Calibration and evaluation of the Sustainable Grazing Systems pasture model for predicting native grass aboveground biomass production in southern Africa

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Simulation modelling of grass biomass production has gained huge attention since the early 2000s, but it has rarely been applied to southern African rangelands, due to limited data availability for model calibration and evaluation. This study was conducted to calibrate the Sustainable Grazing Systems (SGS) pasture model using measured and sourced data, to assess the reliability of model predicted biomass against field measured- and remotely sensed- grass aboveground biomass. Parameter sets were developed for crest-, mid- and foot-slope land types, and *Urochloa mosambicensis* and *Eragrostis curvula* grass species. Short- and long-term simulation experiments for all combinations of land types and grass species were conducted to calibrate and evaluate the model, respectively. The model simulated a growth pattern typical for grasses native to local rangelands. The SGS model represented measured grass biomass moderately well (R^2 = 0.57) at reasonable average error (RMSE, 820 kg DM ha^{-1}), despite huge discrepancy in measured (mean = 3 877 kg DM ha^{-1}) and simulated (mean = 3 071 kg DM ha^{-1}) biomass. Model predictions were also significantly correlated with remotely sensed grass biomass (R^2 = 0.46) at reasonable overall performance error (RMSE, 981 kg DM ha^{-1}). The integrated workflow developed for calibrating and evaluating the pasture simulation model can benefit model users in data-constrained environments.

Keywords: grass biomass, process-based modelling, remote sensing

Introduction

The aboveground biomass of grass has long been recognised as an important feature of grazing lands, as it determines forage availability for animals and measures management effects (Mannetje 2000). In semi-arid rangelands, monitoring grass biomass is challenging given the high variability of production, due to inter-annual climate fluctuations, heterogeneity of the environment and logistical constraints for field measurements (Karl et al. 2017). Thus, rangeland-monitoring activities have been limited to plot scales and short time frames. However, the inherent high variation in grass production caused by complex interactions of broad scale changes in climate and localised events, such as drought, grazing and fire (Hempson et al. 2007), cannot be well understood at such low spatial and temporal scales. Remote sensing has been used to predict grass production from environmental variables (Richard et al. 2012), but it does not represent the processes leading to grass biomass production. In future, climate variability is projected to increase in semi-arid regions (Jia et al. 2019) and this will increase fluctuations in grass production, rendering sustainable management more difficult. Accordingly, monitoring approaches should be tailored to meet information needs for the anticipated more variable or dynamic climate. Understanding the dynamics of grass

production caused by interactions of multiple environmental factors is necessary for predicting the productivity responses to an increasingly fluctuating climate.

Agricultural systems modelling is useful for providing quantitative analyses of complex interactions affecting components of rangeland systems and feedbacks of many variables (Jones et al. 2017). In the past two decades, empirical and mechanistic modelling gained huge attention globally in predicting grass biomass production (Snow et al. 2014). In southern Africa, simulation modelling has been limitedly applied to empirical models for plant growth (Wiegand et al. 1998; Oomen et al. 2016) and a few deterministic and stochastic models for plant and animal production (Illius et al. 1998; Richardson et al. 2000; Kazembe 2010). However, empirical models give spurious results if they are applied to regions that lack the experimental data used to develop them. This highlights the need to embrace robust dynamic models that contain default parameters that are adjustable across regions and use many variables of climate, soil, and vegetation representative of the real system.

Dynamic models, commonly known as process-based biophysical models (PBMs), simulate soil, plant, and animal processes at a high level of detail for individual species

in mixed swards. The PBMs explicitly represent stocks and flows of carbon, nitrogen or energy using differential equations that link the whole plant organism to processes in lower levels, such as cells or organs (Thornley and Johnson 2000). The models were developed with the aim to balance for complexity, realism and flexibility which allow them to be readily applied to regions that lack information about specific grass species (Rickert et al. 2000; Johnson 2011). Process-based models are thus often used as research models, because of their strong theoretical background. The major drawback in applying PBMs in data-limited regions is that, in addition to inherent errors of model structure, there are errors associated with system input variables and data measured for deriving parameters and evaluating the model.

The precision of PBMs depends on their ability to use spatially distributed climate input variables, parameters and constants that should be adjusted. In developing countries, climate data is often unavailable at farm-level, since national meteorological stations are sparsely distributed. Parameters and state variables are also unknown, as they cannot be fully included in experiments, due to their high variability in space (Johnson 2011). The increasing availability of high temporal- and spatial- resolution geographical data of environmental variables provide a means for adapting PBMs to resource-constrained environments (Angerer 2012). Remote sensing and geographic information systems (GIS) are inseparable tools important for retrieving input variables for PBMs (Ovando et al. 2018), yet they have been rarely explored in southern Africa.

Model users in resource-constrained areas can also benefit from using spatial data in providing independent observed data required for evaluating models. Given its large area coverage and high temporal frequencies of data collection, remote sensing has the potential to overcome challenges in obtaining long-term field measurements, as it provides site-specific grass production variables for model evaluation (Scanlon et al. 2005; Angerer 2012). Once discrepancies in model output are adequately assessed, PBMs can be applied with confidence to improve management planning. By predicting grass biomass production on a timely basis, PBMs help to enhance our understanding of the complex interactions that cause inherent variability in rangelands (Rickert et al. 2000). This knowledge assist in screening management practices suitable and effective for maximising grass and animal production. When used to predict future events, models help to identify risk areas that require emphasis on management (Jones et al. 2017). This study was, therefore aimed at developing local parameter sets for the soil water and plant growth submodels of the Sustainable Grazing Systems (SGS) model and, evaluating the model's adequacy in predicting native grass biomass production at a cattle ranch in southern Zimbabwe.

Materials and methods

Study area
The Nuanetsi Cattle ranch is found in the southern region of Zimbabwe (21°25′12″ S, 30°43′48″ E) on an undulating, plane landscape of the northern Limpopo river basin (ISCRI 2005). The ranch covers 113 913 ha of land at an altitude

of 480 m asl. 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 temperatures in summer are frequently above 32 °C (Figure 1), whereas mean annual temperature is 25 °C. 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 soils that cover most of the area. These soils support a medium subcanopy layer of productive, palatable perennial suit of tufted grasses, mostly *Urochloa mosambicensis* and *Panicum maximum*. Some patches of nutrient-poor soils comprising of sparse tree-shrub layer of *Combretum* and *Grewia* spp. that are associated with short wiry, unpalatable grass species, such as *Eragrotis* spp. and *Aristida* spp., are visible at broad scale (Farrell 1968). Forbs contribute a small proportion of the herbaceous vegetation in these savannas and are only found in heavily utilised areas (Taylor and Walker 1978). At local level, three vegetation types dominate the study area namely; closed woody life forms, closed to open tree/shrubland, and open herbaceous vegetation. Extensive commercial cattle ranching has been the main land use since early 1900s (Walker et al. 1981). Cattle are stocked throughout the year at moderate stocking rates in multi-paddock grazing systems. Each management unit comprise of two to five paddocks, with paddocks ranging from 300 to 1 500 ha.

Parameterisation of the modelling tool

Overview of the SGS pasture model
The SGS pasture model is an Australian biophysical model comprising of nested empirical and mechanistic submodels 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 plant growth submodel uses solar radiation to estimate net radiation through calculations of light interception and photosynthesis in a mixture of up to five herbaceous species. Water is included in the grassland through rainfall and is intercepted by the herbaceous canopy, litter, or bare soil. The soil water submodel was upgraded by Johnson et al. (2003), whereas the soil nutrient submodel was also improved by Johnson et al. (2008) and documented by Johnson (2008). The soil water submodel simulates
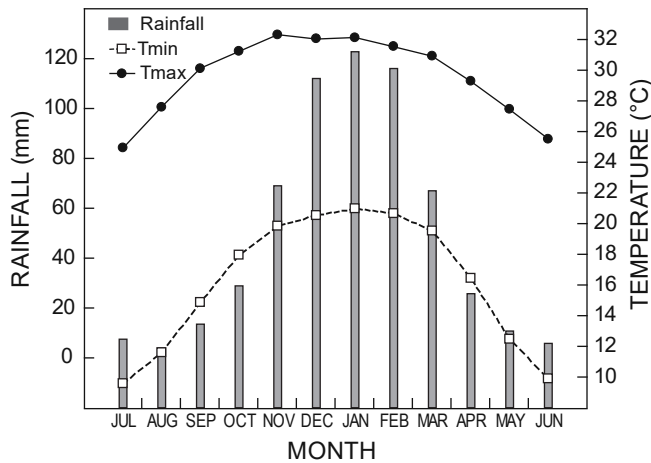
Figure 1: Mean monthly rainfall, minimum and maximum temperature (1976–2017) for the study area

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. The SGS model is large, comprising of many differential equations in its submodels. 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 C_3 and C_4 grasses in subtropical and temperate regions of Australia (Cullen et al. 2009). Recently, the model has been used to simulate the growth of tropical C_4 perennial and annual grasses and legumes in northern Australian rangelands (Doran-Browne et al. 2014).

Derivation of input variables and parameters for the SGS model
The submodels for soil water, nutrients and pasture are the main biophysical components of the SGS pasture model that were parameterised in this study. The submodels 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 study area. To overcome this challenge, an integrated framework was used to derive parameters from geographical layers of topography, climate, soil and vegetation, satellite images and extensive review of published experiments for southern African savannas (see Figure 2). Consequently, a total of eighteen parameters were adjusted and the remainder default parameter values were retained.

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 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 (ISCRI 2005) using GIS software.

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 was obtained from the HelioClim-1 database (Lefevre et al. 2014) and the Solar Radiation Data portal (Schroedter-Homscheidt et al. 2016) at a spatial resolution of 5 km. The Zimbabwe Sugar Association Experiment Station located 60 km north of Nuanetsi ranch provided daily data for solar radiation and minimum and maximum temperature that was used to correct for bias in satellite-based estimates. Daily minimum and maximum temperature were spatially interpolated for each land type using an inverse distance weighting approach (Moeletsi et al. 2016). Daily rainfall data available at a spatial resolution of approximately 10 km were obtained from the National Oceanic and Atmospheric Administration Climate Prediction Centre African Rainfall Climatology version 2 dataset (NOAA-CPC-ARC2) (Novella and Thiaw 2013). A spatio-temporal bias correction scheme was applied to this data using gauge data from the Mwenezi District Agritex office. All GIS processes and cartography were done in ArcGIS software and original projection systems for datasets used were converted to the World Geological Survey 84 datum system.

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 subcatchment 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. These surveys show that mafic gneiss was dominant in 79 and 65% of the pits surveyed in the crest and mid-slope land types, respectively (CSRI 2007), whereas fine alluvium soil family was common in 60% of sampled pits in foot slope (CSRI 2003). The valley-bottom land type was excluded from parameterisation, as it comprises of riparian vegetation, usually occupying insignificant area of some paddocks demarcated by riverbanks. Soil layer depths for the crest land type were adjusted to represent moderately deep soil with a total depth of 80 cm (Table 1). The crest soil profile was set to a relatively deeper A horizon, compared with 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 B horizon of moderate clay content (CSRI 2007). In foot-slope soil catena, soil depth was also adjusted to typify shallow alluvial soils (CSRI 2003). Available water capacity (AWC) was set at between 10.0 and 14.9% volume (CSRI 2007; CSRI 2003).

Plant parameter values were modified for herbaceous species that were identified in a species composition assessment conducted across the study area, as described
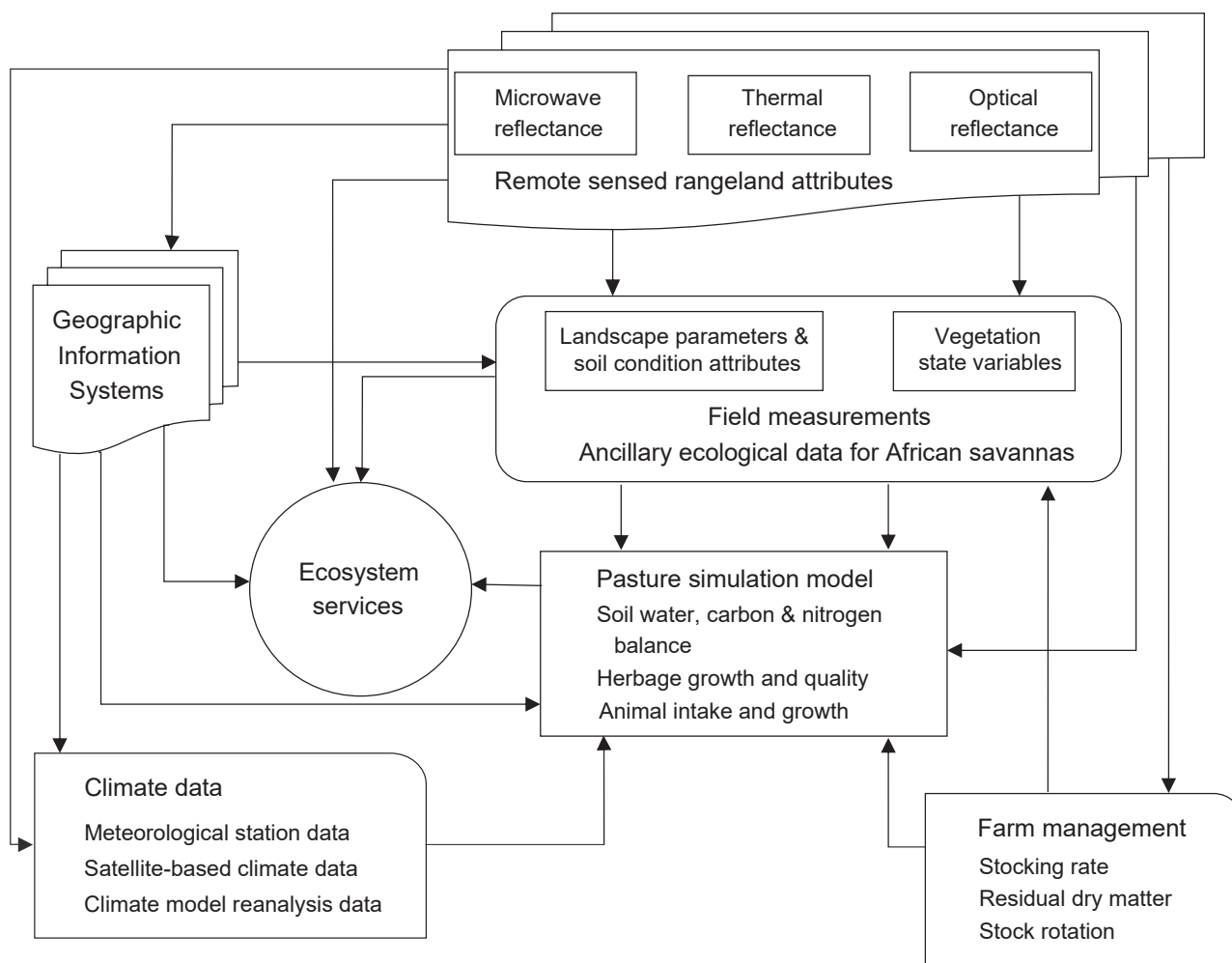
Figure 2: Framework of the flow of information used to parameterise the SGS pasture model

later below. The 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 2). The minimum and maximum temperatures for tropical grasses range between 10 and 15 °C and 30 to 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 µmol m^{-2} s^{-1}, as measured by Mantlana et al. (2008) in south-central Africa. In all submodels used in this study, default data were used where a site or regional data were not available.

Measured and remotely sensed grass aboveground biomass
Grass species composition and biomass were measured across the land types found at Nuanetsi ranch in February 2017 for sampling plots where simulations for calibrating the SGS model were performed. Firstly, the ranch was stratified

into eight vegetation types using FAO's 250 m resolution land cover classification system. Then, forty 30 m x 30 m sampling plots were randomly selected in grassland areas that were at least 0.1 ha and were used for measuring both species composition and biomass. The sample size has previously proved adequate for grass biomass estimation in the study area (Svinurai et al. 2018). For grass species composition assessment, each sampling plot was divided by two transects diagonally, each 43 metres in length, and oriented at 45° and 135° to the magnetic north. Starting at the 1.5 m point along each transect, grass species composition was visually assessed by a field taxonomist in 0.25 m^2 quadrats at 2-m intervals using the dry weight rank method (Mannetje and Haydock 1963). In each quadrat, the first, second, and third most abundant species (on a dry weight basis), were identified to which the ranks of 1, 2, and 3 were assigned, respectively. At the end of sampling, ranks were tallied for each species, and weighted by 0.7, 0.2 and 0.1, the multipliers for ranks 1, 2, and 3, respectively. Approximately twenty grass species were identified, but only two native graminoid herbaceous species were widely spread across the ranch. *Urochloa mosambicensis,* a loosely tufted, productive and highly palatable perennial
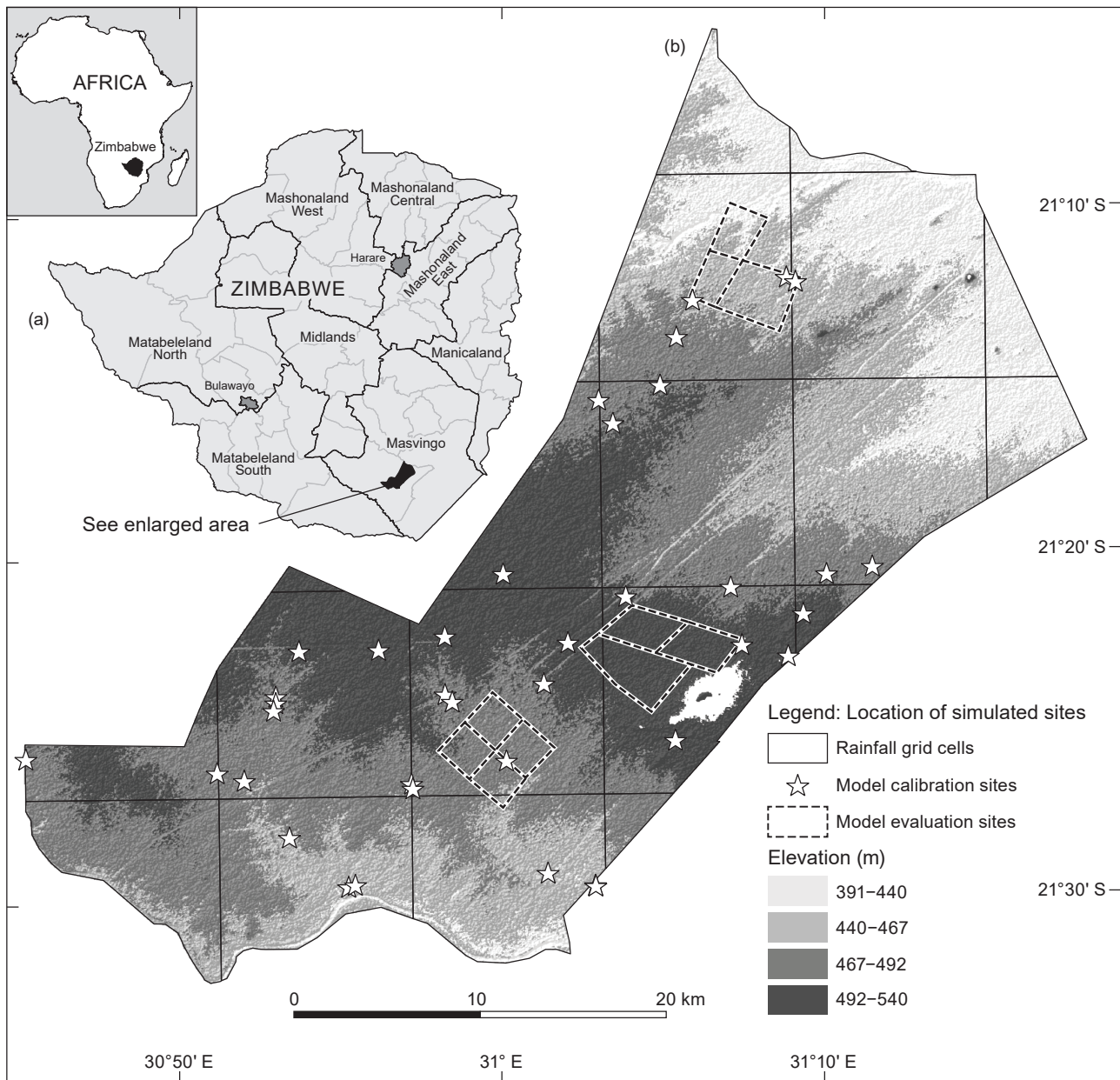
Figure 3: (a) Location of study area in Zimbabwe and (b) catena positions of land types and sites used for model calibration and evaluation

Table 1: Soil physical and chemical variables of land types used for model calibration

Factor	Parameter	Units	Default duplex	Foot slope soil	Default medium	Mid s lope soil	Crest soil
Soil physical variables	Altitude	m asl		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

Table 2: Plant species and community growth parameters values used for grasses at simulated sites

Factor	Parameter	Units	Default native C$_4$ 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^2 leaf kg DM^{-1}	16	15	12	Ernst and Tolsma (1992)
Growth	Maximum leaf net photosynthesis rate at reference conditions	µmol CO$_2$ m^{-2} s^{-1}	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)

grass comprised 90% of species composition i.e. first and second dry-weight ranks in half of sampled plots, whereas *Eragrostis curvula*, another tufted, productive and moderately palatable perennial grass was dominant in a quarter of the surveyed plots. The other plots had mixed grass species in low abundance. Grass aboveground biomass was then measured in four randomly selected 0.25 m^2 quadrats within each sampling plot by clipping to 5 cm stubble aboveground using shears. The biomass was weighted and then pooled and bagged for drying in a hot air oven for determination of dry matter content.

Other than the single-season grass biomass, there were no other observed grass biomass data for calibrating or evaluating the SGS model at the study area. Thus two separate datasets of remotely sensed grass biomass were developed for these purposes. For model calibration, we calculated the normalised difference vegetation index (NDVI), a proxy for grass AGB from spectral reflectance of 30 m pixels of Landsat 8 Operational Land Imager image corresponding to the plots sampled above. Plant biomass data for model evaluation was derived from a statistical model for end-of-season grass AGB that was developed from NOAA-CPC-ARC2 rainfall in combination with grass AGB estimated from peak-season Landsat images. To build the statistical model, a set of nineteen cloud-free pre-processed Landsat images available in May between 1992 and 2017 were classified to mask out the woody vegetation layer. The period coincides with peak grass biomass prior to the onset of grass senescence in southern African savannas. Then, a multivariate regression model for grass AGB developed by Svinurai et al. (2018) for the study area was applied to all images to produce grass AGB maps. Grass AGB for each map was statistically resampled to ~10 km grid-cells to match the resolution of the satellite-based rainfall dataset. Finally, grass biomass for all grid cells were grouped for all years and, paired with corresponding seasonal rainfall into single linear, power, and exponential regression models to screen the most precise and accurate model using the bootstrapping technique. The following exponential regression model produced the most precise ($R^2 = 0.81$) and accurate (RMSE, 1 559 kg ha^{-1}) fit: AGB = $829.9e^{0.0037x}$, where AGB is grass aboveground biomass (kg ha^{-1}) and x is total wet season rainfall (mm). Thus, this statistical model was used to predict grass biomass in grid-cells corresponding to sites where the SGS model was evaluated.

Model simulations

A manual, iterative procedure of manipulating default model parameter values typical for Australian rangeland systems 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 conditions at sampled plots and, best fit with measured or remotely sensed grass aboveground biomass. Simulation runs for grass biomass production were performed in twenty-eight plots, as the other plots comprising of mixed grass species of low abundance were excluded from parameterisation. The simulations were performed between 2007 and 2017 by adjusting parameters accordingly for each climate grid cell, land type and grass species. For model evaluation, three separate simulation experiments were conducted between 1982 and 2017 using

generic values for three land types dominating the study area. These values were obtained by averaging all values for each individual parameter across each land type to produce a single value. Firstly, daily grass biomass production simulations were run separately for all combinations of land type and grass species in three 500 ha paddocks constituting a grazing management unit, using adjusted parameter sets (Figure 3). Then, a global sensitivity analysis was performed to determine the extent of improvement made by parameter adjustments and the deviations of model output behaviour from known behaviour of biomass production by grasses native to the study region. This was achieved by running the model using default (Australian) parameter values of native C_4 grass, and adjusted values for duplex and medium-texture soils corresponding to foot slope and, crest and mid-slope soil types. The third simulation experiment was conducted to show the importance of the hypothesis that residual dry matter of stubble influence leaf regrowth rate after defoliation and subsequent biomass production. This simulation experiment was performed with grass cut to residual dry matter levels of 500, 750 and 1 000 kg DM ha^{-1} at the end of each month. In all simulations for model calibration and evaluation, interpretation of results was simplified by implementing a maintenance growth submodel so that the animal's role in the model was to graze the paddock and return nutrients as urine and dung. Daily simulations of grass biomass production at each plot or paddock were performed between July and June following the summer season weather calendar. In addition, outputs in the first 10-year lead-in period in all simulations were discarded to allow stabilisation of soil organic carbon pools in the simulated system. Thus, outputs for the 2017 and the 1992 to 2017 seasons were used to calibrate and evaluate the SGS model, respectively.

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}). Daily outputs were averaged over each calendar month to convert them to values of monthly averages for each plot or 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 grass growth rates, and biomass production were compared with published literature for tropical grazing lands of southern Africa. A standard procedure for evaluating performance of models involving analysis of summary statistics i.e. mean, minimum, maximum and mean bias, root mean square error (RMSE), decomposition of RMSE, i.e. 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. The coefficient of determination (R^2) was used to measure the precision with which the model predicted measured or remotely sensed grass AGB. Since the sample size

was small relative to the spatial extent of each land type, regression statistics for analysis were generated for the three land types combined. 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).

Results

Calibration of the model

Annual mean grass aboveground biomass measured in all plots retained for model fitting was 3 877 kg DM ha^{-1}, whereas the modelled mean was 3 071 kg DM ha^{-1}. Minimum measured and simulated biomass was 1 450 and 2 968 kg DM ha^{-1}, respectively, whereas maximum values of 5 370 and 3 157 kg DM ha^{-1}, corresponding to measured and simulated biomass was obtained. The mean bias was 807 kg DM ha^{-1}, whereas the relative bias was 0.21. The relationship between measured and modelled grass AGB showed that the SGS model represented herbage biomass reasonably well, accounting for up to 60% variation in grass AGB ($R^2 = 0.57$; $p < 0.01$) (see Figure 4a). Figure 4b is a plot of residuals versus predictor variables that 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 grass AGB fell within the 95% confidence limits of their respective observations, whereas 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 grass AGB were significantly correlated across all land types with an R^2 value of 0.46 for NDVI (Figure 5).

Sensitivity analysis

The grass production trend predicted in this study showed a pattern of growth and aboveground biomass production known for grasses native to tropical rangelands of southern Africa (Figures 6 and 7). In winter, the growth rates of *U. mosambicensis* predicted using adjusted parameters were low, with median biomass production falling below 0.5 kg DM ha^{-1} d^{-1}. The median growth rate increased rapidly, reaching peak biomass of 33 and 21 kg DM ha^{-1} d^{-1} in January and February, respectively. The mean growth rate ranged between 2.9 and 7.2 kg DM ha^{-1} d^{-1} between November and March across land types, whereas the median growth rate varied from 0.9 to 5.5 kg DM ha^{-1} d^{-1} (see Figure 6a). Observable differences in grass growth between land types occurred during peak of season period between December and February. The median growth rate of *U. mosambicensis* in mid-slope land type was 7 to 24% higher than in the upper slope land type at peak of season. There was also an abrupt 18% decline in the median growth rate of local grass species in mid- and foot slope land types in January, whereas a relatively low growth rate was maintained in crest land type (Figure 6a). Highest growth rates of the local grass species were predicted at peak-season at 750 kg DM ha^{-1} residual DM followed by growth rates for simulations run at 1 000 kg DM ha^{-1} residual DM (Figure 6b). The least growth rate predictions were
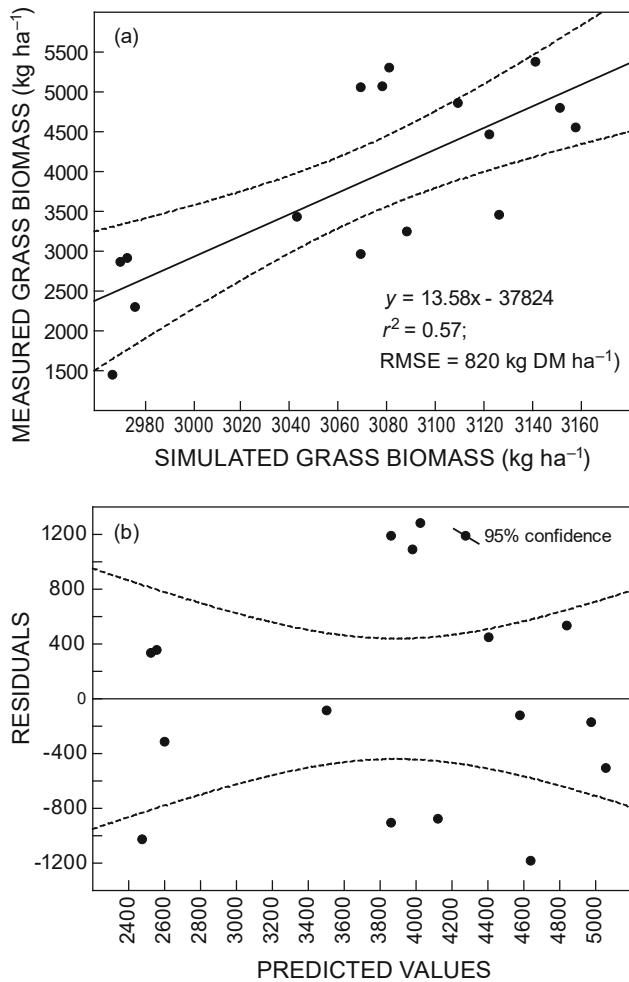
Figure 4: Comparison of (a) simulated and measured grass AGB and (b) predicted values and residuals in all plots. Broken lines denote 95% confidence intervals for the fitted regression model and the line of zero deviation.
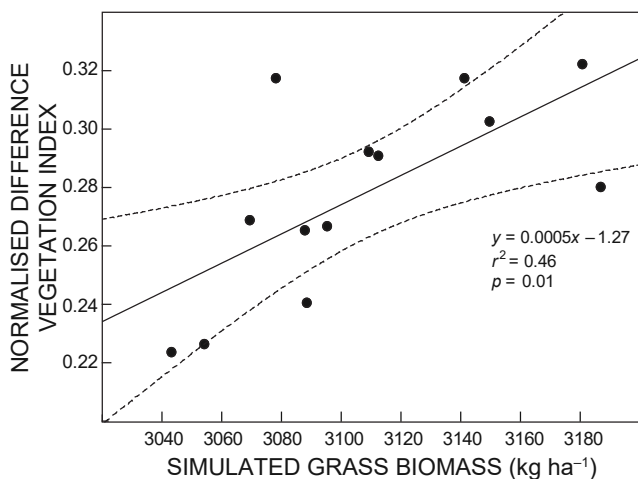

Figure 5: Comparison of simulated and Normalised Difference Vegetation Index of grass aboveground biomass. Broken lines denote 95% confidence intervals for the fitted regression model
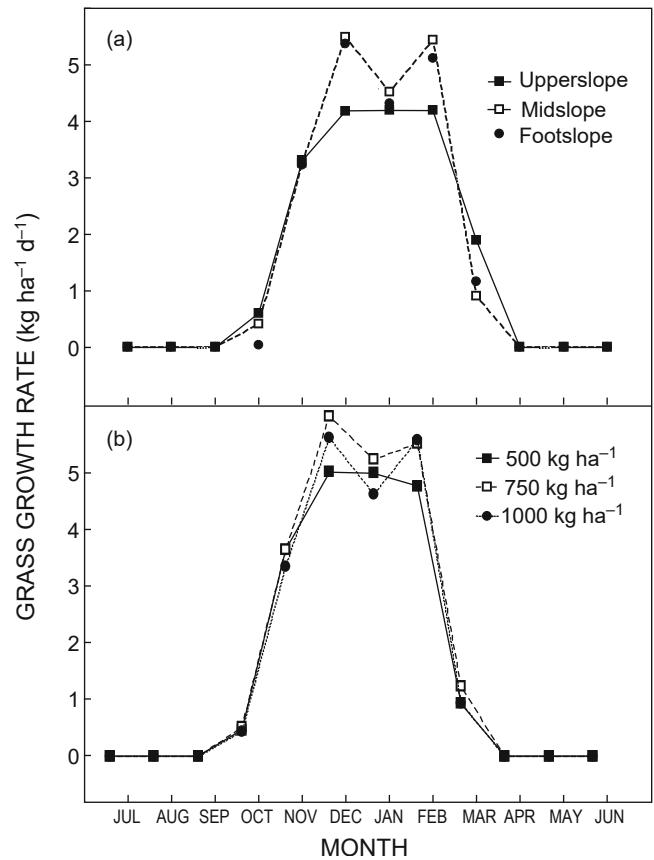

Figure 6: Modelled median growth rate (kg DM ha⁻¹ d⁻¹) of *Urochloa mosambicensis* across (a) land types and (b) grazed residual dry matter levels

obtained when residual DM was cut at 500 kg DM ha⁻¹. The median growth rate of *U. mosambicensis* stands cut to 750 and 1 000 kg DM ha⁻¹ residual DM dropped suddenly by 12 and 18%, respectively, in January.

Simulated grass biomass portrayed a seasonal pattern like that of growth rate (Figure 7). Between November and March, absolute monthly grass AGB production ranged between 115 and 228 kg DM ha⁻¹ across all land types. The maximum monthly grass AGB production during this period was 209, 220 and 228 kg 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 C_4 grass relative to local grass species (Figure 7a). However, in shallow mafic-gneiss derived soils in mid- and foot slope land types, parameter modifications resulted in lower growth rates of default native C_4 grass, compared with local grasses (Figures 7b and 7c). There were no observable differences in biomass production between local grass species across land types. Biomass production by local grass species was 26 to 98% higher than biomass production by default native C_4 grass, with these differences highest at peak of season (Figures 7b and 7c).

Model evaluation

As with predictions for field biomass, there were huge discrepancies in summary statistics and residuals between
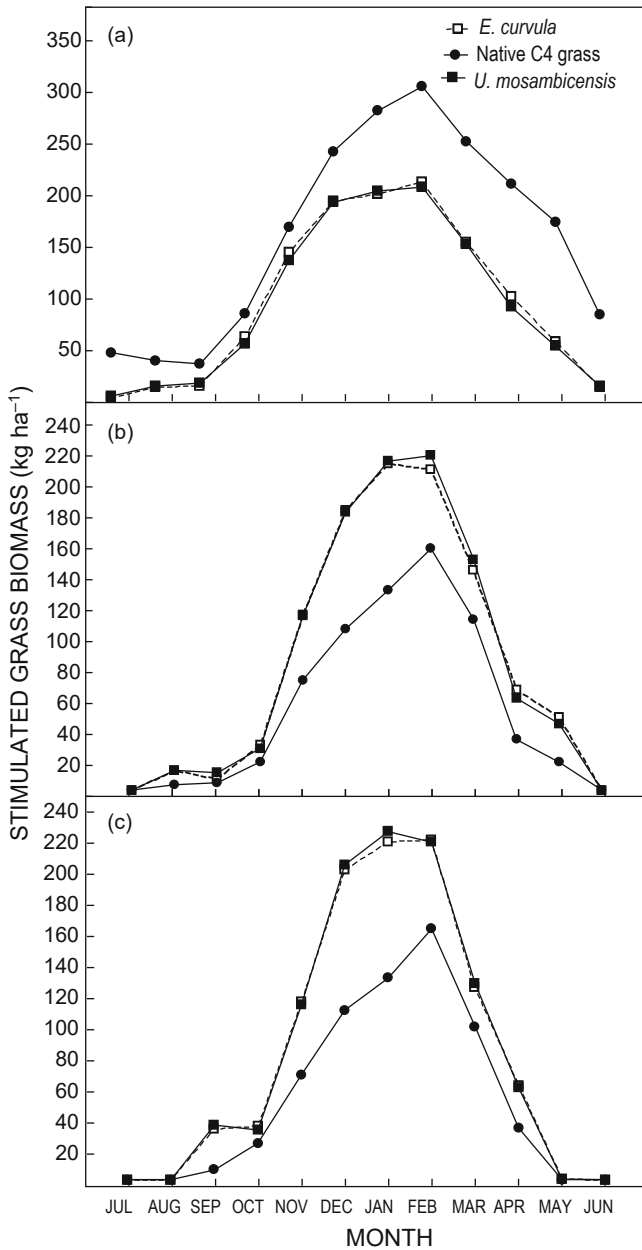
Figure 7: Modelled absolute monthly yield (kg ha⁻¹) of default native C4 and adjusted grass species parameters in a) upper-, b) mid- and c) foot slope land types

−1 970 to −2 461 kg DM ha⁻¹, whereas the relative bias varied from −0.51 to −1.18. Despite the underestimation of remotely sensed grass biomass by the SGS model, the model predictions were significantly correlated with remotely sensed grass biomass ($p < 0.05$), accounting between 63 and 72% of the variation. Analysis of deviation of individual predictions from corresponding observations across all land types reveal that 39% (19 of 49) of all grass biomass predictions fell within the 95% confidence limits of their respective observations, whereas 31 (15 of 49) and 31% were under- and over-predictions, respectively. The RMSE of all predictions across land types was 981 kg DM ha⁻¹ and ranged from 1 122 to 1 396 kg DM ha⁻¹.

Discussion

Calibration of the model

The relationship between measured and simulated grass biomass showed that the SGS model represented herbage biomass reasonably well, accounting for up to 60% variation in grass biomass production. Similar levels of agreements have been observed in simulation studies conducted in other tropical and temperate regions. Using the SGS model, Cullen et al. (2008) observed an R^2 of 0.58 in fertilised perennial grasses in subtropical region of south-eastern Queensland, whereas Doran-Browne et al. (2014) obtained an R^2 of 0.6 in native perennial and annual grasses in tropical region of northern Australia. In temperate prairie grasslands, the APEX model underestimated growth of five individual perennial grass species ($R^2 = 0.25–0.67$) (Zilverberg et al. 2017), whereas the GPFARM model accounted for 66% variability of observed forage production (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 grass biomass are generally obtained for empirical simulation 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 exhibited within local grass communities in southern African rangelands. For example, Svinurai et al. (2018) observed grass production to vary from 1 340 to 7 530 kg DM ha⁻¹ in a season. Poilecot and Gaidet (2011) also observed native grass AGB production to vary from 1 433 to 4 257 kg DM ha⁻¹ in shallow sandy soils in northern Lowveld game ranch of Zimbabwe. In undulating landscapes of Lowveld regions of southern Africa, variability in grass production often results from uneven distribution of rainfall and high diversity of grass species that evolve from their competition for soil water and nutrients (Venter et al. 2003). This random variation leads to huge errors when predicting grass AGB using point-based models and could not be accounted for by the SGS model using the

simulated and remotely sensed grass biomass across all land types. The mean remotely sensed biomass varied between 3 644 and 4 170 kg DM ha⁻¹ whereas the mean simulated biomass ranged between 1 674 and 1 997 kg DM ha⁻¹. Minimum remotely sensed and simulated biomass was 1 445 and 1 249 kg DM ha⁻¹, respectively, whereas maximum values of 7 214 and 2 281 kg DM ha⁻¹ corresponding to remotely sensed and simulated biomass were attained. The SGS model had a tendency of underestimating remotely sensed biomass by between 51 and 59% across all land types, with an overall mean bias error of −1 970 kg DM ha⁻¹. The mean bias ranged from

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). In addition, 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 SGS model predicted grass AGB measured in respective sampling plots with a reasonable average error acceptable for estimating grass AGB in southern African savannas. Trollope and Potgieter (1986) estimated a RMSE of 898 kg DM ha⁻¹ from disc pasture meter measurements across seven vegetation types in the Kruger National Park. 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 evaluate further the stability SGS model in simulating grass biomass in the region.

Sensitivity analysis

The patterns of grass growth displayed by model outputs agree with the typical behaviour of summer growth of perennial grasses in the tropical region of southern Africa. For example, low grass growth rates were observed in winter, because there is no rainfall and temperatures are low, whereas the growth rates in summer increased rapidly, because of high rainfall and temperatures. The SGS model also represented the effects of mid-season dry spells on median grass growth reasonably by showing a decline in growth rate in January (Figure 6). Frequent mid-season dry spells are a characteristic feature of arid savannas in the Limpopo river basin (Huntley 1982). This was confirmed by the DM accumulation pattern of outputs predicted by the SGS model.

In addition, there is a good agreement between estimates of monthly growth rates predicted by the SGS model and growth rates observed in other rangelands in the region. In the northern Limpopo river basin, Kelly and Walker (1976) observed daily growth rate to vary from 6.6 to 11 kg DM ha⁻¹ d⁻¹ in moderately- utilised open vegetation, depending on seasonal rainfall. Cresswell et al. (1982) observed a peak mean grass biomass growth rate of 5 kg DM ha⁻¹ d⁻¹ in the southern Limpopo river basin. In drier Succulent Karoo rangeland where vegetation is less productive, Richardson et al. (2010) simulated optimum forage growth rate of 2 kg DM ha⁻¹ d⁻¹ using a short-term mechanistic model. As with growth rate, the simulated pattern of grass production 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, with mean monthly grass production ranging from 40 to 160 kg DM ha⁻¹ (Alard 2009). In Bloemfontein, monthly growth rates ranged between 100 and 400 kg DM ha⁻¹ at peak of season, depending on seasonal rainfall (de Waal 1990). The model output 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. Thus, the comparability of simulated biomass production to those observed in the region builds model user confidence in

applying the SGS model to similar environments using the parameter sets developed in this study.

Model evaluation

The modelled grass AGB showed an acceptable level of representation of remotely sensed grass AGB for southern African savannas. These findings concur with Boone et al. (2002) and Boone et al. (2004), who found reasonable agreement between the SAVANNA model outputs and NDVI in northern Tanzania ($R^2 \geq 0.60$) and in north-western South Africa ($R^2 = 0.42$), respectively. In addition, Popp et al. (2009) found that NDVI account for most variation ($R^2 = 0.69–0.79$) in modelled vegetation biomass in southern Namibia. The SGS model can thus be used with some confidence basing on its precision level that is comparable to other simulation models. Factors that present challenges when comparing measured with simulated biomass in complex natural systems mentioned earlier also contribute to the moderate performance of correlations between simulated and remotely sensed biomass. Environmental heterogeneity, and inter-annual climate fluctuations cause variation in spectral reflectance properties of grass vegetation. The variation in grass 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). Climate variables also play an important role in systems modelling, as they affect model outputs (Ovando et al. 2018). Daily rainfall and solar radiation inputs used in this study were derived from interpolation of satellite estimates, whereas temperature was spatially interpolated using data measured at 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. However, given that weather data was not available on the ranch, these climate data were the only suitable choices and, were considered as representative. Given the inherent uncertainties associated with inputs, parameters and remotely sensed biomass used in this study, it was imperative to test the extent to which the model predicts responses in the whole set of outputs.

The SGS model output overall predicted remotely sensed grass AGB at an accuracy level that is comparable to field measurements. The average errors values of simulated grass AGB (981 to 1 396 kg DM ha⁻¹) fall within the range of errors of measured (930 kg DM ha⁻¹, Svinurai et al. 2018) and remotely sensed grass biomass (1 171 kg DM ha⁻¹, Dwyer 2011) in the Limpopo river basin. In southern Limpopo river basin, Mutanga and Rugege (2006) found RMSEs ranging from 830 to 1 374 kg DM ha⁻¹ from geospatial and remote sensing models, whereas Dwyer (2011) found the RMSE to vary between 1 171 and 1 711 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.

Overall, the study findings suggest that individual seasonal predictions deviate considerably from both measured and remotely sensed grass AGB and, the high natural variability of semi-arid savannas is the major

source of uncertainty. When summarised, under- and over-predictions refuted each other to produce acceptable error values. Therefore, the parameter sets developed in this study can be used with some confidence for predicting grass biomass in the region. However, the major simplifying assumption made in the SGS model was that grass biomass production and the return of urine are uniform. Although this may be a reasonable approximation for the relatively homogenous grasslands, the phenomenon is rarely true for savanna rangelands in which abiotic and biotic factors have interacted over time, causing a high degree of spatial and temporal variation in grass community production (Venter et al. 2003). This highlights the need for incorporating in the model an automated approach, such as a GIS submodel, to explicitly represent the spatial variation in grass biomass production. Furthermore, the current modelling approach is relevant to commercial ranches in the Limpopo river basin with large, well-managed paddocks. However, these systems preclude proper understanding of the dynamics of grass biomass production under uncontrolled management in common property grazing lands dominant in southern Africa. Thus, further testing of the SGS model under a variety of environmental conditions in communal rangelands is required to gain more confidence in applying the model in the region.

Conclusions

This study developed an integrated workflow for calibrating and evaluating process-based pasture simulation models that can benefit model users in data-constrained environments. The behaviour of SGS model outputs was successfully explored qualitatively by examining the sensitivity of outputs, and quantitatively using regression statistics. The model predicted biomass production patterns known for grasses native to tropical regions of southern Africa. Growth predictions of local grass species were higher than those of default native C_4 grass by 26 to 98% across land types. The SGS model represented measured and remotely sensed grass biomass at reasonable overall performance errors despite huge differences in individual prediction measures. These findings indicate that measures for individual predictions provide low performance scores when dynamic models are tested in natural systems, whereas better scores are obtained with measures for whole predictions. The parameter sets developed can be used to apply the SGS model to similar soil types within the region, where there are no basic data for model calibration and assessment.

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References

Alard FG. 2009. A comparison of grass production and utilisation in sodic and crest patches on a semi-arid granitic savanna catena in the southern Kruger National Park, South Africa. MSc thesis, University of the Witwatersrand, South Africa.

Andales AA, Derner JD, Ahuja LR, Hart RH. 2006. Strategic and tactical prediction of forage production in northern mixed-grass prairie. *Rangeland Ecology and Management* 59: 576–584. https://doi.org/10.2111/06-001R1.1.

Angerer JP. 2012. Technologies, tools, and methodologies for forage evaluation in grasslands and rangelands. In: Coughenour MB, Makkar HPS (Eds), *National Feed Assessments*. Rome: Food and Agriculture Organization of the United Nations. pp 165–200.

Boone RB, Coughenour MB, Galvin KA, Ellis JE. 2002. Addressing management questions for Ngorongoro Conservation Area, Tanzania, using the Savanna modelling system. *African Journal of Ecology* 40: 138–150. https://doi.org/10.1046/j.1365-2028.2002.00357.x.

Boone RB, Galvin KA, Coughenour MB, Hudson JW, Weisberg PJ, Vogel CH, Ellis J. 2004. Ecosystem modelling adds value to a South African climate forecast. *Climatic Change* 64: 317–340. https://doi.org/10.1023/B:CLIM.0000025750.09629.48.

CSRI (Chemistry and Soil Research Institute). 2007. Soils of the proposed Lapache irrigation project. CSRI Report No: A689 prepared for the Department of Research and Specialist Services. Ministry of Agriculture, Mechanisation, and Irrigation Development, Zimbabwe.

CSRI (Chemistry and Soil Research Institute). 2003. Soils of the proposed Nuanetsi irrigation project. CSRI Report No. A670 prepared for the Department of Research and Specialist Services. Ministry of Agriculture, Mechanisation, and Irrigation Development, Zimbabwe.

Cobiac MD. 2006. Predicting native pasture growth in the Victoria River District of the Northern Territory. PhD Thesis, The University of Adelaide, Australia.

Cook B, Pengelly B, Brown S, Donnelly J, Eagles D, Franco A, Hanson J, Mullen B, Partridge I, Peters M, et al. 2005. Tropical forages: an interactive selection tool. Web Tool. CSIRO, DPI&F(Qld), CIAT and ILRI, Brisbane, Australia. https://www.tropicalforages.info/text/entities/index.htm. [Accessed 18 August 2018].

Cooper JP, Tainton NM. 1968. Light and temperature requirements for the growth of tropical and temperate grasses. *Herbage Abstracts* 38: 167–176.

Cresswell CF, Ferrar P, Grunow JO, Grossman D, Rutherford MC, van Wyk JJP. 1982. Phytomass, seasonal phenology and photosynthetic studies. In: Huntley BJ, Walker BH (Eds), *Ecology of Tropical Savannas*. Berlin: Springer-Verlag. pp 476–497. https://doi.org/10.1007/978-3-642-68786-0_22.

Cullen BR, Eckard RJ, Callow MN, Johnson IR, Chapman DF,

Rawnsley RP, Garcia SC, White T, Snow VO. 2008. Simulating pasture growth rates in Australian and New Zealand grazing systems. *Australian Journal of Experimental Agriculture* 59: 761–768. https://doi.org/10.1071/AR07371.

Cullen BR, Johnson IR, Eckard RJ, Lodge GM, Walker RG, Rawnsley RP, McCaskill MR. 2009. Climate change effects on pasture systems in south-eastern Australia. *Crop & Pasture Science* 60: 933–942. https://doi.org/10.1071/CP09019.

de Waal HD. 1990. Animal production from native pasture (veld) in the Free State region: a perspective of the grazing ruminant. *South African Journal of Animal Science* 20: 1–9.

Doran-Browne NA, Bray SG, Johnson IR, O'Reagain PJ, Eckard RJ. 2014. Northern Australian pasture and beef systems. 2. Validation and use of the Sustainable Grazing Systems (SGS) whole-farm biophysical model. *Animal Production Science* 54: 1995–2002. https://doi.org/10.1071/AN14569.

Dwyer P. 2011. Spatial estimation of herbaceous biomass using remote sensing in southern African savannas. MSc thesis, University of the Witwatersrand, South Africa.

Dye PJ, Walker BH. 1980. Vegetation-environment relations on sodic soils of Zimbabwe Rhodesia. *Journal of Ecology* 68: 589–606. https://doi.org/10.2307/2259424.

Ernst WH, Tolsma DJ. 1992. Growth of annual and perennial grasses in a savanna of Botswana under experimental conditions. *Flora* 186: 287–300. https://doi.org/10.1016/S0367-2530(17)30547-9.

Farrell JAK. 1968. Preliminary notes on the vegetation of the lower Sabi-Lundi basin, Rhodesia. *Kirkia* 6: 223–248.

Hempson GP, February EC, Verboom GA. 2007. Determinants of savanna vegetation structure: Insights from *Colophospermum mopane*. *Austral Ecology* 32: 429–435. https://doi.org/10.1111/j.1442-9993.2007.01712.x.

Huntley BJ. 1982. Southern African Savannas. In: Huntley BJ, Walker BH (Eds), *Ecology of Tropical Savannas*. Berlin: Springer-Verlag. pp 101–119. https://doi.org/10.1007/978-3-642-68786-0_6.

Illius AW, Derry JF, Gordon IJ. 1998. Evaluation of strategies for tracking climatic variation in semi-arid grazing systems. *Agricultural Systems* 57: 381–398. https://doi.org/10.1016/S0308-521X(98)00025-0.

ISCRI (International Soil Research Institute). 2005. Atlas of SOTER derived maps of Zimbabwe: Impact of desertification on food security. ISRIC-World Soil Information, Wageningen.

Jia G, Shevliakova E, Artaxo P, Noblet-Ducoudré NDe, Houghton R, House J, Kitajima K, Lennard C, Popp A, Sirin A, et al. 2019. Land–climate interactions. In: Shukla PR, Skea J, Buendia EC, Masson-Delmotte V, Pörtner HO, Roberts DC, Zhai P, Slade R, Connors S, Diemen R van, Ferrat M, Haughey E, Luz S, Neogi S, Pathak M, Petzold J, Pereira JP, Vyas P, Huntley E, Kissick K, Belkacemi M, Malley J (Eds), *Climate change and land: An IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. Cambridge: Cambridge University Press. pp 131–248.

Johnson I. 2016. DairyMod and the SGS pasture model: a mathematical description of the biophysical model structure. IMJ Consultants, Dorrigo, NSW, Australia. http://imj.com.au/wp-content/uploads/2016/05/DM_SGS_documentation.pdf. [Accessed 4 January 2017].

Johnson I, Parsons A, Ludlow M. 1989. Modelling Photosynthesis in Monocultures and Mixtures. *Australian Journal of Plant Physiology* 16: 501–16.

Johnson IR. 2011. Testing and evaluating large-scale agricultural simulation models. In: *Proceedings of the 19th International Congress on Modelling and Simulation*. 12–16 December 2011, Perth, Australia. pp 84–96.

Johnson IR. 2008. Biophysical pasture model documentation: model documentation for DairyMod, EcoMod and the SGS Pasture Model. IMJ Consultants, Dorrigo, NSW, Australia.

http://imj.com.au/wp-content/uploads/2014/08/GrazeMod.pdf. [Accessed 4 January 2017].

Johnson IR, Chapman DF, Snow VO, Eckard RJ, Parsons AJ, Lambert MG, Cullen BR. 2008. DairyMod and EcoMod: biophysical pasture-simulation models for Australia and New Zealand. *Australian Journal of Experimental Agriculture* 48: 621–631. https://doi.org/10.1071/EA07133.

Johnson IR, France J, Thornley JHM, Bell MJ, Eckard RJ. 2012. A generic model of growth, energy metabolism, and body composition for cattle and sheep. *Journal of Animal Science* 90: 4741–4751. https://doi.org/10.2527/jas.2011-5053.

Johnson IR, Lodge GMB, White REC. 2003. The Sustainable Grazing Systems Pasture Model: description, philosophy, and application to the SGS National Experiment. *Australian Journal of Experimental Agriculture* 43: 711–728. https://doi.org/10.1071/EA02213.

Johnson IR, Thornley JH. 1983. Vegetative crop growth model incorporating leaf area expansion and senescence and applied to grass. *Plant, Cell and Environment* 6: 721–729. https://doi.org/10.1111/1365-3040.ep11588103_6_9.

Johnson IR, Thornley JH. 1985. Temperature dependence of plant and crop processes. *Annals of Botany* 55: 1–24. https://doi.org/10.1093/oxfordjournals.aob.a086868.

Johnson IR, Thornley HM. 1987. A model of shoot: root partitioning with optimal growth. *Annals of Botany* 60: 133–142. https://doi.org/10.1093/oxfordjournals.aob.a087429.

Jones JW, Antle JM, Basso B, Boote KJ, Conant RT, Foster I, Godfray HCJ, Herrero M, Howitt RE, et al. 2017. Brief history of agricultural systems modelling. *Agricultural Systems* 155: 240–254. https://doi.org/10.1016/j.agsy.2016.05.014.

Karl JW, Herrick JE, Pyke DA. 2017. Monitoring protocols: options, approaches, implementation, benefits. In: Briske DD (Eds), *Rangeland systems processes, management, and challenges*. Cham: Springer Nature. pp 527–567. https://doi.org/10.1007/978-3-319-46709-2_16.

Kazembe JA. 2010. Modelling the influence of rainfall variability and different grazing systems on the spatiotemporal dynamics and productivity of semi-arid rangelands. PhD thesis, University of Cape Town, South Africa.

Kelly DR, Walker BH. 1976. The effects of different forms of land use on the ecology of a semi-arid region in south-eastern Rhodesia. *Journal of Ecology* 64: 553–576. https://doi.org/10.2307/2258773.

Kumar L, Sinha P, Brown JF, Ramsey RD, Rigge M, Stam CA, Hernandez AJ, Hunt Jr RE, Reeves MC. 2016. Characterization, mapping, and monitoring of rangelands: methods and approaches. In: Thenkabail PS (Ed.), *Remote sensing handbook: land resources monitoring, modelling, and mapping with remote sensing*. Boca Raton: Taylor and Francis Group, CRC Press. pp 309–350.

Lefevre M, Blanc P, Espinar B, Gschwind B, Ménard L, Ranchin T, Wald L, Saboret L, Thomas C, Wey E. 2014. The HelioClim-1 database of daily solar radiation at earth surface: An example of the benefits of GEOSS data-CORE. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 7: 1745–1753. https://doi.org/10.1109/JSTARS.2013.2283791.

Makarau A, Jury MR. 1997. Predictability of Zimbabwe summer rainfall. *International Journal of Climatology* 17: 1421–1432. https://doi.org/10.1002/(SICI)1097-0088(19971115)17:133.0.CO;2-Z.

Mannetje L't, Haydock KP. 1963. The dry-weight rank method for the botanical analysis of pasture. *Journal of the British Grassland Society* 18: 268–275. https://doi.org/10.1111/j.1365-2494.1963.tb00362.x.

Mannetje L't. 2000. Measuring biomass of grassland vegetation. In: Mannetje L't, Jones RM (Eds), *Field and Laboratory Methods for Grassland and Animal Production Research*. London: CABI Publishing. pp 29–66.

Mantlana KB, Arneth A, Veenendaal EM, Wohland P, Wolski P, Kolle O, Wagner M, Lloyd J. 2008. Photosynthetic properties of C_4 plants growing in an African savanna/wetland mosaic. *Journal of Experimental Botany* 59: 3941–3952. https://doi.org/10.1093/jxb/ern237.

Mcphee MJ, Walmsley BJ. 2017. Misuse of coefficient of determination for empirical validation of models. In: *Proceedings of the 22nd International Congress on Modelling and Simulation.* Hobart, Tasmania, Australia. pp 230–236.

Mitchell PL, Sheehy JE. 1997. Comparison of predictions and observations to assess model performance: a method of empirical validation. In: Kropff MJ, Teng PS, Aggarwal PK, Bouma J, Bouman BAM, Laar JJW, van Laar HH (Eds), *Applications of Systems Approaches at the Field Level - Volume 2*: *Proceedings of the Second International Symposium on Systems Approaches for Agricultural Development*. Kluwer, Dordrecht, The Netherlands. pp 437–451. https://doi.org/10.1007/978-94-017-0754-1_31.

Moeletsi ME, Shabalala ZP, Nysschen GDe, Walker S. 2016. Evaluation of an inverse distance weighting method for patching daily and dekadal rainfall over the Free State Province, South Africa. *Water SA* 42: 466–474. https://doi.org/10.4314/wsa.v42i3.12.

Mutanga O, Rugege D. 2006. Integrating remote sensing and spatial statistics to model herbaceous biomass distribution in a tropical savanna. *International Journal of Remote Sensing* 27: 3499–3514. https://doi.org/10.1080/01431160600639735.

Novella NS, Thiaw WM. 2013. African rainfall climatology version 2 for famine early warning systems. *Journal of Applied Meteorology and Climatology* 52: 588–606. https://doi.org/10.1175/JAMC-D-11-0238.1.

Oomen RJ, Ewert F, Snyman HA. 2016. Modelling rangeland productivity in response to degradation in a semi-arid climate. *Ecological Modelling* 322: 54–70. https://doi.org/10.1016/j.ecolmodel.2015.11.001.

Oreskes N, Shrader-Frechette K, Belitz K. 1994. Verification, validation, and confirmation of numerical models in the earth sciences. *Science* 263: 641–646. https://doi.org/10.1126/science.263.5147.641.

Ovando G, Sayago S, Bocco M. 2018. Evaluating accuracy of DSSAT model for soybean yield estimation using satellite weather data. *ISPRS Journal of Photogrammetry and Remote Sensing* 138: 208: 217.

Oxfam-UNDP/GEF. 2015. Scaling up adaptation in Zimbabwe, with a focus on rural livelihoods project: profile of Runde/Nuanetsi sub-catchments in Chiredzi district. Technical report, Harare, Zimbabwe.

Poilecot P, Gaidet N. 2011. A quantitative study of the grass and woody layers of a Mopane (*Colophospermum mopane*) savannah in the mid-Zambezi Valley, Zimbabwe. *African Journal of Ecology* 49: 150–164. https://doi.org/10.1111/j.1365-2028.2010.01241.x.

Popp A, Vogel M, Blaum N, Jeltsch F. 2009. Scaling up ecohydrological processes: Role of surface water flow in water-limited landscapes. *Journal of Geophysical Research* 114:

Richard Y, Martiny N, Rouault M, Philippon N, Tracol Y, Castel T. 2012. Multi-month memory effects on early summer vegetative activity in semi-arid South Africa and their spatial heterogeneity. *International Journal of Remote Sensing* 33: 6763–6782.

Richardson FD, Hahn BD, Schoeman SJ. 2000. Modelling nutrient utilization by livestock grazing semiarid rangeland. In: Mcnamara JP, France J, Beever DE (Eds), *Modelling Nutrient Utilization*. Oxon: CABI Publishing. pp 263–280. https://doi.org/10.1079/9780851994499.0263.

Richardson FD, Hoffman MT, Gillson L. 2010. Modelling the complex dynamics of vegetation, livestock and rainfall in a semiarid rangeland in South Africa. *African Journal of Range & Forage Science* 27: 125–142. https://doi.org/10.2989/10220119.2010.520676.

Rickert KG, Stuth JW, McKeon GM. 2000. Modelling pasture and animal production. In: Mannetje L't, Jones RM (Eds), *Field and Laboratory Methods for Grassland and Animal Production Research*. London: CABI Publishing. pp 29–66. https://doi.org/10.1079/9780851993515.0029.

Scanlon TM, Caylor KK, Manfreda S, Levin SA, Rodriguezituribe I. 2005. Dynamic response of grass cover to rainfall variability: implications for the function and persistence of savanna ecosystems. *Advances in Water Resources* 28: 291–302. https://doi.org/10.1016/j.advwatres.2004.10.014.

Schroedter-Homscheidt M, Arola A, Killius N, Lef M, Saboret L, Wandji W, Wald L, Wey E. 2016. The Copernicus Atmosphere Monitoring Service (CAMS) radiation service in a nutshell. In: *Proceedings of the 22nd SolarPACES Conference 2016.* Abu Dhabi, United Arab Emirates.

Snow VO, Rotz CA, Moore AD, Martin-Clouaire R, Johnson IR, Hutchings NJ, Eckard RJ. 2014. The challenges—and some solutions—to process-based modelling of grazed agricultural systems. *Environmental Modelling & Software* 62: 420–436. https://doi.org/10.1016/j.envsoft.2014.03.009.

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. *Grass and Forage Science* 73: 727–739. https://doi.org/10.1111/gfs.12367.

Taylor RD, Walker BH. 1978. Comparisons of vegetation use and herbivore biomass on a Rhodesian game and cattle ranch. *Journal of Applied Ecology* 15: 565–581. https://doi.org/10.2307/2402611.

Tedeschi LO. 2006. Assessment of the adequacy of mathematical models. *Agricultural Systems* 89: 225–247. https://doi.org/10.1016/j.agsy.2005.11.004.

Thornley JHM, Johnson IR. 2000 (Eds). *Plant and crop modelling: a mathematical approach to plant and crop physiology*. Caldwell: The Blackburn Press.

Trollope WSW, Potgieter ALF. 1986. Estimating grass fuel loads with a disc pasture meter in the Kruger National Park. *Journal of the Grassland Society of Southern Africa* 3: 148–152. https://doi.org/10.1080/02566702.1986.9648053.

Venter FJ, Scholes RJ, Eckhardt HC. 2003. The abiotic template and its associated vegetation pattern. In: Du Toit JT, Rogers KH, Biggs HC (Eds), *The Kruger experience: ecology and management of Savanna heterogeneity*. Washington, DC: Island Press. pp 83–129.

Walker BH, Ludwig D, Holling CS, Peterman RM. 1981. Stability of semi-arid savanna grazing systems. *Journal of Ecology* 69: 473–498. https://doi.org/10.2307/2259679.

Wallach D, Makowski D, Jones JW, Brun F (Eds). 2014. *Working with dynamic crop models: methods, tools, and examples for agriculture and environment*. 2nd edn. Waltham: Academic Press, Elsevier.

Wiegand T, Jeltsch F, Bauer S, Kellner K. 1998. Perspective article: Simulation models for semi-arid rangelands of southern Africa. *African Journal of Range & Forage Science* 15: 48–60. https://doi.org/10.1080/10220119.1998.9647940.

Zilverberg CJ, Williams J, Jones C, Harmoney K, Angerer J, Metz LJ, Fox W. 2017. Process-based simulation of prairie growth. *Ecological Modelling* 351: 24–35. https://doi.org/10.1016/j.ecolmodel.2017.02.004.