Simulating forage yields and soil organic carbon under *Brachiaria* hybrid cv. Cayman in Tanzania with the CROPGRO perennial forage model

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Abstract

Land and soil degradation in cropping systems in sub-Saharan Africa has been exacerbated by inappropriate use of landscapes and poor management practices that result into environmental and subsequential social damages. Biophysical models are key to inform management activities that can restore degraded soils and ultimately improve yields and soil organic carbon (SOC) sequestration. Numerous modelling studies have been conducted on annual cropping systems, however there are no modelling studies on perennial forages. The goal of this study was to (i) Adjust and evaluate the ability of DSSAT CROPGRO-Perennial Forage model version 4.7.5.0, which was initially parameterised for *Brachiaria* cv. Marandu in Brazil, to simulate biomass yields and SOC under *Brachiaria* cv. hybrid Cayman (BHC) in three districts in the southern highlands of Tanzania. The key adjusted parameters were soil water (lower limit, drained upper limit, saturated water content) and stable soil organic carbon. After model calibration, the root means square error ranged from 638 to 2111 kg/ha for harvested biomass. The d-Statistic for harvested biomass ranged from 0.78 to 0.97. The RMSE for % SOC ranged from 0.26 to 1.01 % and 0.23 to 1.55 % at 0-20 cm and 20-40 cm depth respectively. The d-Statistic for SOC from ranged 0.19 to 0.35 and 0.40 to 0.53 for 0-20 cm and 20-40 cm respectively. The results indicate that the model can be used to simulate the growth of *Brachiaria* cv. Cayman under different soils and weather conditions with an acceptable adjustment of specific parameters including soil water (lower limit, drained upper limit, saturated water content) and stable soil organic carbon. Also, the model simulated SOC reasonably well despite the wide variability between observed and simulated values, which was attributed to short period for experimentation and other factors not captured by the model including residue return among others. The adapted parameterised model for *Brachiaria* cv. Marandu performed reasonably well in simulating biomass and SOC in a different region with different soils, climate and management. Hence, the parameterised model for *Brachiaria* cv. Marandu can also be used for *Brachiaria* cv. Cayman in a different region with different soils and climate conditions.

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1. Introduction

Land and soil degradation in cropping systems is characterized by soil erosion, compaction, salinification, acidification, nutrient mining and decline in soil cover (Gomiero, 2016). This can be caused by intensive cultivation and unsustainable land management practices (Hossain et al., 2020; Mulinge et al., 2016). Globally, 33 percent of land is estimated to be affected by soil and land degradation (Lal, 2015). In sub-Saharan Africa, 67 percent of productive land is degraded (UNCCD, 2013; World Bank, 2010). United Nations Environment Programme (UNEP) estimates approximately 20 percent of cropland and 20 to 25 percent of rangeland to be degraded (ELD Initiative and UNEP, 2015). The total annual cost of land degradation in sub-Saharan Africa is estimated at US$65 billion which accounts for about 4% of the total gross domestic product (GDP) (Global Mechanism of the UNCCD, 2018). The severity of land and soil degradation has resulted in lower crop productivity, increased poverty levels and consequently negative impact on livelihoods (Bhattacharyya et al, 2015). The impact is more prevalent in sub-Saharan Africa where hunger, malnutrition due to depletion of nutrients in soils and loss of incomes are becoming more rampant (Lal, 2010; Manna et al., 2015; Tully, 2015).

However, studies have shown degraded land and soil can be restored using best management practices (Das et al., 2017; Lal, 2019; Montgomery, 2021). The best management practices include integrated nutrient management, conservation agriculture and continuous vegetative cover including perennial forage grasses (Lal, 2015). These studies focused on management of annual cropping systems, particularly in improving soil health and soil organic matter content and ultimately soil organic carbon (SOC) sequestration (Tully, 2015). Although these practices may not always result in SOC sequestration especially in high temperature (sub) humid climates (Nyawira et al., 2021; Sommer et al., 2018), they minimize SOC losses; hence contributing to climate change mitigation. Previous studies have focused on annual crops, with limited assessment of the potential of perennial crops in restoring degraded land. Perennial forage grasses have not yet estimated the potential to contribute to achieving the massive targets of restoration (Kitonga, 2019). Forages are plants that are eaten by livestock and they can be herbaceous or dual-purpose legumes, shrubs or grasses. Studies have been carried to assess the contribution of forage grasses in enhancing soil health and soil restoration with reports indicating increase in SOC by 10% and reducing soil loss by half (Chatterjee et al., 2018; Das et al., 2016; De Oliveira et al., 2004; Ferchaud et al., 2016; Horrocks et al., 2019; Molatudi et al., 2015; Paul et al., 2020; Rahetlah et al., 2012; Sundaram et al., 2012; Stewart et al., 2015;). However, the potential of forages grasses in land restoration in SSA remains unexploited (Kitonga, 2019).

Monitoring long-term impact with field experiments, however, is expensive, time consuming and difficult. Thus, models have proven to be an effective and flexible way to project the impact of management practices on soil health (Gupta and Kumar, 2017). Biophysical simulation models represent the interactions of weather, soil, and/or biological processes in agricultural production and /or environmental actions and they simulate the growth of crops (Kogan et al., 2013). According to Andrade et al. (2016), biophysical models have benefits compared to field trials since they can be used for wider region and can predict future conditions over a longer period. These models include DSSAT-CROPGRO, APSIM, ALMANAC (Andrade et al., 2016). Further, models provide understanding of crop growth and productivity under different soil, weather and management conditions (Santos et al., 2019).

The CROPGRO-Perennial Forage model (CFPM) is a module of DSSAT (Decision Support System for Agrotechnology Transfer), and it is a mechanistic model that was developed from the annual crop version of CROPGRO by Rymph (2004). CROPGRO-Perennial Forage model has been used to simulate growth and biomass of different forage grasses under different agronomic practices (Lara et al., 2012; Pequeno et al., 2017; Pequeno et al., 2014; Pedreira et al., 2011; Santos et al., 2019). However, there were no studies within sub-Saharan.

The goal of this study was to Adjust and evaluate the ability of DSSAT CROPGRO-Perennial Forage model version 4.7.5.0, which was initially parameterised for *Brachiaria* cv. Marandu in Brazil, to simulate biomass yields and SOC under *Brachiaria* cv. hybrid Cayman (BHC) in three districts in the southern highlands of Tanzania.

2. Materials and Methods

2.1 Experimental trial, soil and weather data

The data used in the model calibration and validation were collected in a field trial in the Southern Highlands of Tanzania in 3 districts. The trials were established in January/February 2018 in six wards of Kichiwa and Ikuna (Njombe district), Mtwango and Igowole (Mufindi district), Kiwira and Lufingo (Rungwe district) (Table 1). Each trial had 14 treatments; *Brachiaria* cv. hybrid Cayman, ii) *Brachiaria* cv. hybrid Cayman intercropped with *Desmodium intortum*, iii) *Brachiaria* cv. hybrid Cayman intercropped with *Stylosanthes guiyanensis*, iv) *Brachiaria* cv. hybrid Cobra, v) *Brachiaria* cv. hybrid Cobra intercropped with *Desmodium intortum*, vi) *Brachiaria* cv. hybrid Cobra intercropped with *Stylosanthes guiyanensis*, vii) *Pennisetum purpureum* cv. ILRI 16835 (Napier grass), viii) *Pennisetum purpureum* cv. ILRI 16835 intercropped with *Lablab purpureus*, ix) *Pennisetum purpureum* cv. Ouma, x) *Pennisetum purpureum* cv. Ouma intercropped with *Lablab purpureus*, xi) *Chloris gayana*, xii) *Chrloris gayana* intercropped with *Desmodium intortum*, xiii) *Chloris gayana* intercropped with *Stylosanthes guiyanensis*, and xiv) *Tripsacum andersonii* (Guatemala grass) as control with each replicated three times. However, in this study we will focus on *Brachiaria* hybrid cv. Cayman. Net plot size was 10 m^2 which was defined by leaving out the outer-most row on the four sides of the plot. During the time of establishment, both manure and industrial fertilizer Diammonium phosphate (DAP) was applied at the rate of 0.93 t/ha and 273 N kg/ha respectively. In January 2020, urea fertilizer was again applied at the rate of 113 N kg/ha. Manual weeding was done every time after harvesting to allow the forage regrowth smoothly.

Baseline soil data was collected in January/February 2018 which was during the time of establishment. Six composite samples were collected in each ward at the depth of 0-20 cm and 20-50 cm, 3 sample per depth and 6 samples per ward to define the baseline soil data. The samples were taken to the International Institute of Tropical Agriculture (IITA), Dar es Salaam laboratory and analyzed for SOC, soil texture, pH and phosphorus. Subsequent soil samplings in each replicate were done June/July 2019 and Sept/Oct 2020 for all the 14 treatments at two depths, 0-20 cm and 20-50 cm. The samples were analysed for only SOC. In addition, soil profile data for initializing the model was sampled in Jan/Feb 2021 at 0 to 100 cm depth with incremental depths of 20 cm in *Brachiaria* hybrid cv. Cayman and *Brachiaria* hybrid cv. Cobra. The samples were analysed for texture, SOC and bulk density (Table 1).

Biomass samples were collected since July 2018 with a total of ten harvests at an interval of 1 to 3 months depending on the height of the forages - above 30 cm. Before the first harvest, a cut was done in May 2018 to allow all the forages to have uniform conditions for regrowth. Harvesting schedule was as follows: first – July 2018, second – October 2018, third – Jan 2019, fourth – April 2019, fifth – August 2019, sixth – Nov 2019, seventh – Jan 2020, eighth – May 2020, ninth – Sept/ Oct 2020 and tenth harvest Jan – 2021. The forages were harvested at 5 cm height; thus the 5 cm was left on ground as stubble.

Table 1. Soil profile and location data.

Site	Long	Lat	Elev (m)	Depth (cm)	Bulk density (g/cm^3)	Soil organic carbon	Silt (%)	Clay
Igowole	35.32	-8.78	1958	0-20	1.34	2.05	3	38
				20-40	1.38	1.39	5	44
				40-60	1.42	1.19	3	42
				60-80	1.39	0.90	3	44
				80-100	1.35	0.80	3	48
Mtwango	35.58	-8.58	2035	0-20	0.93	4.65	14	39
				20-40	0.98	2.80	14	43
				40-60	1.04	1.74	16	45
				60-80	1.27	1.18	16	45
				80-100	1.52	0.95	14	45
Ikuna	34.94	-9.43	1825	0-20	1.17	2.02	5	50
				20-40	1.31	1.47	3	60
				40-60	1.15	1.27	3	64
				60-80	1.15	1.06	3	68
				80-100	1.22	0.98	3	70
Kichiwa	34.94	-9.39	1833	0-20	1.10	2.25	7	44
				20-40	1.23	1.74	9	46
				40-60	1.13	1.22	5	52
				60-80	1.10	0.94	5	52
				80-100	1.23	0.82	9	54
Kiwira	33.69	-9.15	1412	0-20	-	5.02	23	16
				20-40	-	4.95	23	14
				40-60	-	4.35	23	14
				60-80	-	3.40	25	12
				80-100	-	2.42	25	10
Lufingo	33.68	-9.24	1346	0-20	-	2.97	24	17
				20-40	-	2.74	16	21
				40-60	-	1.27	14	21
				60-80	-	1.58	14	23
				80-100	-	1.02	16	21

Weather data for the experimental period was obtained from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) at a resolution of 0.05 arc degrees and Global Land Data Assimilation System (GLDAS) at a resolution of 0.25 arc degrees (Figure 1). The satellite data was used after comparison with the real-ground measurements because the measured data had a lot of missing values.

Soil samples collected at the establishment of the trial (baseline) were used to initialize the soil organic carbon and texture. The soil profile data in Table 1 was used to estimate the volumetric water content (lower limit, upper limit and saturation) in the profile considering there were no real-ground measurements using the pedotransfer function in the Sbuild programme in the model (Table 3).

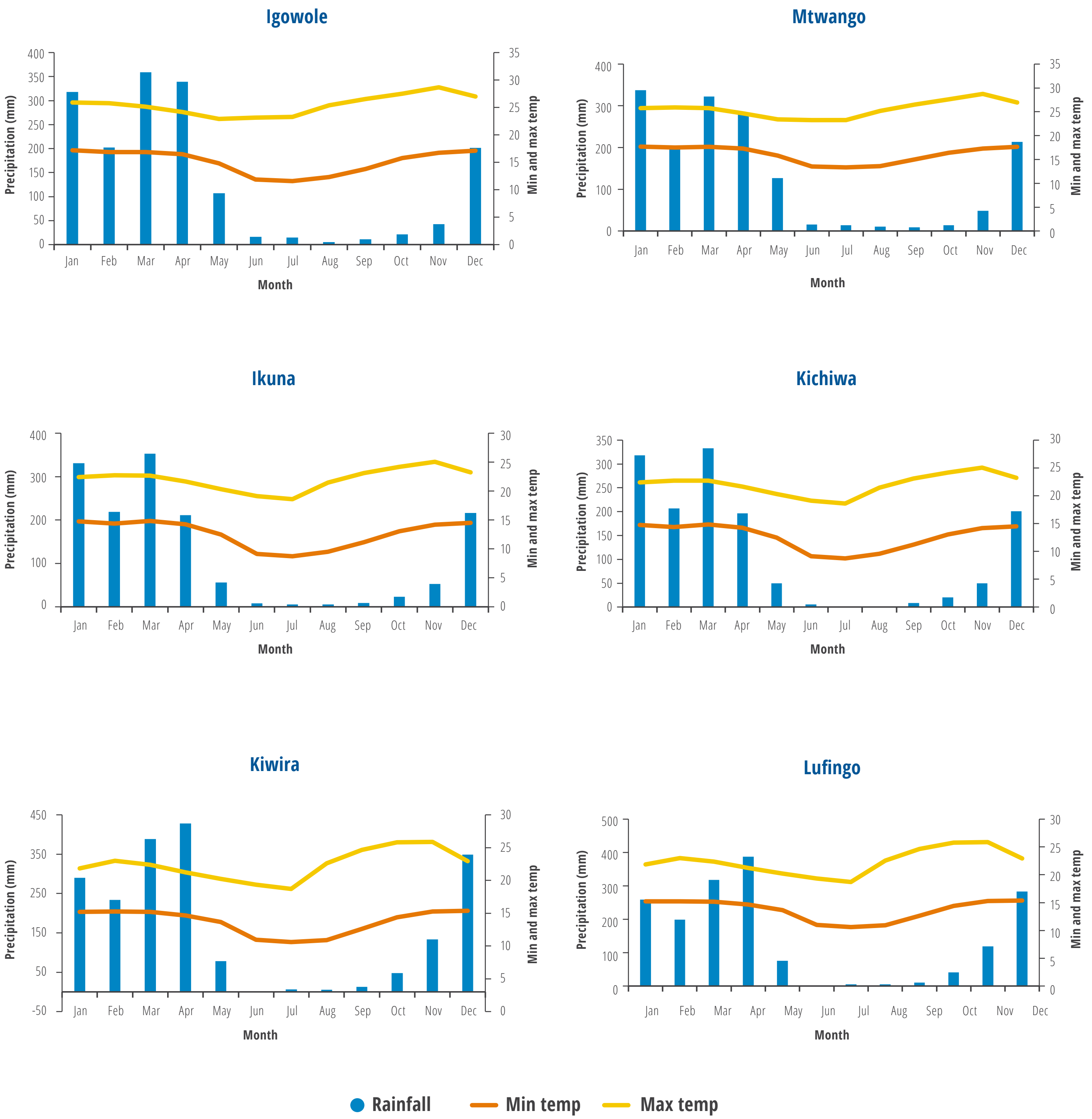

Figure 1. Mean monthly minimum and maximum temperature and monthly sum rainfall from Jan 2018 to Feb 2021. The weather date is an average over the entire period.

2.2 DSSAT CROPGRO Perennial Forage Model

2.2.1 CROPGRO-Perennial Forage model description

The DSSAT CROPGRO-Perennial Forage Model (CROPGRO-PFM) is a process-based model of forage growth and development and is part of DSSAT model. It simulates general biological processes such as photosynthesis and N uptake using parameters unique to each species in order to predict crop growth under a variety of conditions. CROPGRO originated with the development of three separate models: SOYGRO, designed to simulate the growth and development of soybean (*Glycine max* L.), PNUTGRO, designed to simulate the growth and development of peanut (*Arachis hypogaea* L.), and BEANGRO, designed to simulate the growth and development of dry bean (*Phaseolus vulgaris* L.). Because these three models simulated basic physiological processes in much the same way, the main code from each was consolidated to form CROPGRO and the parameters describing traits specific to species and cultivar were moved to parameter files (Boote et al., 1998a, 1998b). Separation of parameter files from the main code makes CROPGRO a versatile model adaptable to new varieties and species upon estimating values for these parameters. Because of this flexibility, CROPGRO has been used to simulate additional annual crops, such as faba bean (*Vicia faba* L.) and tomato (*Lycopersicon esculentum* Mill.) (Scholberg et al., 1997; Boote et al., 2002). These modules have been combined with other modules for crop, weather, and soil processes to form the Cropping Systems Model (CSM) (Jones et al., 27 2003). Rymph (2004) rewrote part of the CROPGRO model code to create the CROPGRO-PFM in order to better simulate the growth of tropical perennial grasses such as Bahia grass. The new code includes a module that simulates rhizome and stolon growth, a module that simulates dormancy, and a change in the module governing plant response to freeze events that allows for progressive freeze damage. In addition, species and cultivar parameters affecting photosynthesis, partitioning of dry matter (DM), carbon (C) and nitrogen (N) remobilization, growth, senescence, and plant phenology were adjusted to reflect Bahia grass growth and development based on literature values and parameter optimization (Rymph et al., 2004). The more important calibrations of these perennial grass growth processes were later based on data from Bracharia and Cynodon (Lara et al., 2012; Pequeno et al., 2017; Pequeno et al., 2014; Pedreira et al., 2011; Santos et al., 2019). CROPGRO-PFM simulates productivity of forages in response to soil, weather and management. It simulates general biological processes such as photosynthesis and nitrogen (N) uptake using parameters unique to each species and cultivar in order to predict crop growth and development under a variety of conditions.

CROPGRO-Perennial Forage model has been widely used and proven effective to simulated growth for different forage species including *Paspalum notatum* (Bahiagrass) in USA and *Brachiaria brizantha* cv. Marandu, *Urochloa brizantha* (Palisade grass), *Cynodon dactylon* (Bermuda grass), *Brachiaria brizantha* (Piatã palisade grass), *Megathyrsus maximus* (Guinea grass), in Brazil (Bosi et al., 2020; Lara et al., 2012; Santos et al., 2019; Pequeno et al., 2014; Pedreira et al., 2011; Rymph 2004). These studies reported good performance of the model to simulate composition and growth, productivity and soil moisture of the above forage species.

The data required to run CROPGRO-PFM include soil (clay and silt percentage, organic carbon, bulk density and pH), weather (solar radiation, maximum and minimum temperature and rainfall) and crop management.

2.2.2 Model calibration and evaluation

The CROPGRO-Perennial Forage model version 4.7.5.0 developed for *Brachiaria brizantha* cv. Marandu (Pequeno et al. 2011) was adapted for our study considering the two species are similar in terms of genetics, cultivar and ecotype. The experimental data used in the simulation, including location, soil initial conditions (SOC and stable carbon pool), crop establishment, fertilizer input, planting and harvest dates were described and entered into an experimental "management" file called "File X". The stable soil organic carbon (SASC) which is based on the Century module was estimated from varying percentage of 50 to 90 % SOC. The biomass harvested and SOC were described in "File T". The amount of stubble mass (non-harvested biomass), leaf fraction (RSPLF) and harvest height were defined in "MOW file". Since there was no field measurement of the stubble mass, values were varied at the range of 1000 kg/ ha, 1200 kg/ha, 1400 kg/ha and 1600 kg/ha to estimate the amount of stubble mass remaining in the field. The final value used was 1200 kg/ha. Sensitivity analysis was done to evaluate biomass production in relation to the amount of forage left on the field as stubble. Soil lower limit, upper limit and saturated upper limit, stable carbon and MOW values were parameters that were modified and final values are indicated in Table 2. The soil water holding traits were modified because they are critical in biomass growth and uptake of nutrients. Crop biomass and harvested biomass (herbage mass) were the targets, while modifying soil water holding and soil C (SASC) parameters. In fact, we discovered that there was no need to modify any of the species, ecotype, or cultivar parameters, because most of the variability was addressed by setting up correct soil water and N supply. The model-evaluation process was based on analysis of the agreement between observed and simulated mean values total biomass (tops weight) and herbage and SOC. The calibration process occurred by adjusting specific parameters, in which parameter values of the stable soil C pool, SOM3, lower limit and drained upper limit were modified and simulations were compared against observed values.

Table 2. Soil profile and stubble mass remaining in the field (MOW) after harvests for all the sites used to initialize the model, where "O" are initial parameter inputs, and "C" are inputs chosen to give best fit based on model sensitivity analysis.

Site	Depth (cm)	LL O (v/v)	LL C	DUL O	DUL C	Sat O	Sat C	BD O (g/cm^3)	MOW O (kg/ha)	MOW C
Igowole	20	0.36	0.22	0.37	0.37	0.46	0.44	1.34	2000	1200
	40	0.37	0.17	0.38	0.38	0.44	0.44	1.38		
	60	0.3	0.25	0.33	0.37	0.44	0.41	1.42		
	80	0.26	0.26	0.34	0.37	0.45	0.41	1.39		
	100	0.28	0.20	0.35	0.35	0.47	0.43	1.35		
	120	0.28	0.20	0.35	0.35	0.47	0.43	1.35		
	140	0.28	0.20	0.35	0.35	0.47	0.43	1.35		
	160	0.28	0.20	0.35	0.35	0.47	0.43	1.35		
Mtwango	20	0.31	0.21	0.47	0.47	0.60	0.60	0.93	2000	1200
	40	0.29	0.19	0.42	0.42	0.59	0.59	0.98		
	60	0.27	0.17	0.36	0.36	0.57	0.57	1.04		
	80	0.26	0.16	0.35	0.35	0.49	0.49	1.27		
	100	0.26	0.26	0.35	0.35	0.49	0.49	1.27		
	120	0.26	0.26	0.35	0.35	0.49	0.49	1.27		
	140	0.26	0.26	0.35	0.35	0.49	0.49	1.27		
	160	0.26	0.26	0.35	0.35	0.49	0.49	1.27		
Kichiwa	20	0.31	0.22	0.45	0.43	0.54	0.53	1.10	2000	1200
	40	0.30	0.20	0.42	0.41	0.50	0.49	1.23		
	60	0.30	0.15	0.38	0.31	0.54	0.46	1.13		
	80	0.32	0.11	0.40	0.34	0.55	0.48	1.10		
	100	0.31	0.09	0.40	0.36	0.51	0.47	1.23		
	120	0.311	0.09	0.40	0.36	0.51	0.47	1.23		
	140	0.31	0.09	0.40	0.36	0.51	0.47	1.23		
	160	0.31	0.09	0.40	0.36	0.51	0.47	1.23		
Ikuna	20	0.35	0.39	0.48	0.48	0.52	0.48	1.17	2000	1200
	40	0.36	0.40	0.47	0.47	0.47	0.48	1.31		
	60	0.36	0.28	0.46	0.46	0.53	0.46	1.15		
	80	0.37	0.29	0.46	0.46	0.54	0.47	1.15		
	100	0.37	0.29	0.46	0.46	0.51	0.47	1.22		
	120	0.37	0.29	0.46	0.46	0.51	0.47	1.22		
	140	0.37	0.29	0.46	0.46	0.51	0.47	1.22		
	160	0.37	0.29	0.46	0.46	0.51	0.47	1.22		
Lufingo	20	0.22	0.25	0.42	0.43	0.54	0.57	1.07	2000	1200
	40	0.19	0.19	0.34	0.36	0.50	0.49	1.21		
	60	0.15	0.15	0.24	0.31	0.41	0.46	1.48		
	80	0.13	0.11	0.21	0.34	0.39	0.48	1.56		
	100	0.13	0.09	0.21	0.36	0.39	0.47	1.57		
	120	0.13	0.09	0.21	0.36	0.38	0.47	1.57		
	140	0.13	0.09	0.21	0.36	0.38	0.47	1.57		
	160	0.13	0.09	0.21	0.36	0.38	0.47	1.57		
Kiwira	20	0.25	0.15	0.44	0.34	0.47	0.57	1.08	2000	1200
	40	0.19	0.19	0.36	0.36	0.39	0.49	1.23		
	60	0.15	0.15	0.31	0.31	0.36	0.46	1.33		
	80	0.09	0.11	0.34	0.34	0.38	0.48	1.45		
	100	0.08	0.09	0.26	0.36	0.33	0.47	1.44		
	120	0.08	0.09	0.26	0.36	0.37	0.47	1.44		
	140	0.08	0.09	0.26	0.36	0.37	0.47	1.44		
	160	0.08	0.09	0.26	0.36	0.37	0.47	1.44		

C= calibrated, O=original, LL=lower limit, DUL= drained upper limit, Sat=saturated upper limit, BD=bulk density, MOW =stubble mass, SASC=stable soil carbon

2.3 Data analysis

The r-Square, root-mean-square error (RMSE) and the Willmott agreement index (d-statistic) (Willmott 1985) were used to assess how well the model simulated the observed data. The equation for RMSE is:

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)2} \qquad \text{Equation 1}$$

where N is the total number of data points for comparison, Y_i is a given observed value, and $\hat{Y}_i$ is the corresponding value predicted by the model. A better model prediction will produce a smaller RMSE. The equation for Willmott agreement index (d-statistic) is:

$$\frac{\sum_{i=1}^{N}(Y_i - \hat{Y}_i)2}{\sum_{i=1}^{N}(\hat{Y}_i - \bar{Y}_i)|+|Y_i - \bar{Y}_i)\ 2} \qquad \text{Equation 2}$$

where N is the number of observed data points, Y_i is a given observed value, $\hat{Y}_i$ is the corresponding value predicted by the model, and Y_i is the mean of the observed data. D-statistic values range from 0 to 1 with values near 1 indicating good model predictions.


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3 Results

3.1 Biomass plots

The CROPGRO-Perennial Forage model parameterised by Pequeno et al. (2011) for *Brachiaria* cv. Marandu simulated the harvested biomass of *Brachiaria* cv. Cayman reasonably well with a RMSE of 1466, 638, 751, 2104, 1367 and 1597 kg/ha for Igowole, Mtwango, Ikuna, Kichiwa, Kiwira and Lufingo respectively. The d-Stat. was 0.89, 0.88, 0.97, 0.85, 0.78, 0.86 for Igowole, Mtwango, Ikuna, Kichiwa, Kiwira and Lufingo respectively which shows, the model performed better in Ikuna and Mtwango compared with other sites with a lower RMSE values and higher d-Stat. close to 1. Lufingo had the highest simulated mean of 3597 kg/ha in terms of harvested biomass which was consistent with the observed mean of 3478 kg/ha, showing good performance of the model. Mtwango had the lowest observed mean of 1328 kg/ha in terms of harvested biomass with a simulated mean of 1596 kg/ha, showing good prediction by the model although there was overestimation. Even though the total biomass was estimated by summing the total harvested above ground biomass (herbage) to the stubble biomass, which was not a real-ground measurement, the model still performed reasonably well in simulating the total biomass with RMSE values ranging from 643 to 2111 kg/ ha and d-Stat. ranging from 0.73 to 0.97 (Table 3).

The CROPGRO-Perennial Forage model also showed adequate performance in the harvested biomass as shown in the scatter plot (Figure 2) with high r-square values ranging from 0.53 to 0.90. The model performed better in Ikuna compared to other sites as represented by the high r-Square which was close to 1 thus high correlation between the observed and simulated values. There was variability between the simulated and observed harvested biomass as denoted by the standard deviation bars (Figure 3). The high variability was attributed to lower harvested biomass simulation due to water and nitrogen stress.

Table 3. Means and statistics for harvested herbage mass, total biomass, and SOC% for all the sites for the period 2018 to 2021. The total biomass is actually an estimated value and not really "observed" which was estimated by summing the total harvested above ground biomass (herbage) to the stubble biomass.

Site	Variable	Observed	Simulated	RMSE	Ratio (obs./sim.)	Willmott's d	r-square
Igowole	Harvested biomass (kg/ha)	3252±2341	3061±2374	1466	1.172	0.893	0.656
	Total biomass (kg/ha)	4452±2341	4452±2148	1296	1.054	0.914	0.711
	SOC (%) 0-20 cm	2.405±0.145	1.649±0.001	0.77	0.688	0.27	0.841
	SOC (%) 20-50 cm	1.39±0.17	1.518±0.019	0.228	1.111	0.416	1
Mtwango	Harvested biomass (kg/ha)	1328±945	1596±926	638	1.311	0.877	0.654
	Total biomass (kg/ha)	2528±945	2755±958	643	1.109	0.877	0.641
Ikuna	Harvested biomass (kg/ha)	2145±2320	2309±2119	751	1.544	0.971	0.901
	Total biomass (kg/ha)	3345±2320	3439±2153	767	1.072	0.97	0.893
	SOC (%) 0-20 cm	2.02±0.03	2.28±0.002	0.258	1.13	0.19	1.052
	SOC (%) 20-40 cm	1.23±0.145	1.49±0.018	0.31	1.23	0.43	1
Kichiwa	Harvested biomass (kg/ha)	3329±3467	3278±2045	2104	1.398	0.845	0.689
	Total biomass (kg/ha)	4529±3467	4432±2023	2111	1.158	0.843	0.691
Kiwira	Harvested biomass (kg/ha)	3375±1948	3250±1173	1367	1.312	0.781	0.527
	Total biomass (kg/ha)	3996±1866	4115±1172	1464	1.171	0.734	0.389
	SOC (%) 0-20 cm	4.69±0.14	4.193±0.02	0.512	0.894	0.353	1.002
	SOC (%) 20-50 cm	3.96±0.53	2.492±0.023	1.553	0.641	0.395	0.999
Lufingo	Harvested biomass (kg/ha)	3478±2638	3597±1843	1597	1.219	0.863	0.646
	Total biomass (kg/ha)	4678±2638	4750±1833	1610	1.114	0.859	0.639
	SOC (%) 0-20 cm	5.29±0.19	4.29±0.023	1.01	0.81	0.275	1.002
	SOC (%) 20-50 cm	3.49±0.505	2.92±0.034	0.74	0.85	0.527	1

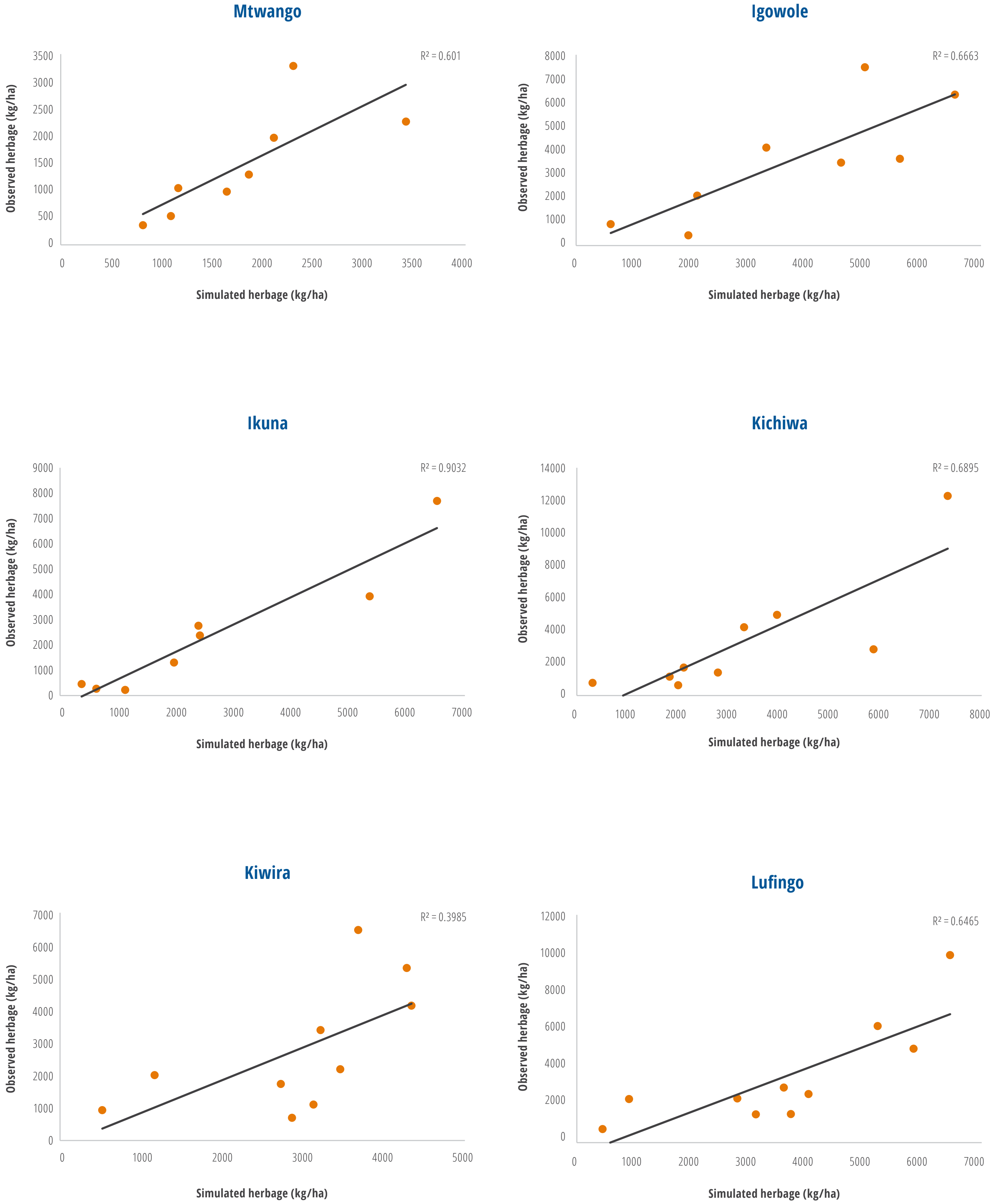

Figure 2. Observed versus simulated harvested biomass (kg/ha).

Figure 3. Harvested biomass for all the sites. Mtwango, Igowole and Ikuna had eight harvests, Kichiwa had nine harvests and Kiwira and Lufingo had ten harvests. The variability in total number of harvests was due to drought in which some sites did not have regrowth of biomass.

3.2 Effects of water and nitrogen stress on simulated biomass

In some cases, the model simulated lower harvested biomass and may have simulated no biomass at all while in other cases, the model simulated harvested biomass reasonably well. To understand better the cause of the above behaviour, additional simulation was conducted and the analysis showed these results was due to water and nitrogen stress (Figure 4, Figure 5). The reduction of biomass occurs matches with the occurrence of water stress, and the model does mimic that relatively well. The stress is represented by index with 0 indicating no stress and 1 indicating maximum stress. In some sites for example Ikuna and Mtwango, water stress was more evident compared to water stress in contributing to lower simulation of biomass by the model. In Igowole, Kichiwa, Kiwira and Lufingo, reduced simulation of biomass was contributed by both water and nitrogen stress. However, both water and nitrogen stress contribute to reduced growth in one way or another by influencing growth and availability of nutrients.

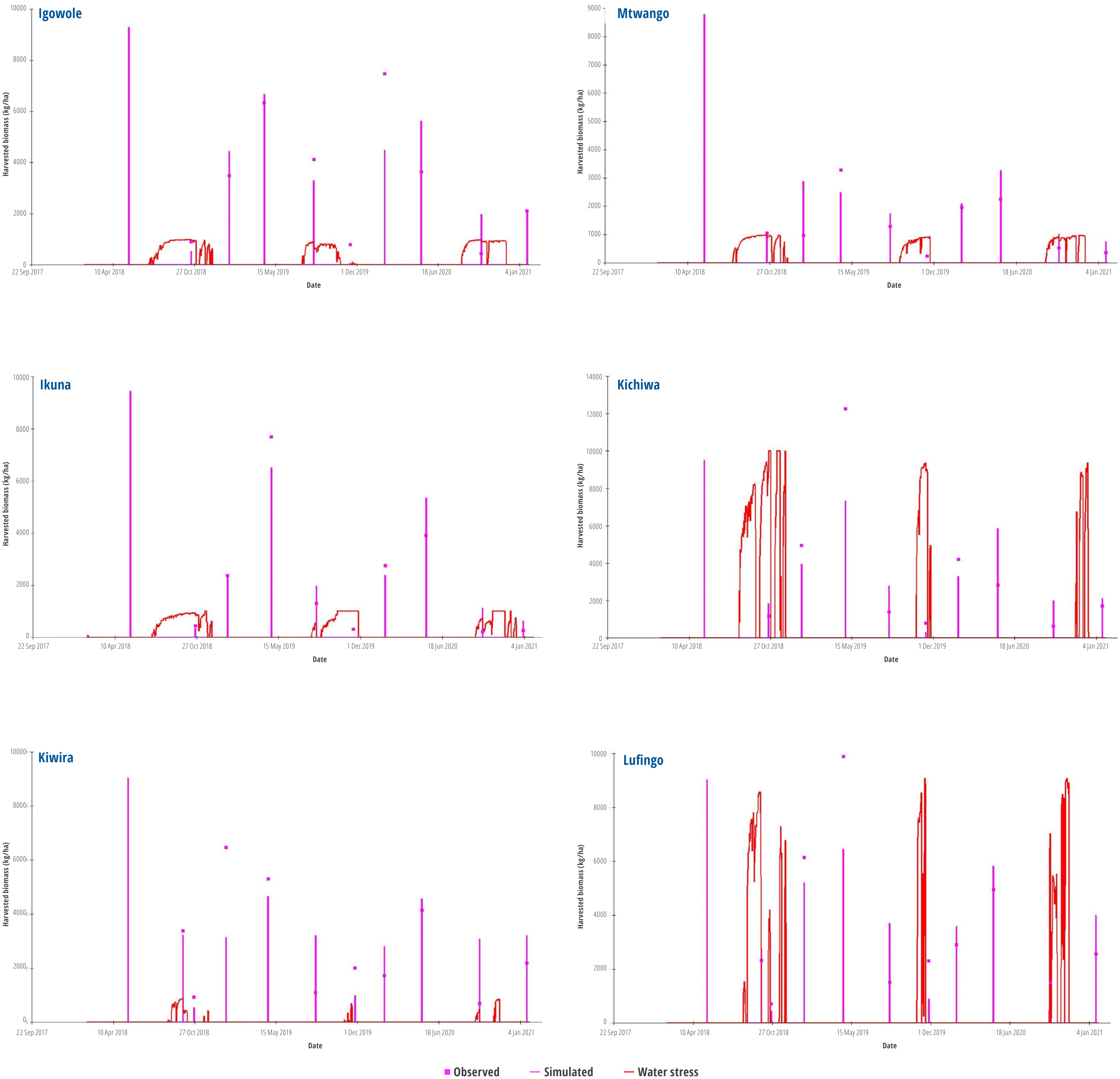

Figure 4. Effect of water stress on harvested biomass for all the sites (Note: Water stress ranges from 0 to 1 and was multiplied by 1000).

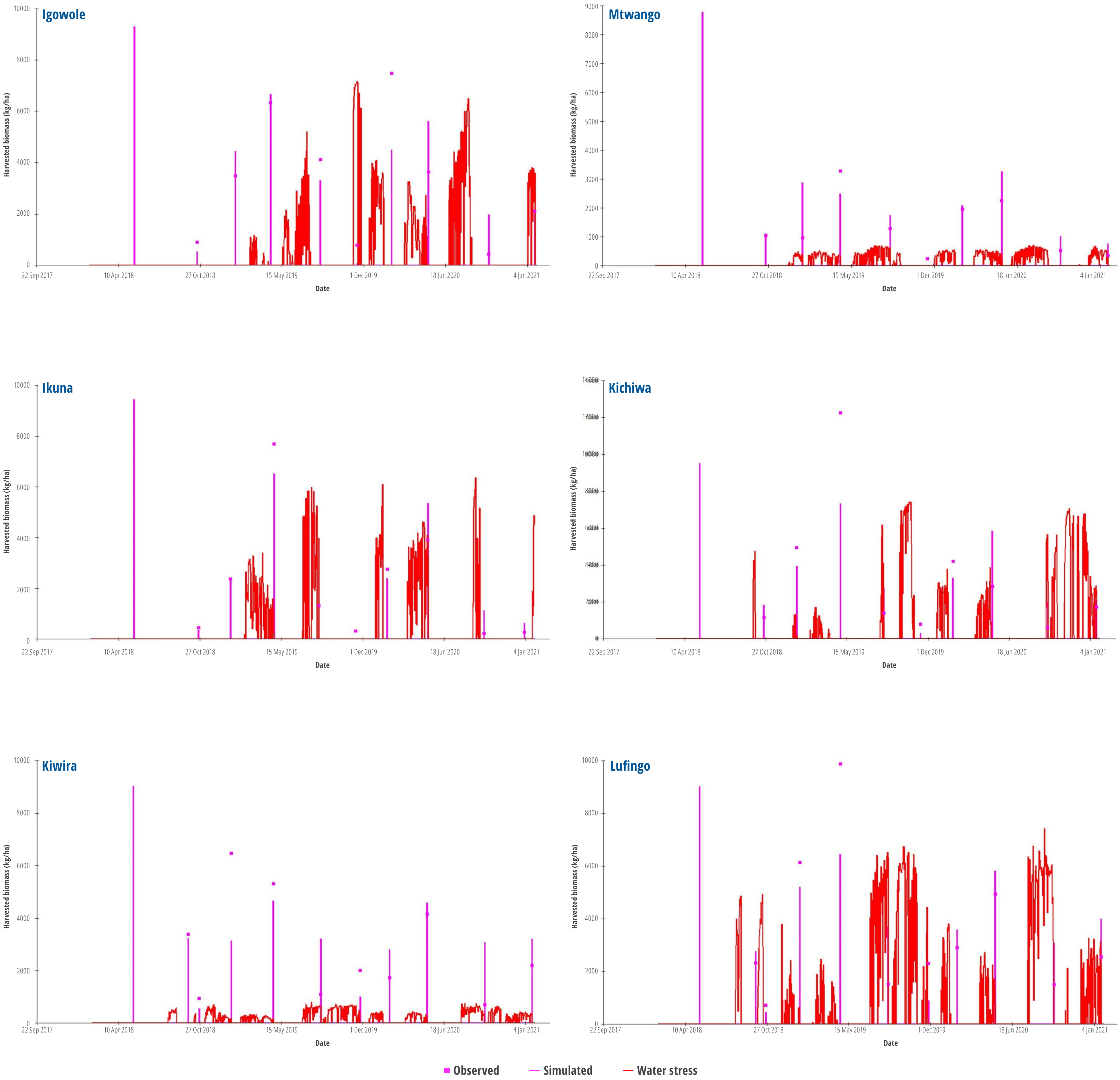

Figure 5. Effect of nitrogen stress on harvested biomass for all the sites (Note: Nitrogen stress ranges from 0 to 1 and was multiplied by 1000).

3.3 Soil organic carbon

The performance of CROPGRO Perennial Forage model in simulating SOC was somewhat well with a RMSE value ranging from 0.26 to 1.01 and 0.23 to 1.55 for 0-20 cm and 20-40 cm depth respectively. The d-Statistic ranged from 0.19 to 0.35% and 0.40 to 0.53 % for 0-20 cm and 20-40 cm depth respectively (Table 3). The model simulated nearly constant values from the initial period for all the sites (Figure 6). The observed SOC initial values for 0-20 cm depth for the sites were 1.63, 2.28, 4.23 and 4.41% for Igowole, Ikuna, Kiwira and Lufingo respectively. The observed SOC initial for 20-50 cm were; 1.61, 1.57, 2.57 and 1.09% for Igowole, Ikuna, Kiwira and Lufingo respectively. At 0-20 cm depth the SOC values were above for threshold value of 2% for all the sites except for Igowole thus considered sufficient for sustaining soil health and quality below which decline may occur. At 20-50 cm depth, SOC values were below the threshold value except for Kiwira and this is expected due to no residue incorporation to lower depths.

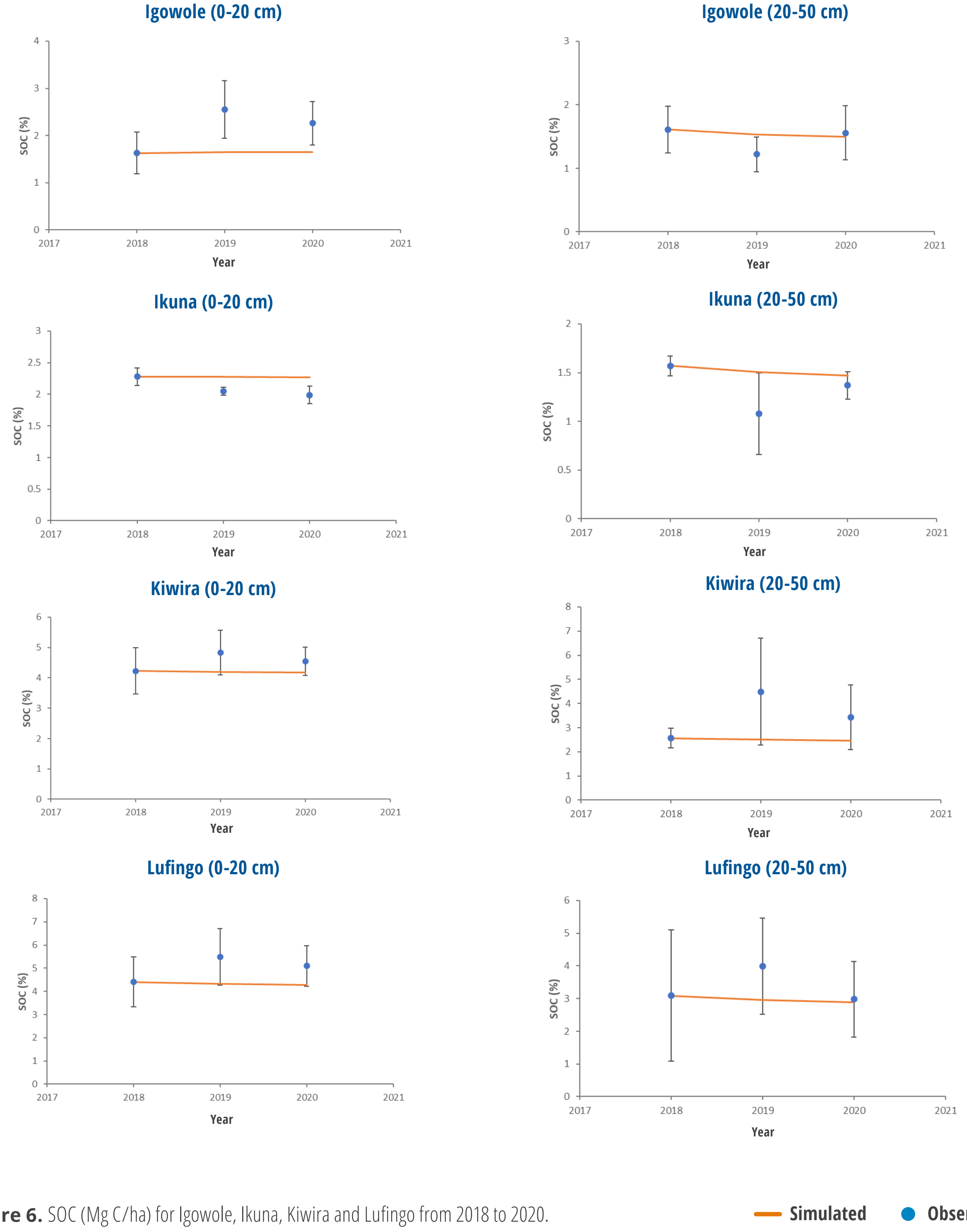

Figure 6. SOC (Mg C/ha) for Igowole, Ikuna, Kiwira and Lufingo from 2018 to 2020.


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4. Discussion

The model simulated the harvested biomass (herbage) reasonably well for all the sites especially for Ikuna, Mtwango and Lufingo. The model correctly reproduced the reduction in observed biomass that was attributed to water and nitrogen stress. Water and nitrogen deficit limits plant growth since they are critical factors determining nutrient availability and photosynthesis. According to Pequeno et al. (2014); Pedreira et al. (2011); Pequeno et al. (2018) and Santos et al. (2019) reduced biomass growth was attributed to nitrogen stress. A study by Santos et al. (2019) showed nitrogen stress lowers photosynthesis rate and ultimately the regrowth after harvest. Further, water stress reduces the uptake of nitrogen by the roots thus low productivity. Water stress also slows the decomposition rate thus reducing the amount of nitrogen mineralised and available for uptake. Water stress was more experienced in the seasons where there was low rainfall while nitrogen stress resulted due to inadequate additions from inputs since nitrogen was applied only twice during establishments and two years after establishment. establishment and two years after Nitrogen stress is caused by low additions of inputs.

The model performance in simulating SOC was reasonably good, however simulated SOC values were almost constant over the simulated period. This is attributed to shorter period of simulation since the model was run for only 3 years and for best observations of observed changes in SOC, there need to be more years of accurate data to document the time course of SOC, and the simulation needs to run for at least 10 years. Further, lack of significant changes in simulated SOC was attributed to no residue return and carbon from the root residues. In addition, significant SOC build-up takes long periods whereas the study had short time frame and the observed SOC measurements showed high variability. Further, the model simulates shift to root under water and nitrogen deficit. The model simulated the biomass and SOC reasonably well; however, data uncertainty affects our statements concerning validity of the model performance.

The model performance was greatly affected by data uncertainty, especially with respect rainfall, temperature and solar radiation. Since available real ground measurement of climate data was limiting, downloaded data from satellite was used and this hinders our interpretation of model performance since the data is not entirely accurate compared to the observed data. Small differences in elevation (altitude) between sites are not accurately captured in the satellite data. Rainfall affects sensitivity of the model to water stress. Solar radiation affects the growth of biomass as high solar radiation increases biomass production while lower solar radiation reduces productivity. According to Lara et al. (2012), increasing or reducing solar radiation influences production of biomass with reported increase or decrease of more than 100 kg/ha of biomass. Also reduced rainfall promotes water stress thus rainfall and solar radiation are critical parameters in influencing growth of forages and the model is very sensitive to these parameters. Hence obtaining climate data of good quality is necessary for good simulation of biomass accumulation by the model.

Slow recovery after water stress periods was caused when there was decreased root mass along with very low levels the carbohydrate and nitrogen reserves in storage. This caused the system to recover slowly after that due to water stress and did not hit the subsequent high point values as expected due to damage and reduced leaf area, which drives growth and biomass accumulation. Senescence particularly of the roots causes delay in regrowth as it negatively affects following water and N uptake after stress, thus causing reduced simulation of biomass by the model (Pedreira et al., 2014).

5. Conclusion

The CROPGRO-Perennial Forage model as parameterised by Pequeno et al. (2011) for Marandu demonstrated adequate abilities to simulate biomass and SOC in southern highlands of Tanzania. To evaluate/calibrate the model, soil moisture content (upper limit, lower limit, saturated upper limit), SASC and MOW (stubble mass) values were adjusted. The model performed quite well after modification of the above soil water and N supply parameters and management inputs (MOW). However, the model performance was limited by data uncertainty, root senescence and water and nitrogen stress. With good quality measured data, the model can be adapted to simulate biomass and SOC under varying soil, climate and management conditions.

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6. References

Andrade, A. S., Santos, P. M., Pezzopane, J. R. M., de Araujo, L. C., Pedreira, B. C., Pedreira, C. G. S., Marin, F. R., Lara, M. A. S. (2016). Simulating tropical forage growth and biomass accumulation: An overview of model development and application. *Grass and Forage Science, 71*(1), 54–65.

Bhattacharyya, R., Ghosh, B. N., Mishra, P. K., Mandal, B., Rao, C. S., Sarkar, D., ... & Franzluebbers, A. J. (2015). Soil degradation in India: Challenges and potential solutions. *Sustainability, 7*(4), 3528-3570.

Chatterjee, A., Long, D. S., Pierce, F. J. (2018). Change in Soil Organic Carbon after Five Years of Continuous Winter Wheat or Switchgrass. *Soil Biology & Biochemistry Change*, 82(2), 332–342.

Das, A., Patel, D. P., Lal, R., Kumar, M., G.I., R., Layek, J., Buragohain, J., Ngachan, S. V., Ghosh, P. K., Choudhury, B. U., Mohapatra, K. P., Shivakumar, B. G. (2016). Impact of fodder grasses and organic amendments on productivity and soil and crop quality in a subtropical region of eastern Himalayas, India. *Agriculture, Ecosystems and Environment, 216,* 274–282.

Das, A., Mohapatra, K. P., & Ngachan, S. V. (2017). Conservation Agriculture for restoration of degraded land and advancing food security. *Conservation Agriculture for Advancing Food Security in Changing Climate, 1,* 1-35.

De Oliveira, O. C., De Oliveira, I. P., Alves, B. J. R., Urquiaga, S., Boddey, R. M. (2004). Chemical and biological indicators of decline/degradation of *Brachiaria* pastures in the Brazilian Cerrado. *Agriculture, Ecosystems and Environment, 103*(2), 289–300.

ELD Initiative and UNEP. (2015). The Economics of Land Degradation in Africa. Benefits of Action Outweigh the Costs. www.eld-initiative.org

Ferchaud, F., Vitte, G., Mary, B. (2016). Changes in soil carbon stocks under perennial and annual bioenergy crops. GCB *Bioenergy, 8*(2), 290–306.

Global Mechanism of the UNCCD. (2018). Country Profile of Zimbabwe. Investing in Land Degradation Neutrality: Making the Case. An Overview of Indicators and Assessments. Bonn, Germany.

Gomiero, T. (2016). Soil degradation, land scarcity and food security: Reviewing a complex challenge. *Sustainability, 8*(3), 281.

Horrocks, C. A., Arango, J., Arevalo, A., Nuñez, J., Cardoso, J. A., Dungait, J. A. J. (2019). Smart forage selection could significantly improve soil health in the tropics. *Science of the Total Environment, 688,* 609–621.

Hossain, A., Krupnik, T. J., Timsina, J., Mahboob, M. G., Chaki, A. K., Farooq, M., ... & Hasanuzzaman, M. (2020). Agricultural land degradation: processes and problems undermining future food security. In *Environment, Climate, Plant and Vegetation Growth* (pp. 17-61). Springer, Cham.

Kitonga, K. (2019). The role of forage genetic diversity in stimulating Africa's agricultural transformation. *6th African Conference of Agricultural Economists.*

Kogan, F., Kussul, N., Adamenko, T., Skakun, S., Kravchenko, O., Kryvobok, O., ... & Lavrenyuk, A. (2013). Winter wheat yield forecasting in Ukraine based on Earth observation, meteorological data and biophysical models. *International Journal of Applied Earth Observation and Geoinformation, 23,* 192-203.

Lal, R. (2010). Managing soils for a warming earth in a food-insecure and energy-starved world. *Journal of Plant Nutrition and Soil Science, 173*(1), 4-15.

Lal, R. (2015). Climate Change and Soil Degradation Mitigation by Sustainable Management of Soils and Other Natural Resources. *Agricultural Research, 1*(3), 199–212.

Lal, R. (2019). Promoting "4 Per Thousand" and "Adapting African Agriculture" by south-south cooperation: Conservation agriculture and sustainable intensification. *Soil and Tillage Research, 188,* 27-34.

Lara, M. A. S., Pedreira, C. G. S., Boote, K. J., Pedreira, B. C., Moreno, L. S. B., Alderman, P. D. (2012). Predicting growth of Panicum maximum: An adaptation of the CROPGRO-Perennial Forage model. *Agronomy Journal, 104*(3), 600–611.

Manna, M. C., Ghosh, P. K., & Acharya, C. L. (2003). Sustainable crop production through management of soil organic carbon in semiarid and tropical India. *Journal of Sustainable Agriculture, 21*(3), 85-114.

Molatudi, R. L., Steinberger, Y., Meng, F. Y., & Xie, G. H. (2015). Effect of switchgrass plantation on soil moisture and nitrogen availability and microbial biomass carbon in a semi-arid ecosystem. *Int. J. Agron. Agric. Res., 7*(2), 130-141.

Montgomery, D. R. (2021). Soil health and the revolutionary potential of Conservation Agriculture. In *Rethinking Food and Agriculture* (pp. 219-229). Woodhead Publishing.

Mulinge, W., Gicheru, P., Murithi, F., Maingi, P., Kihiu, E., Kirui, O. K., & Mirzabaev, A. (2016). Economics of land degradation and improvement in Kenya. In *Economics of land degradation and improvement–A global assessment for sustainable development* (pp. 471-498). Springer, Cham.

Nyawira, S. S., Hartman, M. D., Nguyen, T. H., Margenot, A. J., Kihara, J., Paul, B. K., ... & Sommer, R. (2021). Simulating soil organic carbon in maize-based systems under improved agronomic management in Western Kenya. *Soil and Tillage Research, 211*, 105000.

Paul, B.K., Koge, J., Maass, B.L. *et al*. Tropical forage technologies can deliver multiple benefits in Sub-Saharan Africa. A meta-analysis. *Agron. Sustain. Dev.* 40, 22 (2020). https://doi.org/10.1007/s13593-020-00626-3

Pedreira, B. C., Pedreira, C. G. S., Boote, K. J., Lara, M. A. S., Alderman, P. D. (2011). Adapting the CROPGRO perennial forage model to predict growth of *Brachiaria brizantha*. *Field Crops Research, 120*(3), 370–379.

Pequeno, D. N. L., Pedreira, C. G. S., Boote, K. J. (2014). Simulating forage production of Marandu palisade grass (*Brachiaria* brizantha) with the CROPGRO-Perennial Forage model. *Crop and Pasture Science, 65*(12), 1335– 1348.

Pequeno, D. N. L., Pedreira, C. G. S., Boote, K. J., Alderman, P. D., & Faria, A. F. G. (2018). Species-genotypic parameters of the CROPGRO Perennial Forage Model: Implications for comparison of three tropical pasture grasses. *Grass and Forage Science, 73*(2), 440-455.

Rahetlah, V. B., Randrianaivoarivony, J. M., Andrianarisoa, B., Razafimpamoa, L. H., Ramalanjaona, V. L. (2012). Yield and quality of *Brachiaria* Sp.cv Mulato-forage perennial peanut (Arachis pintoi) mixture in the Highlands of Madagascar. *Livestock Research for Rural Development, 24*(10), 6–11.

Rymph, S. J. (2004). *Modeling growth and composition of perennial tropical forage grasses.* University of Florida.

Santos, M. G., Boote, K. J., Faria, R. T., & Hoogenboom, G. (2019). Simulation of productivity and soil moisture under Marandu palisade grass using the CSM-CROPGRO-Perennial Forage model. *Crop and Pasture Science, 70*(2), 159-168.

Sommer, R., Paul, B. K., Mukalama, J., & Kihara, J. (2018). Reducing losses but failing to sequester carbon in soils–the case of Conservation Agriculture and Integrated Soil Fertility Management in the humid tropical agro-ecosystem of Western Kenya. *Agriculture, ecosystems & environment, 254,* 82-91.

Stewart, C. E., Follett, R. F., Pruessner, E. G., Varvel, G. E., Vogel, K. P., Mitchell, R. B. (2015). Nitrogen and harvest effects on soil properties under rainfed switchgrass and no-till corn over 9 years: *Implications for soil quality. GCB Bioenergy, 7*(2), 288–301.

Sundaram, S. M., Sivakumar, T., Sankaran, V. M., Rajkumar, J. S. I., Nishanth, B. (2012). Distribution of soil organic carbon (SOC) in agricultural lands by farming forage crops for mitigating climate change. *International Journal of Environmental Biology, 2*(3), 165–168.

Tully, K., Sullivan, C., Weil, R., & Sanchez, P. (2015). The state of soil degradation in sub-Saharan Africa: baselines, trajectories, and solutions. *Sustainability 7*: 6523–6552.

United Nations Convention to Combat Desertification (UNCCD) (2013). Background Document: The Economics of Desertification, Land Degradation and Drought: Methodologies and Analysis for Decision-Making. In *2nd Scientific Conference. Economic assessment of desertification, sustainable land management and resilience of arid, semi-arid and dry sub-humid areas.*

World Bank. (2010). Sub-Saharan Africa Managing Land in a Changing Climate: An Operational Perspective for Sub-Saharan Africa Sustainable Development Department Africa Region. Report No.: 54134-AFR.

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