hypothesis to be tested is defined using an inductive or deductive logic and an appropriate processing model. Then, a list of variables or observations to be used during the investigation are identified. Information about the identified variables is collected using *in situ* observations and/or remote sensing (Jensen, 2014). Field and laboratory data of vegetation are often collected in combination with global positioning system and used for calibrating the remote sensing data and to conduct an independent accuracy assessment of results. Measurable biophysical variables of vegetation include pigments (e.g., chlorophyll *a* and *b*), canopy structure and height, biomass, LAI and absorbed photosynthetically active radiation (Panda et al., 2016). Ancillary data such as soil maps, geology maps, digital elevation models and political boundary files are also valuable in remote sensing and are collected using GIS tools. Remote sensing data are collected using passive and active systems as described above.

To convert remote sensing data into information, images are processed in several steps and the results can be used to test hypotheses. Given the error introduced by the sensor system and the atmospheric scattering of light, images are usually pre-processed through radiometric and geometric correction to remove these deleterious effects (Panda et al., 2016). Depending on the problem, the image can be enhanced to extract spectral data, classify land cover, and detect land cover changes among other applications. Extracted spectral data are linearly or non-linearly transformed to information that is highly correlated with actual vegetation features through various vegetation indices (VIs) and principal component analysis. Vegetation indices exploit the difference between strong absorption of light by leaf pigments in the red band from the high reflectance of leaf mesophyll in NIR band to discriminate vegetation components and soil and water (Kumar et al., 2016). The VIs commonly used to predict herbaceous AGB are provided in Table 3.1. Finally, the information processed from images can be represented as enhanced image, image map, statistic, or graph to communicate the findings effectively.

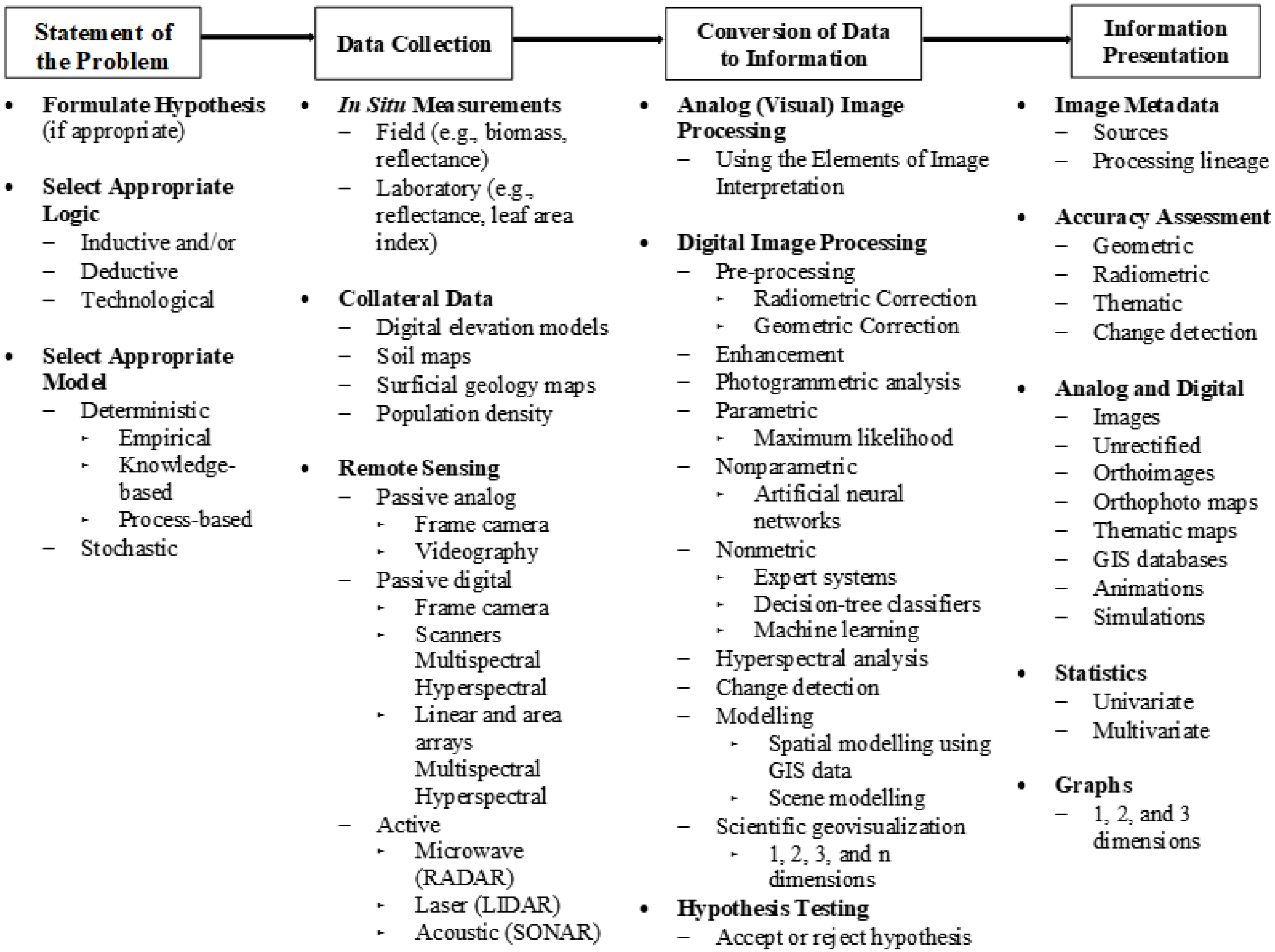

Figure 2. 4: The remote sensing process for extracting information from remotely sensed data (based on Jensen (2014))

2.5.3 Use of optical remote sensing in monitoring herbage production

Developments in remote sensing since early 1980s have provided continuous observations required for analysing climate- and vegetation-based indicators for monitoring climate variation, particularly drought impacts on rangelands (West et al., 2019). Remote sensing provides spatially and temporally consistent and timely information for monitoring drought due to its large area coverage and high temporal frequencies of data collection. Satellite-based VIs have been used as proxies for vegetative biomass to assess the impacts of climate variation at regional (Wang et al., 2018) and continental levels (Winkler et al., 2017). Vegetation anomalies are assessed using optical, thermal and microwave remote sensing but the use of the latter for operational range management is limited to developed countries due to high costs. Instead, drought impacts have been widely assessed using rainfall anomaly indices in conjunction with optical remote sensing VIs such as Normalised Difference Vegetation Index (NDVI) and Vegetation Condition Index (Brown, 2008; Ji and Peters, 2003; Richard and Poccard, 1998). Most of assessments were regional studies and used course resolution satellite such as NOAA AVHRR, including southern Africa (Chamaillé-Jammes and Fritz, 2009; Martiny et al., 2006; Wessels et al., 2006). However, the spatial extent of many grazing lands in southern Africa is too small to allow application of low spatial resolution satellite products for sound decision making. In addition, course resolution satellites do not provide spatially explicit herbaceous biomass data in savanna rangelands, due to high spatial variability of vegetation components at local level (Assal et al., 2016). In southern African savannas, woody cover is usually above 20 % and there is limited herbaceous AGB production such that the woody layer affect VI signal in mixed pixels (Richard et al., 2008). These shortcomings highlight the need to incorporate medium spatial resolution satellite products in vegetation assessments to gain a full understanding of drought impacts at local level.

2.5.4 Future needs for improving optical remote sensing in rangeland monitoring

When retrieving biophysical variables of herbaceous vegetation from statistical relationships or operational algorithms, there are uncertainties associated with input and modelling data. These errors are commonly assessed by comparing remotely sensed biophysical variables with field-measured data. Atmospheric contaminants such as water vapour present the biggest challenge to the utility of multispectral MVIs in herbaceous AGB estimation (Ali et al, 2016). Such contamination could be more pronounced in tropical regions 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 NDVI in high density vegetation is another typical constrain to their use (Mutanga and Skidmore, 2004). Soil background effects are also very important to herbaceous AGB estimation in sparsely covered and heterogeneous vegetation communities in arid and semi-arid rangelands (Jackson and 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 in southern Africa. Broad band MVIs based on medium resolution products thus remain important for monitoring herbaceous AGB at grazing management unit level in savanna rangelands. The need to evaluate their performance under prevailing landscape features using improved and affordable satellite products remains a priority.

For modelling data, strong relationships between observed and remotely sensed biophysical variables the variables are derived from a sensor pixel size that is lower than the extent of the site where the variables are observed (Schellberg et al., 2008). Medium spatial resolution satellite products provide accurate information about condition vegetation components at a timescale long enough for assessing climate variability impacts (Gómez et al., 2016). Due to availability of its satellites since early 1970s, Landsat imagery has explicitly demonstrated the long-term spatial and temporal variability of rainfall in semi-arid regions (Birtwistle et al., 2016). Although the medium resolution products are very useful for drought monitoring, they have been rarely applied to southern African rangelands (Shoko et al., 2019). Only a few studies assessed drought impacts using the convergence of evidence approach (Graw et al., 2017), yet droughts are the major determinant of rangeland sustainability. As a result, the long-term impacts of drought on herbaceous AGB production are still poorly understood. There is need therefore to explore medium spatial resolution satellites in assessing climate variability impacts in southern African rangelands.

Development of accurate herbaceous AGB models using remotely sensed variables from low spatial resolution products is usually challenging. This can be dealt with by using co-images from two different satellites products on the same target area to reduce the limitations of individual satellite sensors (Schellberg and Verbruggen, 2014). For example, Baumann et al. (2017) combined high revisit time MODIS satellites with multi-year, low revisit time Landsat imagery to represent the dynamic patterns of vegetation growth. Despite the importance of remote sensing models in strategic planning for climate variation, they have weak predictive power when applied to other regions (Foody, 2003). Another challenge is that, remote sensing does not represent the interaction effects of climate with SRs on animal intake and weight changes. These limitations highlight the need for systems modelling which provide invaluable information that enhances our understanding of the long-term secondary impacts of grazing management practices on herbage and animal production. This warrants the need to discuss the potential roles, procedure and current and future status of systems modelling to assist in routine assessment of rangeland and animal productivity.

2.6 Rangeland monitoring using systems modelling

Systems analysis a body of theory and techniques studying, describing and making predictions about complex systems which is often characterised by use of advanced statistical and mathematical approaches and by use of computers (Grant et al., 1997). Systems analysis is thus viewed as both a philosophical approach and a collection of techniques or tools developed in a holistic context to explicitly address problems involving complex systems (Jones and Luyten, 1998). The systems approach integrates information obtained from qualitative and quantitative (statistical and mathematical) methods in a way that facilitates formal description of the structure and dynamics of complex systems (Grant et al., 1997). A systems model is 'a mathematical representation of the system, including all interrelationships among components and effects of the environment on these components' (Wallach et al., 2014). Such a model promotes good research design- and sound resource management decision making (Grant et al., 1997). There are several types of models that have been developed for agroecological systems and these are discussed below.

2.6.1 Classification and importance of rangeland systems modelling.

The scheme widely used to classify simulation models for agroecological systems recognises models as being deterministic or stochastic; dynamic or static; mechanistic or empirical (France and Kebreab, 2008; Thornley and Johnson, 2000). A deterministic model does not contain random variables and implies that all prediction of an equation or set of equations under specific conditions are the same. Stochastic models contain one or more random variables and predictions have a probability distribution (Thornley and Johnson, 2000). These models inherently seek to represent the variance that is not fully understood but can be technically difficult to test (Grant et al., 1997). A static model describes a relation or a set of relationships that do not change with time, whilst dynamic model describes the time-varying relationship based on differential equations and do not use time as an independent variable. Empirical models use existing data to describe the relationship of observations between one or two variables using mathematical or statistical equations, without any scientific content, and unconstrained by any scientific principles (Thornley, 2001). Mechanistic models have a highly detailed structure that enable them to represent biophysical process and interactions of components in the soil-plant-animal continuum (France and Kebreab, 2008). Mechanistic models are thus often used as research tools to provide insight and understanding about the biophysical environment and are the focus of this study. A full discussion about the importance of building and applying models for simulating herbage and animal production is provided by Thornley and Johnson (2000), and in summary, models:

- Provide a quantitative description and mechanistic understanding of a biological system.
- Reduce the amount of *ad hoc* experiments as models can be designed to answer focused questions and explore alternative management practices.
- By bringing together knowledge about system components, models provide means for an integrated view of the whole-system behaviour.
- The predictive power of a valid model can be used to forecast future events and answer 'how-, why- and what- if' questions.

2.6.2 Systems modelling process

The generally accepted procedure of developing and applying models for agroecosystems involves four major theoretical phases, namely: conceptual model formulation; quantitative-model specification; model evaluation and model use (Grant et al., 1997). In practice, the four phases are highly interconnected and model development process may be repeated through phases several times. This iterative process has been conceptualised by Sargent (2010) to include the important steps of verifying and validating the system model (Figure 2.5). Systems modelling starts with development of a conceptual or qualitative model of the system of interest. This is achieved by articulating the problem and developing a dynamic hypothesis, also known as conceptual model, through an analysis and modelling phase. Agricultural systems models are developed for the purpose of scientific understanding and decision/policy support (Jones et al., 2017b). Explanatory or research models are developed for the purpose of increasing the scientific understanding of rangeland systems whilst policy models are designed to provide information for supporting decision making and policies. Since research models form the basis for decision support systems (Rickert et al., 2000), the former are chosen as the focus of this study.

The problem entity, that is, the proposed or actual system, situation, policy or phenomena of the system to be modelled (Sargent, 2010), is defined by determining boundaries, variables, time horizons, and data sources. This phase places emphasis on stakeholder engagement through interviews or surveys and collection of reference mode data to help modellers identify the current theories of the problem entity (Turner et al., 2016). These consultations enable modellers to decide the real-system components and relationships to include in the problem entity (Feola et al., 2012). Relationships amongst state variables, parameters and environmental (exogenous, forcing or driving) variables and processes of the conceptual model are then represented through causal loop diagrams and stock-and-flow maps such as Figure 2.2

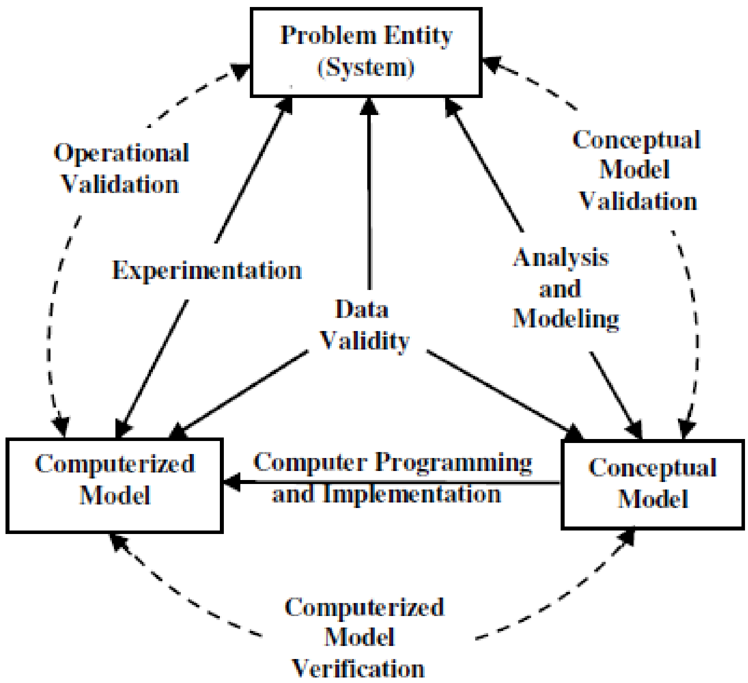

Figure 2. 5: The systems modelling process (Sargent, 2010).

Secondly, the relationships between components of the conceptual model are translated into a series of mathematical equations and their parameter values that collectively form the quantitative model in the computer programming and implementation phase. Then, model undergoes a series of tests to investigate if assumed parameter values are realistic and to check if model responses correspond to anticipated feedbacks to check model consistency (Turner et al., 2016). A mechanistic model is always incomplete, and therefore usually does some things well and other things badly or not at all (Thornley, 2001). Appropriate, accurate and enough data are required for building and testing the conceptual model and for applying the model (Sargent, 2010), but this data is not available resource-constrained environments. Conceptual model validation involves determining whether theories and assumptions underlying the conceptual model are correct or not. Computerised model verification is a test of the internal logic of a model (Jorgensen and Fath, 2011). Operational validation assures that the model's output behaviour has sufficient accuracy of the model's intended purpose over the area of the model's intended applicability (Sargent, 2010). Once satisfactorily evaluated, the model can be applied to answer questions about the problem entity by conducting simulation experiments in the experimentation phase.

2.6.3 Status of systems modelling of herbage and animal production

Development of simulation models started as a parallel process for pasture and animal production systems. Influential developments in pasture growth modelling began in the early 1980s when the Hurley pasture model (Johnson and Thornley, 1983) and SAVANNA model (Coughenour et al., 1984) were developed. Since then, several models have been developed to represent plant growth behaviour and competition among herbaceous plants using approaches based on individual species, plant functional type and plant community (Antle et al., 2017; Wallach et al., 2014). Snow et al. (2014) provided a critical review of the capabilities of different models in representing the biological diversity of plant species and competition among plant functional types and mortality, pasture-animal interactions, nutrient transfers and economic returns.

Models for grazing ruminant systems have been developed for three hierarchical levels of organisation namely, individual animal, herd and whole-farm system. Developed since the 1940s, animal performance models are broadly based on nutrient partition and metabolic processes (Tedeschi et al., 2005). They are used to predict meat and milk production, assess the impacts of alternative feeding practices on yields and of changes in animal breeds or types. Further detail about recent developments in animal performance modelling has been given by McNamara et al. (2016) and Tedeschi (2019). Herd dynamics models represent the development of a herd by predicting numbers and body weights of cohorts of different ages and sex, as influenced by herd management and meat marketing (Jones et al., 2017a). The rates of reproduction, mortality, selling and replacement are specified for each cohort and, offspring from female cohorts may be sold or become part of the next cohort. Herd models have been used to estimate herbaceous biomass removed from pasture systems, optimal SRs and sales policies and herd size (Illius et al., 1998) and, to analyse the effects of reproductive technologies (Jones et al., 2017a).

Integrated livestock systems models, commonly known as whole farm models (WFMs) link simulation models of pasture with models for individual animal performance and/or herd dynamics. They integrate different levels of biological organisation (soil, plant and animal) to understand the behaviour of grazing systems and compare stock management practices that maximise productivity (per area or per animal) and minimise deterioration of the natural resource to increase grazing efficiency and profitability (Tedeschi, 2019). They are a recent development with shorter history compared to pasture and animal systems models because their development is complicated as modelling the animal on pasture involves modelling the pasture as well (Donnelly et al., 1997; Herrero et al., 1999).

Some critical reviews of WFMs for grazing lands have been conducted (Bryant and Snow, 2008; Ma et al., 2019; Snow et al., 2014). WFMs have been used extensively to increase our understanding of the impacts of grazing management practices on soil water and nutrient availability, forage production, animal production, plant-animal and animal-animal interactions, animal health and environment. This review is focused on identifying knowledge gaps in each model's ability to represent forage and animal production and their response to climate variability and management strategies. The key features of six models commonly used for predicting these ecosystem services namely, Pasture Simulation Model: PaSIM (Graux et al., 2011; Riedo et al., 1998; Vuichard et al., 2007), Great Plains Framework for Agricultural Resource Management: GPFARM (Andales et al., 2006; Qi et al., 2012), Integrated Farming Systems Model: IFSM (Rotz et al., 2005), GrazPlan (Donnelly et al., 1997), Sustainable Grazing Systems: SGS model (Johnson et al., 2008) and Richardson Savannah model, VELDSTOCK (Kazembe, 2010; Richardson et al., 2000, 1991) are provided in Table 2.2. A common feature of all these models is their ability to include the animal component. These models are designed for either research purposes e.g. the SGS and VELDSTOCK or as decision support systems (DSSs) (GPFARM, PaSim, IFSM and GRAZPLAN) for rangeland management. Both types of models have many built-in management options that enable them to simulate detailed management actions.

Relative to other models described in Table 2.2, the SGS model portrays the highest level of detail in its representation of nutrient pools and flows in the soil-plant-animal continuum. The model mechanistically simulates competition among plant species and functional types (White et al., 2008) and independent above- and below- ground competition forage mixtures (Snow et al., 2014). The models GRAZPLAN, SGS and VELDSTOCK simulate growth in sheep and goats. Except for PaSim, the other models can simulate mixtures of individual species and functional types. IFSM is a semi mechanistic model that is most applicable for time series analysis because it does not represent within year variation well. Also, the model does not simulate independent below-ground competition. However, IFSM can integrate the assessment of economics with environment (greenhouse gas emissions and phosphorus pollution) to determine the sustainability impacts of grazing management practices.

Table 2. 2: Key characteristics of selected whole-farm simulation models

Model name (Origin)	**Soil moisture dynamics**	**Soil nutrient cycling**	**Plant growth forms (SPP/PFT)**	**Animal growth**
PaSIM (Europe)	Detailed sub model for soil moisture dynamics	simulate C and N flows in pasture across grazing schemes and variable water stress conditions	Species population-based growth simulations	Dairy and beef cattle
GPFARM (North America)	Detailed sub model for soil moisture dynamics	Highly detailed C flow dynamics P cycling excluded	Warm-season grasses, cool-season grasses, legumes, shrubs, and forbs	Beef cattle
IFSM (North America)	Empirical sub model for soil moisture dynamics	Simple C-balance calculation, N and P cycling included	Ecotypes (grass and forage legumes)	Dairy and beef cattle
GRAZPLAN (Australia)	Simple sub model for soil moisture dynamics	Pasture model capable of simulating Simulate N and P dynamics but must be coupled to APSIM*	Individual species	Sheep, beef and dairy cattle. sub-model for energy and protein nutrition drawn from Australian feeding standards
The SGS model (Australia)	Extreme specific technical description of soil physics and hydrological dynamics	Highly detailed C flow dynamics P cycling excluded	Ecotypes (grass and forage legumes)	Dynamic model for dairy, beef and sheep. Adjustable default parameters for species and breed.
Richardson Savannah model, VELDSTOCK (Southern Africa)	Simulate soil water dynamics in response to rainfall and its influence on plant growth at various spatial-temporal scales.	N & P, C sequestration low level of detail for pools and flows of soil organic carbon	Woody plants and grasses.	Beef cattle and goats model.

*APSIM, Agricultural Production Systems Simulator.

It is difficult to compare performance models across locations due to differences in interactions of the biophysical environment and approaches and underlying model assumptions (Ma et al., 2019). The major discrepancy in development and application of whole-farm modelling exists between developed and developing regions. Simulation modelling has been limitedly applied in southern Africa, particularly in Zimbabwe. Examples of simulation models applied include the empirical and semi-mechanistic models, VELDSTOCK (Richardson et al., 2000), the model of Illius et al. (1998) and Livestock simulator (LIVSIM) (Masikati et al., 2015). These models simulate deterministic and stochastic elements of plant and animal responses to environment using multiple regression equations that have been developed from grazing trials. Empirical simulation models, however, give spurious results if they are applied outside the regions where the experimental data for equations were derived. The models are thus limited in their capacity to analyse productivity and sustainability impacts of grazing management practices in rangeland systems. To develop near-real time systems for monitoring grazing management practices that are close to real-world conditions, the integrated approach needs to embrace use of deterministic dynamic simulation models.

Use of complex, dynamic, mechanistic WFMs models known as process-based models in agricultural systems simulation has gained much attention since the past two decades (Thornley and Johnson, 2000). These models mechanistically simulate soil, plant, and animal processes in multispecies herbaceous swards. The WFMs are developed to represent stocks and flows of material or energy using differential equations that link at least two levels of the system from cell to organ level (France and Kebreab, 2008). Balance among complexity, realism and versatility obtained during model development allows WFMs to be readily applied to regions where there is limited information about specific pasture species and animal breeds (Johnson, 2011). The models are often used as research models because of their stronger theoretical base compared to empirical models. Mechanistic models are the focus of this study since the study aims to provide in-depth understanding of the complex interactions affecting herbage and animal production in a savanna rangeland. The overall needs for model development and improvement for mechanistic models is discussed further below.

2.6.4 Areas for improving system models’ predictive capacity for rangeland production

All grazing land models are expected to simulate seasonal dynamics of forage production and quality and subsequent animal weight changes in response to erratic and unevenly distributed rainfall. However, the structure of many models does not adequately simulate the high spatial and temporal variation of seasonal rainfall and the biophysical environment and subsequent seasonal dynamics in forage production. In prairie vegetation, variability of forage production simulated by the GPFARM model was less than observed (Andales et al., 2006). At paddock-scale, variation in forage production is increased by the high diversity in herbaceous species that evolve from grazing and competition for soil water and nutrients (Venter et al., 2003). This random variation leads to huge errors when predicting herbage production. Cullen et al. (2008) and Doran-Browne et al. (2014) observed average performance of SGS model in predicting the growth of C4 perennial and annual grasses native to (sub)tropical regions of Australia. The APEX model underestimated growth of individual herbaceous species (Zilverberg et al., 2017). Oreskes et al. (1994) noted that it is impossible to obtain high agreements between measured and simulated variables in complex natural systems.

Depending on duration and severity, extreme climate events such as high temperature and drought reduce the pool of rangeland resources and may limit available management options. Herbaceous vegetation response to extreme events is not well represented in many farm system models (Kipling et al., 2019). In prairie, GPFARM model could not simulate the rapid recovery of vegetation following severe drought (Andales et al., 2006) whilst forage growth modelled by APEX model did not respond well to late season rainfall (Zilverberg et al., 2017). The SGS model could not adequately represent the changes in nutrient cycling, pasture species composition, reduced plant vigour as well as simulating the option for destock during severe droughts and subsequent recovery (Doran-Browne et al., 2014). As a result, the WFMs provide context-specific benefits in the planning of strategic adaptive management options.

Forage quality is the nutrient, mainly N or energy content which culminates from plant N uptake and assimilation. Plant N uptake is affected by soil clay content, soil C mineralization and competition species (Ma et al., 2019) and transfers of dung and urine by the animal in the paddocks (Eckard et al., 2014). However, most models have limited capacity for predicting dynamics and uptake of soil N and P and subsequent forage quality. Also, many grazing lands models do not explicitly simulate the supply of soil N from soil organic matter (Robertson et al., 2015). Despite there being many inadequacies in the models' capacity to simulate forage quality, N and P are limiting in many semi-arid rangelands of southern Africa. Therefore, future efforts should be focused on improving WFMs' capacity to simulate the dynamics of the major limiting nutrients.

Whilst it is important to integrate the livestock component into WFMs, there are several limitations in animal performance models' ability to represent the dynamics of animal metabolism. There is need to improve the capacity of animal performance models to predict voluntary feed intake and ruminal fermentation processes at high levels of detail (Bryant and Snow, 2008). The SGS model faced difficulties in representing the live weight changes that occur when cattle diet was changed from native forage to supplements in the dry- season (Doran-Browne et al., 2014). This could be due to lack of model responses to microorganisms or palatability. In addition, nutrition and metabolism models do not accurately predict body composition, particularly for fat and protein due to lack of detailed and accurate experimental data (McNamara et al., 2016). Fat and protein deposition are influential variables for predicting nutrients requirements for growth in animals and, they vary from genotype to another (Tedeschi, 2019). Simulation models for animal growth have been limitedly applied to a few genotypes in North American and Australian rangelands yet there is a wide diversity of livestock breeds in other semi-arid regions.

Overall, there is need to reduce uncertainty of model input parameters, such as climate and soil properties by improving experiments and self-training of systems model using big data (Getz et al., 2018). Parameters and state variables are also unknown as they cannot be fully included in experiments due to their high variability in space. The increasing availability of environmental variables from remote sensing and GIS at high temporal- and spatial- resolution provide means for retrieving climate inputs (Ovando et al., 2018) and explanatory variables for WFMs (Schellberg et al., 2008). Therefore, it is evident that the future for extending WFMs to data-constrained environment depends on availability of ancillary data from remote sensing and warrants further attention.

2.7 Integrating remote sensing and systems modelling in rangeland monitoring

The integrated use of remote sensing and systems modelling for estimation of plant production started in the mid-1980s and predominantly applied to crop models (Wiegand et al., 1986). Combined use of these tools is aimed at maximising spatial explicit in remotely sensed landscape attributes and explicit time-dependency of outputs from systems models in order to understand the complex interactions in the soil-plant-animal system. Given the large area-coverage of satellites, remotely sensed state variables of the soil-plant system provide inputs for calibrating biophysical models and independent data for validating model outputs where field observations are not available (Delrcolle et al., 1992). Systems simulation models effectively use these inputs to explicitly simulate a group of interacting components of the system and analyse the implications of management decisions, on a daily time-step (Tedeschi et al., 2017). The approach thus overcome the non-stationarity shortcomings of remotely sensed herbaceous AGB when analysing the response of rangelands to inter-annual climate variability by using simulation models. At the same time, remote sensing can easily characterise random or systemic patterns of spatial and temporal variability in vegetation production that are not analysed by point-based simulation models at paddock scale.

Despite these benefits, the combined use of these tools in assessing spatial and temporal variability of grass quantity and quality is generally limited due to lack of historical data for validation. The main challenge to application of the integrated approach is limited *in situ* observation networks for validating remote sensing and systems models (Schellberg and Verbruggen, 2014). Globally, the integrated approach has been applied to predict AGB in grazing lands using intensive field measurements and high spatial resolution satellite products. For example, proximal sensing techniques have been integrated with pasture simulation models in America (Nouvellon et al., 2001) and Europe (Curnel, 2015). In East Africa, SPOT images were used at microscale (Jarlan et al., 2008) whilst flux tower measurements have been used to evaluate a simulation model in southern Africa (Scanlon et al., 2005). Others have used remotely sensed variable in decision support systems which involved intensive field observations (Kaitho et al., 2007). However, the high costs incurred from these utilities render their use for routine farm-level monitoring of herbaceous biomass in developing countries ineffective. In southern Africa, simulation models have been separately applied using data from long-term grazing trials (Oomen et al., 2016; Wiegand et al., 1998). Only a few cases are known in which remotely sensed data has been used to validate a simulation model (Boone et al., 2004).

The increasing availability of high temporal- and spatial- resolution geographical data of environmental variables provide a means for closing data gaps when adapting system models to resource-constrained environments (Angerer, 2012). Remote sensing and GIS are inseparable tools important for mapping climate input variables for WFMs (Ovando et al., 2018). They also enable stratification of rangeland systems into soil, vegetation and management units for retrieving explanatory variables (Schellberg et al., 2008). These ancillary data are useful in model calibration yet they have been rarely explored in southern Africa. The integrated data sources thus offer complementarities to field experiments and there is need for exploring them to understand their suitability and transferability under specific site conditions.

Summary

This chapter has provided an appraisal of tools available for monitoring herbage and animal production in rangelands at landscape and management unit levels and, opportunities for integrating them. Whilst remote sensing has provided herbaceous vegetation production information in southern African rangelands, many applications are based on low spatial resolution products and at regional scale. Such products do not provide spatially explicit herbaceous biomass data in savanna rangelands, due to high spatial variability of vegetation components at local level. There is need to embrace medium spatial resolution products in order to reduce uncertainty associated with herbaceous AGB estimation in savannas. Efforts to determine the accuracies of various VIs derived from a Landsat 8 image in predicting herbaceous AGB are made in Chapter 3. A time series of Landsat images is further used in conjunction with satellite-based rainfall estimates in Chapter 4 to assess the response of herbaceous AGB to climate variability. The potential of six WFSM models to analyse the responses of herbage and animal production to different grazing strategies were also reviewed. The SGS model portrays the highest level of detail in its representation of nutrient pools and flows in the soil-plant-animal continuum. The model also has a farm management scheme that allows different grazing management to be simulated in native grazing lands. The SGS model was thus considered suitable tool for achieving the aims of this study and further detail to its calibration, evaluation and application to a southern African savanna is given in Chapters 5, 6 and 7, respectively. Further improvements in WFSM should aim to improve their capacity to predict the spatial and temporal variations in herbage and animal production in native grazing lands.

CHAPTER 3

Performance of ratio-based, soil-adjusted, and atmospherically corrected multispectral vegetation indices in predicting herbaceous aboveground biomass in a *Colophospermum mopane* tree - shrub savanna

Abstract

Accurate and near-real time estimation of herbaceous aboveground biomass (AGB) at farm level is crucial for monitoring pasture production 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 classical multispectral vegetation indices (MVIs) when either singly regressed with measured herbaceous AGB or combined with other visible spectral bands in predicting herbaceous AGB in a *Colophospermum mopane* savanna. Field herbaceous AGB and corresponding Landsat 8 Operational Land Imager (OLI) visible spectral data were collected during the 2016-17 rainy season. Relationships between measured AGB and classical MVIs and extended models of MVIs combined with other visible bands were analysed using bootstrapped simple and stepwise multiple linear regression functions. When MVIs were singly regressed with measured AGB, ratio-based indices yielded the highest r^2 value of 0.64 followed by soil adjusted indices (r^2 = 0.61) whilst atmospheric corrected MVIs showed the lowest r^2 of 0.58 (p = 0.00). A significant improvement in herbaceous AGB estimation was obtained by using a combination of MVIs and other visible bands. Soil adjusted MVIs showed the greatest increase (44-46 %) in r^2 whilst atmospheric corrected and ratio based MVIs poorly improved (<5 %). The findings demonstrate that combining MVIs with Landsat 8 optical bands, especially 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: biomass, regression, multispectral vegetation indices, savanna,

3.1 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 occupy 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 aboveground 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 SRs 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 and 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 and 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 and 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. Broad band 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 and 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 and 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, MVIs’ 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 and Mutanga,

2015) and grass leaf area index (LAI) (Masemola et al, 2016). In addition, accuracy of classical MVIs based on red and near-infra red waveband reflectance for AGB estimation becomes insensitive when LAI increase and grass canopies become dense. Combining two or more wavebands with classical MVIs have improved the prediction of vegetation biochemicals (Fourty and Baret, 1997). However, information about accuracy of extended regression models containing other optical bands in estimating herbaceous AGB is limited for southern African savannas.

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. The utility of MVI-based regression functions is site specific due to variable soil and vegetation characteristics hence the need to evaluate their performance in the study area. This study therefore seeks to examine the use of MVIs and assess accuracy of extended regression models containing classical MVIs and two or more optical bands for herbaceous AGB production estimation 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.

3.1.1 Objectives

The objectives of the study were to:

- evaluate the performance of ratio- based, soil adjusted and atmospherically corrected MVIs for estimation of herbaceous AGB production in *C. mopane* savanna
- assess accuracy of extended regression models containing classical MVIs and two or more optical bands for estimation of herbaceous AGB production in *C. mopane* savanna

3.2 Materials and methods

3.2.1 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 3.1). The plane landform is generally 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 and 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 a dense layer of moderately tall, palatable perennial C4 grasses such as *Urochloa mosambicensis* and *Panicum maximum* and sparsely dense, short sub stratum of 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 stocked at the rate of 1 livestock unit (450 kg mature cow) per 12 hectares in paddocks ranging from 300 to 1200 hectares has been the main land use since 1940s.

3.2.2 Data collection

3.2.2.1 Field measurement of herbaceous aboveground biomass

A vegetation survey was conducted between 5 and 11 February 2017 through visits to the Nuanetsi cattle ranch section. 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 represent sampling frame as shown in Figure 3.1. Areas covered by at least 0.1 hectares of grassland within vegetation cover classes 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. Firstly, a stratified random sampling procedure was 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). Herbaceous AGB within each elementary sampling unit was then measured in 4 randomly selected, second- stage sampling units (0.25 m^2 quadrats). 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 1000 m apart depending on homogeneity and accessibility of the area. The plot size corresponds to the pixel resolution (30 m) for Landsat 8 OLI images that were used as observed vegetation reflectance data. The central position of the four corners of the plots was recorded using a Garmin Etex 20 Global Positioning System (GPS) to geo-reference spectral reflectance information. 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. Herbaceous AGB in the sub plots were clipped to 5 cm stubble aboveground using shears to represent minimum residual dry matter yield recommended for moderate forage utilisation (41- 50 %) by cattle grazing in extensive rangelands. The biomass was 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 kg m^{-2} and averaged at elementary sampling plot level.

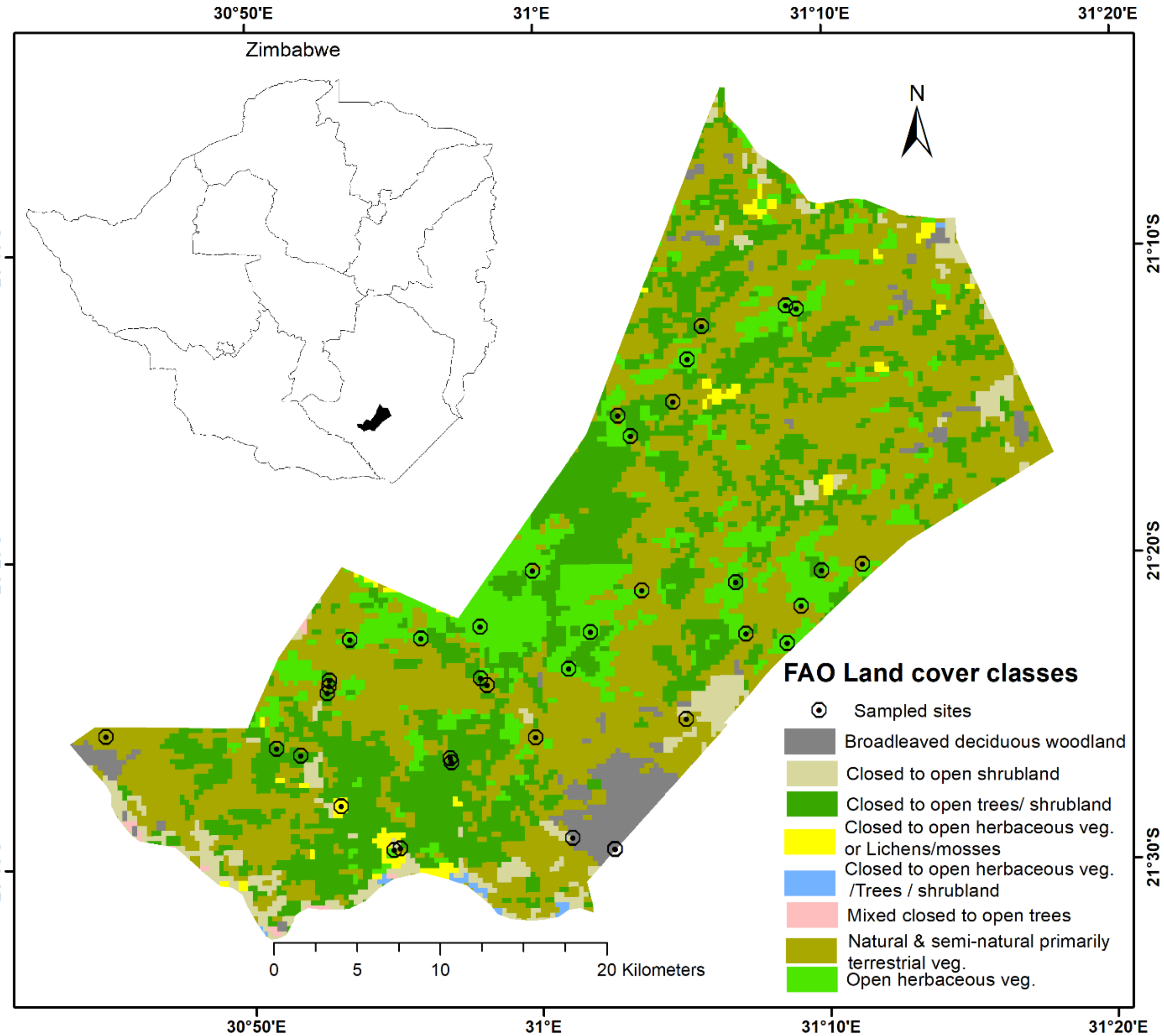

Figure 3. 1: Location of Nuanetsi ranch in Zimbabwe (insert) and of sampled plots and FAO land cover classes for the ranch

3.2.2.2 Image acquisition and derivation of multispectral vegetation indices

A Landsat 8 OLI image (30 m 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 30 November 2016 from Earth explorer (path 169, row 075). This is the only cloud-free image for the scene that was available before vegetation sampling was done which was used to study the utilities of MVIs. The image acquisition date represents the green-up period in which grass contribute 90 % of total landscape LAI in southern African savannas (Archibald and Scholes 2007) and it was assumed that the herbaceous layer retained similar spectral reflectance characteristics up to the time of ground measurements. The Landsat image has four bands in the visual domain of the spectra i.e., blue at 0.452-0.512 µm (band 2), green at 0.533-0.590 µm (band 3), red at 0.636-0.673 µm (band 4) and near infra-red at 0.851-0.879 µm (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 3.1. 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 indices; Atmospherically Resistant Vegetation Index (ARVI), Soil and Atmospherically Resistant Vegetation Index (SARVI) and Enhanced Vegetation Index (EVI).

Table 3. 1: Formula of vegetation indices evaluated for herbaceous aboveground biomass estimation utilities in the study
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

	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 = $\frac{NIR-Red}{NIR+C_1Red-C_2Blue+L}$	Huete et al. (2002)

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).

3.2.3 Statistical analyses

3.2.3.1 Evaluation of vegetation indices for aboveground herbaceous biomass estimation

Simple and stepwise multiple linear regression (SMLR) analyses were used to determine the appropriate models for predicting herbaceous AGB measured in forty elementary sampling plots using ten MVIs and four Landsat8 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 herbaceous AGB measured in kg m^{-2}. Measured herbaceous AGB values from sampling plots that poorly represented waveband values of the corresponding pixels were discarded as outliers and thirty-one values were retained for model fitting. 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 then used to determine the other visible bands that appropriately combined with classical MVIs in multiple regression function, herein referred to as extended MVI models. In this approach, each MVI was firstly combined with all 4 visible spectral bands (blue, green, red and near infrared) into a SMLR model. In each successive step, spectral band(s) that did not significantly interact with the MVI to predict measured herbaceous AGB was removed. The procedure was repeated with relevant spectral bands until a satisfactory multilinear regression function was obtained or forward stepping was no longer possible.

3.2.3.2 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-Studio programming language, version 3.4.1. 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 production and n is the sample size.

3.3 Results

Prior to data analysis, descriptive statistics of the measured herbaceous AGB were estimated. Average herbaceous AGB was 0.324 kgm^{-2} and ranged from 0.134 to 0.753 kgm^{-2} (Table 3.2). 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 3.3. 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 3.2 (a) - (c) and 2.3 (a)), explaining a maximum biomass variance of 0. 64 at the highest accuracy (RMSE range between 0.089 and 0.094 kgm^{-2}). Atmospheric-corrected MVIs ranked second in accurately predicting herbaceous AGB with a coefficient of determination value between 0.55 and 0.58 (Figure 3.4 (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 3.3 (a) – (c)) with an r^2 value ranging between 0.004 and 0.21 and very sensitive compared to ratio-based MVIs (RMSE varied from 0.132 to 0.148 kgm^{-2}).

Table 3. 2: Descriptive statistics of herbaceous aboveground biomass measured

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

AGB, aboveground biomass; †CV, coefficient of variation.

Table 3. 3: Performance of classical and extended MVI models for herbaceous AGB estimation (n=31)

VIs	**Remote sensing variables**	**Regression model**	**r^2**	**Adj r^2**	**RMSE (kgm^{-2})**	**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

MVIs, multispectral vegetation indices; AGB, herbaceous aboveground 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.

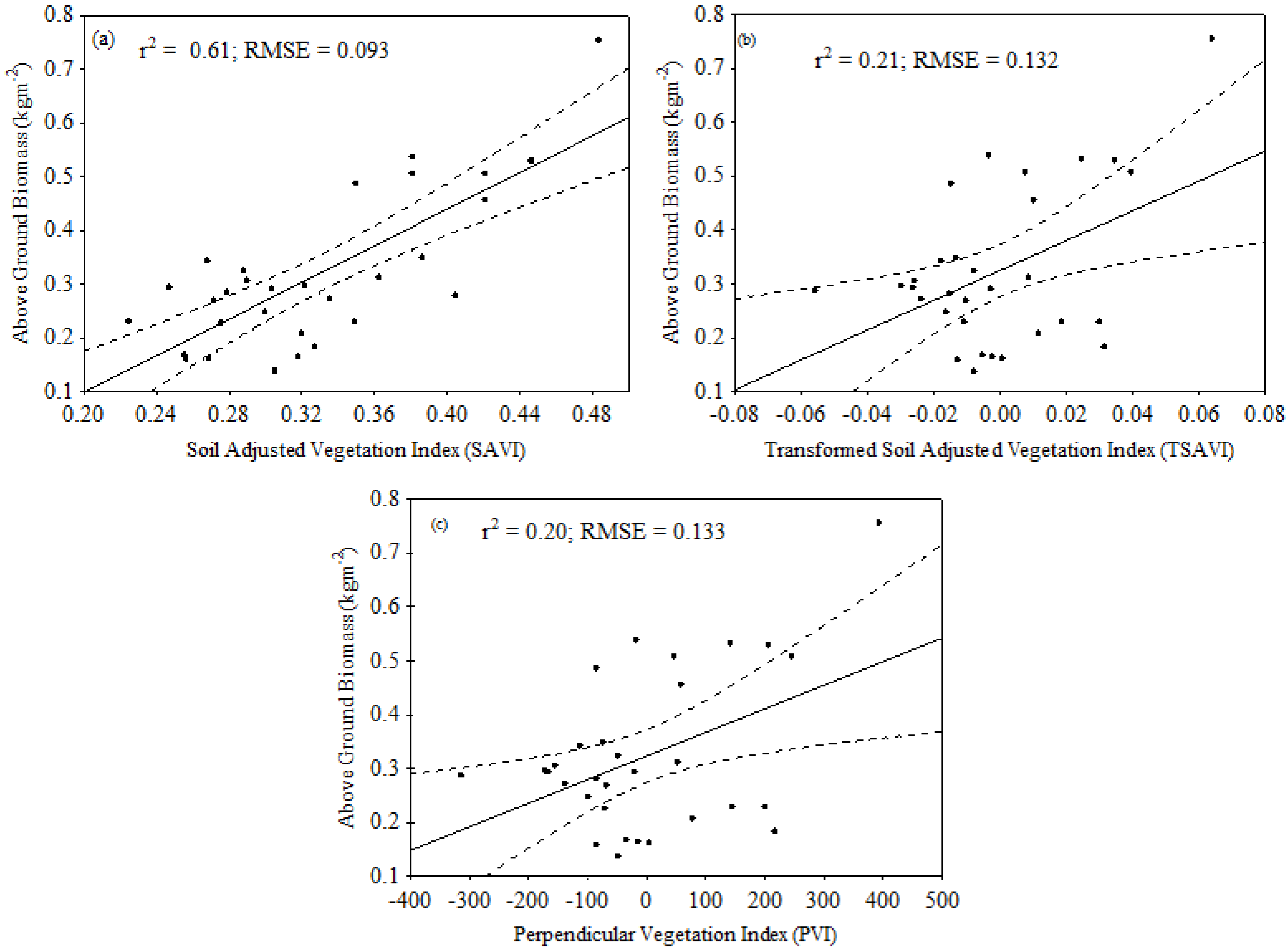

Figure 3. 2: Performance of ratio-based vegetation indices; (a) SR, (b) NDVI (c) TVI in predicting aboveground biomass (AGB) production.

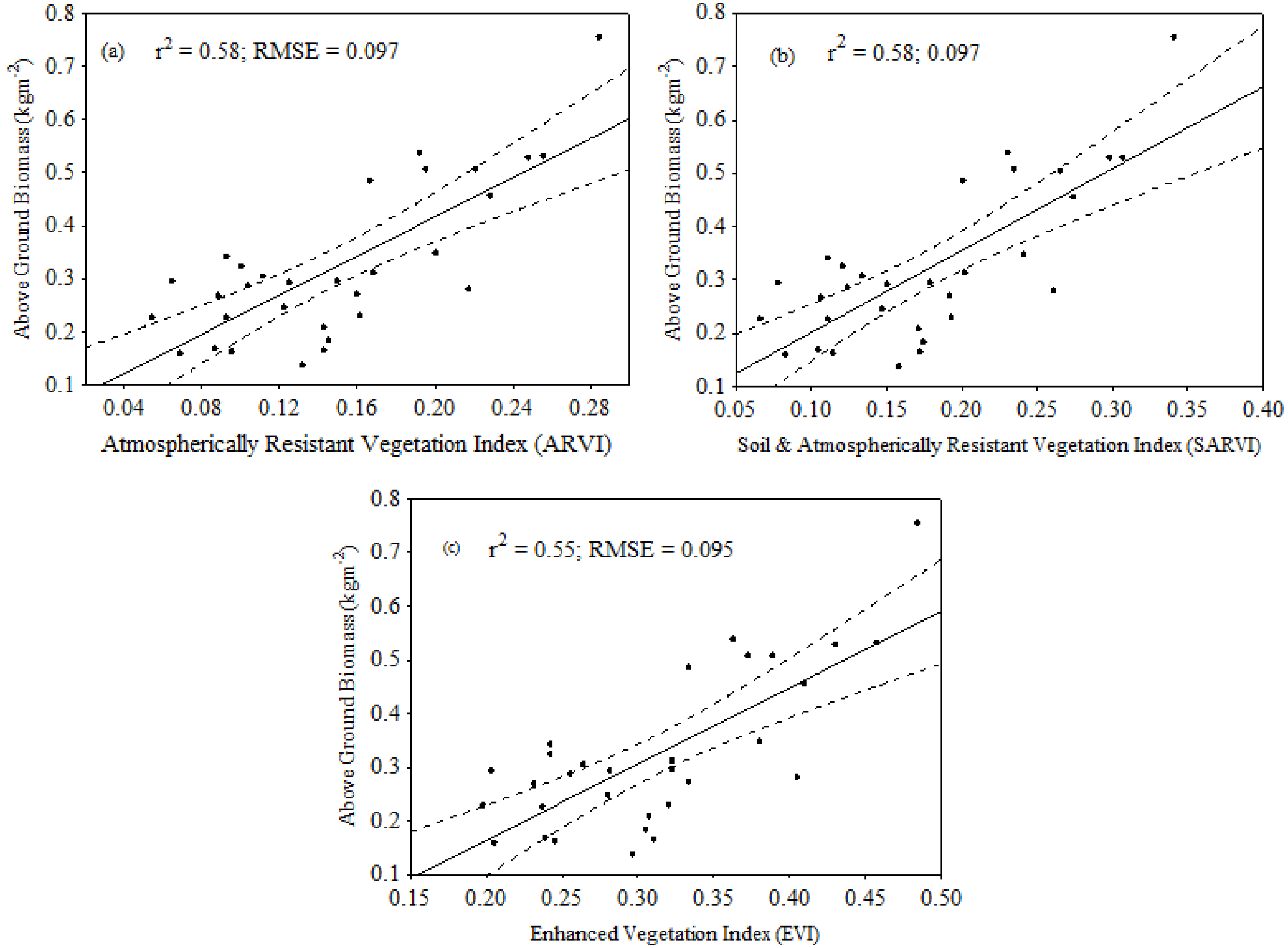

Figure 3. 3: Performance of soil-adjusted vegetation indices; (a) SAVI, (b) TSAVI and (c) PVI.

After forward SMLR, combining classical MVIs with other visible spectral bands improved herbaceous AGB estimation accuracy with an r^2 ranging from 0.55 to 0.71 for the extended EVI and SR models, respectively (Table 3.3). The general decrease in the RMSE of the extended regression models also portray improved accuracy for herbaceous AGB. 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 extended SR model, the MVI remained the most appropriate variable that combines with bands 3, 4 and 5 when estimating herbaceous AGB in the study area ($p = 0.03$) (Figure 3.5 (a) – (c)). The extended regression model of TSAVI and other visible spectral bands was appropriate for bands 2, 3, and 4 ($p = 0.00$) whilst PVI significantly combined with bands 2 and 4 ($p = 0.00$). The rest of the extended models of classical MVIs, NDVI, TVI, SAVI, ARVI and SARVI significantly combined with the Landsat 8 OLI green band (band 3) ($p < 0.05$) and their predictive performance improved by at least 3 % (Figure 6 (a) – (d) and 7 (a) and (b)).Although extending TSAVI and PVI regression models by combining with other visible spectral bands portrayed plausible predictions of herbaceous AGB, these extended MVIs estimated herbaceous AGB with the same accuracy as extended ratio-based MVIs. In particular, the extended NDVI regression model had an RMSE of 0.091 kgm^{-2} whilst the extended ARVI model had an RMSE of 0.093 kgm^{-2}. Based on these findings, the following SMLR predictive model that yielded the highest r^2 and lowest RMSE was chosen to produce an herbaceous AGB map for the Nuanetsi ranch (Figure 3.8) and for validation:

$$\mathrm{AGB}\ (\mathrm{kgDMm^{-2}}) = 1.267985 \times \mathrm{SR} + 0.00120 \times \mathrm{R} - 0.00045 \times \mathrm{G} - 0.00061 \times \mathrm{NIR} - 1.70743$$

Where; AGB is herbaceous aboveground biomass; SR is simple ratio; R, G and NIR are red green and near infra-red bands, respectively.

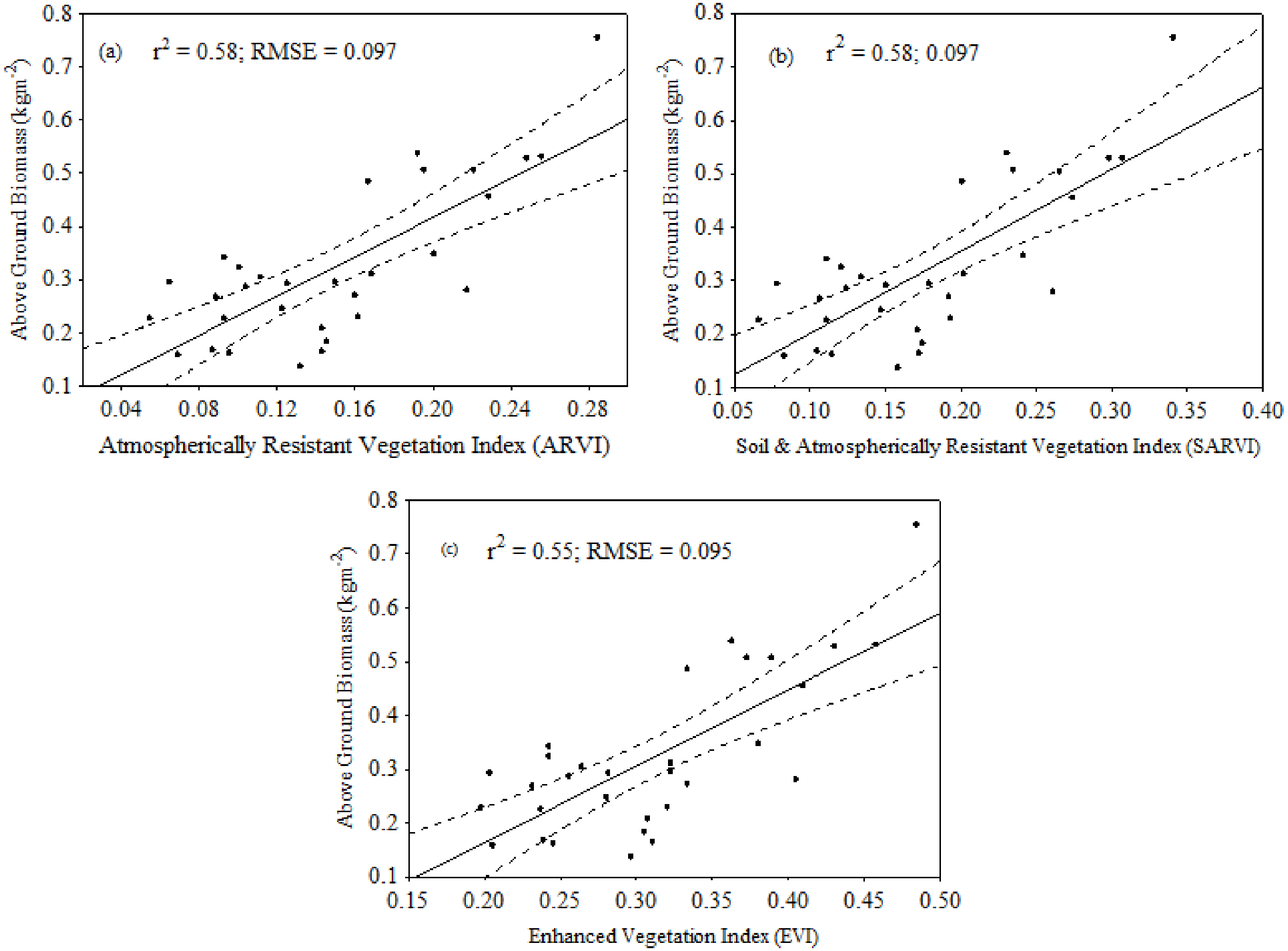

Figure 3. 4: Performance of atmospherically corrected vegetation indices (a) ARVI, (b) SARVI and(c) EVI in predicting aboveground biomass (AGB) production.

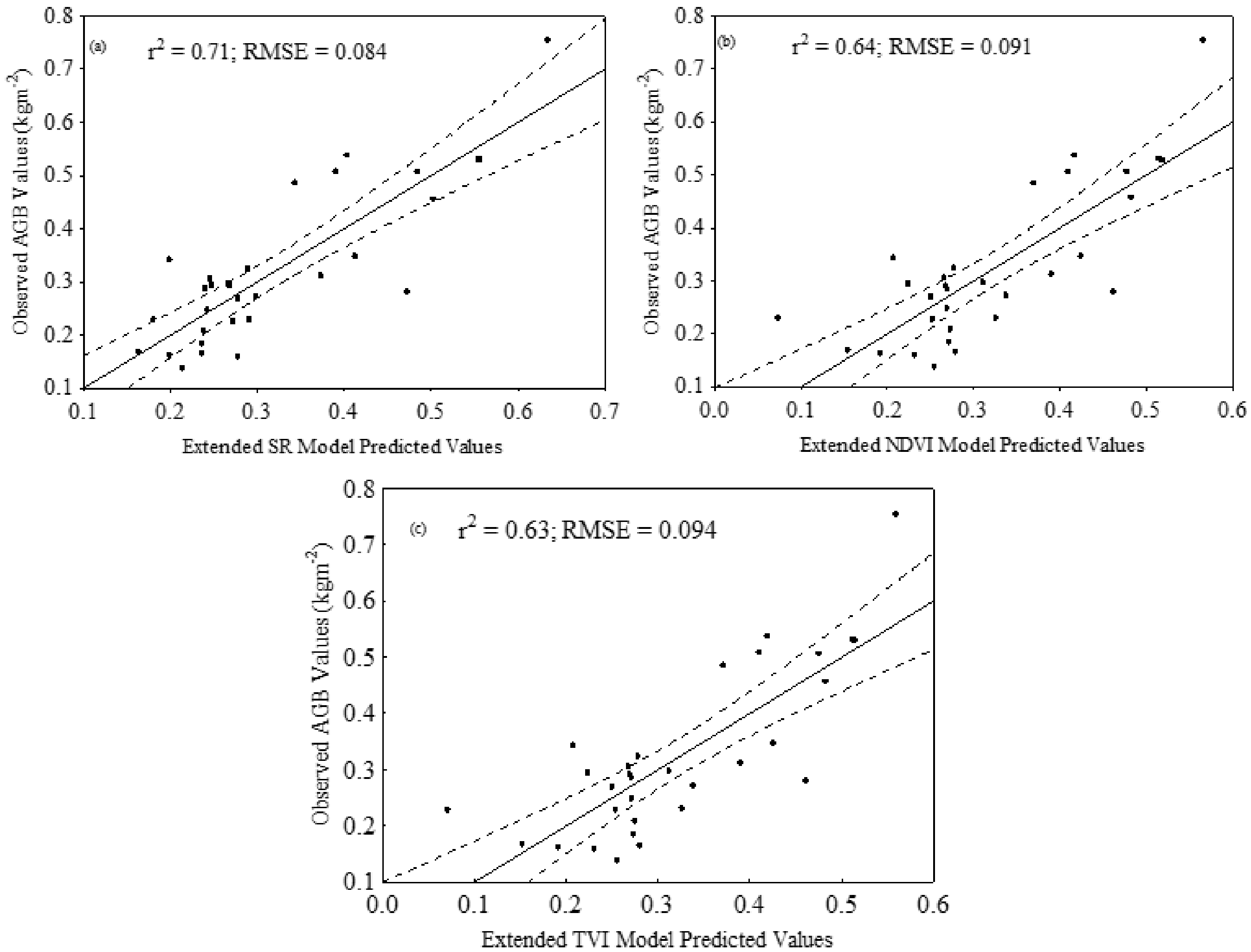

Figure 3. 5: Comparison of measured values of aboveground biomass (AGB) and extended ratio-based MVI model predicted AGB values for (a) SR, (b) NDVI and (c) TVI.

3.4 Discussion

The observed 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 considered to have generated realistic herbaceous AGB data that could build realistic relationships with MVIs and visible spectral bands. The findings of ratio based MVIs outperforming soil adjusted and atmospheric corrected MVIs when singly regressed with measured herbaceous AGB in chromic luvisols soils of *C. mopane* savannas of southern African ($r^2 = 0.64$) concur with some previous studies done in other biomes. According to Ren and Feng (2014) soil adjusted MVIs did not improve green AGB estimation over ratio-based MVIs in semi-arid rangelands. Gara et al. (2016) made a similar observation for woody biomass in *C. mopane savanna*. A work based on HVIs 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 plausible performance of ratio-based MVIs relative to other MVIs tested could be due to high model stability as indicated by their low RMSEs and others have already shown a good relationship between MVIs and LAI in similar savannas of South Africa (Masemola et al, 2016).

The soil adjusted MVIs poorly predicted herbaceous AGB, only SAVI had a similar accuracy as ratio based MVIs ($r^2 = 0.61$, $p < 0.05$). The inclusion of a soil line in the derivation of TSAVI and PVI could have greatly reduced their utility in predicting herbaceous AGB (Ren and 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 and 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) and (Ringrose et al. (1989) in southern African savanna rangelands and Todd et al. (1998) in short grass steppe ecosystem or *in situ* (Huete and Jackson, 1987). This could also explain the dominance of ratio-based MVIs over soil adjusted MVIs as described by Todd and Hoffer (1998) and the failure of MSAVI to account for any variation in herbaceous AGB at the study site ($p > 0.05$). 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.

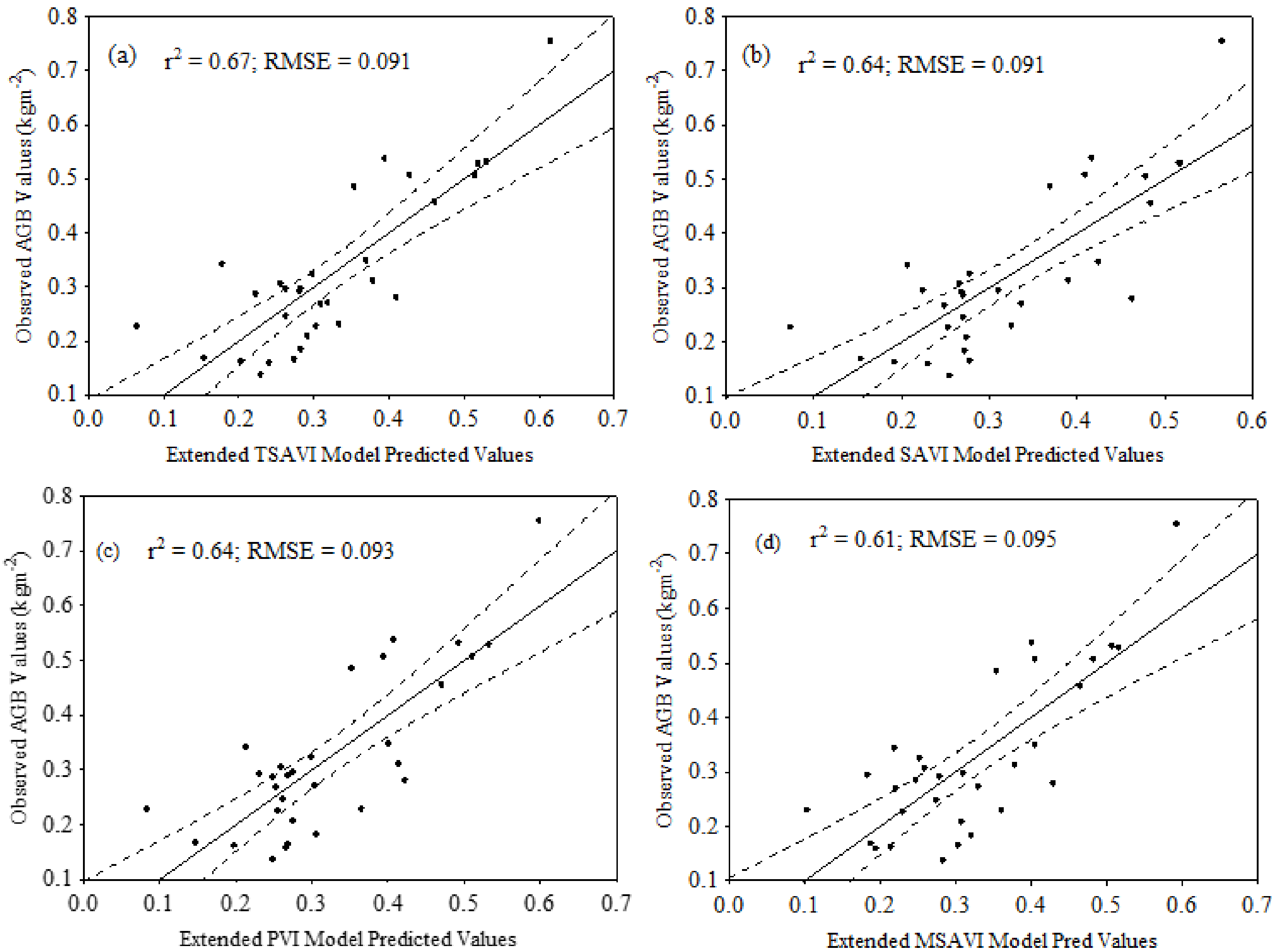

Figure 3. 6: Comparison of measured values of aboveground biomass (AGB) and extended soil adjusted MVI model predicted AGB values for (a) TSAVI, (b) SAVI, (c) PVI and (d) MSAVI.

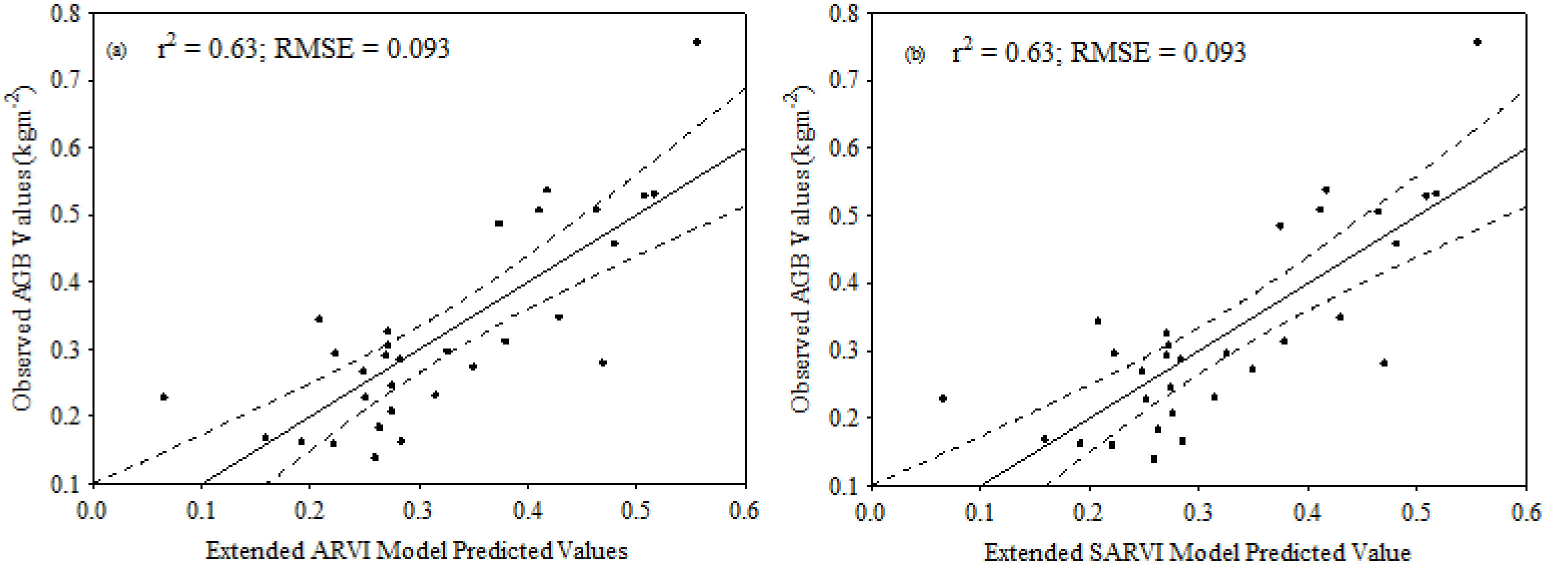

Figure 3. 7: Comparison of measured values of aboveground biomass (AGB) and extended atmospheric corrected MVI model predicted AGB values for (a) ARVI (b) SARVI.

The observed good accuracy of herbaceous AGB estimation yielded by atmospheric corrected MVIs (ARVI-RMSE of 0.097 kgm^{-2}) that was comparable to ratio-based MVIs (TVI-RMSE of 0.094 kgm^{-2}) indicates high model stability and good relationship with grass biophysical parameters. 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. However, it was expected that atmospheric corrected MVIs could give relatively higher accuracies than ratio- based MVIs because atmospheric corrected MVIs are adjusted for background soil reflectance in their formula. The good accuracy of atmospheric corrected MVIs that was far much better than soil adjusted MVIs was anticipated as observed for highveld grasslands of south central Africa (Masemola et al, 2016). 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.

Combining other visible spectral bands with classical MVIs improved the capacity of extended regression models for predicting observed herbaceous AGB as planned and observed in other studies (Fourty and Baret, 1997). Extended soil adjusted MVIs, PVI and TSAVI and the extended SR regression function accounted for 44, 46 and 7 % more of the variability in measured herbaceous AGB respectively through their combinations with bands 2, 3, 4 and 5. Using Landsat 7 TM, Kraus and 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 classical MVIs (NDVI, TVI, SAVI, ARVI and SARVI) significantly combined with the green band (Landsat 8 OLI band 3) ($p < 0.05$) and improved the predictive performance of the extended models by at least 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 and Guyot, 1991; Bannari et al, 1995). The green band therefore improved the accuracy of extended ratio-based regression functions as the ratio MVIs have been shown to increase their utility in dark coloured, low reflecting soils (Huete and Jackson, 1987).

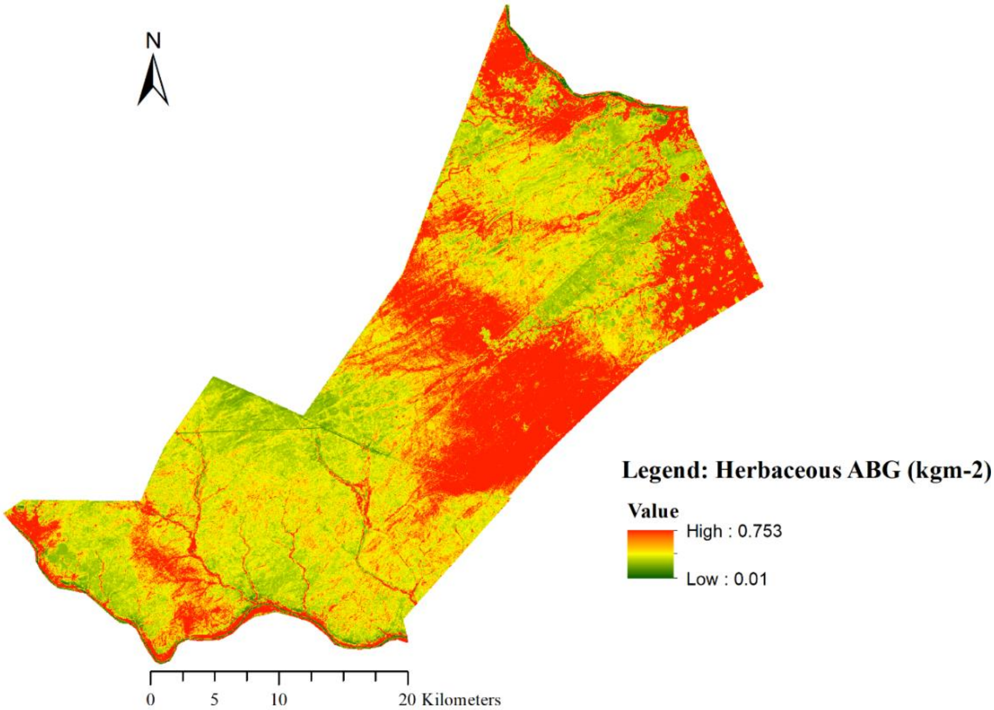

Figure 3. 8: Herbaceous aboveground biomass (AGB) map for Nuanetsi ranch.

The improvement in accuracy of classical MVIs extended with the Landsat 8 green band 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 and Kraus (2004) found high correlation coefficients between NDVI and Landsat TM spectral bands red (band 3) and green (band 4) whilst Calvão and Palmeirim (2004) found similar relationships in the Mediterranean scrub. In this study, the combination of 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 extended ratio-based MVIs and atmospheric corrected MVIs (ARVI and SARVI). High r^2 values above 0.71 for various combinations of Landsat ETM+ optical bands have been observed in southern Africa by Kraus and Samimi (2002). In the current study the mismatch between image acquisition date and time for field measurement of AGB could have affected the accuracy of derived regression models.

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. 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. To get more accurate values for r^2 between measured herbaceous AGB and vegetation reflectance, satellite images should be collected at the closest time before ground measurements are done. In addition, the number of sampling plots can be increased whilst the number of quadrats can also be increased, or quadrat size can be enlarged to enhance accuracy of herbaceous AGB estimation. It would be more useful to apply these models to other range sites that portray diverse soil types and herbaceous vegetation cover in southern African savannas to determine their consistency and further improvements.

3.5 Conclusions

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 multi linear 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. Extended soil adjusted MVIs showed the greatest increase in coefficient of determination after SMLR though the relationships were not as accurate as atmospherically corrected and ratio based MVIs. Inclusion of the Landsat 8 OLI green band in most MVIs that were evaluated for extended regression models significantly improved their performance for herbaceous AGB prediction. The findings demonstrate that the combination of classical MVIs and other Landsat 8 optical spectral bands, especial the green band provides the best models for estimating AGB in *C. mopane* savanna rangelands. The extended SR model that yielded the highest r^2 and lowest RMSE is recommended for farmers when estimating herbaceous AGB in similar southern African savannas. It is suggested that other MVIs not tested in this study and HVIs should be evaluated to enhance our understanding about their accuracies for herbaceous AGB prediction in *C. mopane* rangelands in this biome.

CHAPTER 4

Response of remotely sensed herbaceous aboveground biomass to rainfall variability and droughts in a south-central African savanna

Abstract

Herbaceous aboveground biomass (AGB) production in semi-arid regions is highly sensitive to erratic seasonal rainfall and frequent droughts. Adaptive management of cattle at broad scale is often difficult due to unavailability of site-specific, long-term data for monitoring rainfall variation and subsequent herbaceous AGB production. This study examined the response of spatial and temporal variation of AGB production within and across herbaceous communities to rainfall variability and drought intensity using AGB derived from peak-season Landsat images available between 1992 and 2017. Rainfall variability was evaluated using coefficient of variation (CV) while the frequency and intensity of droughts were assessed using a 6-month standardised precipitation index (6SPI) for November to April. Standardised anomalies of herbaceous AGB yields were derived to detect deviations from normal conditions. The CV of total wet season rainfall was high, varying between 33 and 40 %. Different drought intensities occurred concurrently in dry years. Spatial heterogeneity of AGB production across herbaceous communities were high and deviated from mean AGB by 51 to 69 %. The spatial pattern of herbaceous AGB production was highly sensitive to seasonal rainfall distribution, particularly in dry years when different drought intensities occur concurrently. Temporal variability of AGB production within herbaceous communities fluctuated by 18 to 35 % more than rainfall. However, the landscape-level temporal variation of AGB production remained stable despite the increase of drought incidences experienced in the region in the last fifty years. This highlights the need by range managers to put more management emphasis towards maintaining or enhancing inherent unevenness within local herbaceous communities to increase the stability of rangeland productivity and, to adapt to anticipated climatic changes. The study demonstrates a workflow for estimating and visualising the spatio-temporal variation in AGB that can be effectively generalised for other ranches in the regions to improve management planning.

Key words: satellite, drought, herbage, monitoring, variability.

4.1 Introduction

Semi-arid rangelands are ecologically and economically important in southern Africa as they occupy 40.2 % of total land covered by savannas (Rutherford et al., 2006) and support livestock and wildlife ranching. These rangelands have evolved from broad-scale, long term changes in climate particularly rainfall variability and localised, short term disturbance events such as drought, grazing and fire (Hempson et al., 2007; Mberego et al., 2013). The abiotic and biotic factors have interacted over time to create complexity in the system at a high degree of spatial and temporal variation in plant community production (Scoones, 1995). Such large and complex rangeland systems are associated with inherent heterogeneity that provides these systems with some internal properties which enhance their stability to environmental variation (Fynn, 2012). However, rangeland management has long relied on experimental knowledge derived from fine-scale observations (Teague et al., 2013), and sought to override the inherent heterogeneity across multiple scales and behaviour of disturbances (Fuhlendorf et al., 2017). With the anticipated increases in rainfall variability and drought frequency, understanding the landscape-scale relationships between spatial and temporal variation in aboveground biomass (AGB) would enhance our ability to predict the productivity changes in herbaceous communities due to climatic changes.

Recent advances in landscape ecology concept stipulate that, high spatial variability across local communities is naturally associated with greater temporal stability at landscape level, whereas variability within local communities is related to lower temporal stability (McGranahan et al., 2016). The robustness of these relationships in the herbaceous layer has long been demonstrated for community composition and biodiversity attributes as drivers of ecosystem functioning and stability in pyric herbivory in livestock systems in mesic- (Wang and Loreau, 2014) and in wildlife systems in dry rangelands (Coller and Siebert, 2015; Kennedy et al., 2003). But in dry rangelands of southern Africa where grazing is driven by droughts, herbaceous community production dynamics are mostly influenced by inter-annual rainfall variation (Buitenwerf et al., 2011) and, drought influences the spatio-temporal heterogeneity of community composition and production (Connor, 2015; Vetter, 2009). Lack of ecological data at appropriate spatial and time scales has limited our ability to analyse these multiscale relationships in herbaceous community production and its response to drought disturbances.

Remote sensing tools have long provided spatially, and temporally consistent information required for monitoring community heterogeneity and drought disturbances in rangelands. Most of these assessments used low spatial resolution satellites (Brown, 2008) at regional (Chamaillé-Jammes and Fritz, 2009; Wessels et al., 2006) and continental scales (Winkler et al., 2017). However, low resolution satellites do not provide spatially explicit representations of AGB among herbaceous communities in savanna rangelands due to high plant diversity at local scale. More so, the spatial coverage of many grazing lands in southern Africa is too small to allow application of low spatial resolution satellite products for effective decision-making. This highlight the need for embracing new-generation, medium spatial resolution imagery which enable spatially explicit assessments of herbaceous community heterogeneity and behaviour of short-term disturbances in rangelands.

Medium spatial resolution remote sensing products have the potential to provide detailed spatial representation of AGB production at multiple scales and at timescales sufficient for long term assessment of heterogeneity in herbaceous communities. For example, Sentinel imagery has demonstrated the intra-seasonal spatial and temporal variability of herbaceous AGB in tropical southern Africa (Shoko et al., 2019). Given the increase in frequency and intensity of dry conditions and decrease in wet years that occurred after the global climate shifted in the 1970s (Gaughan et al., 2016), the interannual variation of herbaceous AGB production might have shifted too. Such climatic changes prompt the need for developing a context-specific methodological framework for assessing the temporal response of herbaceous community production to drought disturbances to inform management planning.

In this study, we used peak-season Landsat images and satellite-based rainfall estimates to develop and validate a statistical model for estimating herbaceous AGB and, used the model to analyse the spatial and temporal variability in AGB production across herbaceous communities at landscape level. A six-month standardised precipitation index for drought was used in a convergence-of-evidence approach with standardised anomalies of herbaceous AGB production to detect deviations from normal conditions. This workflow could be used to enhance our understanding of herbaceous community stability under local drought disturbances. This understanding can help in predicting the effects of projected climatic changes on the spatial and temporal patterns of AGB production across herbaceous communities (Fuhlendorf et al., 2017).

4.1.1 Objectives

This study aimed to:

- characterise rainfall variability and drought intensity and frequency at ranch-scale to inform opportunistic management decision-making
- develop and use a remote sensing model for predicting the response of herbaceous AGB to rainfall variability and droughts between 1992 and 2017.

4.2 Materials and methods

4.2.1 Ecological features of Nuanetsi cattle ranch

Nuanetsi Cattle Ranch is located on a low altitude (480 m.a.s.l), undulating plane semi-arid region in the south of Zimbabwe and covers 1139.13 km^2 of land. The climate is warm, with strongly seasonal wet summers and long cool dry winters. The rainfall pattern is sharply unimodal and most of the rain occurs between November and March, often as high intensity storms of short duration that are unevenly distributed. The long term mean annual rainfall (40-year mean) is 462 mm with an interannual coefficient of variation of 35 % (Oxfam-UNDP/GEF 2015), with the late summer (January to March) contributing 40 % of the annual rainfall. Wet season rainfall is strongly affected by El Nino and La Nina phenomena (Makarau and Jury, 1997). Maximum daily temperature in summer are frequently above 32 °C while mean annual temperature is 25 °C (Mason, 2001). The length of growing period ranges between 90 and 120 days.

The soils are formed from gneiss and granite geological formations (Farrell, 1968). At landscape scale, the vegetation is dominated by moderately tall *C. mopane* tree stands in nutrient-rich, mafic-gneiss derived soils that are predominant at the study area. These soils tend to support a medium substratum of productive, palatable perennial suit of tufted grasses, particularly *Urochloa mosambicensis* and *Panicum maximum* that are sensitive to grazing. Some patches of nutrient-poor, heavily utilized areas comprising of sparse tree-shrub layer of *Combretum* and *Grewia* spp. that are associated with short substrata of wiry, unpalatable grass species such as *Eragrotis spp.* and *Aristida* spp. (Farrell, 1968), are visible at broad scale. annual grass species and forbs are commonly found (Taylor and Walker, 1978). At community level, the 250-metre resolution land cover map of the Food and Agricultural Organisation (FAO)'s land cover classification system (LCCS) show up to eight vegetation types, which vary from closed- tree/shrubland to open herbaceous vegetation are identified across Nuanetsi ranch (Figure 3.1). As in other semi-arid savannas of southern Africa, forbs contributed a small proportion of the herbaceous vegetation across all communities. Extensive commercial cattle ranching has been the main land use since early 1900s (Walker et al., 1981). Within each vegetation type, beef cattle are stocked throughout the year at moderate stocking rates in multi-paddock grazing systems. Each management unit comprised of 2- to 5- paddocks per herd, with paddocks ranging from 300 to 1500 hectares.

4.2.2 Land cover assessment

A vegetation survey was conducted between 3 and 18 February 2017 to collect data for performing a satellite-based land cover classification scheme. Seventeen and forty ground control points (GCPs) for woody and herbaceous vegetation, respectively were identified in separate 30 x 30 m plots that were selected across the eight vegetation types found at Nuanetsi ranch. The vegetation types were delineated by overlaying the FAO's LCCS map with a spatial resolution of 250 m (Di Gregorio et al., 2016) on the ranch map (see Figure 3.1). The major and minor horizontal axes of the canopy of all woody species identified in the sampled plots were measured and used to estimate canopy cover of each woody species using the formula of Smith and Walker (1983). The GCPs for herbaceous vegetation were determined in 30 m x 30 m plots of pure grassland that were surveyed by Svinurai et al. (2018).

To select images suitable for classifying vegetation cover components, two assumptions usually accepted in studying land surface phenology in southern African savannas were considered. Firstly, given no major change in land use, the proportion of tree cover that is measured as maximum tree greenness is constant between years and the grass layer causes most variation in greenness (Scanlon et al., 2002). Secondly, tree green-up rates are constant and longer but grasses have a higher landscape-leaf area index (LAI) than trees at the peak of the season (Archibald and Scholes, 2007). Following these assumptions, cloud-free, 30 m spatial resolution Landsat images of 1993, 1999, 2006, 2013 and 2017 were selected in April or May for classifying land cover components. These months were considered the best time for herbaceous AGB analysis since maximum leaf green up for herbaceous cover occurs 4 to 5 months into the growing season (Archibald and Scholes 2007) and has the best contrast between tree and herbage cover.

The images were processed by the United States Geological Survey (USGS) data management unit and downloaded from Earth Explorer. Landsat thematic mapper 5 (TM) sensor (1992-1998) images were atmospherically corrected using Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) in ENVI software. Landsat 5 thematic mapper (TM), Landsat 7 enhanced TM plus (ETM+) and Landsat 8 Operational Land Imager (OLI) images were corrected for surface reflectance by the USGS prior to download. A supervised classification approach was used to train and classify the five selected images to delineate land surface cover into three classes namely, woody (tree and shrub), herbaceous (grass and forb) and bare ground using the approach of Eastman (2003). Firstly, training and validation data sets were determined using random polygon files generated in the Landsat 8 image of May 2017 and overlaid as KML files on Google Earth images using a method described by Ludwig et al. (2016). The spectral characteristics of each cover class were then acquired from GCPs and high spatial resolution (2.5m) SPOT images embedded in Google Earth domain to train a classification algorithm. Using the training data sets, maximum likelihood classifier (MLC) was used to classify land cover into woody, herbaceous and bare ground in the three RGB layers of raster image file.

The other four historical Landsat images were then separately classified using the image differencing technique (Eastman, 2003) based on training sites defined above. Each band in each polygon was subtracted from the respective band in the 2017 image at a threshold value of ±1 around the mean to ascertain that only polygons that have not undergone changes between 1993 and 2017 were retained for classification. Using validation data sets, classification accuracy for land cover map for each year was assessed using the kappa statistic. An example of the classified image is shown in Fig.4.1. The woody cover layer from the five maps was masked out to constrain AGB prediction to herbaceous vegetation areas.

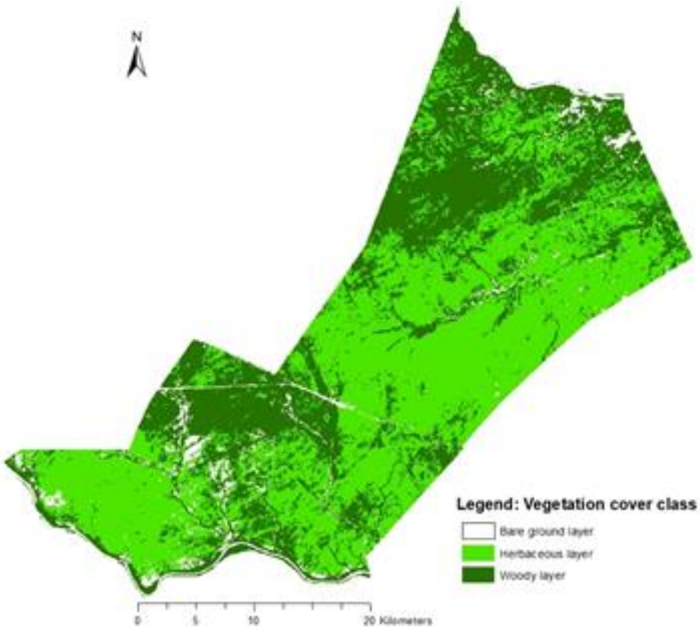

Figure 4. 1: Land cover class map of Nuanetsi ranch (09 May 2017)

4.2.3 Rainfall data

Daily rainfall (mm) is the climate variable that was used for predicting remotely sensed herbaceous AGB. An open access RFE database, the NOAA- CPC -ARC2 (Novella and Thiaw, 2013) was chosen for its utilities that enabled the aim of the study to be achieved. The dataset provides a long-time series of daily rainfall (1983 to present) at a spatial resolution of 0.01° (~10 km), suitable for analysis of rainfall and herbaceous AGB production at local level. This data is built by the NOAA CPC from quality-controlled Global Telecommunication System (GTS) rain gauge data and thermal infra-red derived rainfall estimates available for Africa and Europe from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT). The data was downloaded in geotiff file format from the NOAA CPC servers and processed using ArcGIS to produce area-weighted averages of grid-cell rainfall data over Nuanetsi ranch. Only pixels with 30 % or more area lying within the study area were used in the analysis. To test accuracy of the RFE data prior to use, the data compared with gauge data from Mwenezi District Agritex (MDA) office located 10 km southwest of Nuanetsi ranch. The CPC-ARC2 rainfall underestimated total wet season rainfall for MDA by between 11 and 21 % (47 to 91 mm) across grid-cells (see Figure 4.2). These findings prompted the need to correct the drier RFEs for the local conditions.

A spatio-temporal bias correction scheme was applied to the ARC2 rainfall data using daily gauge data for MDA for the 1988 to 2017 period. This is a linear-based scheme that corrects bias for individual rain gauge stations by calculating the bias correction factor for a given day. Bias correction factor is only calculated for a given day if a minimum of 5 rainy days occurred within the preceding ten-day period that received a minimum rainfall accumulation depth of 5 mm. Final estimates are obtained by multiplying daily RFEs by the bias correction factor of the corresponding 10-day period. The linear-based bias correction scheme was chosen since it is effective in reducing daily mean RFE bias in semi-arid regions of Zimbabwe (Gumindoga et al., 2016). After bias-correction, the rainfall data preserved an increasing trend in the raw NOAA- CPC -ARC2 rainfall data over the 26 year period and was considered suitable for predicting herbaceous AGB.

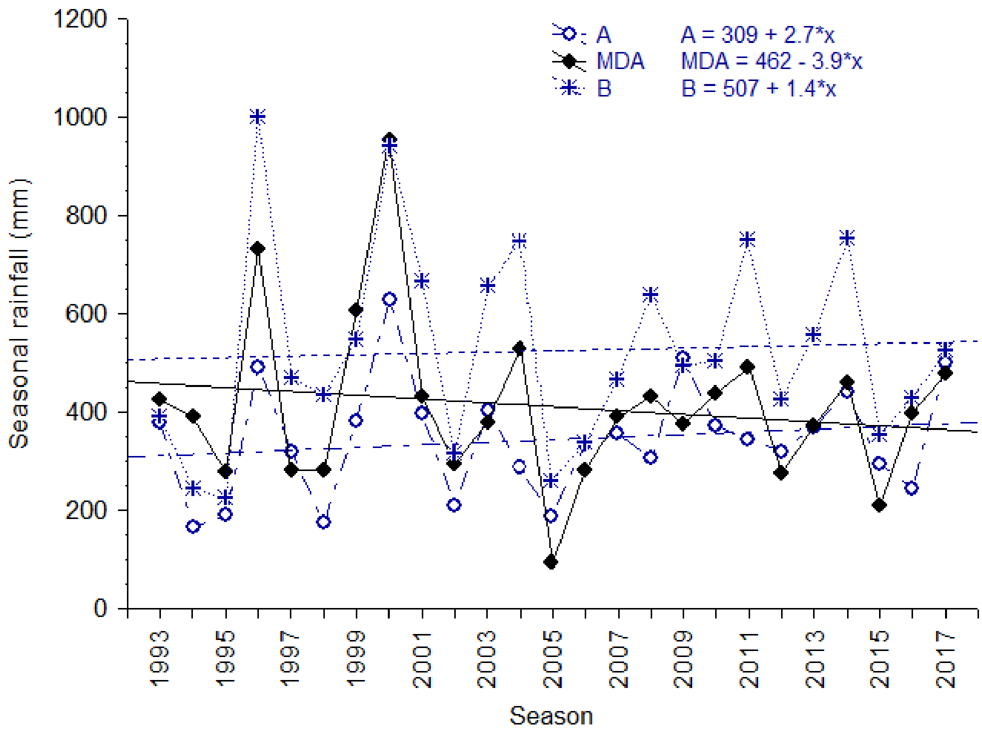

Figure 4. 2: Seasonal rainfall measured at MDA station and estimated by the CPC-ARC2 rainfall on a grid cell before (A) and after (B) bias correction.

4.2.4 Modelling remotely sensed herbaceous aboveground biomass

A dataset of 19 cloud-free, Landsat images (path 169, row 075) available between April and May (91 and 151 days of year) 1992 to 2017 was processed and downloaded from USGS's Earth Explorer (Table 4.1). Landsat 5 TM images were processed using the procedure described in Section 4.2.2. Landsat 7 EMT+ images for the period after 2010 were intentionally removed from the processed dataset since they had scan-line errors (stripes). A multilinear regression model developed from a Landsat 8 image for Nuanetsi ranch in 2017 (Svinurai et al. 2018) was applied to all processed images in the Landsat time series to produce herbaceous AGB maps for the entire period. The herbaceous biomass derived from 30-m pixels of the grass layer were statistically resampled to ~10 km grid-cells to match the spatial resolution of ARC2 rainfall data. In south-central Africa, growing season ends in first week of April with a standard deviation 4 weeks (Mupangwa et al., 2011). This period coincides with peak grass growth prior to onset of grass senescence biomass and biomass estimates are least affected by dead plant material and possible grazing. Herbaceous AGB estimated from Landsat images for the April to May period were thus considered as the appropriate proxy for total end-of-season (EOS) herbaceous AGB and were used to construct rainfall-biomass relationships.

Table 4. 1: Landsat satellite images used in this study

Landsat imagery	Spectral bandwidth (μm)			Period	No. of images
	Green	Red	Near Infrared		
TM	0.520-0.600	0.630-0.690	0.760-0.900	April & May 1993 to 2005	7
ETM+	0.519-0.601	0.631-0.692	0.772-0.898	April & May 2006 to 2012	3
OLI	0.533-0.590	0.636-0.673	0.851-0.879	April & May 2013 to 2017	9

TM, thematic mapper; ETM+, enhanced TM plus; OLI, Operational Land Imager.

To develop the best model for predicting remotely sensed herbaceous AGB using wet season rainfall, two sets of models were separately derived for April and May. Multiyear EOS herbaceous AGB averages estimated in all grid cells for April and May image scenes were separately grouped and paired with corresponding total rainfall into single regression equations. The emphasis was to develop a relationship between the whole range of rainfall received at the study site and herbaceous AGB for each EOS month (April or May) over the years for which the images were available. During preliminary model fitting, a highly sensitive rainfall- herbaceous AGB relationship was observed for seasons that received 600 mm or more rainfall. To approximate this behaviour, linear, power and exponential regressions were fitted between rainfall and herbaceous biomass, if the data for these variables were normally distributed. The leave-out-one method was used to select the best rainfall-herbaceous AGB model based on precision and accuracy. The following exponential regression model for May produced the most precise ($r^2 = 0.81$) and accurate (RMSE, 1559 $kgha^{-1}$) fit.

$$AGB = 829.9e^{0.0037x} \quad \text{where:}$$

AGB is herbaceous aboveground biomass ($kgha^{-1}$) and, *x* is total wet season rainfall (mm) (Figure 4.3). The model's prediction error falls within the range of uncertainty for other herbaceous AGB models developed from multispectral vegetation indices in the broad-leaved savanna biome of southern Africa (Dwyer, 2011). Thus, the model was considered appropriate for assessing the response of herbaceous AGB to rainfall variation and drought intensity.

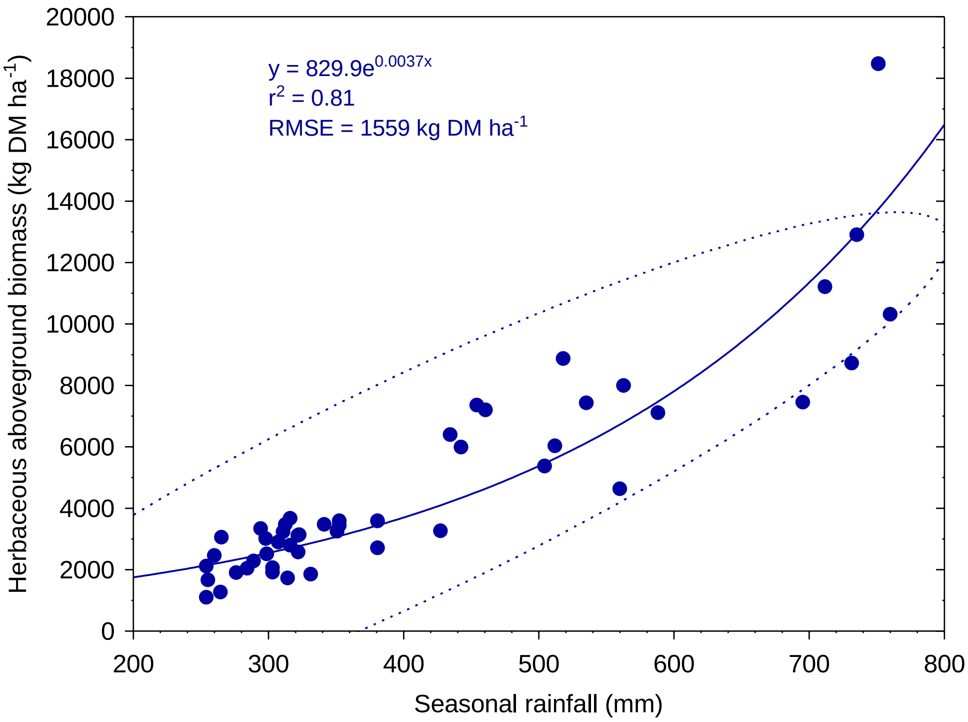

Figure 4. 3: Exponential regression for predicting remotely sensed herbaceous aboveground biomass using seasonal rainfall. Broken lines denote 95% confidence intervals for the fitted exponential regression model.

4.2.5. Data analyses

Daily rainfall data for 26 years (1992 to 2017) were used to analyse seasonal rainfall variation in all grid cells defined for Nuanetsi ranch in the CPC-ARC2 dataset. Seasonal mean and percentage coefficient of variation were examined for raw grid-cell rainfall and herbaceous AGB to characterise spatial and temporal variability. The standardised precipitation index (SPI) of Mckee et al. (1993) was used to analyse the frequency, intensity and spatial extent of drought events. The SPI is based on the normalised long-term probability distribution function of observed rainfall such that SPI values are considered as standard deviations from the climatological median (WMO, 2012). Though the time series should be 30 years minimum, SPI can still be calculated on 20 years' data (WMO and GWP, 2016). A 6-month, November to April, SPI (6SPI) for each grid cell was calculated for the period between 1992 and 2017 using FORTRAN software. Seasonal rainfall greater than median rainfall are indicated by positive SPI values whilst negative SPI values indicate less than median rainfall (Table 4.2). Drought starts when the SPI value is -1.0 or less and ends when the value becomes positive (WMO, 2012).

Response of herbaceous AGB to drought intensity was assessed by calculating the relative percent changes in EOS herbageproduction before and after the rainfall event. The relative increase in range of production between years was calculated from the lower values of the ranges since safe stocking rates for livestock are determined by the herbaceous biomass available in seasons of lowest production (Danckwerts et al., 1993). Only drought events where pre- and post-drought years received normal rainfall were considered in the analysis to avoid the confounding effects of herbaceous AGB in pre- and -post drought conditions. A graph of standard anomaly scores of EOS herbaceous AGB production was plotted for each grid cell to determine deviations of datum from median value. The median value represents the normal herbaceous AGB production while deviations above or below the median value mean that current season differs from 70 % of the previous seasons in the time series, assuming a normal distribution. The graph was drawn on the same x-axis with the graph for SPI to provide a robust analysis of rainfall and herbaceous AGB anomalies. If one of the variables shows an anomaly and the other one is close to normal conditions, anomalies in herbaceous AGB are considered unrelated to rainfall.

Table 4. 2: Classification of intensity and probability of occurrence of drought events

SPI value	**Drought intensity**	**Probability of occurrence, % (years)**
2 or more	Extremely wet	2.3 (1 in 50 yrs)
1.5 to 1.99	Severely wet	4.4 (1 in 20 yrs)
1.0 to 1.49	Moderately wet	9.2 (1 in 10 yrs)
0 to 0.99	Mildly wet	34.1 (1 in 3 yrs)
-0.99 to 0	Mild drought	34.1 (1 in 3 yrs)
-1.0 to -1.49	Moderate drought	9.2 (1 in 10 yrs)
-1.5 to -1.99	Severe drought	4.4 (1 in 20 yrs)
-2 or less	Extreme drought	2.3 (1 in 50 yrs)

4.3 Results

4.3.1 Spatial and temporal variability of rainfall and drought events.

Overall, rainfall varied widely in space and over time whilst the frequency of moderate and severe drought occurrence has increased. The mean, median, minimum and maximum total seasonal rainfall across grid cells were 528, 478, 207 and 1030 mm, respectively. The coefficient of variation of total wet season rainfall was very high, varying between 33 and 46 %. About half of the rainfall grid cells (7 of 12) had a CV between 33 and 35 % predominantly in the north-central areas whilst the other areas in southwestern region had CV between 36 and 40 % (Figure 4.4). The 6SPI values for the 26-year climate window differed both spatially and temporally as portrayed in Figure 4.5 Different drought intensities occurred concurrently in some dry years as indicated by the ranges of SPI values in Table 4.3. For example, one fifth of the grid cells experienced severely dry conditions during the extreme drought of 1992 while about a third of the study area experienced moderately dry conditions during the mild drought of 1998. These anomalies in spatial representation of drought intensity were pronounced in the southwestern areas of the ranch.

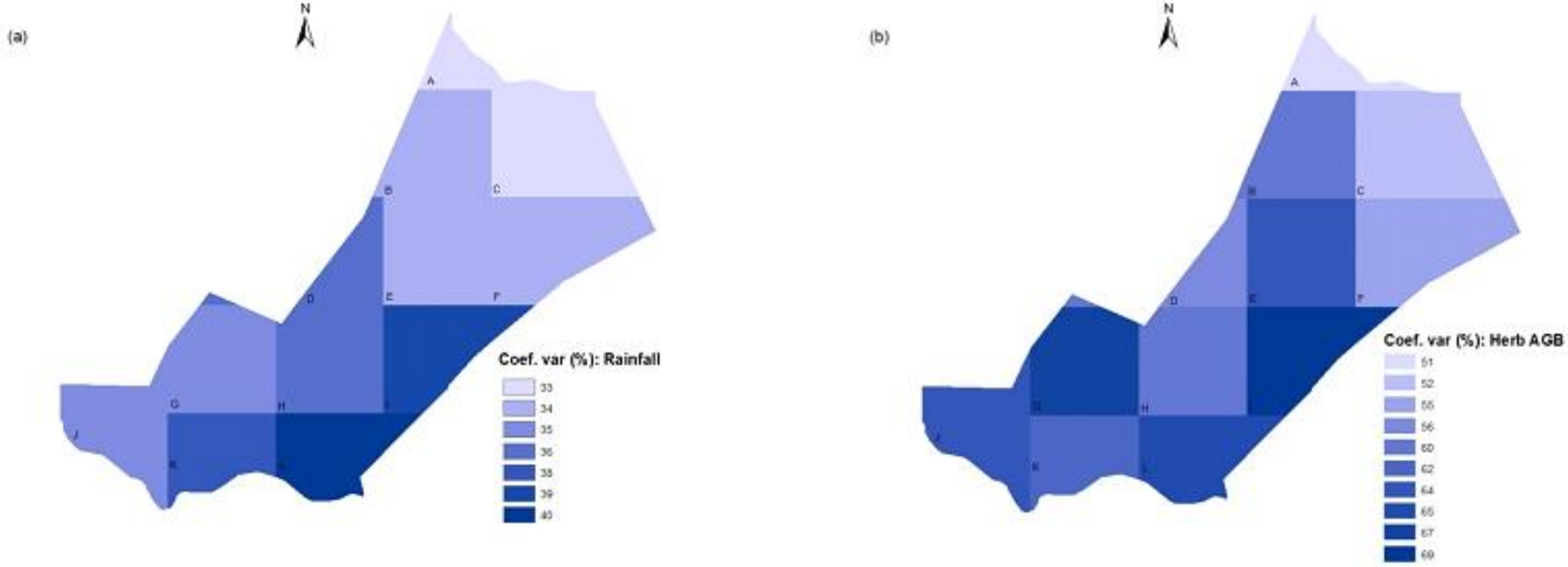

Figure 4. 4: Coefficients of variation of seasonal (a) rainfall and (b) herbaceous aboveground biomass (AGB) for the period 1992 to 2017.

4.3.2 Response of herbaceous biomass to rainfall variability and drought.

Total mean, minimum and maximum wet season herbaceous AGB ranged from 4350 to 5100, 1260 to 1700 and 9440 to 14450 kg DM ha^{-1} respectively across grid-cells. The median herbaceous AGB ranged between 3650 and 4890 kg DM ha^{-1}. Figure 4.5 illustrates the variability in herbaceous AGB for the study area estimated using Landsat 7 EM+ and Landsat 8 OLI images. Overall, the area produced noticeable variations in herbaceous AGB, both in space and over time. The highest accumulation in herbaceous AGB production across the ranch were observed between moderately dry and mildly wet seasons (Figure 4.6 (a) and (b)) whilst, low variations were observed between mildly dry and mildly wet seasons (Figure 4.6 (a) and (b)).

Seasonal herbaceous AGB production among grid cells was very unstable, having a very high, wide-range standard deviation (2300 to 3000 kg DM ha^{-1}) that varies by 51 to 69 % more than mean AGB. Herbaceous AGB changes across the study areas were variable and highly sensitive to seasonal rainfall variation. The south-western areas of the ranch experienced notable changes over time (e.g. grid cells bounded in red, Figure 4.6) whilst the north-central areas remained stable (e.g. grid cells bounded in black, Figure 4.6), despite the seasonal changes. Herbaceous AGB production was at least 18 % more variable than rainfall across grid cells. Grid cells that showed relatively low rainfall variability (< 35 % C.V.) were 18 to 21 % more variable in herbaceous AGB production, while grid cells that experienced relatively high rainfall variation (>35 % C.V.) experienced 28 to 35 % more variation in herbaceous AGB.

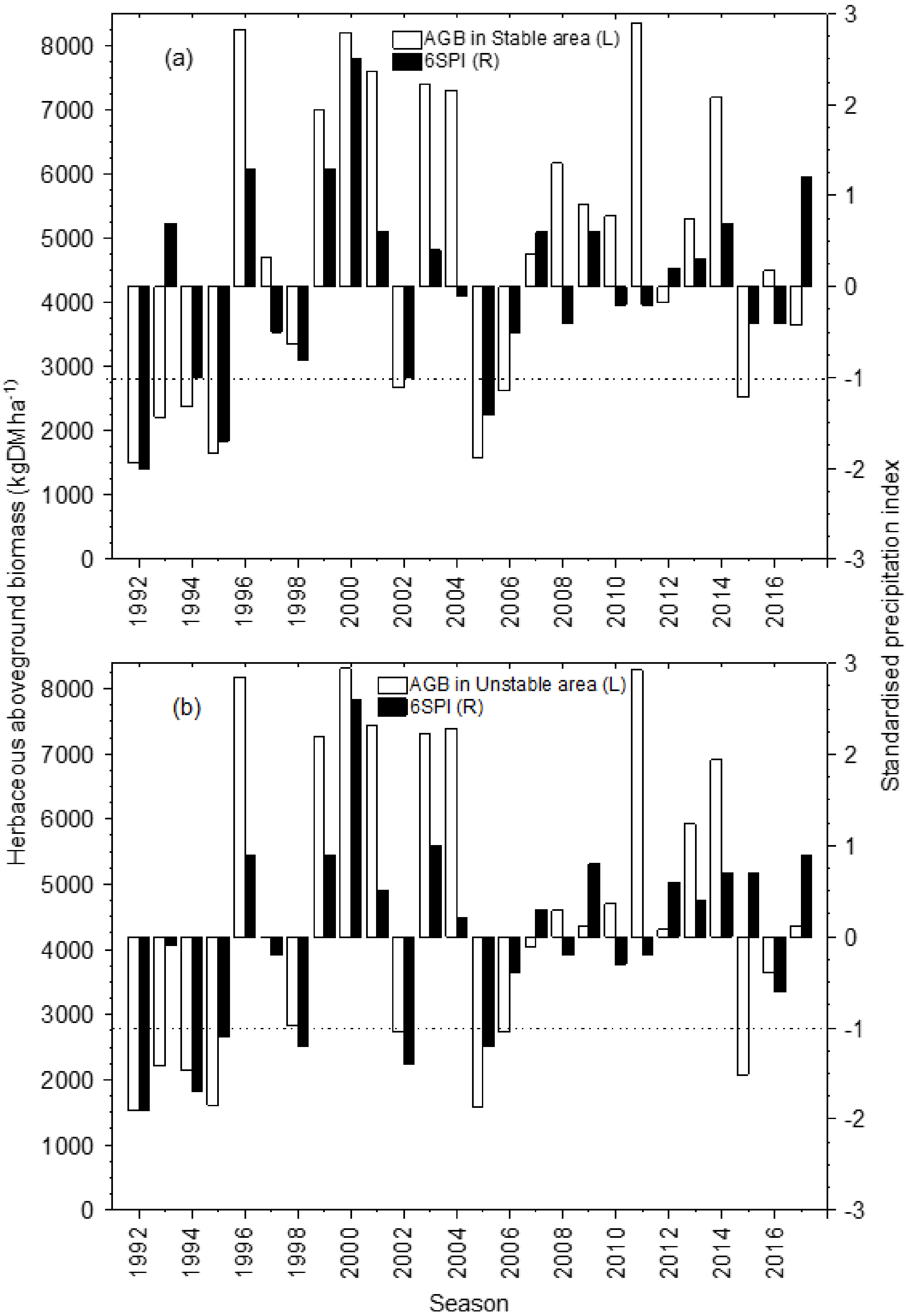

Figure 4. 5: Six-month (NDJFMA) standardised precipitation index (SPI) and herbaceous aboveground biomass deviation from median for typical (a) stable and (b) unstable areas between 1992 and 2017. Broken line represents threshold for onset of moderate drought, SPI $\leq$ -1.

Table 4.3 provides the responses of seasonal herbaceous AGB production to drought seasons. The response of herbaceous AGB to dry conditions was widely variable across drought intensities. Mean relative production increases varied with different drought intensities in the order of 153 to 214 % following extreme and mild droughts, but were exceptionally greater, 426 %, following moderate drought. The poorest relative herbaceous AGB production increase, 160 %, occurred when post drought seasonal rainfall fell below the long-term median e.g in 1993 and 2006. In contrary, herbaceous AGB production improved by at least two-fold when post drought seasonal rainfall fell near or above the long-term median e.g in 1999 and 2003. Ranges in herbage production between post drought years were also greatest seasons that received rainfall near or above long-term median, while least ranges in AGB production were observed for post drought seasons with below-normal rainfall. The ranges in herbage production were also relatively small in wet seasons succeeding mild droughts, particularly in the stable north-central areas of the ranch. Stable and unstable areas showed the same response to rainfall anomalies across seasons, but they differed in their magnitude of response e.g. in 2008 and 2015 (Figure 4.5).

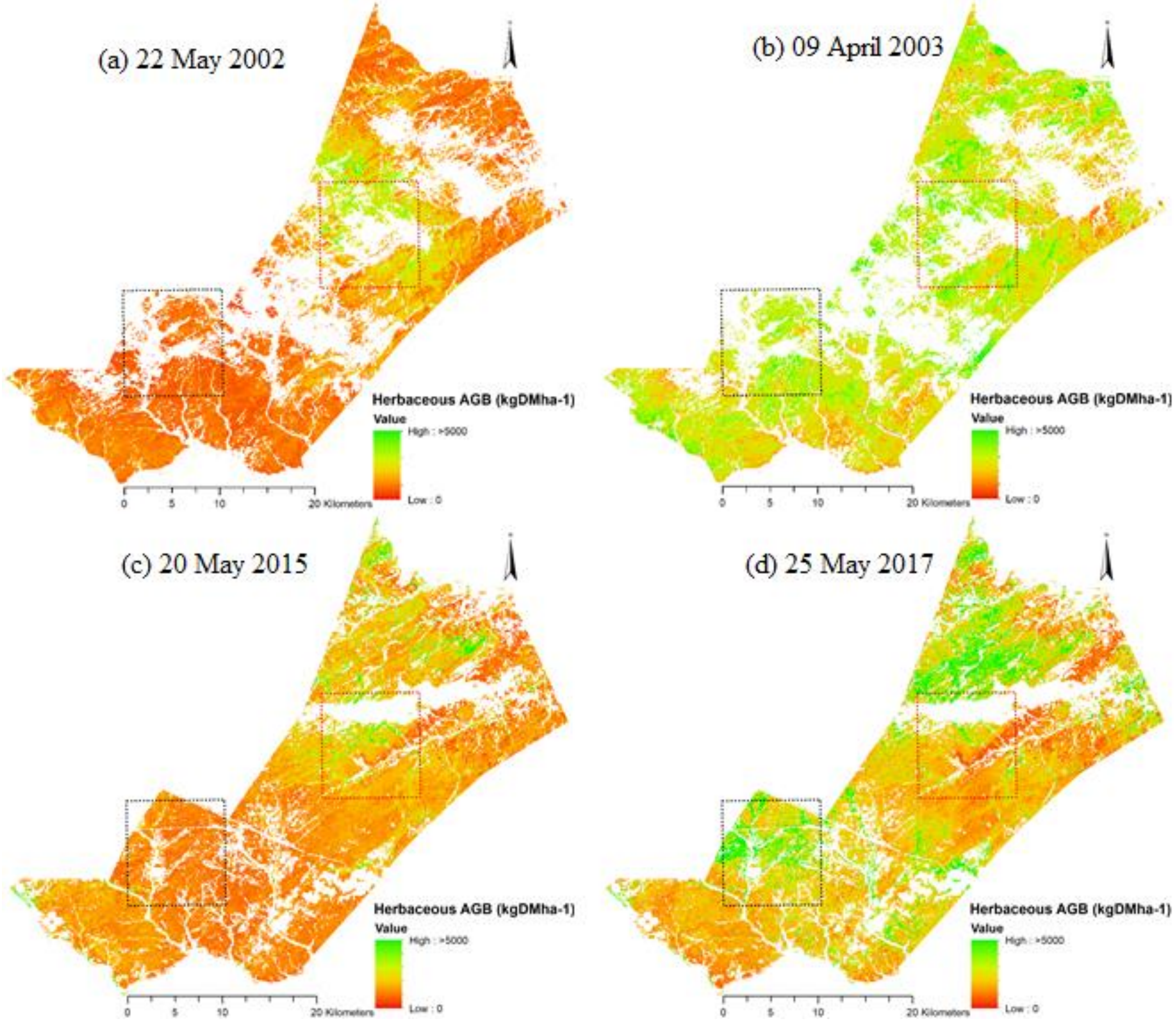

Figure 4. 6: Variability in herbaceous aboveground biomass in stable (red) and unstable (black) areas in (a) moderate drought and (b) mildly wet season, and in (c) mildly dry and (d) mildly wet season.

4.4 Discussion

We demonstrate a methodological framework for characterising the spatio-temporal variation in AGB within a landscape that can be generalized for other ranches in the study region to improve management planning. As expected for semi-arid savanna rangelands, high and unstable spatial variations of AGB production across herbaceous communities were observed over time. The results indicated that the spatial pattern of herbaceous AGB production is highly sensitive to seasonal rainfall distribution, particularly in dry years when different drought intensities occur concurrently. Temporal variability of AGB production within herbaceous communities fluctuated more than rainfall but the landscape-level temporal variation of AGB production was stable despite the increase in drought disturbances experienced in the past fifty years in southern Africa. The findings emphasise the importance for building knowledge about management practices that maintain or enhance inherent heterogeneity in herbaceous communities and lead to increased stability of rangeland productivity in face of the anticipated climatic changes.

4.4.1 Spatial and temporal variability of rainfall and drought events.

The study findings reveal high variability in wet season rainfall within and between seasons as expected for sub-tropical rangelands. These findings concur with many studies that CV of rainfall in southern lowveld of Zimbabwe is very high (Oxfam-UNDP/GEF, 2015). In the Nuanetsi catchment, Barnes and Mcneill (1978), Fuller and Prince (1996) and Oxfam-UNDP/GEF (2015) observed rainfall variabilities to be 35.8, 31.7 and 35 %, respectively. In south eastern lowveld of Zimbabwe, Dye and Spear (1982) observed a CV of 47 % at Tuli. The differences in rainfall variability within the same region among these studies emanate from variances in starting year of analysis and time scales.

Significant spatial variations in rainfall were also observed across the study area, with different drought intensities occurring simultaneously in some dry years. These variations are inherent in south-central Africa because the convection movements that frequently induce rainfall cause intra-seasonal patchiness in distribution (Makarau and Jury, 1997). Frequency of occurrence and intensity of moderate drought was also found to be increasing in the past three decades. In southern Africa, the frequency and intensity of dry years have significantly increased since the global climate shift in the 1970s (Gaughan et al., 2016). Projected climate change for this region also predict increase in intra- and inter-seasonal rainfall variability and drought frequency and intensity (Jia et al., 2019). Thus, the observed and anticipated increases in rainfall variation pinpoints the importance of using cheaply available satellite observational tools to provide ranch managers with information for effectively monitoring climate risks and improving management planning.

4.4.2 Response of herbaceous biomass to rainfall variability and drought events

The spatial representation of herbaceous AGB observed in this study indicate that variations in AGB production are variable across the ranch and over time, a characteristic feature of grazed C4 grass communities in semi-arid rangelands of southern Africa. In agreement with these findings, it has been long established that these rangelands portray high spatial heterogeneity in herbaceous AGB production, for example in northern (Svinurai et al. 2018) and southern Limpopo river basins (Dwyer, 2011; Mutanga and Rugege, 2006) and Drakensberg (Shoko et al., 2019). Herbaceous AGB changes across the ranch were variable over time, especially between drought and post-drought seasons. Some areas showed notable changes in AGB while others remained stable. Mapping the spatial representation of AGB helps ranch managers in adjusting animal distribution relative to spatial heterogeneity in forage resources among paddocks to prevent excessive use of unstable areas.

Higher temporal variability in seasonal herbaceous AGB than seasonal rainfall variability was detected in this study. This study corroborates other field and remote sensing studies that have been conducted at local and regional levels in south-central Africa. For example in field studies, Dye and Spear (1982) and Kelly and Walker (1976) made similar observations in south eastern lowveld of Zimbabwe while O´Connor et al. (2001) found more than 50 % variation in AGB compared to rainfall CV in the northern lowveld of South Africa. Using low spatial resolution imagery at regional scale, Fuller and Prince (1996) and Mberego and Gwenzi (2014) also observed high sensitivity of NDVI to rainfall in southern Zimbabwe while Chidumayo (2001), Martiny et al. (2006), and Wessels et al. (2006) made similar findings in south-central Africa. However, there was no observable change in temporal variability of AGB production despite the increase in frequency and intensity of dry conditions that has been observed after the global climate shifted in 1970s.

Table 4.3: Response of seasonal herbaceous aboveground biomass yield to drought intensity

Drought intensity	**Season**	**Mean SPI for drought event**	**Mean seasonal rainfall (mm)**		**Mean seasonal herbaceous AGB production (kg DM ha^{-1})**		**Relative seasonal AGB production increase (%)**
			Drought year	Post drought year	Drought year	Post drought year	
Mild drought	1998	-0.8	370	576	3278	7020	214
	Range	-1.3 to 0.1	332-422	546-609	2838-3949	6261-7906	221*
Moderate droughts	2002	-1.2	301	694	2557	10897	426
	Range	-1.4 to -1	226-381	633-755	1914-3394	8645-13575	452
	2005	-1.3	196	321	1723	2728	160
	Range	-1.4 to -1.1	164-252	294-351	1522-2025	2464-3037	162
Extreme drought	1992	-2.1	186	300	1678	2566	153
	Range	-2.34 to -1.76	113-277	254-399	1260-2300	2100-3600	167

SPI, six-month (November to April) Standardised Precipitation Index for the period between 1992 and 2017. *Relative AGB yield increase was calculated from values of lower limits of the range of AGB production in drought and post drought year.

The response of herbaceous AGB to dry conditions was highly variable across drought intensities and differed with the amount of post drought rainfall relative to the long-term median. Low herbaceous AGB production occurred when post drought rainfall was below average. For semi-arid environments, it is well known that a rainfall deficit in the previous year will result in production lower than expected for the current rain season (Sala et al. 2012). In semi-arid *Colophospermum mopane* savannas, herbage recovery immediately following drought is usually slow as drought may cause increased mortality of herbaceous species as well as reducing seed production (Jordaan et al., 2004; O'Connor, 1998). This may limit recruitment of perennial grasses in subsequent years. The short-term responses of herbaceous AGB to the spatial patterns of drought intensity estimated in this study can help ranch managers to develop a more flexible grazing program to respond to drought.

Relatively high herbaceous AGB production increases across the ranch were detected in above-normal post drought seasons. Such high production increases can be attributed to rejuvenation of annual grasses which vary in production by up to four-fold (Kelly and Walker, 1976). It was also found that wide ranges in herbaceous AGB response to dry seasons occurred in above-normal post drought seasons. This possibly occurred due to high variation in aridity as different drought intensities occurred concurrently in dry years. In semi-arid rangeland ecosystems, wet and dry seasons are characterised by different distributions in rainfall events (Schwinning and Sala, 2004). As cited previously, tropical regions of southern Africa portray high patchiness in rainfall distribution at local level. High spatial variability in rainfall causes high spatial and temporal variability in herbage production (Mberego et al., 2013). These findings provide guidance to ranch managers to adjust stocking in above-average seasons to maximise livestock carrying capacity.

Overall, high spatial variation among herbaceous communities and absence of change in temporal variability indicate the greater stability in the herbaceous layer in the study landscape. Our findings concur with McGranahan et al. (2016)'s concept of landscape ecology theory which suggest that spatial variability of local communities influences the temporal stability in AGB production at landscape level. The enhanced stability properties of the herbaceous layer in semi-arid *C. mopane* savannas has been observed for species richness and abundance attributes (Buitenwerf et al., 2011; Coller and Siebert, 2015). Productive, palatable perennial grasses contribute significantly to forage stability in this savanna (Tessema et al., 2016). In semi-arid *C. mopane* savannas of the Limpopo river basin, *U. mosambicensis* has a high relative abundance and is able to increase and decrease in abundance in above- and below-average seasons, respectively (Kennedy et al., 2003; O'Connor, 2015). Thus, there is need for range managers in this region to put more management emphasis towards strategies that maintain or enhance inherent heterogeneity within the landscape and increase the stability of rangeland productivity and resilience to future climate change.

4.5 Conclusions

Spatial heterogeneity of AGB production across herbaceous communities were high and deviated from the mean AGB by 51 to 69 %. The results indicated that the spatial pattern of herbaceous AGB production is highly sensitive to seasonal rainfall distribution, with greatest unevenness occurring in dry years when different drought intensities occur concurrently. Temporal variability of AGB production within herbaceous communities fluctuated by 18 to 35 % more than rainfall. However, the landscape-level C.V. of AGB production remained stable despite that the frequency and intensity of droughts has increased in the last fifty years in tropical southern Africa. These findings support the emerging concept in landscape ecology theory which suggest that, high spatial unevenness of AGB production across local herbaceous communities reduces temporal variability in AGB production at landscape level. This highlights the need by range managers to put more management emphasis towards maintaining or enhancing inherent unevenness within local herbaceous communities to increase the stability of rangeland productivity and, to adapt to anticipated climatic changes.

CHAPTER 5

Parameterization and calibration of the Sustainable Grazing Systems model for simulating native grass growth with limited data

Abstract

Despite the economic challenges faced by cattle ranch managers to capitalise in systems for monitoring herbage biomass, simulation modelling present opportunities for estimating herbage and animal production on a near real-time basis. This study was conducted to parameterise the Sustainable Grazing Systems (SGS) model using geographical layers of landscape and soil data obtained from previous soil surveys conducted at Nuanetsi ranch and, to calibrate the model using measured herbaceous aboveground biomass (AGB). Herbaceous AGB was measured in forty 0.1 ha plots in the 2016/17 season to provide data for fitting model outputs. Demarcation of the entire slope into four catena units revealed a distinctive downslope sequence of bands of land types that were up to 5 kilometres wide. Mafic gneiss, siliceous gneiss and alluvium are the main soil families that separately dominated in three land types. The soils were very shallow with a maximum topsoil and total effective depth of 20 and 85 cm, respectively across land types. Annual mean measured and modelled herbaceous AGB was 3877 and 3071 kg DM ha^{-1}, respectively. The SGS model significantly represented measured herbage AGB ($P < 0.01$), accounting for up to 60 % variation in herbaceous AGB ($r^2 = 0.57$). The relationship between model outputs and corresponding field measured herbage biomass was very stable with an average error of 820 kg DM ha^{-1}. An integrated methodological framework for parameterising and calibrating the SGSs pasture-simulation model developed in this study can benefit model users in data-constrained environments.

Keywords

Parameterisation, calibration, simulation, prediction error

5.1 Introduction

Landscape-level assessments of remotely sensed herbaceous AGB production presented in Chapter 3 and 4 are quick and plausible for describing the static behaviour of rangeland systems. The assessments consider the whole ranch as the system boundary and rainfall as a state or internal variable. However, empirical remote sensing models fails to explicitly characterise the dynamic growth of herbaceous AGB under local environmental conditions and have weak predictive power when applied to other regions (Foody, 2003). At paddock-level, rainfall assumes a forcing role in the land-vegetation system with the efficiency of rain use for biomass production being determined by the influence of intra-seasonal rainfall distribution on soil moisture content in sweetveld (Ellery et al., 1995; Veenendaal et al., 1996). The effects are further modified by topographic variation which cause soil fertility differences that are difficult to observe (Pickup, 1991; Scholes, 1990). Soil water, above- and below- ground plant growth and animal responses to variable climate, topography and herbivory thus depend on the complexity of interactions among these factors (Frost et al., 1986; Scholes et al., 2003). Death of long-term measurements of herbaceous AGB on research stations and farms in developing countries due to inadequate resources has resulted in lack of updated information about these interactions. There is need to embrace research tools that account for many factors that influence herbaceous AGB production.

The basis for improving extensive beef systems is to build knowledge about herbage and animal production under prevailing conditions at whole farm level. Systems analysis modelling is the only useful approach for understanding the complex interactions affecting components of a system (Grant et al., 1997). System models provide a quantitative analysis of complex interactions and feedbacks of many variables under local environmental and management conditions (Rickert et al., 2000). In the past two decades, empirical and mechanistic modelling gained huge attention globally in predicting herbage and animal production (Snow et al., 2014). However, in semi-arid rangelands of southern Africa, simulation modelling has been limitedly applied to empirical models for plant growth (Oomen et al., 2016; Wiegand et al., 1998) and a few deterministic and stochastic models for herbage and animal production (Illius et al., 1998; Kazembe, 2010; Richardson et al., 2000). Moreover, empirical models give false results if they are applied to regions that lack the experimental data used to develop them. Mechanistic WFMs are more realistic than empirical models as they are capable of simulating soil, plant and animal processes at a high level of detail.

Mechanistic models such as the Sustainable Grazing Systems (SGS) model are capable of simulating herbage growth in multi-species swards and deal adequately with long-term herbage production dynamics. The balance among complexity, realism and versatility obtained during construction of mechanistic models enable the models to be applied to new regions by adjusting default model parameters (Johnson, 2011). Such models have been limitedly applied to high rainfall and semi-arid biomes in Australia (Doran-Browne et al., 2014; Johnson et al., 2003) and rarely used in southern Africa savanna rangelands (Andrade et al., 2016). But, other than the inherent errors of model structure, their application has been limited due to errors associated with system input variables and data measured for deriving parameters.

The precision of WFMs depends on their ability to use spatially distributed climate input data and parameters and constants that should be adjusted. In developing countries, climate data is rarely available at ranch-level due to sparse national meteorological stations. Also, system parameters and state variables are unknown as they cannot be fully included in experiments due to high environmental variation (Johnson, 2011). The increasing availability of high temporal- and spatial- resolution geographical data of environmental variables provide a means for closing data gaps when adapting WFMs to resource-constrained environments (Angerer, 2012). Remote sensing and geographic information systems (GIS) are inseparable tools important for mapping climate input variables for WFMs (Ovando et al., 2018). They also enable stratification of rangeland systems into soil, vegetation and management units for retrieving explanatory variables (Schellberg et al., 2008). These ancillary data are useful in model calibration yet they have been rarely explored in southern Africa. The integrated data sources thus offer complementarities to field experiments that need to be explored to understand their suitability and transferability under specific site conditions. This improves accuracy of forage production estimates modelled by WFMs and confidence in using them, enables identification of drivers of forage production, development of local forage maps and prioritisation of areas for management. This study was aimed at developing SGS model parameter sets for simulating native grass production in *C. mopane* rangelands and evaluting performance of model output.

5.1.1 Objectives

The specific objectives of this study were to:

- develop soil and plant module parameters and site-specific inputs of the SGS pasture model for predicting grass production in a *C. mopane* tree-shrub savanna.
- evaluate the performance of SGS pasture model in simulating inter-canopy native grass growth in a *C. mopane* tree-shrub savanna.

5.2 Materials and methods

5.2.1 Ecological structure of *Colosphermum mopane* savanna at Nuatesi ranch

The geographical location and ecological characteristics of the Nuanetsi beef cattle ranch have been described in Sections 3.2.1 and 4.2.1. The specific environmental features of sampled plots to which the SGS model was calibrated were derived from various spatial data layers as outlined in Section 5.2.3 below. The region receives low annual rainfall ranging from 300 to 500 mm mainly in summer between November and March, with the late summer (January to March) contributing 40 % of the annual rainfall (Figure 5.1).

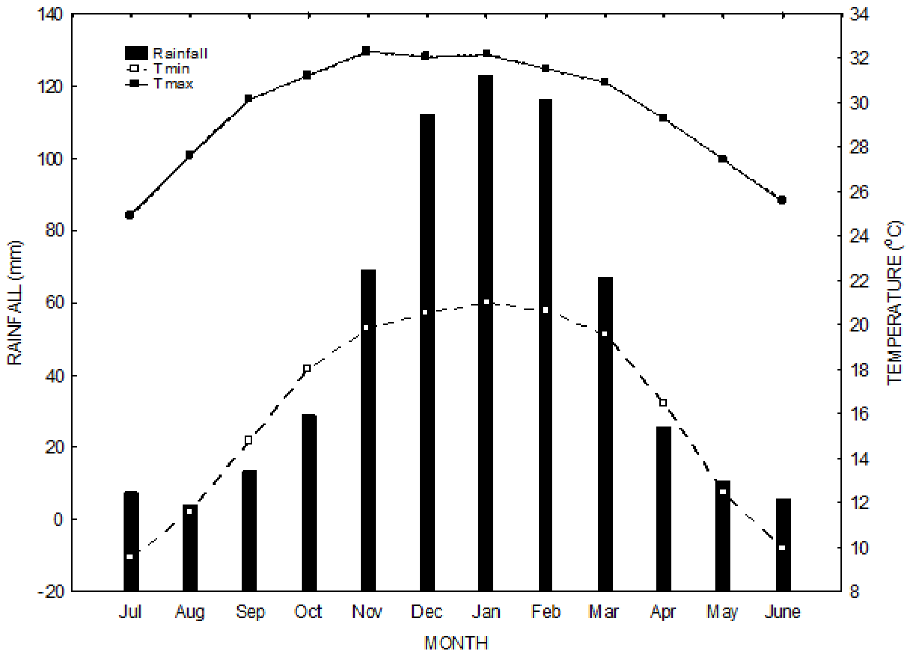

Figure 5. 1: Mean total seasonal rainfall, minimum and maximum monthly temperature for Nuanetsi ranch (1992-2017).

5.2.2 Overview of the Sustainable Grazing Systems pasture model

The SGS pasture model is an Australian biophysical model comprising of nested empirical and mechanistic sub-models that seek to analyse and explain interlinked processes amongst water, nutrients, herbaceous plants, animals and management components in grazing lands. Processes amongst components are driven by daily weather variables at the plot or paddock level. The model was originally developed by Johnson and Thornley (1983) and Johnson and Thornley (1985) with the main emphasis on the cell-level physiological response of pasture species to climatic conditions, with subsequent improvements by Johnson and Thornley (1987) and Johnson et al. (1989). The soil water module was upgraded by Johnson et al. (2003) whilst the soil nutrient module was also improved and documented by Johnson et al. (2008) and Johnson (2008), respectively. Further effort to improve the model's animal component was based on the metabolizable energy (ME) intake system (Johnson et al. 2012). The SGS model is large, comprising of many differential equations in its sub-models. Detailed equations used in model development can be found in Johnson (2008) and Johnson (2016). The model has been used to assess pasture growth rates (Cullen et al., 2008) and impacts of climate change on C3 and C4 grasses in subtropical and temperate regions of Australia (Cullen et al., 2009). Recently, the model has been used to simulate the growth of tropical C4 perennial and annual grasses and legumes in northern Australian rangelands (Doran-Browne et al., 2014).

5.2.3 Derivation of model parameters

The soil water, nutrients (C, N) and pasture modules are the main biophysical components of the SGS pasture model that were parameterised in this study. The modules have over 100 biophysical system parameters of soil water and nutrients, canopy structure and growth of pasture species that could potentially be adjusted. However, these parameters were not available at the level of detail required to allow the model to be adapted to the Nuanetsi ranch. To overcome this challenge, an integrated framework was used to derive parameters from geographical layers of climate, topography, soil and vegetation, satellite images and extensive review of published experiments for southern African savannas (see Figure 5.2). Consequently, a total of eighteen parameters were adjusted and the remainder was used as default values.

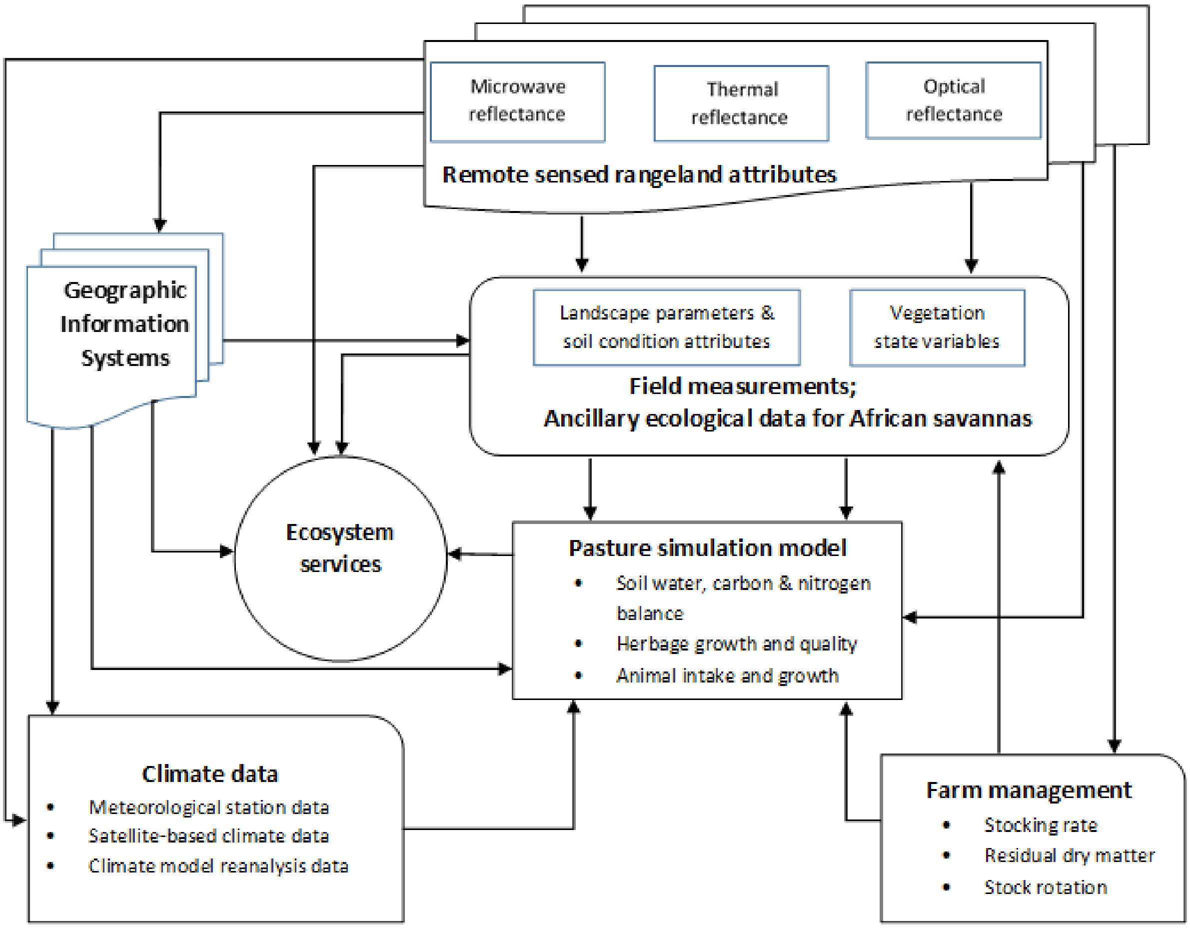

Figure 5. 2: Framework of the flow of information used to parameterise the SGS pasture model.

5.2.3.1 Landscape and climate variables

In flat undulating landscapes of the Lowveld, soil water and nutrients are redistributed from crest to adjacent foot slope areas over time and the process results in zonal patterns of both woody and herbaceous vegetation (Witkowski and O'Connor, 1996). To represent this effect, the Advanced Spaceborne Thermal Emission and Reflection Radiometer digital elevation model (ASTER DEM) was used to stratify the whole ranch into four land types following the patch hierarchy approach of Venter et al. (2003) (Figure 5.3). In this approach, the terms crest, mid-slope, foot slope, and valley bottom are used to refer to the relative topographic position of land types starting from interfluve to drainage channel. Elevation, slope, aspect, and latitude of plots or paddocks for land types to which the model was applied were derived from the ASTER DEM. Additional information about geology and landform was obtained by overlaying the Nuanetsi ranch map on the map of the Soil and Terrain of Southern Africa database (SOTERSAF) (ISCRI, 2005) using GIS software.

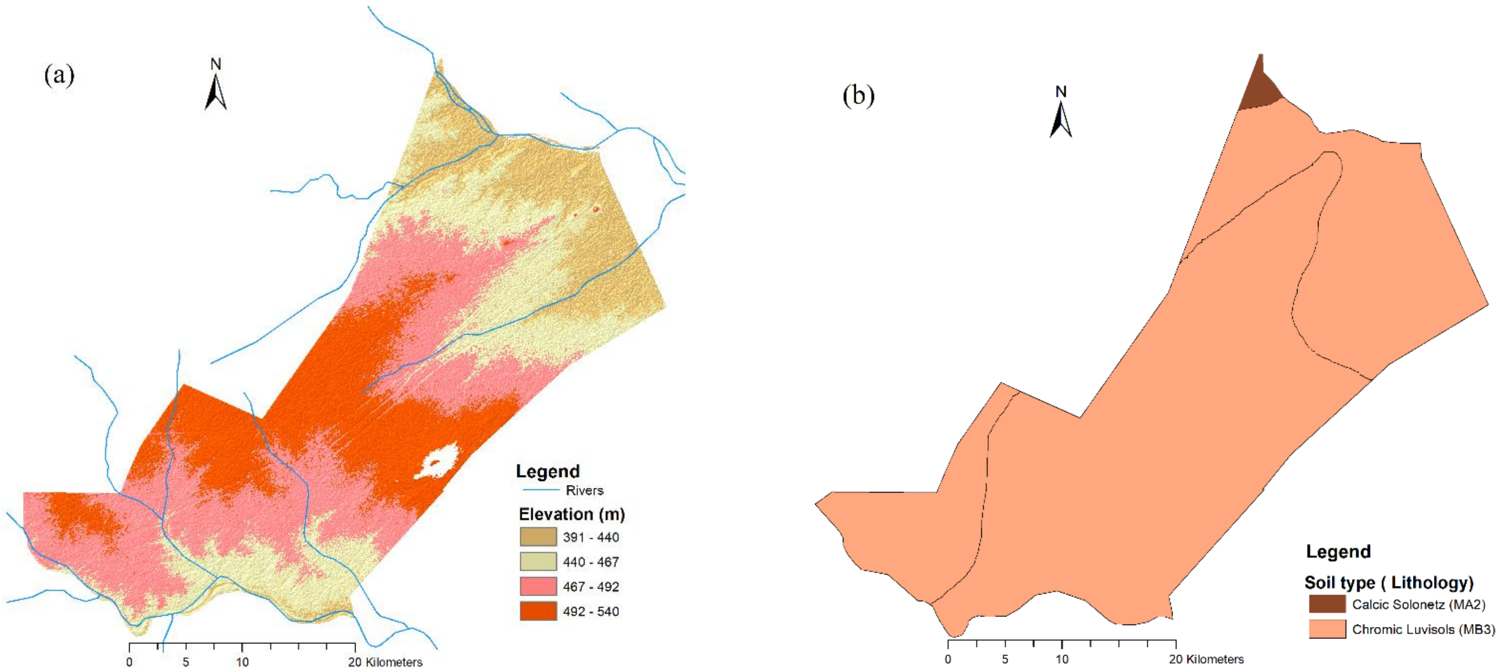

Figure 5. 3: Map of (a) elevation of land types and rivers and (b) soil type (based on ISCRI (2005)) of Nuanetsi ranch

Spatially aggregated data for daily solar radiation (Wm^{-2}) and rainfall (mm) and spatially interpolated data for daily minimum and maximum temperature (°C) for the 1982 to 2017 period were used as inputs to run the SGS pasture model. Daily global solar radiation for the period 1985 to 2005 that has been validated for the southern African region by Lefèvre et al. (2012) was obtained from the HelioClim-1 database (Lefevre et al., 2014). Other solar radiation data for 2006 to 2017 were downloaded from the (Copernicus Atmospheric Monitoring Service (CAMS) servers through the Solar Radiation Data (SODA) portal (Schroedter-Homscheidt et al., 2016). The Zimbabwe Sugar Association Experiment Station (ZSAES), located 60 km north of Nuanetsi ranch, has been measuring solar radiation and minimum and maximum temperature at a daily time step since 1967. Solar radiation data from this weather station was used to correct the bias of satellite solar radiation estimates. Daily minimum and maximum temperature were spatially interpolated for the four land types using an inverse distance weighting approach (Moeletsi et al., 2016). Daily rainfall data available from the National Oceanic and Atmospheric Administration Climate Prediction Centre African Rainfall Climatology version 2 (NOAA-CPC-ARC2) at a spatial resolution of approximately 10 km (0.01°) at the equator since 1980 (Novella and Thiaw, 2013) was downloaded from NOAA-CPC servers. This data was processed by applying a spatio-temporal bias correction scheme using gauge data from the Mwenezi District Agritex Office. The spatial resolution of ancillary data sources used in the SGS model parameterisation is given in Table 5.1. All GIS processes and cartography were done in ArcGIS® (ESRI, Redlands, CA, USA) and original projection systems for datasets used were all converted to the World Geological Survey (WGS) 84 datum system.

Table 5. 1: Sources and spatial resolution of ancillary data used in model parameterisation

Environmental variable	Source	Spatial resolution
Soil lithology and type	SOTERSAF[†]	1:1 000 000
Altitude, aspect, slope	ASTER DEM[‡]	30 m
Rainfall	NOAA CPC ARC2[⁋]	10 km
Solar radiation	Soda HeleoClim1	5 km
Temperature	Interpolation	80 km
Land cover	FAO LCCS[ǂ]	250 m
Herbaceous biomass	Landsat 5 to 8	30 m

[†]Soil and Terrain of Southern Africa database; [‡]Advanced Spaceborne Thermal Emission and Reflection Radiometer Digital Elevation Model; [⁋]National Oceanic and Atmospheric Administration Climate Prediction Centre African Rainfall Climatology version 2; [ǂ]Food and Agriculture Organisation Land Cover Classification System.

5.2.3.2 Soil and plant parameters

Explanatory variables of soil profile layers of sites used in model calibration were singled out from soil survey data previously collected across the Nuanetsi sub-catchment by the Chemistry and Soil Research Institute (CSRI) of the Department of Research and Specialist Services. Estimates of soil physical variables of the crest- and mid-slope soils and, foot slope soil were obtained from CSRI (2007) and CSRI (2003), respectively. The surveys show that crest- and mid-slope soils have medium-grained sandy loam over medium-grained sandy whilst foot slope soil comprise of coarse-grained loamy sands over medium-grained loamy sands. Soil layer depths for the crest land type were adjusted to represent moderately deep soil with a total depth of 80 cm (Table 5.2). The crest soil profile was set to a relatively deeper A horizon compared to the corresponding horizon in mid-slope soil. Parameters for the mid-slope land type were set to a shallow depth of 60 cm, with a horizon A of intermediate-depth underlying horizon B of moderate clay content (CSRI, 2007). In foot-slope soil catena, soil depth was also adjusted to typify shallow alluvial soils (CSRI, 2003). These soil properties resemble the dominant soil catena usually associated with medium *C. mopane* tree/shrub vegetation types in southern Lowveld of Zimbabwe (Dye and Walker 1980).

In the SGS soil water module, water is included in the grassland through rainfall and is intercepted by the herbaceous canopy, litter or bare soil (Johnson et al., 2003). The water balance was assumed to be different in soil profiles from crest- to foot- slope since soil texture and profile depth determine the soil moisture dynamics. In an unimodal growing season experienced in southern Africa, soil moisture held by shallow surface horizon deplete rapidly after rainfall events and may drop below the wilting point for several weeks between rainfall events (Scholes and Walker 1993). Available water capacity (AWC) is moderately small across soil families in semi-arid regions and soil moisture is rarely at field capacity. Therefore, AWC was set between 10.0 - 14.9 % volume (CSRI, 2007; CSRI, 2003).

Table 5. 2: Soil physical and chemical variables of land types used for model calibration

Factor	Parameter	Units	Default Duplex	Foot slope soil	Default Medium	Mid slope soil	Crest soil
Soil physical variables	Altitude	m.a.s.l		404		441	487
	Parent material	-	-	Alluvium	-	Mafic gneiss	Mafic gneiss
	A horizon depth	cm	50	12.8	50	11.3	17.2
	B1 horizon depth	cm	100	16.4	100	18.6	25
	B2 horizon depth	cm	200	30	200	30	40
Soil chemical variables	A horizon clay composition	%	30	10	30	12	12
	B1 horizon clay composition	%	30	17	30	18	20
	B2 horizon clay composition	%	30	17	30	18	20

The plant growth module in the SGS model uses solar radiation to estimate net radiation through calculations of light interception and photosynthesis in a mixture of up to five herbaceous species. The module also simulates uptake of nutrients and water from the soil by each species and their partition between roots, shoots and seeds, plant development, tissue turnover, and senescence, and respiration from plant growth and maintenance. Herbaceous species composition was assessed in the 2016/17 season for forty sampling plots where the SGS model run was conducted. Herbaceous species composition was visually assessed in ten 0.25 m^2 quadrats for each sampling plot by a field taxonomist using the dry weight rank method (Mannetje and Haydock 1963). Over twenty grass species were identified during the assessment of species composition, only two native graminoid herbaceous species were dominant: *Urochloa mosambicensis,* a loosely tufted, productive, palatable, perennial grass and, *Eragrostis curvula,* a tufted, productive, unpalatable perennial grass. *U. mosambicensis* and *E. curvula* were widely spread across the ranch, representing 90 % (first and second dry-weight ranks) of species composition in 56 and 14 % of all plots, respectively. The other plots had mixed herbaceous species that were low in abundance and were excluded from parameterisation. Default growth parameter values were adjusted for the two grasss species to acceptable ranges using data from published independent experiments. Species parameter values for canopy height were obtained from the Tropical Forages online database (Cook et al., 2005). Adjustments to parameter values for dry matter partitioned to shoot, leaf fraction of new shoot growth, leaves per tiller and specific leaf area were based on Ernst and Tolsma (1992). The maximum rooting depths of grasses were set at 15 and 25 cm for stands occurring in the crest and mid- and foot slope land types, respectively (CSRI, 2003; 2007) (Table 5.3). The minimum and maximum temperatures for tropical grasses range between 10 and 15°C and, 30-35°C, respectively (Cooper and Tainton, 1968). The default minimum and optimum growth temperatures of 12 and 35°C were thus retained. The maximum leaf net photosynthesis rate was adjusted to 35 $\mu molm^{-2}s^{-1}$ as measured by Mantlana et al. (2008) in south-central Africa. In all submodules used in this study, default data were used where a site or regional data were not available.

5.2.3 Measured and remotely sensed herbaceous biomass

Herbaceous AGB data for calibrating the SGS model were measured in forty sampling plots in the 2016/17 growing season using the total-cut technique as described in Section 3.2.2.1. Remotely sensed MVIs for herbaceous AGB, namely SR, NDVI and SAVI were calculated from spectral reflectance of Landsat 8 image pixels corresponding to the sampled plots as outlined in Section 3.2.2.2. The field and spectral data were separately compared with herbaceous biomass outputs simulated in the respective sampling plots to adapt the SGS pasture model to site conditions.

Table 5. 3: Plant species and community growth parameters and initial condition values used for grasses at simulated sites

Factor	**Parameter**	**Units**	**Default Native-C4 grass**	***Urochloa mosambicensis***	***Eragrostis curvula***	**Reference**
Canopy	Maximum height	cm	50	100	120	Cook et al. (2005)
	Specific leaf area at ambient CO_2	m^2leaf $kgDM^{-1}$	16	15	12	Ernst and Tolsma (1992)
Growth	Maximum leaf net photosynthesis rate at reference conditions	µml $CO_2/m^2/s$	20	35	35	Mantlana et al. (2008)
Root	Maximum root depth	cm	100	20	20	Dye and Walker (1980)
	Depth to 50 % of root mass	cm	20	10	10	CSRI (2007)
Temperature	Low-temperature effects: Full	°C	3	3	3	Cooper and Tainton (1968)
	Low-temperature effects: Initial	°C	7	7	7	Cooper and Tainton (1968)

5.2.4. Calibration of the model

A manual, iterative procedure of manipulating default model parameter values for Australian rangelands was used to adapt the model to local agro-ecological conditions. The procedure was aimed to provide one set of parameters that represent the real rangeland conditions at sampled plots and, best fit with measured or remotely sensed herbaceous AGB. Point calibration and annual simulation runs for herbage growth were performed in twenty-eight plots by adjusting parameters accordingly for each climate grid, land type, soil family and grass species. Daily grass growth simulations at each plot were performed between July 2007 and June 2017 following the summer season weather calendar to produce 11 plot-by-year assessments. Model outputs from the first 10 year-lead in period (2007 and 2016) were discarded to allow stabilisation of model parameters and output from the 2017 growing season were used to calibrate the model.

5.2.5 Analysis of model outputs

The model outputs analysed included daily grass growth rate (kg DM $ha^{-1}d^{-1}$) and biomass production (kg DM ha^{-1}). A standard procedure for evaluating performance of models involving calculation of summary statistics (mean, minimum, maximum, mean bias), root mean square error (RMSE), decomposition of RMSE (bias, slope, and random components) and graphical analysis of residuals (Mcphee and Walmsley, 2017) was used to analyse the measured, remotely-sensed and simulated data. In fitting values of measured or remotely sensed biomass with model predicted values, simulated biomass was used in the *x*-axis as they are assumed to be without errors. Values of measured and remotely sensed herbaceous AGB that poorly represented modelled values in corresponding plots were discarded from model fitting as outliers. Model parameters were adjusted until mean biomass yield simulated by the SGS pasture model was maximised within 5 % of measured and remotely sensed biomass. The coefficient of determination (r^2) was used to measure the precision with which the model predicted measured or remotely sensed herbaceous AGB. A plot of residuals versus predictor variables was used to assess the envelope of acceptable precision around the line of zero deviation and the proportion of points that lie within it (Mitchell and Sheehy, 1997). The RMSE was included as the appropriate measure for assessing the predictive accuracy of a model calibrated with parameters from independent experiments (Tedeschi 2006).

5.3 Results

Annual mean herbaceous AGB measured in all plots retained for model fitting was 3877 kg DM ha^{-1} whilst the modelled mean 3071 kg DM ha^{-1}. Minimum measured and simulated biomass was 1450 and 2968 kg DM ha^{-1}, respectively whilst maximum values of 5370 and 3157 kg DM ha^{-1} corresponding to measured and simulated biomass were obtained. The mean bias was 807 kg DM ha^{-1} whilst the relative bias of 0.21 was obtained. The relationship between measured and modelled herbaceous AGB showed that the SGS model represented herbage biomass reasonably well, accounting for up to 60 % variation in herbaceous AGB ($r^2 = 0.57$; $P < 0.01$) (see Figure 5.4 (a)). Figure 5.4 (b) is a plot of residuals versus predictor variables which shows the deviation of individual predictions from the paired observations (line of zero deviation) for the whole dataset. The results show that 56 % (9 of 16) of all predictions of herbaceous AGB fell within the 95 % confidence limits of their respective observations whilst 25 % (4 of 16) and 19 % (3 of 16) were under- and over-predictions, respectively. The RMSE calculated from the study revealed that model outputs deviated from the corresponding field measured herbage biomass by 820 kg DM ha^{-1}. Modelled and remotely sensed herbaceous AGB were reasonably correlated across all land types with an r^2 value of 0.46 for NDVI (Figure 5.5).

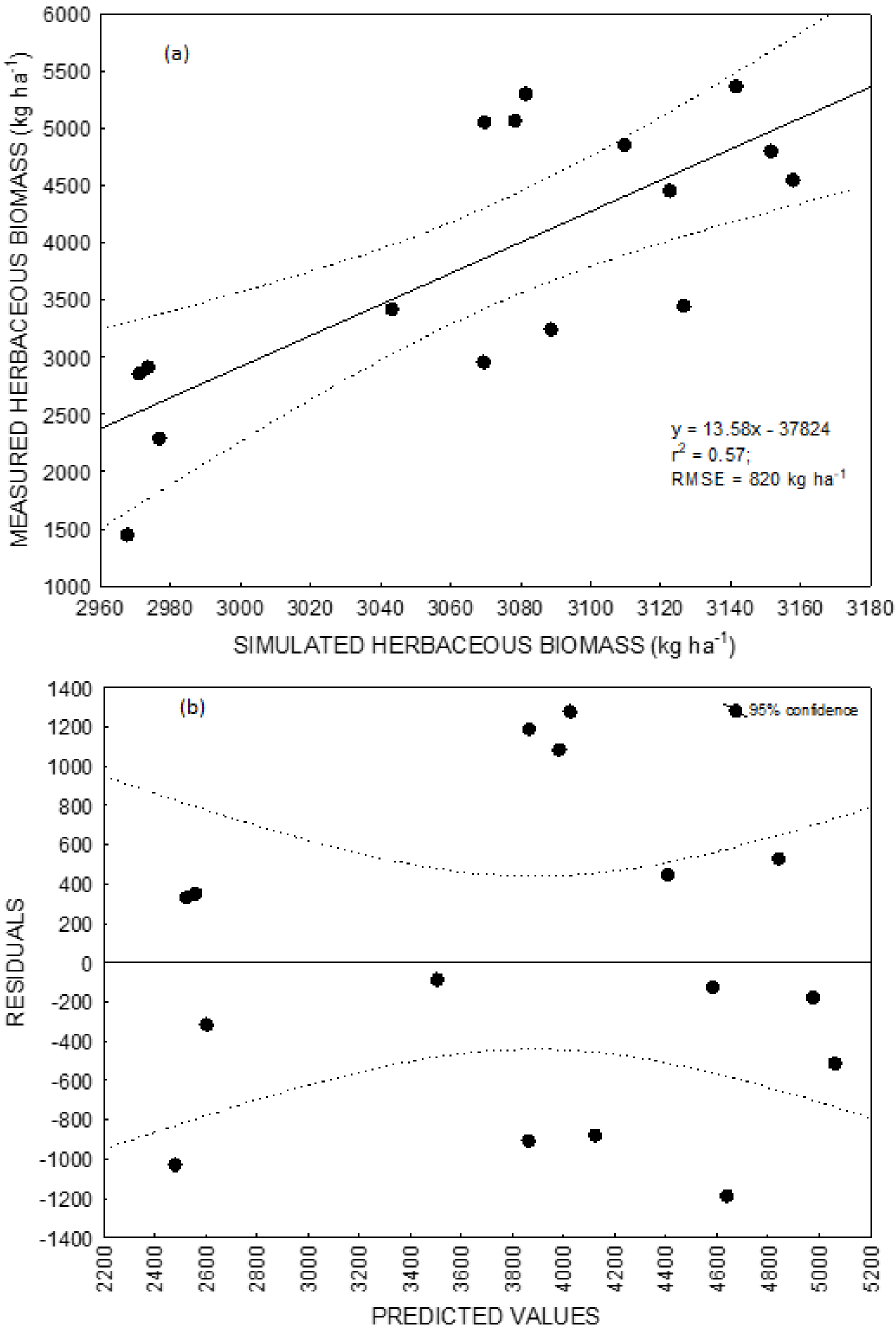

Figure 5. 4: Comparison of (a) simulated and measured herbaceous AGB and (b) predicted values and residuals in all plots

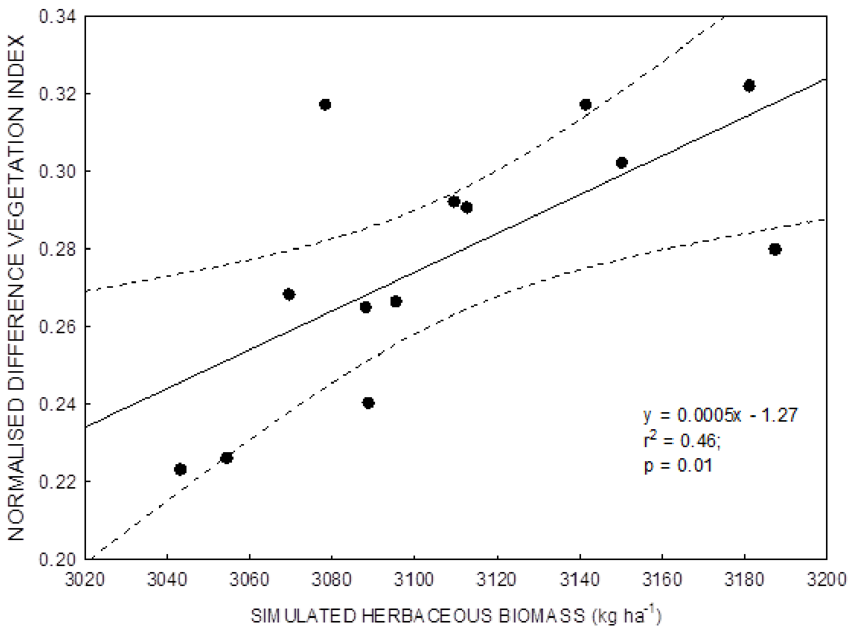

Figure 5. 5: Comparison of simulated herbaceous AGB and Normalised Difference Vegetation Index (NDVI).

5.4 Discussion

The relationship between measured and modelled herbaceous AGB showed that the SGS model represented herbage biomass reasonably well, accounting for up to 60 % variation in herbaceous AGB. Similar levels of agreements have been observed in other tropical regions where pasture models have been applied. Using the SGS model, Cullen et al. (2008) observed an r^2 of 0.58 in subtropical perennial grasses in south-eastern Queensland whilst Doran-Browne et al. (2014) obtained an r^2 of 0.6 in native C4 perennial and annual grasses in northern Australia. In mixed prairie, the APEX model underestimated growth of five individual herbaceous species (r^2 range from 0.25 to 0.67) (Zilverberg et al., 2017). In addition, the GPFARM model accounted for 66 % variability of observed forage production in mixed prairie (Andales et al., 2006). These agreements are below the commonly accepted level of high agreements ($r^2 > 0.8$) for model calibration. High agreements between measured and predicted herbaceous biomass are generally obtained for empirical models because their parameters fit well with measured data (Thornley and Johnson, 2000; Wallach et al., 2014). Notwithstanding the high accuracy of empirical models, outputs still vary considerably in native pastures due to random spatial variability. In northern Australian rangelands, 47 to 64 % of end-of-season biomass predictions from GRASP were within 95 % confidence intervals of field data (Cobiac, 2006). Such large deviations of individual seasonal predictions from measured grass biomass were observed in this study.

High spatial variability in grass production is an inherent feature of semi-arid regions of Zimbabwe that exists at plot-scale (Kelly and Mcneill, 1980). For example, Svinurai et al. (2018) observed grass production to vary from 1340 to 7530 kg DM ha^{-1} in a season. Poilecot and Gaidet (2011) also observed native grass biomass yield to vary from 1433 to 4257 kg DM ha^{-1} in shallow sandy soils in northern lowveld game ranch of Zimbabwe. In undulating landscapes of lowveld regions, variability in grass production often results from uneven distribution of rainfall and high diversity of grass species which evolve from their competition for soil water and nutrients (Venter et al., 2003). This random variation leads to huge errors when predicting herbaceous AGB and could not be accounted for by the SGS model using the current parameter sets. It is thus challenging to obtain high agreements between measured and simulated variables in complex natural systems because natural variability is high (Oreskes et al., 1994). Also, the assumptions of linear regression could not be met, and this highlights the need for testing other assessment measures that do not consider individual seasonal predictions.

The use of plant parameters from literature gathered from times and locations not covered by field observations to calibrate the SGS model is subject to errors. The RMSE can be reliably used to assess the accuracy of models calibrated with such parameters derived from independent experiments (Tedeschi 2006). The SGS model predicted herbaceous AGB measured in respective sampling plots with a reasonable average error. Model outputs predicted the observed herbaceous AGB at an RMSE value (820 kg DM ha^{-1}) which lies within the acceptable level of accuracy for estimating herbaceous AGB in southern African broad-leaved savannas. Trollope and Potgieter (1986) estimated a RMSE of 898 kg DM ha^{-1} from herbaceous data measured across seven vegetation types in the KNP using the disc pasture meter. Given that plant parameters used in this study were derived from times and locations not covered by field measurements, long-term simulations are required to further evaluate the SGS model's stability are recommended.

5.5 Conclusions

An integrative and iterative procedure was used in this study to build parameter sets for calibrating the SGS model to simulate grass growth. The SGS model represented measured herbaceous biomass reasonably well, accounting for up to 60 % variation in herbaceous AGB at low average error (RMSE, 820 kg DM ha^{-1}) despite there being a huge discrepancy in summary statistics and residuals. Model predictions were also significantly correlated with NDVI (r^2, 0.52). These findings indicate that, when dynamic models are tested in natural systems, measures for individual predictions provide low performance scores while better scores are obtained with measures for whole set of predictions. The integrated workflow for parameterising and calibrating the SGSs pasture-simulation model developed in this study can benefit other model users in data-constrained environments.

CHAPTER 6

Evaluation of the Sustainable Grazing Systems pasture simulation model's predictive capacity

Abstract

Whilst pasture simulation models enable a mechanistic assessment of grass growth, their outputs are associated with inherent uncertainty when applied in seasons and locations where field measurements of parameters used to calibrate the models are unavailable. To build confidence in using these models under such conditions, there is need for independent data to quantify errors associated with simulated outputs. This study was aimed at assessing the adequacy of the SGS pasture model in simulating grass growth over 26 years using parameter sensitivity analysis and comparison of model output with remotely sensed herbaceous AGB. Total end-of-season herbaceous AGB estimated by the rainfall- AGB model developed in Section 3.2.6.2. was used as independent data for testing model outputs. Adjustment of parameters for shallow mafic-gneiss derived soils in mid- and foot slope land types and *U. mosambicensis* and *E. curvula* resulted in higher growth rate of these species relative to native C4 grass simulated from default soil and plant parameter settings. Growth predictions of both *U. mosambicensis* and *E. curvula* were higher than yield estimates of default native C4 grass by 26 to 98 % between November and April in the mid- and foot slope land types. Across all land types, mean remotely sensed- and modelled AGB was 3644 and 1674 kg DM ha^{-1}, respectively. The SGS model underestimated remotely sensed AGB by 51 % across all land types, with an overall mean bias error of -1970 kg DM ha^{-1}. Despite these under estimations, model predictions were significantly correlated with remotely sensed herbaceous AGB ($P < 0.05$) ($r^2 = 0.63$ to 0.72; RMSE range = 981 to 1396 kg DM ha^{-1}). These findings highlight the importance of testing measures for individual and whole predictions when evaluating process-based models in natural environments.

Key words

Independent data, model evaluation, sensitivity

6.1 Introduction

Precision of WFMs relies on the model's ability to use many input parameters and initial states at a wider scale that may be unknown in a landscape (Johnson, 2011). The parameters and inputs are highly variable in space whilst their adjustment in the model is required for upscaling point simulations. The process of parameterising and calibrating of simulation models includes errors associated with measurements of parameters in experiments and unavailability of parameters at specific locations and times. Similar uncertainties are found in the previous chapter in which soil and plant parameters and outputs from times and locations not covered by field observations were used to calibrate the SGS model. The fundamental test for building confidence in using system models involves quantifying the uncertainties through comparison of outputs from simulation models with observed data independent from model calibration data (Grant et al., 1997). Validation is a process that determine whether the behaviour of simulation model output has satisfactory accuracy for the model's intended purpose over the domain to which the model is applied or not (Sargent, 2010). The process enables the general behaviour of the model to be examined to check for inconsistences with patterns for behaviour of the actual system.

For measured data to be valid for use in simulation model validation, it must have been collected on the system specifically for developing and testing a model (Sargent, 2010). However, availability of appropriate, accurate and enough site-specific observed data of state variables remains a challenge (Walker and Langridge, 1996). It is difficult, time consuming and expensive to collect appropriate, accurate and enough data for validating simulation models. Only a few short-term grazing trials have been conducted specifically for modelling studies in the sourveld e.g. Dye and Walker (1987), Richardson's Savanna model (Kazembe, 2010; Richardson et al., 2000) and Illius et al. (1998). Short-term simulation experiments do not represent actual paddock conditions which are a result of long-term impacts of determinants in the rangeland system. As a result, there is little and old information known about the application of simulation models in ecology and management of sweetveld in Zimbabwe. There is need for alternative methods for evaluating the accuracy with which WFMs reproduce the known theoretical knowledge in regions where field observations are limited or not available.

Use of combinations of validation techniques is a commonly accepted approach that can benefit model users (Tedeschi 2006), especially in data limited environments. Model users can benefit from exploring the behaviour of model outputs and where possible, behaviour of model output should be compared with behaviour of another model's output (Sargent, 2010).

Behaviour of simulated grass growth rates can be examined to check for general consistencies with patterns and behaviour of the actual system. The outputs are usually compared with information published for different locations within a biome to identify any irregularities. While this form of model evaluation is essential, remote sensing is also important in providing long-term data for assessing simulation models (Angerer, 2012; Scanlon et al., 2005).

Herbaceous biomass modelling using remote sensing is increasingly becoming an attractive source of independent data for evaluating simulation models due to its large area cover and higher temporal frequencies of collection than field measurements. For example, in East Africa Jarlan et al. (2008) used SPOT at microscale whilst in southern Africa Scanlon et al. (2005) flux tower measurements have been used to evaluate a simulation model. Most of these studies incurred highly expensive equipment for *in situ* measurements rendering use of the approach ineffective for routine herbage monitoring. Herbaceous AGB modelled from cheap, medium resolution satellite images such as those in Chapter 4 can be matched with simulated outputs to validate WFMs.

Once discrepancies in model output are adequately assessed, WFMs can be applied with confidence to predict grass growth and production on a timely basis. The information can help to enhance our understanding of the complex interactions that cause inherent variability in rangelands (Rickert et al., 2000). Pasture simulation models can also assist to identify suitable and effective management practices for maximising production of grasses and animals (Jones et al., 2017b). When used to forecast future events, the models can help to identify risk areas that require emphasis on management. This study was aimed at evaluating the adequacy of SGS modules of soil water and plant growth in predicting growth of productive native grass species that are the key determinants to animal productivity in sweetveld.

6.1.1 Objectives

The purposes of the study were to:

- Test the effects of varying specific parameter values of identified soil-plant factors in the SGS pasture model on native grass growth rates and production.
- Compare output from the SGS pasture simulation model with remotely sensed herbaceous aboveground biomass.

6.2 Materials and methods

6.2.1 Description of sites and parameters used for model evaluation

The geographical location and ecological characteristics of the Nuanetsi beef cattle ranch have been described in Sections 3.2.1 and 4.2.1. In order to select sites for validating the SGS model, grazing management units were subjectively delineated in each land type based on distinctive rainfall regimes. This was achieved by overlaying a 10-km resolution map of CPC-ARC2 rainfall product on the elevation map (Figure 5.3) of Nuanetsi ranch. The rainfall regimes were characterised from the gridded map according to median rainfall, coefficient of variation and frequency of drought events experienced in each grid-cell between 1992 and 2017. This process led to selection of three grid cells that represented the land types and rainfall regimes found across the ranch (see Table 6.1). Elevation, latitude, and profile inclination (%) at each grazing management unit were derived from the DEM.

Table 6. 1: Landscape attributes of simulated paddocks

Land type (Grid cell)	**Median rainfall (mm)**	**C.V rainfall (%)**	**Drought events (1992-2017)**	**Paddock ID**	**Location (Lat/Lon)**	**Elevation (m)**	**Paddock size (ha)**	**Woody cover (%)**
Crest (I)	452	39	6	B33	-21.37 31.07	517	627	18
				B34	-21.38 31.10	510	680	23
				Vet 2	-21.39 31.07	511	1131	21
Mid slope (H)	447	36	5	B19	-21.41 30.99	480	489	16
				B20	-21.43 30.98	484	457	14
				B30	-21.43 31.01	483	526	11
Foot slope (B)	468	34	4	A18	-21.18 31.12	448	518	24
				A24	-21.21 31.13	454	1010	26
				A25	-21.20 31.11	464	434	22

The final grazing management units that were chosen for validating the SGS model in each land type are shown in Figure 6.1. Each land type was assumed to contain vegetation that has a unique response to rainfall due to natural variability within the landscape, resource (water and nutrients) redistribution and their interactions that influence the level and direction of change in herbaceous AGB production. In order to evaluate the SGS model using independent data, many plot-specific parameter values described in Chapter 5 were averaged to single values that were generic to each land type. The generic parameters that represent common land types within a land system enables the model to be applied to other similar land systems within the lowveld region. The plots to which the SGS model was calibrated in Chapter 5 were grouped according to soil (land) type, herbaceous species composition and a combination of both.

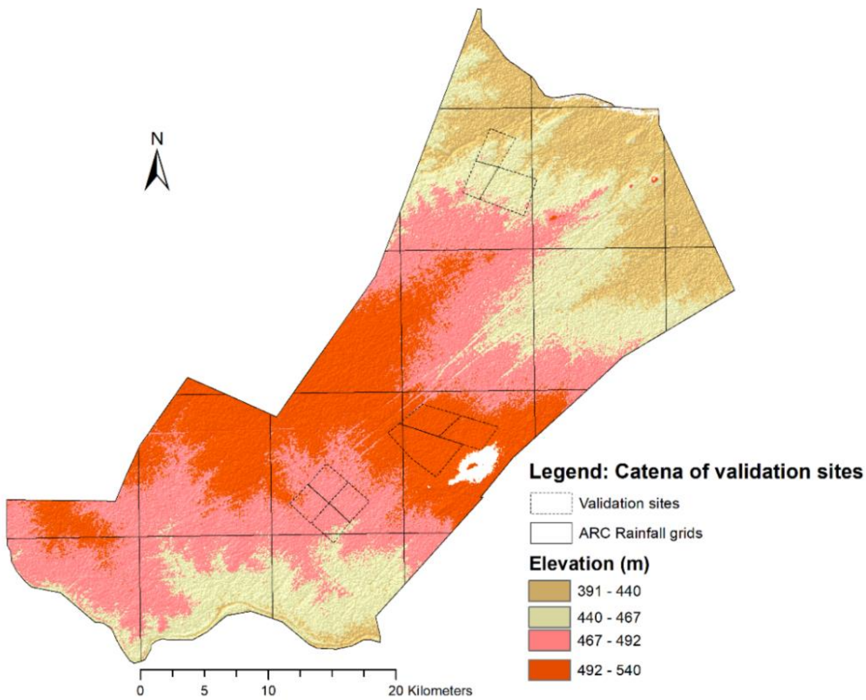

Figure 6. 1: Location of model validation sites and ARC2 rainfall grid-cells overlaid on elevation map of Nuanetsi ranch

Based on field results from CSRI (2003) for foot slope soil and CSRI (2007) for crestal and mid slope soils, there were two soil families in each land type. In crest and mid slope land types, mafic gneiss soil family was found in 79 % (11 of 14) and 65 % (11 of 17) of the surveyed pits, respectively. In foot slope soil, fine alluvium soil family was found in 60 % (6 of 10) plots. The plots occurring in the above dominant soil families were grouped to represent generic parameters of the respective land types. All values of individual parameters were averaged across each year and each land type to produce single values for that land type. The resultant soil parameters used for validating the SGS model are presented in Table 6.2.

Table 6. 2: Soil geology and physical properties of sites used for model validation

Soil Catena	Geology/ parent material	Range (mean) altitude (m)	Texture	Slope (%)	Soil depth (cm)			
					Total	Effective	A	B1
Crestal soil	Mafic gneiss	480-500 (487)	mSaL/ mSaL or mSaCL	2	50-100	79.9	17.17	25
Mid slope soils	Mafic gneiss	435- 480 (441)	mSaL/ mSaL or mSaCL	2	40-60	62	11.3	18.6
Foot slope soils	Med Alluvium	380- 415 (404)	cLS/ mLS-mSL	1	> 150	152.5	12.8	16.4

mSaL/ mSaL or mSaCL, Medium grained sandy loam topsoil over medium grained sandy loam or sandy clay loam sub-soil; cLS/ mLS-mSL, coarse grained loamy sands topsoil over medium grained loamy sands to sandy loams.

6.2.2 Model evaluation techniques

There are no formally acceptable and completely objective techniques for validating the adequacy of predictions from simulations models (Grant et al., 1997). The best approach to assess the adequacy of performance of mathematical models when comparing model-predicted and observed values is to use a variety of evaluation measurements (Sargent, 2010; Tedeschi, 2006). Other than the single-season herbaceous biomass data, there were no other historical observed data, yet the data is needed for testing simulation models. To close this data gap, parameter sensitivity analysis and comparison of model output with output from other reliable models are the techniques that were used to evaluate the SGS model. Parameter sensitivity analysis was conducted to test the effect of adjusting different parameters of three land (soil) types and two pasture species. All parameters that were adjusted in SGS model to suite site conditions were obtained from literature and therefore hold some level of uncertainty. To test the extent of change that modifications to parameter settings made in the soil water and grass growth modules, the model was also run using default parameter settings for the respective soil types and grass species family. To evaluate the model using statistical tests, estimates of herbaceous AGB predicted by a rainfall-based model for herbaceous AGB model for grid cells corresponding to sites where long-term model simulations were performed were used. The rainfall-herbaceous AGB model was developed from satellite-based estimates of rainfall and remotely sensed herbaceous AGB and, validated as outlined in Section 4.2.4.

6.2.3 Model simulations

Plot-specific parameters developed in Chapter 5 were reduced to single, generic values for common soil families found at Nuanetsi ranch to enable the model to be evaluated on a long-time basis and be applicable to similar soil types in the region. Based on results from soil surveys conducted by CRSI, fine alluvium soil family was common in 60 % of sampled pits in foot slope (CSRI, 2003) while mafic gneiss was dominant in 79 and 65 % of the pits surveyed in the crest and mid-slope land types, respectively (CSRI, 2007). All values for each individual parameter were averaged across each soil family to produce a single value for the land type. A simulation experiment was then conducted over 36 years (1982 to 2017) to analyse the extent of improvement made by parameter adjustments and to check for deviations of model behaviour from real system behaviour. Firstly, daily grass growth simulations were run separately for all combinations of land type and pasture species using adjusted parameter sets in three 500-ha paddocks constituting a grazing management unit. Then, growth simulations of default native C4 grass were performed using default parameters of duplex and medium-texture soils corresponding to foot slope and, crest and mid-slope soil types. Another simulation experiment was conducted over the same period to show the importance of the hypothesis that leaf regrowth rate after defoliation is dependent on carbohydrate reserves in roots and residual dry matter of stubble. Simulations were performed with grass cut to residual dry matter levels of 500, 750 and 1000 kg DM ha^{-1} at the end of each month. Observed values of initial conditions of state variables were considered as parameters because the data was not available at the start of simulations. In addition, outputs in the first 10-year lead-in period of all simulations were discarded to allow the model to stabilise. Thus, outputs between 1992 and 2017 seasons were used respectively to calibrate and evaluate the SGS model.

6.2.4: Analysis of model output

The model outputs analysed includ daily grass growth rate (kg DM $ha^{-1}d^{-1}$) and biomass production (kg DM ha^{-1}). Daily outputs were averaged over each calendar month to convert them to values of monthly averages for each paddock. Model outputs for the three paddocks were averaged to come up with weighted grass growth rates and production for each grazing management unit. The behaviour of model outputs was explored qualitatively by examining the percent decrease or increase in outputs resulting from default and adjusted parameters. Percentiles of monthly growth rates were then calculated, and comparisons were made between outputs obtained from default and adjusted parameters of soil and grass species. To ascertain the reliability of outputs, the growth rates were compared with values published in the literature for broad-leaved savannas of south-central Africa.

A standard procedure for evaluating performance of models involving calculation of summary statistics (mean, minimum, maximum, mean bias), root mean square error (RMSE), decomposition of RMSE (bias, slope, and random components) and graphical analysis of residuals (Mcphee and Walmsley, 2017) was used to analyse the measured, remotely-sensed and simulated data. In fitting values of measured or remotely sensed biomass with model predicted values, simulated biomass was used in the *x*-axis as they are assumed to be without errors. The coefficient of determination (r^2) was used to measure the precision with which the model predicted measured or remotely sensed herbaceous AGB. A plot of residuals versus predictor variables was used to assess the envelope of acceptable precision around the line of zero deviation and the proportion of points that lie within it (Mitchell and Sheehy, 1997). The RMSE was included as the appropriate measure for assessing the predictive accuracy of a model calibrated with parameters from independent experiments (Tedeschi 2006).

6.3 Results

6.3.1 Sensitivity analysis

The grass production predicted in this study portray a typical growth and yield pattern known for grasses native to the broad-leafed savanna of southern Africa (Figures 6.2 and 6.3). In winter, the growth rates of *U. mosambicensis* predicted using adjusted parameters were low, with a mean, median and maximum yield falling below 0.06, 0.0 and 0.6 kg DM ha^{-1} d^{-1}, respectively. The growth rate increased rapidly, reaching mean, median and maximum peak biomass corresponding to 7.3, 4.5 and 33 kg DM ha^{-1} d^{-1} in January, respectively. The mean growth rate across land types between November and March ranged between 2.9 and 7.2 kg DM ha^{-1} d^{-1} whilst the median growth rate varied from 0.9 to 5.5 kg DM ha^{-1} d^{-1} (see Figure 6.2 (a)). However, there was an abrupt 18 % decline in the median growth rate of *U. mosambicensis* and *E. curvula* stands in mid- and foot slope land types in January while a steady growth rate was maintained in crest land type between December and February (Figure 6.2 (a)). The median growth rate of *U. mosambicensis* in mid-slope land type was 7 to 24 % high relative to the upper slope land type, at peak period (December to February).

The highest growth rates of *U. mosambicensis* were predicted between December and February when residual DM was cut at 750 kg DM ha^{-1} followed by growth rates from simulations run with cutting set at 1000 kg DM ha^{-1}. The least growth rate predictions were obtained when residual DM was cut at 500 kg DM ha^{-1} (Figure 6.2 (b)). The median growth rate of *U. mosambicensis* stands cut to 750 and 1000 kg DM ha^{-1} residual DM suddenly dropped by 12 and 18 %, respectively in January whilst grass cut at residual DM of 500kg DM ha^{-1} maintained a stable growth rate between December and February.

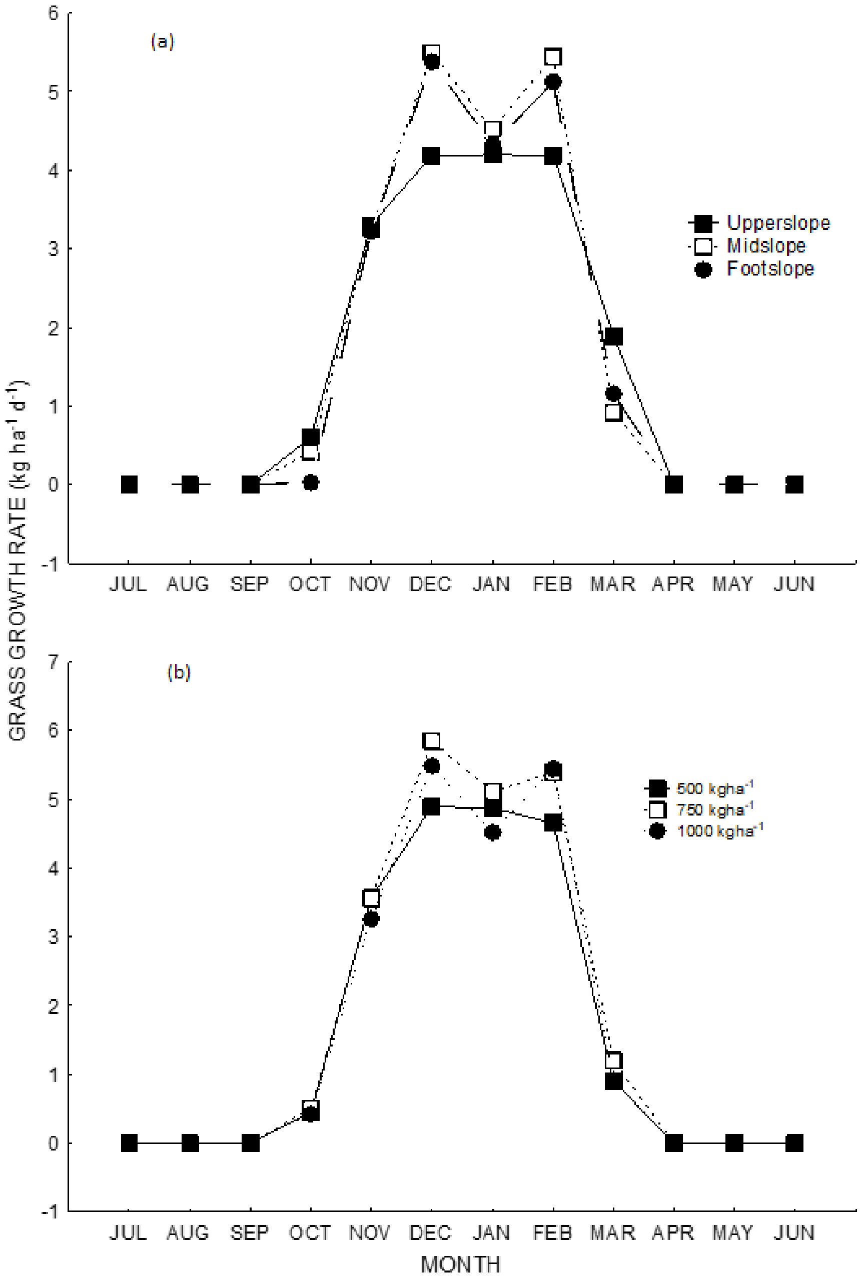

Figure 6. 2: Modelled median grass growth rate (kg DM $ha^{-1}d^{-1}$) of *Urochloa mosambicensis* across (a) land types and (b) grazed residual dry matter levels.

Simulated grass production portrayed a seasonal pattern identical to that of growth rate (Figure 6.3). Between November and March, absolute monthly grass biomass yield ranged between 115 and 228 kg DM ha^{-1} across all land types. The maximum monthly grass biomass yield during this period was 209, 220 and 228kg DM ha^{-1} for crest-, mid- and foot-slope land types, respectively. Adjustment of parameters for moderately deep soil in crest land type led to high growth by the default native C4 grass relative to local grass species (Figure 6.3 (a)). However, in shallow mafic-gneiss derived soils in mid- and foot slope land types, parameter modifications resulted in lower growth rates of default native C4 grass compared to local grasses (Figure 6.3 (b) and (c)). Grass production between local grass species showed less difference in all land types. Grass yield predictions for both *U. mosambicensis* and *E. curvula* between November and April were higher than yield estimates of default native C4 grass by 29 to 98 % and 26 to 86 % in mid- and foot slope land types, respectively (Figure 6.3 (b) and (c)). These differences were biggest between November and January.

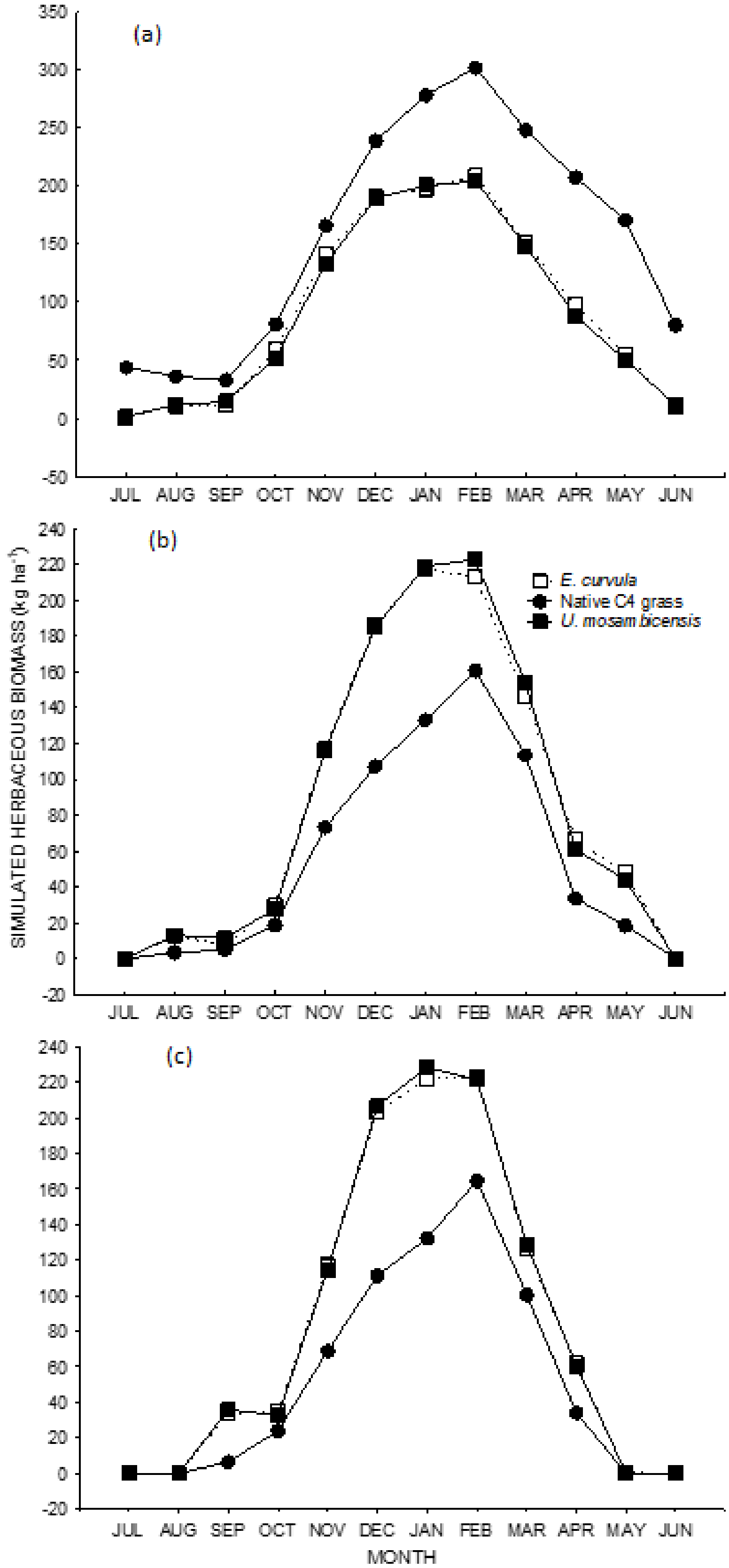

Figure 6. 3: Modelled absolute monthly herbaceous aboveground (kg DM ha^{-1}) of default native C4 and adjusted grass species parameters in (a) upper-, (b) mid- and (c) foot slope land types.

6.3.2 Comparison of SGS model output with remotely sensed herbaceous aboveground biomass

As with predictions for field biomass data, there were huge discrepancies in summary statistics and residuals between simulated and remotely sensed AGB across all datasets. The mean remotely sensed AGB varied between 3644 and 4170 kg DM ha^{-1} whilst the mean modelled AGB ranged between 1674 and 1997 kg DM ha^{-1}. Minimum remotely sensed and simulated biomass was 1445 and 1249 kg DM ha^{-1}, respectively whilst maximum values of 7214 and 2281 kg DM ha^{-1} corresponding to remotely sensed and simulated biomass, respectively, were attained. The SGS model had a tendency of underestimating remotely sensed AGB by between 51 and 59 % across all land types. The mean bias ranged from -1970 to -2461 kg DM ha^{-1} whilst the relative bias varied from -0.51 to -1.18. Despite the underestimation of remotely sensed herbaceous AGB by the SGS model, the model predictions were significantly correlated with remotely sensed herbaceous AGB ($P < 0.05$), accounting for between 63 and 72 % of the variation (Figure 6.4 (a)). A plot of residuals versus predictor variables shows the deviation of individual predictions from corresponding observations across all land types (Figure 6.4 (b)). The results illustrate that 39 % (19 of 49) of all predictions of herbaceous AGB fell within the 95 % confidence limits of their respective observations whilst 30.6 (15 of 49) and 30.6 % (15 of 49) were under- and over-predictions, respectively. The RMSE of all predictions across land types was 981 kg DM ha^{-1} and ranged from 1122 to 1396 kg DM ha^{-1} with predictions in the upper slope having the lowest accuracy.

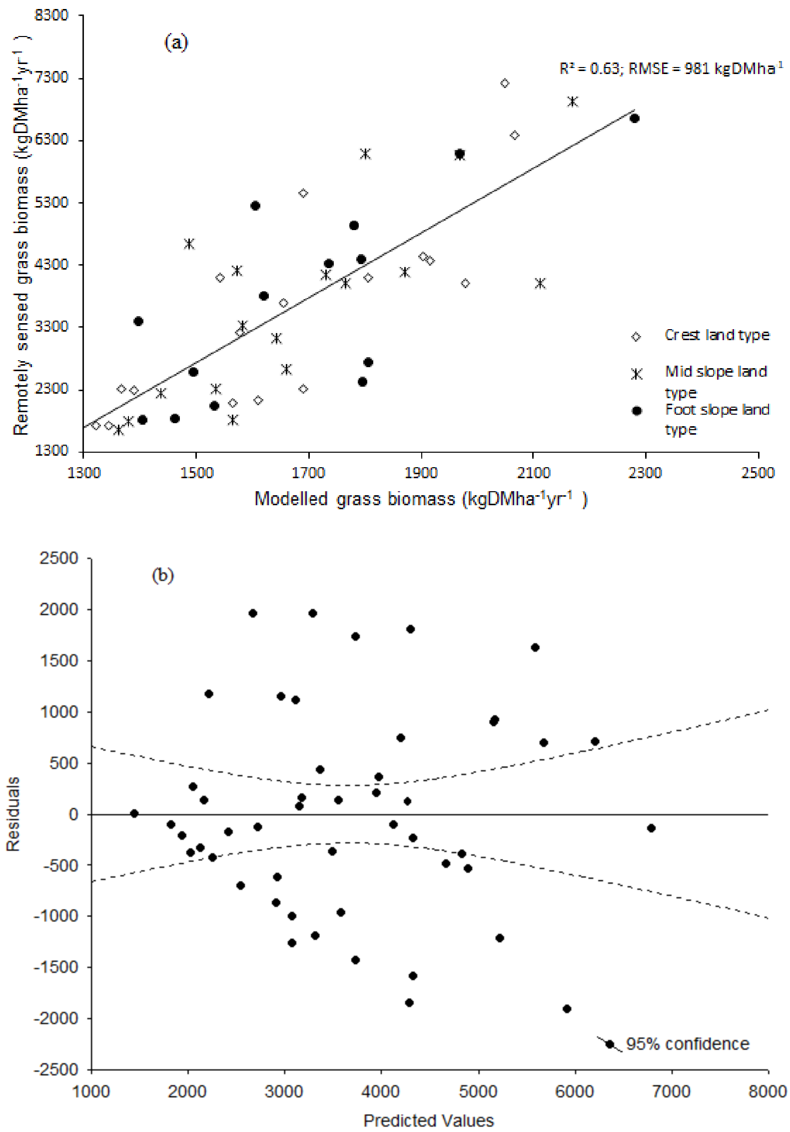

Figure 6. 4: Plot of (a) remotely sensed and modelled grass biomass and (b) residuals and model predicted values of grass biomass

6.4 Discussions

6.4.1 Sensitivity analysis

The long-term patterns of pasture growth displayed by model outputs agree with the typical behaviour of summer growth of perennial grasses in the tropical biome of southern Africa. For example, low growth rates of DM were observed in winter because there is no rainfall and temperatures are low whilst the grass growth rate in summer increased rapidly because of high rainfall and temperatures which can rise beyond 30°C. The SGS model also represented the effects of mid-summer droughts on median grass growth reasonably by showing a decline in growth rate in January (Figure 6.2). Frequent mid-summer droughts or dry spells are a characteristic feature of arid savannas receiving annual rainfall below 600 mm in the Limpopo river basin (Huntley, 1982). This was confirmed by the DM accumulation pattern of outputs predicted by the SGS model. Also, there is a good agreement between estimates of monthly growth rates predicted by the SGS model and growth rates measured in other rangelands of southern Africa. In the south-eastern lowveld region of Zimbabwe, Kelly and Walker (1976) observed daily growth rate to vary from 9 to 11.5, 6.6 to 11 and 5 to 10 kg DM $ha^{-1}d^{-1}$ in open vegetation corresponding to lightly-, moderately- utilised and non-utilised stands, depending on seasonal rainfall. Creswell et al. (1982) observed a peak mean herbaceous biomass growth rate of 5kg $DMha^{-1}$ in mid-November in a semi-arid savanna of northern South Africa. Thus, the comparability of growth rates of local grasses predicted by the model to those observed in the region builds confidence in parameter sets used.

Default model parameters were intentionally adjusted within acceptable ranges representative of the southern African savanna biome to explore their effect on grass growth. This was necessary because the optimum growing conditions of local native grasses and their responses to available soil water and nutrients differ from those in tropical regions of Australia where the SGS model was developed and tested. The model was able to illustrate the effect of adjusted soil depth parameters on soil moisture infiltration and retention and subsequent plant growth, meaningfully. For example, in deep sandy loam soils of arid southern Australia, summer-season growth rates of 50 or more kg DM $ha^{-1}d^{-1}$ have been predicted (Descheemaeker et al., 2014), that is, 65 % higher than maximum growth rates simulated in this study. The model output from modified parameters also successfully showed the pattern in grass production known to exist along the slope of lowveld granitic/gneiss catena. Dye and Walker (1980) also observed lower grass productivity in crest- relative to mid- and foot- slope land types. These results illustrate that the same model structure with different parameters for soil and plant species produced grass growth patterns that are consistent with expectations for lowveld granitic/gneiss catena. This gives confidence in applying the model to new regions.

As with the growth rate, the pattern of grass production simulated in this study was expected for shallow sandy-loam soils. Similar grass production trends have been observed in shallow crest soils of the southern region of Kruger National Park mean monthly grass production ranging from 40 to 160 kg DM ha^{-1} between December and June (Alard 2009). In Bloemfontein, monthly growth rates ranged between 100 and 400 kg DM ha^{-1} between November and March, depending on seasonal rainfall (de Waal, 1990). These findings suggest that local variation in grass production in semi-arid rangelands of southern Africa could be caused by natural variability in soil moisture and soil nutrient availability that cannot be simulated by point-based models.

6.4.2 Comparison of SGS model output with remotely sensed herbaceous aboveground biomass

Findings from this study demonstrate that the SGS model can display a logistic growth and response of native grasses to seasonal effects of climate under south-central African conditions. The modelled herbaceous AGB showed an acceptable level of representation of remotely sensed herbaceous AGB for African savanna. These findings concur with Boone et al. (2002) who obtained a good illustration ($r^2 \geq 0.60$) between SAVANNA model outputs and NDVI derived from low spatial resolution (1-km) AVHRR across grass-, shrub- and woodlands in northern Tanzania. Using the same model and satellite product in the Kalahari thornveld and shrub bushveld in north western South Africa, Boone et al. (2004) found reasonable agreement between NDVI and modelled vegetation biomass ($r^2 = 0.42$). Also, Popp et al. (2009) found that NDVI account for most variation ($r^2 = 0.69$ to 0.79) is modelled vegetation biomass in the Nama karoo shrub savanna of southern Namibia. The SGS model can thus be used with some confidence basing on its precision level that is comparable to other simulation models.

As mentioned earlier about the comparison of measured and simulated data in complex natural systems, there are also challenges associated with comparing the output of another model with simulated herbage biomass. Climate variables are important in systems analysis of rangelands as they affect herbaceous biomass production (Scholes and Walker 1993). Daily rainfall and solar radiation inputs used in this study were derived from interpolation of satellite estimates whilst temperature was spatially interpolated using data collected at two sparse weather stations. The process of deriving these inputs might have introduced substantial amounts of non-random errors due to the absence of measured weather data at the study area. Thus, the climate data used in this study has its flaws which might have affected model outputs. However, given that weather data was not available on the ranch, satellite-based and spatially interpolated data were the only suitable choices and, were considered as representative.

As with predictions for field biomass data, low performance scores for measures of individual predictions were observed between simulated and remotely sensed herbaceous AGB. Minimum and maximum herbaceous biomass production simulated in this study are also above and below the respective production often observed in southern African savanna (Mutanga and Rugege 2006). Low and high herbaceous biomass yield responses to corresponding extreme dry and wet years are often observed in semi-arid regions where rainfall variability is high. Failure by the SGS model to reproduce these dynamics as expected for rangelands indicates the model's limited capacity to simulate some of the biophysical processes involved. Poor agreement between simulated and remotely sensed biomass values can be attributed to errors of climate inputs and parameters cited previously and those associated with variation in spectral reflectance properties of herbaceous vegetation. Variation in herbaceous vegetation reflectance is affected by vegetation structure, density and condition which vary in space due to wide species diversity and grazing (Kumar et al., 2016). Given the inherent uncertainties associated with inputs, parameters and remotely sensed biomass used in this study, it is imperative to test the extent to which the model predicts responses in the whole set of predictions.

A comparison of the overall prediction error of a simulation model with the error of the empirical remote sensing model is an alternative test that provides confidence in the performance of simulation models. The SGS model output predicted remotely sensed herbaceous AGB at an accuracy level that is comparable to field measurements. The average errors values of simulated herbaceous AGB (981 to 1396 kg DM ha^{-1}) fall within the range of errors of measured (930 kg DM ha^{-1}, Svinurai et al. 2018) and satellite-derived herbaceous biomass (1171 kg DM ha^{-1}, Dwyer 2011) for broad-leaved savannas of southern Africa. In the savannas of KNP, Mutanga and Rugege (2006) found RMSEs ranging from 830 to 1374 kg DM ha^{-1} from geospatial and remote sensing regression modelling, respectively whilst Dwyer (2011) found the RMSE to vary between 1171 and 1711 kg DM ha^{-1}. These results imply that when model parameters are derived from independent experiments to represent natural systems, statistical tests that consider complete set of predictions provide plausible assessment of model accuracy.

The findings from this study suggest that individual seasonal predictions deviate considerably from measured and remotely sensed herbaceous AGB and, the high natural variability of southern African savannas is the major source of uncertainty. When summarised, under- and over-predictions refute each other to produce acceptable error values. This is supported by predicted growth rate values of *U. mozambisensis* which typified growth rates of grasses native to southern Africa savannas. Errors of SGS model outputs associated with the modified inputs and parameters fell within acceptable levels of measurement error. Therefore, the parameter sets developed in this study can be used with some confidence as they give overall model error comparable to other empirical methods of herbaceous biomass estimation in the region. Further testing of the SGS model under a variety of environmental conditions in southern Africa is required to gain more confidence in applying the model.

6.5 Conclusions

The behaviour of SGS model outputs was successfully explored qualitatively by examining the sensitivity of outputs resulting from default and adjusted parameters and quantitatively in a linear regression between remotely sensed- and model-predicted values. The model predicted the typical growth pattern known for grasses native to semi-arid region of southern Africa. Growth predictions of *U. mosambicensis* and *E. curvula* were higher than yield estimates of default native C4 grass by 26 to 98 % between November and April across mid- and foot slope land types. Model predictions were also significantly correlated with remotely sensed AGB at reasonable overall performance error (RMSE, 981 kg DM ha^{-1}). However, modelled AGB underestimated remotely sensed AGB across land types. These findings indicate that, when dynamic models are tested in natural systems, measures for individual predictions provide low performance scores while better scores are obtained with measures for whole set of predictions.

CHAPTER 7

Modelling the effects of grazing strategies on native grass production, animal intake and growth in Brahman steers

Abstract

Inadequate information about the long-term effects of grazing strategies on native grass production and animal growth poses limitations to sustainable management of beef cattle. A simulation study was conducted over 20-years to analyse the implications of different stocking rates (SRs) and multi-paddock grazing systems for Brahman steers grazing in mopane tree-shrub savanna. Simulations included three multi-paddock grazing systems (2-, 3- and 4-paddocks per herd) and four SRs that were compared for their effects on herbage production, dry matter intake (DMI) and steer liveweight gain (LWG) using the SGS model. The four SRs included the recommended SR (10haLU^{-1}), 30 % higher (7 haLU^{-1}) and, 50 and 100 % lower (15 and 20 haLU^{-1}, respectively) SR. Overall, no observable differences were found in herbage production and DMI response to all treatments for multi-paddock grazing systems and SRs. Average herbage yield and animal production of weaners were 2540 kg DM ha^{-1} and 5 kghead^{-1}day^{-1}, respectively. Also, multi-paddock grazing effects on animal production were approximately similar across treatments but differential responses of LWG to SRs were more pronounced. Weaners stocked at the recommended SR grew persistently at high rate, reaching a maximum LWG of 234 kgyear^{-1} but animal productivity was adversely affected in the long-term. Increasing the recommended SR by 30 % resulted in reduced DMI and LWG of weaners in the short term whereas reducing the benchmark SR by 50 % or more enabled persistent high animal intake and growth in the long term. These results provide a useful criterion for choosing an effective SR to achieve sustained herbage and animal production with minimum risk. The findings suggest that ranch managers should put more management emphasis on SRs over multi-paddock grazing systems since proper SRs enable maximised rangeland and cattle productivity over time.

Keywords

Stocking rate, grazing system, animal production, sustainability

7.1 Introduction

Despite their importance to economic development, extensive beef production systems in semi-arid rangelands of southern Africa have evolved from highly variable climatic conditions (Walker et al., 1981). Management of these rangelands is difficult as decisions must be adapted to large variation of seasonal climate and persistent droughts. In the past fifty years, grazing experiments led to advances in grazing management concepts aimed to enhance the decision-making skills of ranch managers (Stuth and Maraschin, 2000). However, experiments are have limited scope to represent the huge variation in climate and environment in rangelands and, have often provided inconclusive results about the viability of grazing strategies across locations (Briske et al. 2008). Moreover, there are disagreements between experimental and experiential knowledge about the effects of grazing systems and SRs on forage and animal production (Teague et al., 2013). Recently, research emphasis has shifted to the overriding interactive influence of climate variation and SRs on forage production and cattle weight gains (Reeves et al., 2014, 2013). For research to be valuable to managers, there is need for embracing a systems analysis approach which enables recommendations to be made at grazing management unit level based on long-term, landscape level changes.

Whole farm systems models give quantitative description of interactions of components in rangeland systems, some of which have opposing effects and are too complex to be analysed by the human mind (Rickert et al., 2000). Simulation models provide state variables of the soil-plant-animal system that enable the analysis of the long-term growth patterns of herbage and cattle relative to climate conditions (Doran-Browne et al., 2014; Fang et al., 2014). In southern African savanna rangelands, previous efforts in modelling the impacts of grazing strategies have been limited to deterministic and stochastic approaches (Illius et al., 1998; Richardson et al., 2000), mostly applied on a short-term basis (Kazembe, 2010). These types of models, however, are founded on animal component models that do not accurately predict body composition due to lack of detailed and accurate experimental data (McNamara et al., 2016). However, fat and protein deposition are influential variables for predicting nutrients requirements for growth in animals which vary with breeds (Tedeschi, 2019). Given that mechanistic models contain default parameters for body composition that are adjustable across genotypes, they offer model users in resource-limited regions opportunities to adequately represent the dynamics of metabolism and growth. Thus, extending the use of mechanistic models to long-term impact assessments of grazing strategies will assist ranch managers in making strategic decisions.

Process-based models (PBMs) are a subset of mechanistic models that explicitly integrate different levels of biological organisation to understand the behaviour of grazing systems and to compare the productivity and sustainability impacts of management practices (Tedeschi, 2019). The models have many built in management options that enable detailed simulation and impact analysis of management actions. In semi-arid rangelands of southern Africa, SR and adequate resting are key management factors that influence animal production (van de Pol and Jordaan, 2008)**.** Stocking rate causes variability in herbaceous vegetation community and production (Derner and Hart, 2007) and animal weight gains (Derner et al., 2008), with the grazing effects varying with location, climate and timing and period of grazing (Teague et al., 2008). The interactions between biophysical and management factors are complicated and difficult to quantify or comprehend yet they are important in decision making. There is need, therefore, for broadening experimental knowledge by using PBMs that effectively incorporate soil, plant, and animal inputs to explicitly represent the complex interactions in rangelands and improve management planning.

Process-based models have been widely applied to assess the influence of grazing systems and SRs on rangeland and cattle production in the wet and dry regions of North America (Fang et al., 2014) and northern Australia (Doran-Browne et al., 2014), respectively but rarely in southern African rangelands. Nevertheless, the current SRs for Zimbabwean rangelands are still based on archaic recommendations for agroecological regions (Vincent and Thomas, 1960). Considering the increase in dry years and decrease in wet years that occurred in the region after the 1970s' global climate shift (Gaughan et al., 2016), there is possibility that the seasonal dynamics of herbage production and livestock carrying capacities changed too. This emphasises the need for re-evaluating grazing strategies under changing grazing pressures to prevent degradation of herbaceous vegetation to a less productive community. Process-based models provide useful information needed to improve ranch managers' skills for selecting effective long-term SRs that avoid deterioration of herbage condition (O'Reagain et al., 2014). These models are capable of resolving the proper combination of grazing systems and SRs, thus enabling ranch managers to choose grazing strategies that maintain plant vigour, composition and productivity (Teague et al., 2013). This study, therefore, aimed to parametrise the animal module of the SGS model and use the whole model to analyse the effects of multi-paddock grazing systems and SRs on herbage production, intake, and growth of Brahman weaner steers.

7.1.1 Objectives

The aims of this study were to:

- parameterise the animal sub module of the SGS pasture model to simulate growth of Brahman weaners in a south-central African savanna.
- apply a newly parameterised SGS model to analyse the effects of multi-paddock grazing systems and stocking rates on herbaceous AGB production, intake and growth of beef weaner steers.

7.2 Materials and methods

7.2.1 Description of the commercial beef ranching system

Zimbabwe has about 5 million beef cattle and about 75 % of the herd is raised under extensive management in four southern provinces which have comparative advantages for commercial beef production (Mavedzenge et al., 2006). The commercial beef systems are based exclusively on exotic breeds which are dominated by the Brahman genotype. To evaluate the impact of grazing strategies, Nuanetsi cattle ranch was chosen as the representative farm which implements the animal husbandry practises widely used in southern Zimbabwe. The ranch lies in the semi-arid region with a long-term annual mean rainfall of 460 mm and has an area of 113 9.13 km^2. The area is predominantly covered by *Colophospermum mopane* tree/shrub savanna and a sub canopy layer of native, multispecies herbaceous community. The dominant soil type is dark brown, shallow chromic luvisol of medium texture that is formed from mafic-gneiss parent material. A detailed ecological description of the ranch is provided Sections 3.2.1, 4.2.1 and 5.2.1. Given its large spatial coverage, the ranch presents a complicated land use system which requires high level of management for viability of large herd sizes.

The ranch operates an extensive 'breed and sell' beef production system with a capacity of 10000 heads. The 'breed and sell' beef production system involve two intermeshed systems, that is, a breeding system of cows with calves for herd replacement and bulls and, cows with bulls producing steers and heifers for sale. The paddocks range in size from 350 to 1500 hectares with an average size of 500 hectares. Depending on size, each paddock has up to 3 water points that are sited strategically to achieve homogenous use of forage resources. Each herd is managed in a grazing management unit comprising of 2, 3 or 4 paddocks. Cows are bred between December and March so that calving would occur in summer and, are culled based on their performance records. Supplementation with protein-rich supplements is done in some dry seasons when necessary. Calves, i.e. progeny less than 120 kg, are weaned at 7 months of age, reared on the veld until they reach 18 months at which they are either upgraded to 1-year old steers and heifers or sold. Animal productivity is very high and up to 100kg per head per year post-weaning weight gain can be achieved.

7.2.2 The animal growth modelling tool

7.2.2.1 Overview of the SGS animal module

The SGS animal module was developed by Johnson et al. (2012) with the intention of integrating it with the pasture module into a whole-system biophysical model. The whole-system model is meant to simulate animal growth and its response to pasture, forage, concentrate and mixed ration when supplied as combined feed (Johnson, 2016). The animal module was developed to simulate intake in cattle and sheep in relation to feed composition (protein, neutral detergent fibre (NDF) and neutral detergent solubles (NDS)), animal weight and pasture quality and availability. The intake is then converted into ME which is used for metabolic processes of growth, maintenance, lactation and pregnancy in the simulation, thus affecting these processes directly.

Energy dynamics in the animal's body depend on the balance between ME intake and the ME requirement for a class and breed of animal. Growth and energy dynamics are simulated in response to energy available in the body, which include water, protein and fat (Johnson et al. 2012). The module simulates animal growth by partitioning metabolizable energy intake into maintenance and growth or pregnancy, lactation and nitrogen dynamics which were recently included in the model by Johnson et al. (2016). Animal protein content determines the state of metabolism and its growth is simulated as a function of protein weight using the rate-state, Gompertz equation denoted as:

$$\frac{\mathrm{d}Wp}{\mathrm{d}t} = \mu Wp\mathrm{e}^{-Dt} \text{ where;}$$

Wp is empty body weight protein content, t (d) is time, μ (d-1) is initial specific growth rate for Wp, and D (d-1) is a parameter for the decay with time of the specific growth rate, μ is the Gompertz coefficient: initial protein specific growth rate during growth. The potential protein growth is thus the net accumulation of protein which is the difference between protein synthesis and degradation. To derive the actual protein growth from this equation energy available from intake is used.

Fat growth is modelled as a secondary process related to protein growth and maximum potential fat fraction of body weight, a factor that varies throughout the growth of the animal depending on total body weight. Body fat is used to provide metabolic energy for resynthesis of degraded protein to maintain the animal during time of low body energy reserves. The energy for protein resynthesis and activity energy provided by body fats take precedence over the growth of new tissue. Availability of energy also determines body composition during growth and at maturity. When energy intake is enough for potential protein growth and associated fat growth, normal growth occurs. Body fat content increases linearly with body weight under normal growth and the fat was modelled using the following equation as described by Johnson (2016):

$$f_{F,norm} = f_{F,b} + \left(f_{F,mat,norm} - f_{F,b}\right)\left(\frac{W_{norm} - Wb}{W_{mat,norm} - Wb}\right) \text{ where;}$$

Wb, kg, is the birth weight, $f_{F,b}$ is the fat fraction at birth and subscripts mat and $norm$ refer to 'mature' and 'normal'. The model contains default parameters for energy that have been defined for energy densities and efficiencies of synthesis for protein and fat, and efficiencies of fat catabolism and protein degradation.

7.2.2.2 Animal and feed management parameters

The SGS animal module has many parameters for growth and reproduction that were not available at the mechanistic level required for all cattle classes found at the ranch and, thus the animal module was parameterised for steer calves only. The parameter values were prescribed using published literature whilst default values were maintained where information was not available (see Table7.1). A Gompertz coefficient of 2.6 % per day for initial specific growth rate of EBW protein content in Brahman cattle was used (Miguel et al., 2012). The fat growth coefficient of 0.03 kg fat per kg protein per day set in the model as the maximum daily fat deposition as a fraction of EBW protein content was also used for cattle (Johnson et al., 2012). The protein and fat content of body weight gain and expected body fat content at a given weight depend on rate of daily weight gain (National Research Council, 2000). Parameters for body fat content were adjusted for three levels of productivity i.e., average daily gain (ADG) of 0.6, 0.8 and 1 kg for medium-frame beef cattle.

Table 7. 1: Animal weight, body composition and growth parameters used for Brahman weaner steers

Animal parameter (units)	**Default Value**	**Growth rate ($kghd^{-1}day^{-1}$)**			**Reference**
		0.6	0.8	1.0	
Birth weight (kg)	50	32	32	32	Pico et al. (2004)
*Normal mature weight (kg)	600	431	431	431	Schoeman (1996)
Fat at normal mature weight (%)	30	13.4	19.4	25.6	National Research Council (2000)
Fat at maximum mature weight (%)	45	14.5	21.4	28.5	National Research Council (2000)
Gompertz coefficient: initial protein specific growth rate during growth (%/day)	1.2	2.6	2.6	2.6	Miguel et al. (2012).

*Body weight of steers at approximately 430 days of age.

To assess the effect of manipulating animal body composition parameters and to select the growth rate representative of Brahman weaner steers stocked at moderate SR, the model was set to simulate animal growth using adjusted and default animal parameter sets and outputs of were compared with published experiments. The model adequately represented the characteristic growth patterns known for weaner steers raised in semi-arid rangelands of southern Africa (see Figure 7.1). Simulated median LWG ranged between 169 and 228 $kghead^{-1}yr^{-1}$ and these predictions fall within the range of published weight gains for beef cattle stocked at moderate levels. For example, LWG between 82 and 220 kg $head^{-1}yr^{-1}$ have been observed in crossbred Brahman weaners stocked at medium SR (Fynn and Connor 2000) while modelled LWG of steers varied between and 250 kg $head^{-1}yr^{-1}$ (Kazembe 2010). Parameter sets for steers growing at an ADG of 1 kg produced LWG values closest to published literature and were thus used in all simulations for assessing grazing strategies.

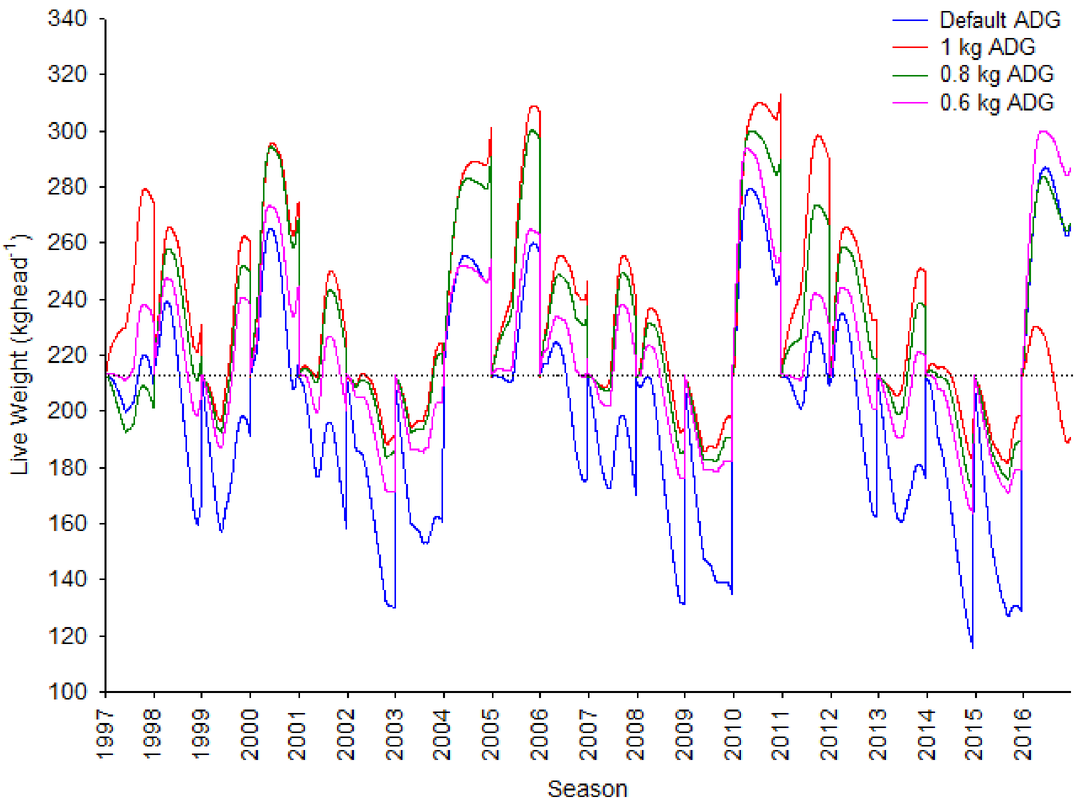

Figure 7. 1: Liveweight of weaner steers weaned in July (even numbered years) and January (odd numbered years) under three growth rates. Dotted line represents the weaning weight of calves.

The feed management parameters of the SGS were adjusted on the basis that beef cattle raised on sweetveld maintain or gain body weight during the dry season due to the presence of palatable browse that is consistently available throughout the year (Barnes, 1979; Clatworthy, 1998). Thus, the composition of forage supplement component in the SGS model was set to represent the average nutritive value of three browse species dominant in the study area namely, *Colophospermum mopane*, *Combretum apiculatum and Grewia flavescenes*. The CP content of foliage of these trees and shrubs range between 10.9 to 15.9 % (Walker, 1974), 10.5 to 15.7 % (Barnes, 1979), 12.6 to 15.6 % (Clatworthy, 1998; Lukhele and Ryssen, 2003). An average value of 13 % CP was thus used in the model for the forage supplement. *In vitro* studies conducted by Lukhele and Ryssen (2003) show that NDF range from 32 % for *C. apiculatum* to 38 % for *C. mopane* while NDF digestibility range from 53 % for *C. mopane* to 64 % for *C. apiculatum*. Therefore, average values of 35 and 50 % corresponding to NDF % and NDF digestibility were used for forage composition in the model. The maximum forage intake was set at 2.5 % of mature body weight since the herbage in sweetveld is palatable and highly digestible. The CP %, NDF % and NDF digestibility values of 12, 20 and 60 % were set concentrate composition in the SGS model based on recommendations of nutrient requirements for steers growing on native pasture (Sibanda, 1998).

Preliminary model simulations were run to test whether animal production can be sustained with grass only, grass and forage supplement or grass supplemented with forage and concentrate. These simulations revealed that cattle under a grass-based diet persistently lost weight over time while adding concentrate to grass and forage in the animal diet provided marginal growth benefits (see Figure 7.2). Therefore, feed management parameters for grass supplemented with browse foliage were used in all simulations for evaluating grazing management impacts.

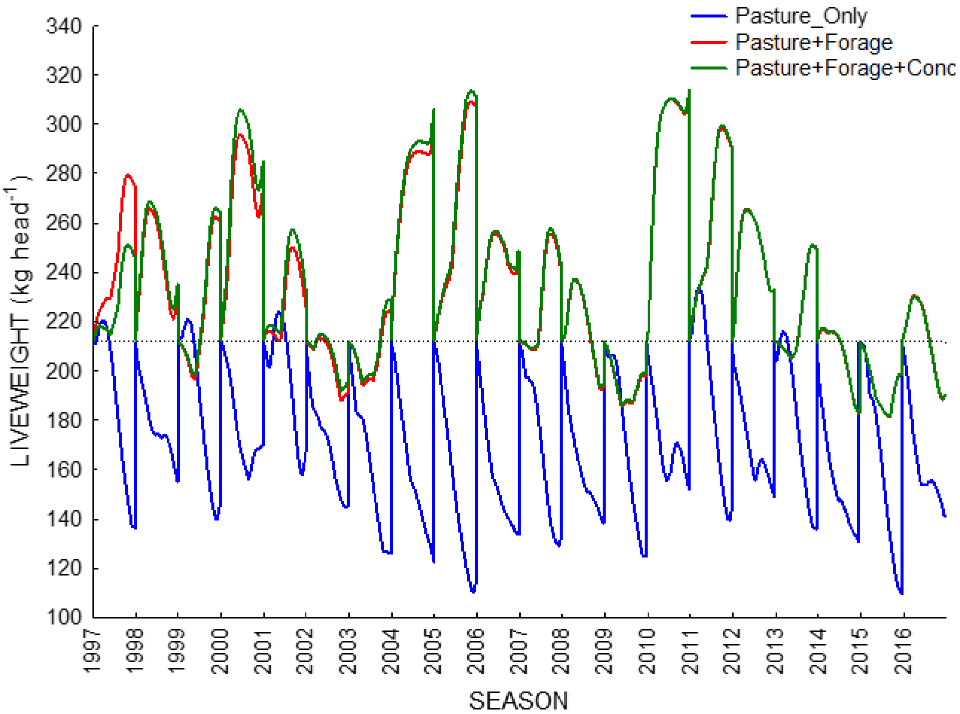

Figure 7. 2: Liveweight of weaner steers weaned in July (even numbered years) and January (odd numbered years) under three feed management practices. Dotted line represents the weaning weight of calves.

7.2.3 Evaluation of herbage and animal responses to gazing strategies.

Ecological considerations for managing semi-arid rangelands of southern Africa depict that grazing strategies should be designed with a view to maintain or improve the grazing resource by fixed moderate but persistent level of stocking (Danckwerts et al., 1993; Walker et al., 1981). This is achieved by controlling the period of stay and absence of grazing to enable palatable, productive perennial grasses to grow at desired quality (van de Pol and Jordaan, 2008). Based on these propositions, two facets of grazing management were analysed. Firstly, the impacts of multi-paddock grazing systems were analysed followed by evaluation of the sustainability of SRs widely recognised for the region.

In sweetveld, Barnes (1979) reported that use of 3-paddocks or less per herd provide the basis for maintaining or improving the grazing resource whilst Danckwerts and Daines (1981) recommended use of 2, 3 or 4 paddocks per herd. High herbaceous biomass production in semi-arid rangelands is enhanced by short period of stay and long periods of absence by cattle (Kazembe, 2010). As a result, the effects of periods of stay of 5, 10, 15 and 20 days were tested by running the model for each period of stay and multi-paddock grazing system. The most bearable period of stay for each multi-paddock grazing system was used to compare the impacts of the three multi-paddock grazing systems. The most sustainable multi-paddock grazing system was then considered for the assessment of SRs.

A preliminary review of SR recommendations for the region suggest SRs of 1 livestock unit (LU): 9.6 and 1LU: 10 hectares for cattle grazing for Nuanetsi cattle ranch (Walker, 1975) and Bufallo Range ranch (Taylor and Walker 1978), respectively. The SR of 1LU: 10 hectares was thus considered as the recommended rate for the ranch. Regional recommendations of SRs for the semi-arid rangelands of southern Zimbabwe vary widely from 1 LU: 12 to 20 hectares (Vincent and Thomas, 1960) to 1LU: 6 to 12 or more hectares (Barnes1979). To represent the wide variation in SRs for region, the recommended SR was increased to 1LU: 7 hectares and lowered to 15 and 20 haLU^{-1}. The impacts of four SRs on the sustainability of herbaceous plant and animal production were analysed. The number of weaners steer required to match each of the SRs was determined using the formulae:

$$LU = 450^{0.75} / W^{0.75}; \text{ where:}$$

W is the average weight of an animal; and LU, also known as an animal unit (AU) is defined as medium-frame beef steer with a live weight of 450 kg, which gains 0.5 kg per day on grass pasture with a digestible energy of 55 % (Mesinerr, 1983). The animal requires 75MJ of metabolizable energy (ME) per day.

7.2.4 Model simulation runs

The SGS pasture model has up to 100 paddocks that can be modelled individually in different soil types, soil nutrient conditions, pasture species and stock management practices. Daily climate data for Nuanetsi ranch, namely solar radiation (Wm^{-2}), rainfall (mm) and minimum and maximum temperature (°C) for the July 1988 to June 2017 period were obtained from different spatial data sources. Daily global solar radiation and rainfall were obtained from servers of the HelioClim-1 (Lefevre et al., 2014) and the National Oceanic and Atmospheric Administration Climate Prediction Centre African Rainfall Climatology version 2 (Novella and Thiaw, 2013), respectively. Daily minimum and maximum temperature were spatially interpolated from weather station data using an inverse distance weighting method. Soil properties of sandy loam chromic luvisol, the dominant soil type at the study area (Figure 5.3 (b)), were obtained from soil surveys for ranch.

Simulation experiments were performed in individual paddocks to examine grass growth and animal production response to separate treatments of three multi-paddock grazing systems and four SRs. The grazing management units were constituted by 2-, 3- or 4- paddocks per herd in the grazing system simulation experiment, whilst a 3-paddock per herd system was used for the SR simulation experiment. The area of paddocks modelled was set at 500 ha representing the average size of paddocks at the study site. The starting weight for Brahman weaners, that is 205-day weight at about 7 months, was set at 212 (Pico et al., 2004) whilst normal mature weight of Brahman cattle was set at 431 kg (Schoeman, 1996). The weaner steers were brought into the paddocks in July and January in even- and odd- numbered years, respectively to represent the recommended weaning periods in the region. The weaners were managed on a fixed-time rotation basis in three 4-month phases and were removed after one year. Twenty repeated annual assessments of grass production, intake and animal growth were performed for each treatment in 2, 3 or 4 replicate paddocks to produce 40, 60 and 80 site-by-year observations corresponding to the three multi-paddock grazing systems. At the beginning of each simulation run, coordinates and elevation of the central point of each paddock were entered in the model to enable adjustment for atmospheric pressure at that paddock. Output from the first 10 years of each simulation were discarded as this period was regarded for allowing model parameters to stabilise to levels that are typical of the real system. Daily model outputs produced in each paddock were averaged to come up with weighted grass production (kg DM ha^{-1}), dry matter intake ($kghead^{-1}day^{-1}$) and live weight ($kghead^{-1}$) for each grazing management unit.

7.2.5 Analysis of model outputs

The behaviour of model outputs from simulation runs for three multi-paddock grazing systems and four SRs were separately analysed over a 20-year period. Graphical analysis of time series was done to detect differences in response of herbage and animal to grazing management practices. The mean, median, minimum and maximum derived from box and whisker plots were used to determined herbage and animal responses in selected individual seasons. The box and whisker plot describe the central tendency of the variable in terms of the median of the values. The variability in the values of variables is represented in this plot by the 25th and 75th percentiles, (larger box in the plot) and the minimum and maximum values of the variable represented by the "whiskers" in the plot. Relative difference in herbage production, animal intake and liveweight gain between simulated outputs of grazing management options were also calculated.

7.3 Results

Overall, there were no observable differences found in response of herbage production and DMI to all treatments for multi-paddock grazing systems and SRs. Also, multi-paddock grazing effects on animal production were almost similar across treatments but differential responses of LWG to SRs were more pronounced. Weaners stocked at the recommended SR grew persistently at high rate, reaching a maximum LWG of 234 kgyear^{-1} but animal productivity was adversely affected in the long-term. Increasing the recommended SR by 30 % resulted in reduced DMI and LWG of weaners over 4- to 5-year cycles whereas 50 % lower SR achieved sustained high animal intake and growth in the long term.

7.3.1: Effects of stocking rates on plant and animal responses

The effects of four SRs on herbage production, DMI and LWG are presented Figure 7.3. Descriptive statistics of herbage production modelled between 1998 and 2017 show that herbage yield averaged approximately the same (2524 to 2586 kg DM ha^{-1}) across the four SRs, ranging from 990 to 3700 kg DM ha^{-1} (see Figure 7.4 (a)). The coefficient of variation in herbage production ranged from 23 % for high SR (7haLU^{-1}) to 27 % for SRs of 15 and 20 haLU^{-1} over the 20 years. The DMI of weaners was approximately similar among the four SRs with an average of 5 kghead^{-1}day^{-1} and ranging between 3.8 and 7.3 kghead^{-1}day^{-1}. Mean LWG of weaners stocked at 7haLU^{-1} varied by 9 kg from the LWG of weaners (234 kg) stocked at the recommended or lower SRs. The minimum liveweight of weaners ranged from 179kg in 20 haLU^{-1} to 183 kg in 7 haLU^{-1} (Figure 7.3 (c)). Maximum LWG of 345 kg head^{-1} for weaners stocked at the recommended rate was 32 kg more than maximum LWG of weaners stocked at 15 haLU^{-1} over the 20-year period.

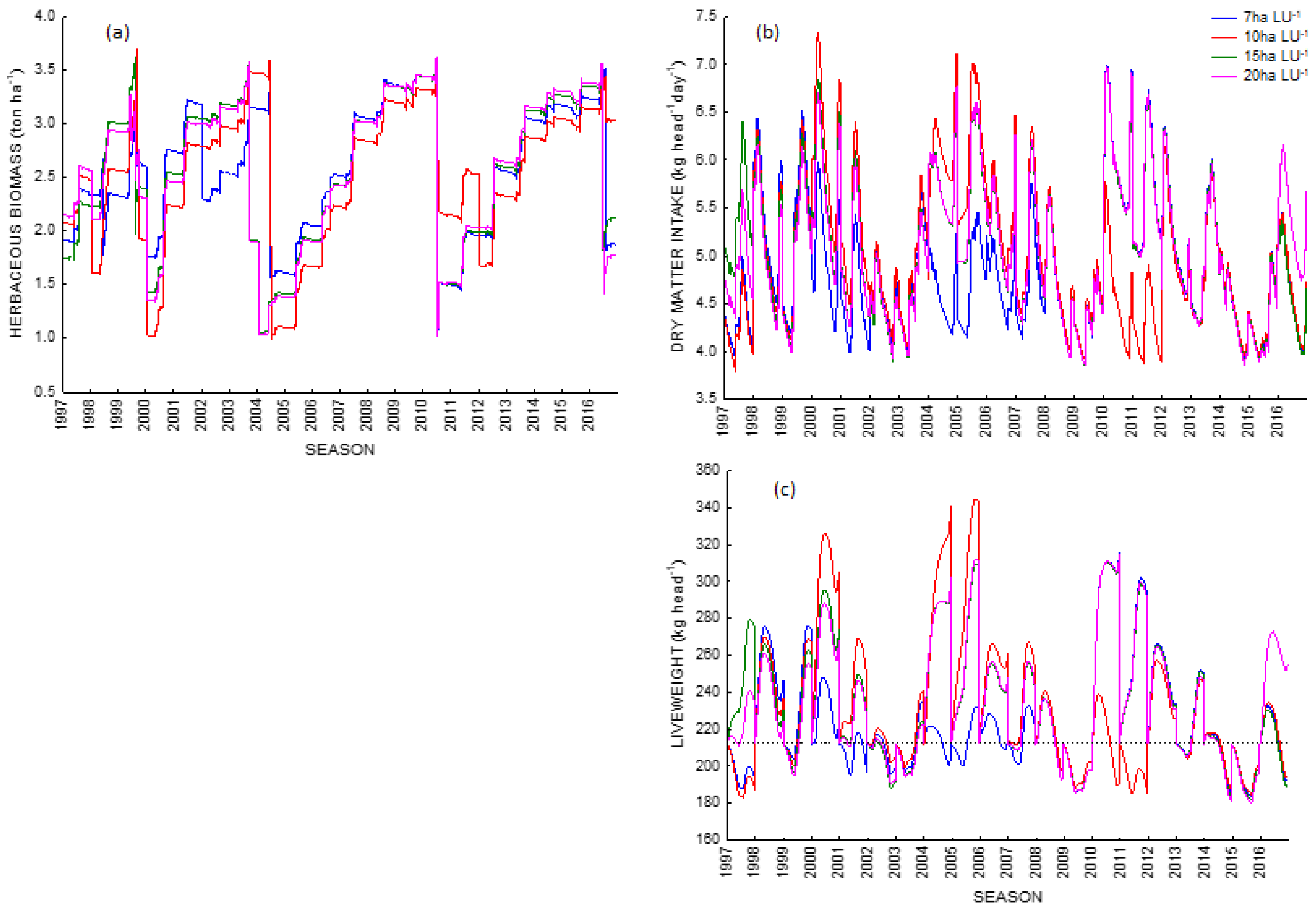

Figure 7. 3: Model outputs of (a) herbaceous aboveground biomass (b) dry matter intake and (c) liveweight of weaner steers weaned in July (even numbered years) and January (odd numbered years) under three stocking rates. Dotted line in (c) represents the weaning weight of calves at the start of the simulation.

Despite the high LWG response, the pasture stocked at the recommended rate only supported a sustained DMI and LWG during the first 13 years after which animal productivity was adversely affected (Figure 7.3). Increasing SR by 30 % from the recommended rate resulted in reduced DMI and LWG of weaners over 4 to 5 years seasonal cycles (Figure 7.3 (b) and (c)). Pasture in paddocks stocked at 50 to 100 % lower SRs than the recommended rate persistently supported animal intake and growth over the 20 years (Figure 7.3 (b) and (c)) though there were no justifiable animal responses for increasing the SR beyond 50 %.

Differences in model outputs of herbage and animal production among the four SR treatments were also pronounced during moderate and mild drought seasons. For example, during the mild drought season of 1998, DMI and LW of cattle stocked at 15 haLU^{-1} exceeded that of cattle under stocked at recommended rate by 1 kghead^{-1}day^{-1} and 45 kg kghead^{-1}, respectively despite having herbage yield that is 14 % (300 kg DM ha^{-1}) less (Figure 7.4). During the moderate drought season of 2005, LWG of weaners was almost similar between cattle stocked at recommended rate and 15 haLU^{-1} though herbage yield from paddocks stocked at recommended rate was 66 % higher. The greatest loss in DMI and LW between a 30 % high SR and the recommended rate was observed in successive mild drought seasons. For example, in 2006 and 2007, the DMI of weaners stocked at the recommended rate fell by 1.1 and 0.7 kghead^{-1}day^{-1} whilst the LWG was 81.7 and 35.6 kghead^{-1} lower, respectively (Figure 7.4).

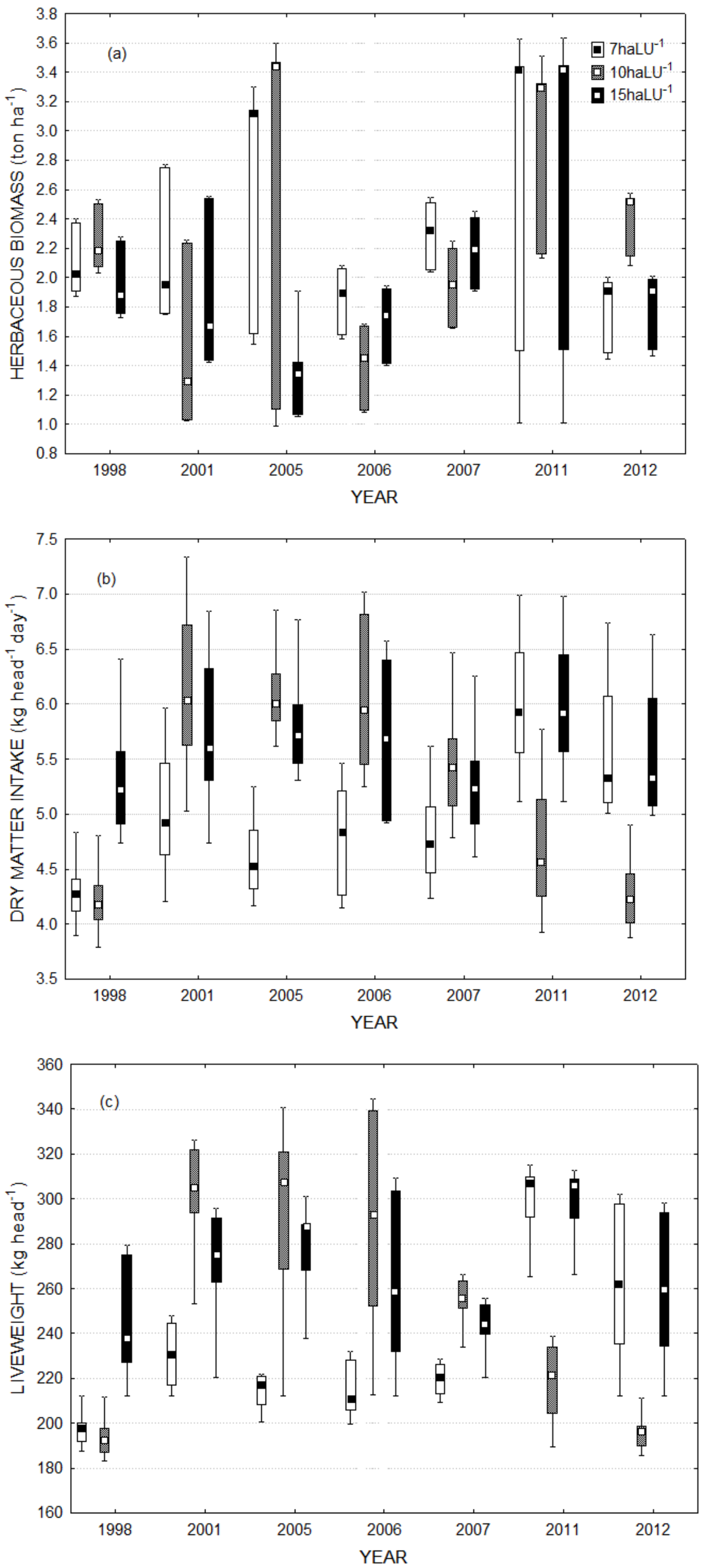

Figure 7. 4: Box and whisker plot of (a) Herbaceous biomass (b) Dry matter intake and (c) Liveweight of weaner steers stocked at three stocking rates for selected years between 1998 and 2017. The smallest box in the box plot represent median values.

7.3.2 Effects of multi-paddock grazing systems on plant and animal responses

Aboveground herbage production modelled between 1998 and 2017 show that herbage yield averaged approximately the same (2515 - 2560 kg DM ha^{-1}) across the three multi-paddock grazing systems, ranging from 1000 to 3600 kg DM ha^{-1} (see Figure 7.5 (a)). The lowest coefficient of variation in herbage production of 23 % was observed in the alternate stocking system whilst the three and four multi-paddock grazing systems had the highest CV of 27 % over the 20 years. Alternate stocking showed a consistently opposing trend in herbage production relative to the three- and four- paddocks per herd systems. The DMI of weaners did not vary widely among the three multi-paddock grazing systems. It ranged between 3.8 and 7 $kghead^{-1}day^{-1}$ and averaged at 5 $kghead^{-1}day^{-1}$. Also, the mean LW of weaners was almost similar (231-234 kg) across the three multi-paddock grazing systems. The minimum loss of liveweight of weaners to 180kg was the same across the three multi-paddock grazing systems evaluated (Figure 7.5 (c)). Maximum LWG of weaners in the alternate stocking system of 331 kg $head^{-1}$, however exceeded the maximum LWG of weaners in the recommended grazing system of 3-paddocks per herd by 17 kg over the 20-year period. Dry matter intake and LWG of weaners in the alternate stocking system declined drastically after 13 years (Figure 7.5 (b) and (c)).

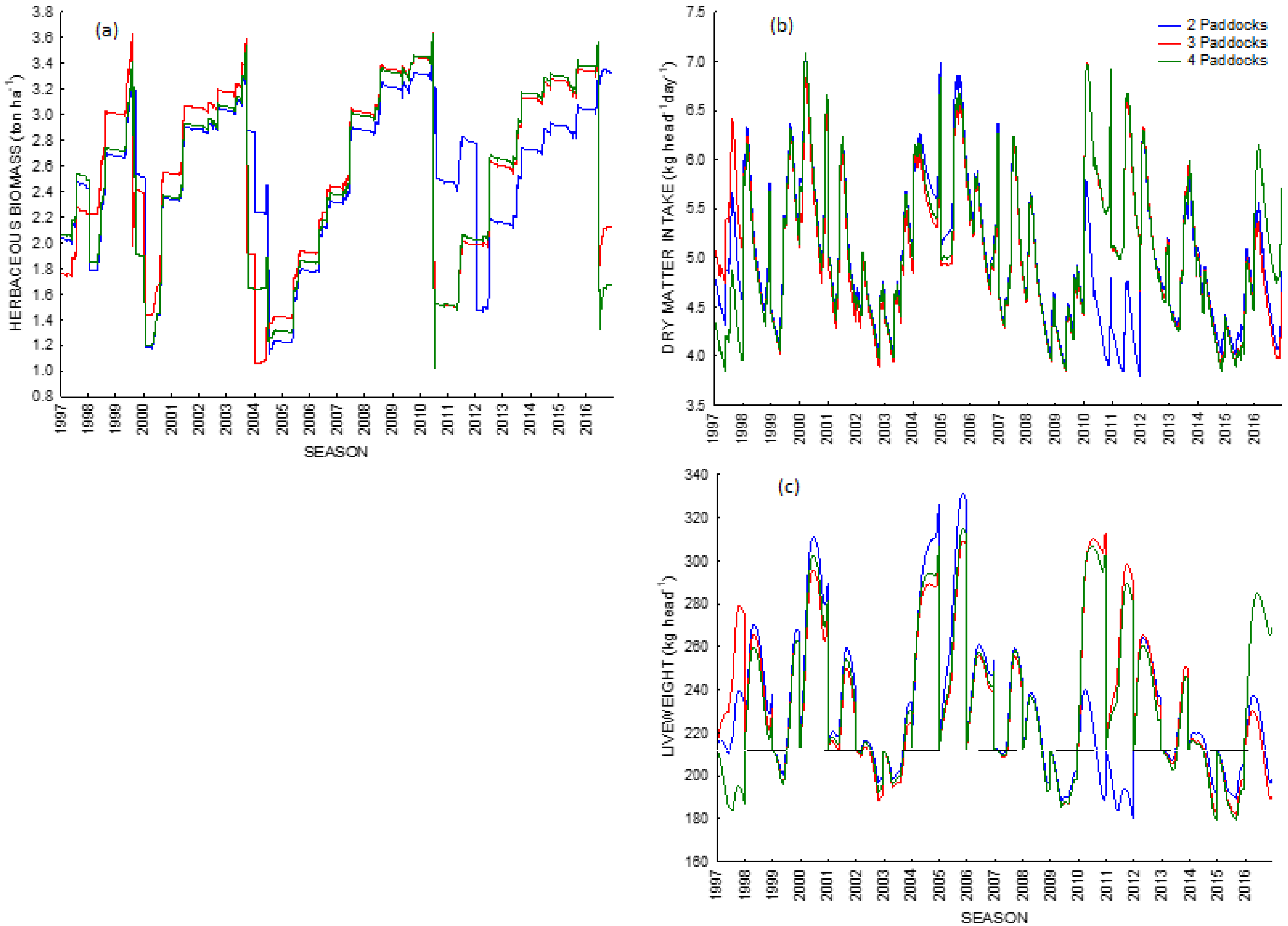

Figure 7. 5: Model outputs of (a) herbaceous aboveground biomass, (b) dry matter intake and (c) liveweight of weaner steers weaned in July (even numbered years) and January (odd numbered years) under 3 paddock systems. Dotted line in (c) represents the weaning weight of calves at the start of the simulation.

The most noticeable differences in herbage and animal productivity among the three multi-paddock grazing systems were observed during mild and moderate drought seasons. Despite 14 % (300 kg DM ha^{-1}) more herbage yield than the 3- paddocks per herd system during the mild drought season of 1998, LWG of weaners in the alternate stocking system was 20.4 kg lower. During the moderately dry season of 2005, LWG of weaners was almost similar between the alternate stocking and the 3- and 4-paddocks per herd systems though herbage yield was 66 % higher in the alternate stocking system. The greatest loss in DMI and LW was observed in successive mild drought seasons. For example, in 2011 and 2012, the DMI of weaners reared under the alternate stocking system fell by 1.4 and 1.2 $kghead^{-1}day^{-1}$ whilst the LWG was 85.1 and 65.4 kg lower, respectively (Figure 7.6).

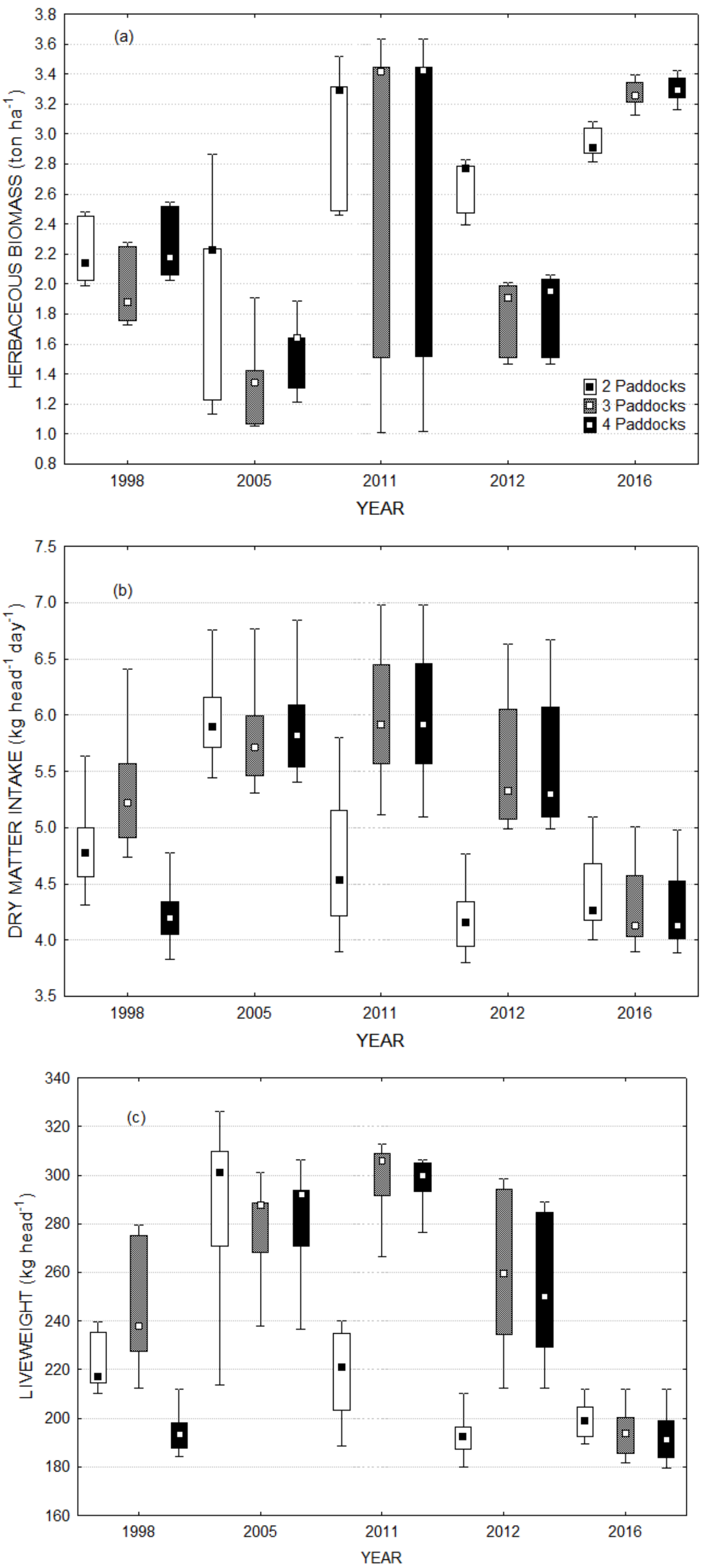

Figure 7. 6: Box and whisker plot of (a) Herbaceous biomass, (b) Dry matter intake and (c) liveweight of weaner steers stocked in three paddock systems for selected years between 1998 and 2017. The smallest box in the box plot represent median values.

7.4 Discussion

This study has demonstrated the effect of multi-paddock grazing systems and SRs on plant and animal responses. Overall findings showed that there are no observable differences in herbage production and DMI response to all treatments for multi-paddock grazing systems and SRs. Also, multi-paddock grazing systems displayed approximately similar effects on animal production across treatments but differential responses of LWG to SRs were more pronounced. Increasing the recommended SR resulted in reduced DMI and LWG of weaners in the short term while persistently high animal intake and growth occurred in the long term under reduced SR. These results illustrate the potential of PBMs in providing direction for selecting the appropriate SR that achieves a continuous herbage and animal production with minimum risk in the long term. Generally, the findings suggest that ranch managers should put more management emphasis on SRs over multi-paddock grazing systems since proper SRs enable maximised cattle productivity over time.

7.4.1 Effects of stocking rates on plant and animal responses

The findings reveal that, irrespective of the SR, there are no observable differences in herbage production. As reported in many field studies, increasing or decreasing SR from the recommended rate does not show distinguished differences on herbage production. In in south western rangelands of Zimbabwe, Denny and Barnes (1977) and Barnes and Denny (1991) made the same observation in open savanna grassland whilst Gammon (1978) obtained similar results in granite sand veld. Also Derner and Hart (2007) and Biondini et al. (1998) did not find any consistent effects of increasing grazing intensity on aboveground grass production in semi-arid mixed-grass prairie of North America. Using a modelling approach in native pastures of northern Australia, a modest increase in SRs above the recommended rate posed little adverse effects on pasture condition or individual animal performance (Scanlan et al., 2013). However, a decline in pasture condition was realised when SR was further increased above the long-term carrying capacity in simulations across nine regions (Scanlan et al., 2011). These inconsistences in herbage response reveal that the extent to which SRs can be increased without reducing herbage production is not clear. Some studies have noted that herbage responses to various SRs differ across climate regions and locations due to differences in soil nutrient status (Illius et al., 2000; Smart et al., 2010). The systems model enabled further assessment of the subsequent effects of high SRs on DMI and LWG and provided a better understanding of the biophysical impacts.

The findings showed that increasing SR from the prescribed rate reduces animal production, a widely recognized opinion. Very high SRs led to reduction in LWG per hectare and economic returns in northern Australian rangelands (Scanlan et al., 2013). In mixed- prairie in central North American plains, individual steer weights decreased with increasing SR (Derner et al., 2008). The reduction in animal performance at high SR shown in this study can be attributed to reduction in herbage availability per animal. Stocking rates higher than the recommended rates often result in reduced plant vigour and productivity due to reduced root energy reserves necessary for quick regrowth (Peddie et al., 1995). Considering that increasing the prescribed SR by 30 % resulted in reduced DMI and LWG of weaners after every 4 to 5 years in study area, stoking cattle at the rate of $7haLU^{-1}$ is very risky.

However, other field studies showed that steer production per hectare increased with increasing SRs but production was also highly sensitive to climate variability (Reeves et al., 2013). In southwestern Zimbabwe, Barnes and Denny (1991) observed that a SR twice the recommended regional average sustained steer weight gains per hectare for 5 years without causing adverse effects on rangeland condition. Their grazing experiment was conducted in small paddocks that are below 50 hectares and over short to medium timeframes (5-11 years). Such field studies do not represent all the actual conditions in rangelands where paddocks are large, up to 1500 hectares, and are grazed over many decades at low SRs (Teague et al., 2013). These findings illustrate that animal production responses to high SRs are difficult to compare across grazing systems and depend on productivity units used. As such, the extent to which SRs can be increased to attain optimum animal production and sustain herbage production over long timeframes across locations is not clear (Smart et al., 2010). This emphasises the need for site- and time-specific comparisons of performance of different SRs on cattle productivity.

7.4.2 Effects of multi-paddock grazing systems on plant and animal responses

Strategies of using 2 to 4 paddocks per herd at a SR 50 % lower than the recommended rate enabled pastures to recover periodically throughout the growing season and sustained steer production over time. Similar findings were obtained for a grazing trial in the mesic regions of central Zimbabwe in which 20-day periods of stay gave lower gains of Afrikander steers than 5- and 10-day periods of stay (Denny et al. 1974). These simple, less intensive management strategies can allow one-third of the grazing management unit to be utilised and two-thirds to be rested and, enable adequate growing season recovery in each paddock every 2-4 years (van de Pol and Jordaan, 2008). This creates forage reserve that can be carried over to the next season to reduce forage deficits associated with climate variability.

As with varying SRs, many studies have illustrated that responses of herbage production are the same irrespective of grazing system used (Barnes and Denny, 1991; Heitschmidt et al., 1987) or SR (Norton, 1998). Using a modelling approach, Noy-meir (1976) found little effect of moderate rotation with few paddocks and short grazing cycles on plant productivity in arid rangelands. As expected, increasing the number of paddocks from 2 to 4 per herd resulted increased anima intake and liveweight gain. The findings concur with those from Kazembe (2010) who found a linear increase in cattle growth when paddocks per herd were increased from 1 to 12 in a simulation study, though this was a short -term study. The benefit of increasing the number of paddocks per herd is that the period of stay in individual paddocks and subsequent defoliation effects on grass growth is reduced, leaving more days for resting pasture (Barnes, 1972; Teague et al., 2008). In addition, the option enables range managers to control grazing resources and manage other factors such as diseases, reproduction, mortalities, and breeding, which could not be simulated by the SGS model. It is worth noting that conclusive experimental evidence about the effect of grazing systems on animal production are generally lacking in southern African savannas, particularly sweetveld. This could be attributed to the difficulty of controlling the large number of variables that influence comparison of grazing systems (Barnes et al., 2008; Briske et al., 2008).

Overall, this study adds value to previous grazing experiments (Barnes and Denny 1991) and modelling studies (Kazembe, 2010; Richardson et al., 2000) performed in semi-arid rangelands of southern Africa by assessing the long-term effects of multi-paddock grazing systems and SRs on herbage and animal production using a whole-farm mechanistic model. The modelling exercise identified 15haLU^{-1} as the SR that attains optimum cattle production and sustain herbage production over long timeframes. The study provides evidence that SR has greater effect on animal intake and production than multi-paddock grazing systems and, ranch managers should prioritise SRs management over grazing systems to maximise productivity. The study findings demonstrate the potential of PBMs in providing direction for selecting the appropriate SR that achieves a continuous herbage and animal production with minimum risk in the long term. Though the biophysical impacts of the grazing systems and SRs were assessed, their effects on economic viability of the ranch enterprise remains unknown. For the current findings to be valuable to ranch managers, further efforts are required to quantify the economic effects of the SRs recommended for southern African rangelands.

7.5 Conclusions

The whole SGS model produced reasonable illustrations about the effects of varying SRs and multi-paddock grazing systems on Brahman weaner steers grazing natural pasture. Overall, there were no observable differences found in response of herbage production and DMI to all treatments for multi-paddock grazing systems and SRs. Also, multi-paddock grazing effects on animal production were almost similar across treatments but differential responses of LWG to SRs were more pronounced. Weaners stocked at the recommended SR grew persistently at high rate, but animal productivity was adversely affected in the long-term. Increasing the recommended SR by 30 % resulted in reduced DMI and LWG of weaners in the short term whereas 50 % lower SR achieved sustained high animal intake and growth over time. Since there were no reasonable animal responses for decreasing the recommended SR beyond 50 % in this study, $15 haLU^{-1}$ should be regarded as the long-term carrying capacity. The findings illustrate the potential of PBMs in providing direction for selecting the appropriate SR that achieves continued herbage and animal production with minimum risk in the long term.

CHAPTER 8

General discussion and conclusions

8.1 Introduction

The design and improvement of sustainable grazing management practices is necessary for the continued growth of beef production in these semi-arid rangelands of southern Africa. With the beef sector's potential to contribute up to 24 % of agricultural GDP and the likelihood of increasing rainfall variability due to climate change, evaluation of the long-term implications of recommended and alternative grazing management practices on the viability of beef enterprises is essential. Reliable data on herbage and animal production in response to the seasons likely to be experienced is needed for these evaluations. Such data were not available at Nuanetsi ranch prior to this study and it was impossible to undertake these evaluations. This study reduced these data gaps by developing empirical models for predicting herbaceous AGB from Landsat satellite images and using these models and other remotely sensed variables to calibrate and evaluate the SGS model. It is now possible to apply the simulation model to analyse the sustainability of different grazing management practices in studied land types using the datasets of satellite-derived variables.

This chapter aims to discuss the capability of combing empirical remote sensing models with a simulation model in predicting herbaceous AGB and, the implications of grazing management practices on herbage and animal production. An overview of the potential of using optical remote sensing models developed in this study to predict herbaceous biomass and assess its response to climate variability is presented in Section 8.2. This is followed by a discussion of the capability of the SGS model in analysing the sustainability impacts of various SRs and multi-paddock grazing systems on herbage and animal production in Section 8.3. Section 8.4 highlights the effects of environmental factors on the quality of visible spectral reflectance data used to predict herbaceous AGB. Errors associated with data used to calibrate and evaluate the simulation model and inadequacy of the model's structure pose limitations to model use. It is important to know these limitations as outlined in Section 8.5. In Section 8.6. the major conclusions are presented in whilst Section 8.7, the recommendations for future research to build on the results of this study are suggested

8.2 Performance of optical remote sensing in predicting herbaceous biomass

This study has developed capacity to predict herbage production in the tree/shrub savanna using empirical remote sensing models constructed from visible spectra. By using visible spectral bands which account for site specific effects of atmospheric contaminants, vegetation properties and soil background features, classical and extended MVIs models for herbaceous

AGB estimation with high accuracy were developed. In Chapter 3, very stable relationships were constructed between herbaceous AGB measured in field and predicted by the empirical models, with a standard error between 840 and 1480 $kgha^{-1}$. The accuracy is comparable to that obtained in field measurements e.g. an RMSE of 898 kg DM ha^{-1} observed by Trollope and Potgieter (1986). In many savanna vegetation types of KNP, Mutanga and Rugege (2006) found an RMSE of 1374 kg DM ha^{-1} for a remote sensing regression model trained from single season data, whilst Dwyer (2011) found the RMSE to vary from 1171 to 1711 kg DM ha^{-1} using data trained from individual and combined seasons. These models enable mapping of the spatial representation of AGB which helps ranch managers in adjusting animal distribution relative to spatial heterogeneity in forage resources to prevent excessive use of preferred areas.

In Chapter 4, a rainfall- AGB model generated reasonable estimates of herbage biomass (RMSE, 1557 kg DM ha^{-1}) at a large spatial extent. Such landscape metrices of herbage production are important for near-real time monitoring of the spatial pattern of herbaceous AGB production. Temporal variability of AGB production within herbaceous communities fluctuated by 18 to 35 % more than rainfall. However, the landscape-level temporal variation of AGB production remained stable despite the increase of drought incidences experienced in the region in the last fifty years. This highlights the need by range managers to put more management emphasis towards maintaining or enhancing inherent unevenness within local herbaceous communities to increase the stability of rangeland productivity and, to adapt to anticipated climatic changes. In addition, the rainfall- AGB model produced a 26-year dataset of herbaceous AGB across three land types, despite the high sensitivity of the model to rainfall variation. The data provided independent data for evaluating the behaviour of outputs of the SGS model in Chapter 6.

8.3 Capacity of SGS model to predict herbage and animal production

The integration of spatial data layers such as DEMs, soil and land cover maps and satellite images using GIS software enabled demarcation of sites for applying the SGS model. These sites were objectively defined for SGS model calibration depending on uniformity of environmental and management factors. Spatial data layers developed from this study can now be used to define monitoring sites for routine vegetation measurements or validating models. The use of site-specific and generic parameters of soil and plant enabled the SGS model to predict measured (RMSE, 820 kg DM ha^{-1}) and remotely sensed herbaceous AGB production (RMSE, 981 kg DM ha^{-1}) at reasonable levels of accuracy. These average errors fall within the range of the lowest error values obtained from field measured and remotely sensed herbaceous AGB in semi-arid rangelands of southern Africa. These findings indicate that the framework of combining measured and spatial data layers adopted in this study can reasonably represent the key processes that influence growth of *U. mosambicensis* and *E. curvula* under the three land types found at Nuanetsi ranch. However, measures for individual predictions provided low performance scores for both field-measured and remotely sensed AGB.

Despite the huge individual prediction errors, the SGS model predicted cattle production within reasonable ranges for southern African rangelands using parameter sets developed for the animal module. For example, Fynn and Connor (2000) observed LWG of crossbred Brahman weaners to vary between 86 and 225 kg $head^{-1}yr^{-1}$ for medium SR in a grazing trial conducted in semi-arid savanna of southern Africa. The SGS model also demonstrated that forage supplement from trees and shrubs enable animal production to be sustained throughout the dry season in semi-arid rangelands, a nutrition experience widely acknowledged in southern Africa (Clatworthy, 1998). Given these reasonable cattle growth predictions by the SGS model, it can be implied that the model compensated plant biomass prediction error by adjusting animal parameters (Ma et al., 2019).

The SGS model can potentially be applied to evaluate the impacts of other grazing management practices on sustainability of rangeland productivity using animal growth parameters compiled in this study that are specific to Brahman breed. Based on these parameter sets, it was possible to analyse the impact of varying SR from the recommended rate for the region. The model could also illustrate that, irrespective of the grazing system, the are no observable differences in plant responses. This is an undisputed opinion construed from grazing trials that have been performed over different vegetation types (Briske et al., 2008) and, because the SGS model outputs showed the same trend, it can be used with much greater confidence.

8.4 Limitations to remote sensing application in predicting herbaceous biomass

The main limitation of using remote sensing to predict herbaceous AGB demonstrated in Chapter 3 is that extrapolation of the empirical models from the study area to new areas is problematic. Herbaceous AGB estimates from empirical models are site specific because soil background features and atmospheric contaminants that affect soil reflectance and sensor response to vegetation reflectance of the visible spectrum vary widely across land systems. These factors limit the use of empirical models for descriptive and predictive purposes as they do not have adequate predictive power when they are applied to other sites within the region where they were developed from. Similarly, the non-stationarity problem applies to rainfall-AGB models developed in Chapter 4 due the high spatial variability of vegetation and soil characteristics and sensitivity of spectral reflectance values to rainfall variation.

Another limitation is that, it is impossible to use remote sensing to predict biomass for specific livestock species utilising the vegetation. In this study, empirical models were developed to predict herbaceous AGB which contributes up to 70 % of cattle diet. However, despite contributing the smaller portion of cattle diets, woody biomass is responsible for the consistent availability of forage quantity and quality in sweetveld and enable animal condition to be sustained throughout the year as illustrated in Chapter 7. It is prudent therefore, to develop empirical remote sensing models that account for biomass of trees and shrubs that are palatable or available to specific livestock species (Angerer, 2012).

The outcome of field measurements of herbaceous AGB in Chapter 3 was premeditated to provide data required for calibrating the SGS model when it was applied to 0.1-hectare plots. The data were peak biomass clippings that were collected in one growing season due to high resource requirements. The soil parameters used were also measured in two different seasons for the crest and mid- and foot slope land types. These parameter sets are of limited value if the SGS model is to be applied to other seasons and land types. To build confidence in using simulation models, long-term independent data is required for historical data validation (Grant et al., 1997). A rainfall- AGB model for predicting annual herbage yield was therefore developed in Chapter 4 for this purpose. Whilst the statistical model generated output behaviour that mimics the behaviour of simulated outputs, the mean bias error was huge. Combing images from satellites products with low revisit time with images from high revisit time satellites such as Sentinel and MODIS (Baumann et al., 2017) can enable development of models that are capable of mimicking the large-scale dynamic behaviour of grass growth.

It was emphasised in Chapter 4 that rainfall is the primary climate variable that determine herbage production while solar radiation and temperature are known to affect evaporative demand in sweetveld (Scholes and Walker, 1993). Except for rainfall data obtained from a local rain gauge, data for the other climate variables were only available at meteorological stations that are hundreds of kilometres away from the ranch. Spatially aggregated data for daily rainfall and solar radiation derived from satellite-based estimates and temperature data interpolated from two distant weather stations were thus used. The spatial aggregation and interpolation of the climate variables to fill such data gaps may introduce substantial error. It can be reasonably assumed that, from time to time, the interpolated data may be different from the actual conditions on the simulated site thus, limiting the accuracy of model predictions. In most resource-constrained environments, the availability of on-site daily climate data remains a challenge for applying simulation models and satellite-based estimates are the alternative data available. An attempt to reduce the errors associated with the processed climate data was done by applying bias correction schemes in Chapter 4 and 5 and the output were considered as representative of the simulated sites.

8.5 Limitations to SGS model application in grazing management

Improvement in understanding of the dynamics of natural systems and computational capability has led to the development of highly complicated, mechanistic models such as the SGS model. These developments have raised the need for robust methods to quantify the increasing uncertainty associated with the models for research purposes. The major sources of error associated with simulation models relate to model structure, measurement, and natural variability. Errors due to measurement and natural variability result from lack of complete knowledge about model inputs. When there is unreasonable prediction error from a simulation, the importance of the prediction in management decisions is limited. It is thus important to know the different sources of error to identify areas for improving field measurements and model structure in future.

Data from geographical layers of climate, topography, soil and vegetation, and remote sensing and field experiments conducted in the southern African savanna biome were used to parameterise and evaluate the SGS model in this study. Such an integrated data gathering approach for model calibration results in a cascade of errors which affect the simulation outputs (Angerer, 2012). For example, the process of deriving climate inputs might have introduced substantial non-random errors due to the absence of measured weather data at the study area. Similarly, use of plant parameters from literature gathered from times and locations not covered by field observations includes errors arising from systemic differences in environmental conditions (Katz, 2002). These errors possibly account for the relatively low agreements between measured and simulated herbaceous AGB values obtained in this study. However, it was difficult to accurately estimate values of initial conditions and state variables for the study area and, a tiered approach was the only suitable choice due to differences in data availability. Where resources are available, intensive field experiments should be conducted to provide data for parametrising and evaluating simulation models.

Model structure error is the most difficult error to quantify and there are some limitations associated with the structure of the SGS model (Doran-Browne et al., 2014). In this study, three major limitations were detected with regards to the structure of the SGS model. Firstly, the model was not sensitive to extreme wet and dry weather conditions as indicated by the low coefficient of variation of seasonal herbage production (CV range from 15 to 22 % across land types). However, herbaceous biomass predictions in semi-arid regions are very sensitive to climate variability as typified by *Colophospermum mopane* savanna rangelands (Buitenwerf et al., 2011). Many models for grazing lands do not adequately simulate the response of herbaceous vegetation to extreme climate events (Kipling et al., 2019). Therefore, further improvements in SGS model structure are required to enable realistic predictions of herbaceous AGB under extreme weather events.

Another limitation is that, as with many grazing land models (Robertson et al., 2015), the SGS model does not explicitly model dynamics of soil nutrients, especially N and P. These nutrients are however limiting in Mopane savannas to which the SGS model was applied yet they are the primary determinants of seasonal herbage production and quality (Hempson et al., 2007). Soil moisture and soil nutrient availability also determine the spatial variation in productivity within a land system (Fritz and Duncan, 1994). It is therefore imperative to put further efforts towards improving the N, P and S dynamics in the SGS model to enable a better representation of nutrient cycling in soils with low macro-nutrient content.

Lastly, inclusion of an explicit tree/shrub growth module in the SGS model can enable a more realistic representation of the biophysical processes occurring in savanna rangelands. In savanna rangelands, trees and shrubs pose negative, neutral and positive effects on herbaceous production and biomass allocation and the effects can vary with tree age, size and density (Scholes, 2003). On one hand, woody vegetation supress productivity of subcanopy grasses by intercepting solar radiation and rainfall and by competing for water and nutrients when their root systems intersect. On the other hand, productivity of subcanopy layer can be enhanced by reduced soil temperature and plant water stress and by improved soil nutrient status. These interactions need to be considered in grass growth simulations to enable effective management decisions to be made.

8.6 General conclusions

- Combining MVIs with Landsat 8 optical bands, especially green band, provides the best models for estimating AGB in *C. mopane* savanna rangelands.
- Spatial heterogeneity of AGB production across herbaceous communities were high and deviated from mean AGB by 51 to 69 %.
- Temporal variability of AGB production within herbaceous communities fluctuated by 18 to 35 % more than rainfall
- Landscape-level temporal variation of AGB production was stable despite the increase in drought disturbances experienced in the region
- Herbaceous AGB yield response to droughts was highly variable across drought intensities, depending on post-drought rainfall amount relative to long-term median.
- Growth predictions of grass species simulated with adjusted parameters were 26 to 98 % higher than native C4 grass production predicted from default parameters.
- The SGS model represented measured herbage AGB reasonably well, accounting for up to 60 % variation in herbaceous AGB.
- The SGS model underestimated remotely sensed AGB though predictions for whole dataset were significant and reasonably accurate.
- No observable differences were found in herbage production and DMI response to all treatments for multi-paddock grazing systems and SRs.
- Multi-paddock grazing effects on animal production were approximately similar across treatments but differential responses of LWG to SRs were more pronounced
- Increasing the recommended SR resulted in reduced DMI and LWG of weaners in the short term whereas reducing the benchmark SR enabled persistent animal intake and growth in the long term.

8.7 Recommendations for future research

Field data collection for calibrating remote sensing and pasture simulation models

- Develop models capable of representing the dynamic behaviour of grass growth by combing Landsat data with data from high revisit time, hyperspectral satellites such as MODIS.
- Improve empirical remote sensing models to include tree and shrub biomass that is palatable or available to specific livestock species.
- Evaluate the effect of various satellite-based estimates of climate variables on accuracy of SGS model predictions.
- Generate intensive field measurements of most influential factors limiting herbage growth to improve performance simulation models.

Improvements to model structure

- Improve SGS model’s sensitivity to extreme wet and dry conditions typical of semi-arid regions.
- Include dynamics of cycling of N and P that are limiting in mafic gneiss derived soils which dominate lowveld rangelands.
- Inclusion of a tree/shrub growth component since tree-grass interactions are characteristic determinants of savanna functioning.

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Annex I: Vegetation composition at Nuanetsi ranch

Grass species

Botanical name	Common name	Botanical name	Common name
Aristida junciformis	Bristle grass	*Hyparrhenia filipendula*	Thatching grass
Aristida congesta	Bristle grass	*Panicum maximum*	Guinea grass (Sabi panicum)
Bracharia nigropedata	Black footed bracharia	*Perotis patens*	Bottlebrush / Rainbow grass
Bothriochloa insculpta	Pinhole grass	*Pogonathria squarosa*	Herringbone grass
Chloris virgate	Old lands grass	*Rhynchelytrum repens*	Natal red top
Cynodon dactylon	Couch grass	*Setaria pallidifusca*	Annual timothy
Dactyloctenium aegpytium	Crow’s foot	*Setaria verticillata*	Bur grass
Digitaria milanjiana	Mlanje finger grass	*Sporobolous panicoides*	Famine grass
Digitaria eriantha	Finger grass	*Stereochlaena cameronii*	Gilston grass
Eragrotis superba	Heart seed love grass	*Trachyprogon spicata*	Giant spear grass
Eragrotis curvula	Weeping love grass	*Urochloa mosambicensis*	Gonya grass

Forb species

Botanical name	Common name	Botanical name	Common name
Aloe cameronii var. cameronii	Cameron's ruwari aloe	*Justicia kirkiana*	-
Amaranthus hybridus	Pigweed	*Lactuca capensis*	Wild lettuce
Borreria dibrachiata	Winged forget-me-not	*Nidorella resedifolia*	Poverty, common nidorella
Boophone distacha	Tumble weed or veld fan	*Ocimum gratissimum*	Wild basil
Cichorium intybus	Chicory	*Oldenlandia corymbose*	-
Clotoraria kirkia	Rattlepods	*Richardia brasiliensis*	Mexican clover
Commelina benghalensis	Wandering jew	*Tagetes minuta*	Mexican marigold
Cucumis metuliferus Naudin	African horned cucumber	*Tephrosia radicans*	-
Cyperaceae	Sedge	*Tribulus zeyheri*	Large-flowered devil-thorns
Gisekia Africana	Dungambizi		

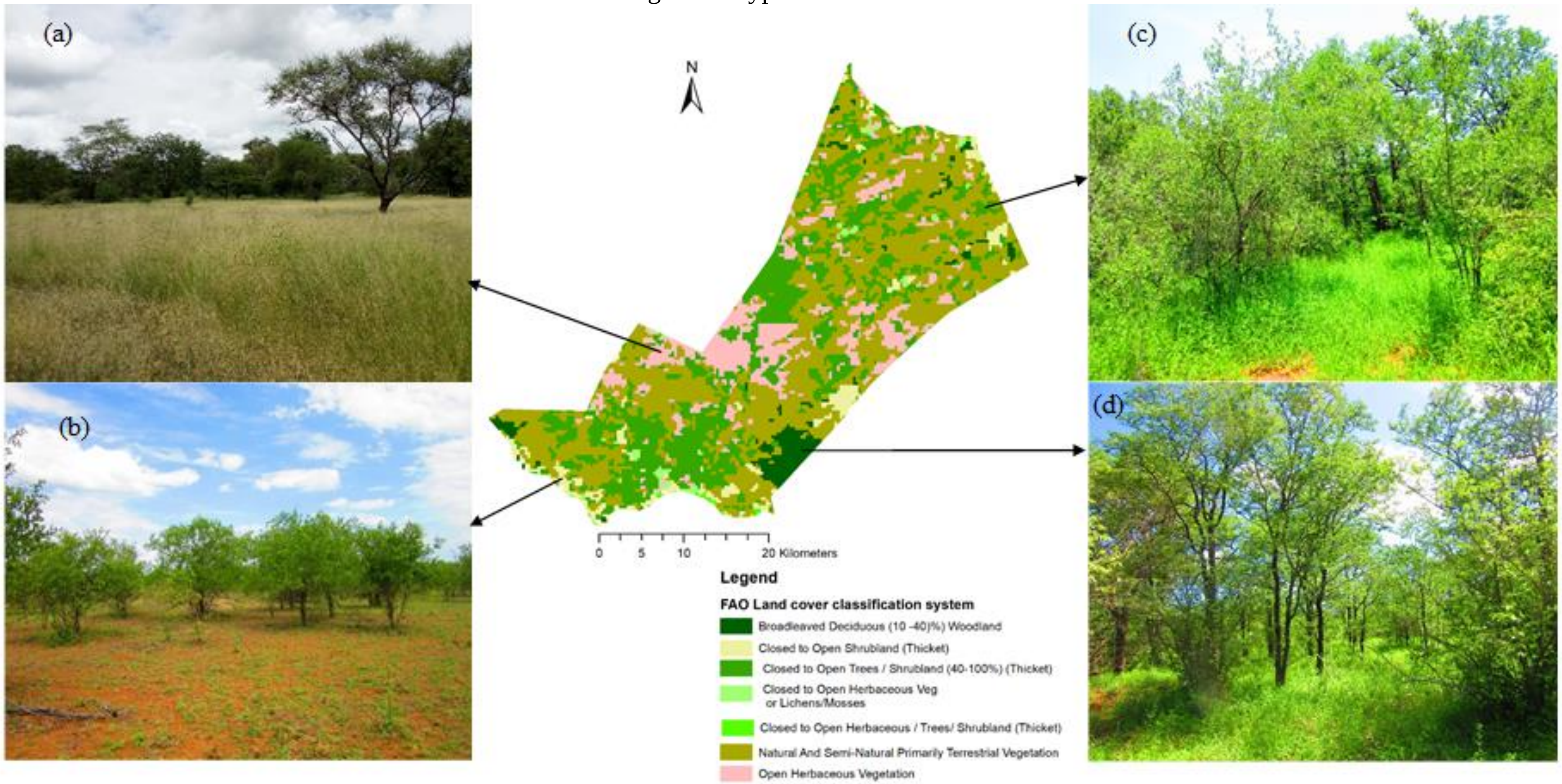
Tree species

Botanical name	Common name (Shona)	Botanical name	Common name (Shona)
Acacia nicolita	Scented-pod acacia (muwunga)	*Commiphora marlotii*	Paperbark (mupepe/munyera)
Acacia nigriscens	Knobthorn (munanga/ chinanga)	*Dichrostachys ceneria*	Sickle bush (mupangara)
Albizia amara A harveyi	Muwora	*Kirkia acuminata*	Bastard marula (mubvumira)
Colophospermum mopane	Mopane (mupani)	*Lannea stuhlmannii*	L. Kirkia Burtt Davy (musvinwa)
Celtis Africana	White stinkwood / Common celtis	*Sesbania grandiflora*	Agati or hummingbird tree
Combretum apiculatum	russet compretum (mubondo)	*Sclerocarya caffra*	Marula (mupfura)
Combretum molle	soft-leaved compretum (mubondo)	*Ziziphus mucronata*	Buffalo thorn (muchecheni)
Combretum imberbe	leadwood (mutsviru)		
Combretum hereroense	mouse-eared combretum (murovamhuru)		

Shrub species

Botanical name	Common name (Shona)	Botanical name	Common name (Shona)
Acanthospermum hispidum	Upright starbur	*Indigofera arrecta*	African indigo (mutsvairo)
Cassia abbreviata	Long-tail cassia	*Indigofera vicioides*	-
Cissus cornifolia	Wild grape (muzambiringa)	*Securinega virosa*	Snow berry (musosoti)
Dalbergia melanoxylon	African blackwood (mugwiti)	*Sida cordifolia maculate*	Flannel weed
Grewia decemovulata	Miombo dwarf donkey-berry	*Solanum panduriforme*	Bitter / Snake / Thorn apple
Grewia flavescenes	Donkey berry (mubhubhunu)	*Tramfta rhomboidia*	Diamond burbark / Chinese bur
Grewia inaequilatera	Donkey berry (mutehwa)		

Annex II: Vegetation types found at Nuanetsi ranch



FAO Land cover classification map for Nuanetsi ranch (after (Di Gregorio et al., 2016)) and photos of dominant vegetation types (a) *Acacia* and *eragrostis*, (b) *Combretum apiculutum* (c) *C. apiculutum* and *panicum maximum* and, (d) *Colophospermum mopane* and *panicum maximum* (obtained in February 2017).

Annex III: Screenshot of the user interface of soil water module part of the SGS model