

# Simulating tropical forage growth and biomass accumulation: an overview of model development and application

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## Abstract

Crop models can aid the synthesis and application of knowledge, planning of experiments and forecasting in agricultural systems. Few studies have reviewed the uses and applications of these models for tropical forages. The purpose of this study was to review the information available in this scientific area, highlighting the main models, their applications and limitations. Several empirical models have been developed to predict the growth and biomass accumulation of tropical forages, especially for the genera *Cynodon*, *Paspalum*, *Panicum* and *Brachiaria*. Their application, however, is often location or region specific. The adaptation of mechanistic models to accurately predict biomass accumulation in tropical grasses is still limited. Recent advances have been made on the plot-scale and farm-scale process-based models ALMANAC, CROPGRO *Perennial Forage* and agricultural production systems simulator (APSIM), with promising results. In addition, global-scale process-based models, such as the Century Agroecosystem Model and the Orchidee Grassland Management Model, have been tested for tropical grassland areas. A greater number of region-specific calibrations of empirical models can enhance their use, and improved databases and model parameterizations for a wide range of tropical grasses will enable the continuous improvement of mechanistic models.

**Keywords:** agricultural production systems simulator, CROPGRO, grass, modelling, pasture

## Introduction

Crop models can be valuable tools to evaluate long-term effects of environmental variations (e.g. weather patterns and soil characteristics) and management on plant responses, but they must be tested and calibrated for new regions before their application can be extrapolated to predict crop responses accurately (Wu *et al.*, 1996). Models can summarize a great deal of information, facilitate knowledge application and be used in defining agricultural policies, agro-climatic zoning, climate change studies and production planning.

Crop models are used to integrate multidisciplinary knowledge, based on processes regarding soil physics and chemistry, plant physiology and genetics, weather and farming management. The effects of these processes can be coded as simple written verbal description or may be a comprehensive set of equations used in the simulation of a given system (Sinclair and Seligman, 1996) which is used to predict growth, development and yield (Hoogenboom, 2000), even for large-scale applications (Rosenzweig *et al.*, 2013a). Thus, models can aid in the organization, interpretation and application of current scientific knowledge, identifying research priorities in areas where current knowledge is insufficient and favouring the appearance of new ideas.

Crop modelling has been an effective tool in simulating plant growth, and since the 1980s there have been significant advances, mainly due to the increased demand for accurate predictions in crop management scenarios, as well as in studies on climate change and

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as a result of advancements in information technology (Dourado-Neto *et al.*, 1998a).

Model users have followed this progress, which is best expressed by the increase in the number and complexity of models available (Grable, 1987) and on the extension of their applicability (Holzworth *et al.*, 2014). Users should be cautious, however, with regard to inherent limitations of crop modelling, including the need for time–space–crop evaluation and uncertainty quantification. In general, the greatest limitation for developing and improving crop models is the limited availability of information and knowledge about the physical and physiological processes involved (Marin *et al.*, 2014), the responses of the system to be simulated, and data availability (Hoogenboom, 2000). Therefore, model users should choose the model that can achieve their objectives with the available data (Dourado-Neto *et al.*, 1998b).

Despite their importance and dissemination, crop models are still little used in most tropical areas, and few studies have reviewed or evaluated the application of models created or adapted for tropical forages. This is partially explained by the lack of understanding of their capabilities and limitations, lack of experience in calibrating, evaluating and using models, and a general lack of model credibility in tropical areas (Marin and Jones, 2014).

The objective of this review was to report the main aspects regarding the use of models to predict tropical grass growth and biomass accumulation (often expressed as net accumulation of above-ground dry matter, DM), including a brief historical perspective, major advances achieved, types of models created and adapted, and their applications and limitations.

## Classification and use of models

Across the various scientific disciplines, models range from very simple, with only one linear equation, to extremely complex, with thousands of equations (Hoogenboom, 2000). Ideally, models to predict crop growth and yield should be sufficiently simple to be readily understood and used, and yet include sufficient detail to allow for application under a wide range of conditions (Dourado-Neto *et al.*, 1998c).

Models have multiple classifications. They can be static or dynamic, discrete or continuous, deterministic or stochastic, and mechanistic or empirical. Dynamic models describe how state variables evolve over time, while static models do not. Both the discrete and continuous models are dynamic; in continuous models, time is an actual value (e.g. 2–24 h), whereas in the discrete models, time is determined by integer values (e.g. 2 h). Stochastic models include a random factor or probability distributions, while the deterministic

models do not (Teh, 2006). Models to simulate crop yield are generally dynamic and deterministic models: they represent how a system responds over time without an associated probability distribution (Thornley and Johnson, 1990). They can be mechanistic and empirical, and these are the models targeted in this review.

Mechanistic models consider the knowledge of physical, chemical and biological processes that govern the phenomena under study. Sometimes they are considered explanatory because they express a cause–effect relationship between the variables (Teh, 2006). Empirical models are also called correlative or statistical models (Dourado-Neto *et al.*, 1998b), offering little or nothing to the understanding of the cause–effect processes involved, and are designed to obtain the correlation between crop production with one or more variables such as temperature, radiation, water availability and nutrients, especially nitrogen. The empirical models are currently the most widely studied and used under tropical conditions (Overman *et al.*, 1990; Tonato *et al.*, 2010; Cruz *et al.*, 2011).

The choice of model will depend on the objectives of the simulation and the information (data) available. Mechanistic models are developed based on the understanding of the phenomena which allow for their use under several conditions, but this requires more information and data. These models are more commonly used in research environments. Empirical models are simple to develop and easy to apply. They are, however, more prone to error and are limited to the range of conditions under which they were calibrated (Dourado-Neto *et al.*, 1998b).

To a certain degree and observation level, most crop models are empirical (Dourado-Neto *et al.*, 1998b). For example, considering a whole plant, a model is mechanistic if it simulates leaf area generation and light interception, photosynthesis, assimilate partitioning, water balance, and nutrient status in the soil–plant–atmosphere complex. Conversely, the model is empirical in estimating, for example, the rate of leaf photosynthesis, because the processes involved (capture of light, electron transport, synthesis of ATP and NADPH, CO<sub>2</sub> fixation, etc.) are not represented, and photosynthetic rate is estimated empirically according to leaf conditions.

An international survey of the Climate Change, Agriculture, and Food Security Program revealed that 57% of the individuals polled indicated their preference for mechanistic models, 14% for empirical models and 29% used other models (Rivington and Koo, 2010). These results reflect the increased demand for improving the understanding of processes, which according to the survey is the most important purpose of modelling. By improving this understanding,

models can assist in the decision-making, in simulating production, in research on crop management and genetic improvement, among others, which together comprise the main objectives of model developers and users (Table 1).

Mechanistic models have been chosen by scientists because they are scientifically accepted as predictors of a wide range of responses, either for large-scale simulations or farm- and plot-scale studies. Simulations on impacts of climate change are examples of current applications of mechanistic crop models, given that they rely on the state-of-the-art of the physiological and physical principles for a given species (Rosenzweig *et al.*, 2013b). In addition, previous studies with maize and wheat have shown how prediction uncertainty can be reduced using model ensembles (or multimodel simulations) (Palosuo *et al.*, 2011; Rötter *et al.*, 2011; Asseng *et al.*, 2013), indicating that there are differences among approaches used in these models and emphasizing the complementary benefits of having several models as estimators of biophysical processes.

Physiological processes are essential elements for improving plant modelling, and most model weaknesses would be overcome by better understanding the main physiological aspects related to plant growth and development (Marin *et al.*, 2014). Besides being genotype-dependent, photosynthesis, respiration, carbon partitioning and water relations are differentially affected by the agricultural environment. Long-term climate projections have shown that air temperature, rainfall, air CO<sub>2</sub> concentration and solar radiation are the most likely climate variables to be changed in the future (Trenberth *et al.*, 2007). In fact, most crop mod-

elling has been developed to understand the effects of agricultural practices and environmental factors on crop production and particularly food and energy supply (Jones *et al.*, 2003; Keating *et al.*, 2003).

## Empirical models

Regression analysis is the most commonly used technique to generate empirical models. It is a statistical approach used to define functional relationships among experimental data and has been used since the early 1900s when wheat (*Triticum aestivum* L.) yield was correlated with the amount of rainfall at the Rothamsted Experimental Station, England (Fisher, 1925). Since then, many studies have used regression analysis in order to generate equations to estimate crop production (dependent variable) as a function of environmental factors (independent variables).

Empirical models are often also based on other derivative variables such as (i) growing degree days (GDD); (ii) photothermal units (PU) (Villa Nova *et al.*, 1999), which consider GDD and day length; and (iii) climatic growth index (CGI) (Fitzpatrick and Nix, 1973), which takes into account the global radiation (R<sub>g</sub>), a thermal growth index and a drought attenuation factor, usually the ratio between actual (AET) and potential (PET) evapotranspiration.

The GDD value expresses the accumulated thermal energy that can be effectively used by crops for growth. To estimate the GDD, the base temperature (T<sub>b</sub>) for crop growth is needed, in addition to air temperature. Under tropical conditions, Equation 1 is the most common method to estimate GDD for one day.

$$\text{GDD} = T_{\text{mean}} - T_{\text{b}} \quad (1)$$

where T<sub>mean</sub> is the mean temperature of the day.

The lower base temperature can be accurately determined in growth chambers, isolated from other factors. However, recent studies have estimated the lower base temperature from field experiment data by regression of forage accumulation with average air temperature, considering as base temperature the one at which herbage accumulation rate is zero (Cruz *et al.*, 2011; Araujo *et al.*, 2013; Moreno *et al.*, 2014).

Despite the controversy regarding this method, due to the extrapolation of results to the zero-accumulation rate (seldom observed in those studies), the simulated biomass values have shown consistent results when compared to observed data. In these simulations, it is common to use a generalized value (15°C) as T<sub>b</sub> for tropical forages (Cooper and Tainton, 1968; Moore *et al.*, 2004), although the exact T<sub>b</sub> is often unknown. Thus, it is important that the T<sub>b</sub> used or

**Table 1** Percentage (%) of responses to the question ‘What are the models used for?’ aimed at the creators and users of models, according to the sample survey held worldwide.

Response	Main objective	Secondary objective
Assist in decision-making	25	13
Impacts and/or adapts to climate changes	24	28
Simulation/prediction of yields/productivity	22	23
Research for improved management	19	19
Research for genetic improvement	7	5
Education/training	3	7
Optimized operations	1	5

Source: Rivington and Koo (2010).

estimated by the author of the model be considered, because although it is constant within species, variations have been observed across studies (Table 2).

The PU method considers the combined effect of air temperature and day length, according to Villa Nova *et al.* (1999). PUs are calculated as follows:

$$PU = \left[ (n/2 * GDD)^{(Nf/Ni+1)} \right] / (Nf/Ni + 1) \quad (2)$$

where GDD is calculated according to Ometto (1981),  $n$  is the number of days in the growth cycle, and  $Ni$  and  $Nf$  are the initial and final day length values of the growth period, which are calculated as follows:

$$N = 24/\pi * \cos^{-1} [\cos(109/106 * \pi) - \sin(\lambda) * \sin(\varphi)] / [\cos(\lambda) * \cos(\varphi)] \quad (3)$$

where  $\lambda$  is the latitude and  $\varphi$  is the solar declination, given by:

$$\varphi = 23.5\pi/180 * \cos[2\pi/365 * (DOY - 173)] \quad (4)$$

where DOY is the day of the year.

**Table 2** Base temperature (Tb) for different tropical and subtropical grasses in specific field conditions.

Grasses	Tb (°C)	Reference
<i>Brachiaria brizantha</i> cv. Marandu	17.2	Cruz <i>et al.</i> (2011)
<i>Brachiaria brizantha</i> cv. Marandu	15	Mendonça and Rassini (2006)
<i>Brachiaria decumbens</i> cv. Basilisk	16.7	Mendonça and Rassini (2006)
<i>Pennisetum purpureum</i> cv. Napier	13.9	Mendonça and Rassini (2006)
<i>Pennisetum purpureum</i> cv. Napier	15	Villa Nova <i>et al.</i> (2007)
<i>Panicum maximum</i> cv. Mombaça	15.6	Araujo <i>et al.</i> (2013)
<i>Panicum maximum</i> cv. Tanzânia	15	Mendonça and Rassini (2006)
<i>Paspalum atratum</i> cv. Pojuca	15.6	Mendonça and Rassini (2006)
<i>Cynodon nlemfuensis</i> cv. Florico	11.5	Villa Nova <i>et al.</i> (2007)

The CGI can be calculated according to Fitzpatrick and Nix (1973) as follows:

$$CGI = LI * TI * WI \quad (5)$$

where LI is the light index given by:

$$LI = 1 - \exp[-3.5(Rg/750)] \quad (6)$$

where Rg is incoming global solar radiation (cal cm<sup>-2</sup> day<sup>-1</sup>), TI is the thermal index, derived from the curves relating to DM yield and average daily air temperature, and WI is the water-index ratio calculated as follows:

$$WI = \frac{\text{Actual Evapotranspiration (mm)}}{\text{Potential Evapotranspiration (mm)}} \quad (7)$$

Predicting biomass accumulation by regression with air temperature has been widely used due to its conceptual simplicity and applicability, as well as the good association between temperature and photosynthetically active radiation. Good predictions have been obtained by regressing growth of *Brachiaria* (Syn. *Urochloa*), *Panicum* (Syn. *Megathyrsus*) and *Cynodon* grasses against daily minimum temperature (Tonato *et al.*, 2010; Cruz *et al.*, 2011); (Table 3).

Tonato *et al.* (2010) analysed empirical forage biomass prediction models using the weather variables: Tmin, Tmax, Tmean and Rg. The authors compiled data from five independent experiments, including four from south-eastern and one from central Brazil, and concluded that Tmin had the greatest predictive power for forage accumulation rate (kg DM ha<sup>-1</sup> day<sup>-1</sup>) for *Brachiaria*, *Panicum* and *Cynodon* (Table 3).

The marked effect of temperature on plant growth is mainly related to the strong effect of temperature on enzyme activity, including effects on photosynthesis and transport processes in membranes (Salisbury and Ross, 1991; Moore *et al.*, 2004). The balance between the reaction rate and the enzyme denaturation rate provides the activity rate, thereby the minimum, maximum and optimum cardinal temperatures (Salisbury and Ross, 1991). The cardinal temperatures for tropical forages often found are of approximately -9.7 to -2°C as minimum for survival, 15°C as minimum for growth, 30–35°C as optimal for growth and 50°C as the threshold for physiological disorders (Cooper and Tainton, 1968; Ludlow, 1980; Jones, 1985; Moore *et al.*, 2004).

**Table 3** Univariate linear empirical models correlating dry-matter production with temperature or related variables.

Grass	Variable	Slope	Intercept	R <sup>2</sup>	Reference
<i>B. brizantha</i> cv. Marandu	Tmin	11.93	-134.95	0.73	Cruz <i>et al.</i> (2011)
<i>B. brizantha</i> cv. Marandu	Tmin <sub>corr</sub>	5.78	-17.24	0.75	Cruz <i>et al.</i> (2011)
<i>B. brizantha</i> cv. Marandu	GDD <sub>corr</sub> *	12.9	6.52	0.75	Cruz <i>et al.</i> (2011)
<i>Brachiaria</i> Group 1§	Tmin	8.19	-94.92	0.55 to 0.5	Tonato <i>et al.</i> (2010)
<i>Brachiaria</i> Group 2¶	Tmin	10.66	-128.07	0.55 to 0.6	Tonato <i>et al.</i> (2010)
<i>Cynodon</i> Group 1†	Tmin	9.06	-84.69	0.6 to 0.7	Tonato <i>et al.</i> (2010)
<i>Cynodon</i> Group 2	Tmin	7.97	-67.01	0.6 to 0.7	Tonato <i>et al.</i> (2010)
<i>Panicum</i> Group 1††	Tmin	6.36	-55.22	<0.4	Tonato <i>et al.</i> (2010)
<i>Panicum</i> Group 2‡	Tmin	5.93	-29.15	<0.4	Tonato <i>et al.</i> (2010)
<i>P. maximum</i> cv. Mombaça	ΣUF	0.226	600.01	0.86	Araujo <i>et al.</i> (2013)
<i>P. maximum</i> cv. Mombaça	ΣICC	368.14	-311.94	0.83	Araujo <i>et al.</i> (2013)
<i>P. maximum</i> cv. Mombaça	ΣGDD	11.52	-304.8	0.78	Araujo <i>et al.</i> (2013)
<i>P. maximum</i> cv. Tanzânia	AET	34.73	-21.58	0.87	Pezzopane <i>et al.</i> (2012)
<i>P. maximum</i> cv. Tanzânia	GDD <sub>corr</sub> *	18.80	-17.02	0.84	Pezzopane <i>et al.</i> (2012)
<i>P. maximum</i> cv. Tanzânia	GDD <sub>corr</sub> **	18.90	-6.38	0.87	Pezzopane <i>et al.</i> (2012)
<i>P. maximum</i> cv. Tanzânia	CGI	330.09	-12.88	0.84	Pezzopane <i>et al.</i> (2012)

(i) the response variable ( $y$ ) is the forage accumulation rate ( $\text{kg DM ha}^{-1} \text{ day}^{-1}$ ), except for the models of Araujo *et al.* (2013), which were generated with the daily sums of the entire cycle; hence, the response variable ( $y$ ) is the total forage mass in each cycle. (ii) The temperature values are given in degrees Celsius ( $^{\circ}\text{C}$ ). Tmin<sub>corr</sub>, minimum temperature corrected by a drought attenuation factor; GDD<sub>corr</sub>, growing degree days (calculated based on Tb) corrected by a water penalty factor: \*by the AET/PET ratio and \*\*by the current/maximum soil storage ratio; CGI = daily climatic growth index; ΣUF = sum of daily photothermal units; ΣICC = sum of CGI; ΣGD = sum of degree days. †Tifton 85 and Estrela. ‡Tanzânia and Tobiatã. §Marandu, Basilisk and Arapoty. ¶Capiporã and Xaraés. ||Coastcross, Florico and Florona. ††Atlas and Mombaça.

Cruz *et al.* (2011) evaluated several meteorological variables (Tmin, Tmax, Tmean, Rg, GDD, CGI, PU and AET), corrected or not by a drought attenuation factor (AET/PET), in predicting the dry biomass yield of *B. brizantha* cv. Marandu with data obtained in south-eastern Brazil. The best results were achieved using multivariate linear regression for Tmin, Rg and AET and with the univariate regression against corrected GDD, corrected Tmin or CGI (Table 3). The inclusion of the drought attenuation factor in the model improved the predictive power of the variables (highest determination coefficient, R<sup>2</sup> and lower Akaike information criterion, AIC; Table 3) indicating it can be a good option for rainfed conditions.

Pezzopane *et al.* (2012) used such a correction factor for estimating Tanzania guineagrass (*P. maximum*) yields. The factors were given by the AET/PET ratio or by the current/maximum soil moisture storage ratio, considering the sequential water balance (scale of five days) and storage capacity of 100 mm. The best-fit variables were those simultaneously associated with temperature and water availability such as AET, GDD corrected by the two water factors and the CGI (Table 3). Although the variables that considered the two water correction factors (DDWI and DDWS) showed high correlation and similar statistics for the

tested conditions, Pezzopane *et al.* (2012) pointed out differences in yield estimates between the two water availability correction factors. In very dry periods and at the onset of the rainy season, the current/maximum soil moisture storage ratio index seems to perform better than the AET/PET ratio, probably because the latter is not sensitive to the lag time for soil water replenishment.

A series of papers (Tonato *et al.*, 2010; Cruz *et al.*, 2011; Pezzopane *et al.*, 2012; Araujo *et al.*, 2013) reporting on the calibration of empirical models for tropical forage grasses, showed that the average temperature of the experiments used to generate these models ranged from about 16–26 $^{\circ}\text{C}$ . The experiments used a variety of forage genotypes, but some models were grouped for forages with similar responses. In general, the models were univariate and linear, therefore simple and easy to apply. The fit ranged from R<sup>2</sup> between 0.40 and 0.87, depending on the genotype and the variable used (Table 3).

Forage production during the regrowth of elephantgrass (*Pennisetum purpureum* Schum.) as a function of PU was estimated by the equation  $P = 1.261 / (1 + e^{2.85 - 0.008133 \times \text{PU}})$  by Villa Nova *et al.* (1999) in south-eastern Brazil, where  $P$  is the amount of dry matter produced and PU is the total of photothermal units accumulated during the growth cycle.

The CGI concept (Fitzpatrick and Nix, 1973) was used in southern Brazil (Mota *et al.*, 1981) and for 47 locations in the state of São Paulo (Pedro, 1995) in comparison with the observed forage accumulation rates for guineagrass, molasses grass (*Melinis minutiflora* Beauv.), jaraguagrass (*Hyparrhenia rufa* Nees.) and pangola digitgrass (*Digitaria pentzii* Stent.). The best-fit curves were exponential and  $R^2$  values ranged from 0.58 to 0.81 for guineagrass and molasses grass respectively.

Empirical models where production is predicted as a function of nitrogen availability have also been developed. Overman and Angley (1986) and Overman *et al.* (1988) suggested and evaluated models considering nitrogen availability for bermudagrass [*Cynodon dactylon* (L.) Pers.] from data obtained in the south-eastern USA. Overman *et al.* (1990) adjusted the equation  $y = A/(1 + e^{b-cN})$ , where  $y$  is the estimated annual DM yield ( $\text{Mg ha}^{-1}$ ),  $N$  is the nitrogen applied ( $\text{Mg ha}^{-1}$ ),  $A$  is the maximum annual yield ( $\text{Mg ha}^{-1}$ ),  $b$  is the intercept with the  $y$ -axis, and  $c$  is the response coefficient ( $\text{ha kg}^{-1}$ ). The parameters  $A$ ,  $b$  and  $c$  are estimated empirically by experimentation.

Almeida *et al.* (2011) associated PU with nitrogen fertilization and water availability to simulate growth of Tanzania guineagrass. This approach allows simulation of forage production under different levels of fertilization for irrigated or rainfed conditions, thus expanding the applicability of this type of model. The major limitation of the study was that it used only greenhouse data, which were collected at a single location. Thus, further calibration with field experiment data is needed if application of the model to production systems is intended.

Some of the empirical models already developed for tropical grasses have good predictive capability and are easy to apply because the input variables, especially temperature, are often easy to obtain in most tropical regions (Table 3). The major limitation of these studies is their geographic concentration, especially in south-eastern Brazil and in the south-eastern United States. This limits the range of environments (climatic conditions) represented, as well as the use of these models in regions other than those where the data sets were collected and the models developed. In addition, interactions among factors (temperature, light, moisture, nitrogen, etc.) used as forage accumulation predictors may further limit model predictive power, if application conditions are not similar to those used to develop the model. Further experimentation in this field should consider especially equatorial regions (latitudes lower than  $16^\circ$  and mean temperature above  $26^\circ\text{C}$ ), where tropical grass production is relevant.

## Mechanistic models

Several mechanistic models have been developed or adapted for forages in different regions of the world. Most, however, include the basic knowledge derived from models developed for row crops or have been evaluated and/or are only available for temperate forage species. Since mechanistic models simulate growth based on plant processes, they can be adapted for conditions other than those under which they were originally generated. Examples include recent adaptations of models that were originally developed for row crops or for temperate forages in the USA and Australia and which have been calibrated for tropical forages in Brazil (Pedreira *et al.*, 2011; Lara *et al.*, 2012; Araujo *et al.*, 2013).

These models are usually based on hundreds (or thousands) of equations for many individual processes, often organized in algorithms and user-friendly interfaces. Generating a mechanistic model involves knowledge about the system to be simulated (Dourado-Neto *et al.*, 1998b), organization, interpretation and a massive knowledge of physiology, beyond validating the model with experimental data.

A basic understanding and appreciation of the key plant physiological processes and the interactions with other processes in the farming system is the basis for mechanistic crop modelling. This knowledge also aids in developing decision-making criteria, from selecting crop genotype and field site, to defining strategic crop management and infrastructure investments (Lisson *et al.*, 2005). This kind of decision support based on modelling arose in the early 1990s, as the generation of new data through traditional agronomic research methods was not sufficient to meet the increasing demand for answers from research. Traditional agronomic experiments are restricted in time and space, making results site- and season-specific, time-consuming and expensive. McCown *et al.* (1996) stated that among the many changes taking place in agricultural research, there is an increased recognition that a 'systems approach' is needed to meet the challenges presented by the complexities, uncertainties and conflicts in modern agricultural production systems.

A comprehensive evaluation of forage models, developed over nearly three decades ago, may be found in Hanson *et al.* (1985), who evaluated the models AFRICA, BLUE GRAMA, ELM, LINEAR, RANGES, ROOTS, SHEEP, SAGE and SPUR. In a recent work, Kiniry *et al.* (2007) developed field parameters to enable the use of the ALMANAC (*Agricultural Land Management Alternative with Numerical Assessment Criteria*) model for simulating growth and yield of bermudagrass [*Cynodon dactylon* (L.) Pers.],

Pensacola bahiagrass (*Paspalum notatum* Flugge) and two warm-season range grasses native to Texas, USA.

The ALMANAC model considers water and nutrient balance and interception of solar radiation. With this model, it is possible to simulate a single plant species or several species in competition. It was developed to require only readily available inputs. The biomass growth is simulated with a radiation-use efficiency (RUE) approach, considering the leaf area index (LAI) and extinction coefficient developed throughout the seasons. The biomass growth rate considers flowering effects and can be reduced by stresses such as nutrient deficiency, drought or temperature extremes (Kiniry *et al.*, 2007).

In the study of Kiniry *et al.* (2007), the maximum leaf area index obtained for bermudagrass and bahiagrass was about 2.2, mean light-extinction coefficient ranged from 0.7 to 2.1 and radiation-use efficiency of four of the five species evaluated ranged between 1 and 2 g MJ<sup>-1</sup>. The authors concluded that the model simulated mean forage biomass reasonably well and that it is a useful tool to simulate the soil and climate effects on the evaluated species and locations.

The CROPGRO and APSIM models were recently adapted for growth simulations of tropical forages in Brazil (Pedreira *et al.*, 2011; Lara *et al.*, 2012; Araujo *et al.*, 2013; Pequeno *et al.*, 2014). CROPGRO predicts the growth and composition dynamics of crops based on input data of the physiological plant processes, soil characteristics, climate and management (Boote *et al.*, 1998). These are included in the software DSSAT (*Decision Support System for Agrotechnology Transfer*), which has models for simulating the growth of 28 crops in the most recent version 4.5 (Decision Support System for Agrotechnology Transfer [DSSAT], 2013).

From the general CROPGRO model, adaptations have been made to simulate the growth of bahiagrass in a rotation system with peanuts (*Arachis hypogaea*, L.) in Florida (USA) and to simulate the growth of palisadegrass [*Brachiaria decumbens* cv. Basilisk (Stapf.)] in the low-latitude regions of Colombia (Giraldo *et al.*, 1998). The annualized version of CROPGRO model consistently overpredicted the dry-matter yields of bahiagrass, particularly in cooler months (Rymph *et al.*, 2004). The desire for more rigorous applications and use of the model imposed the need for higher accuracy, which required better prediction capability and more realistic representation of the seasonal and rapid patterns of regrowth, including a storage organ for reserves (Rymph *et al.*, 2004). For these reasons, Rymph *et al.* (2004) added code to the model to create a true perennial CROPGRO bahiagrass model which included a perennating storage organ (rhizome/stolon) for replenishment of reserves and use of stored carbohydrate and N for regrowth, as well as dormancy and

partitioning that responded to day length. This coding together with more vigorous parameterization and testing was included in the CROPGRO v 4.0 growth model, thus conferring on the model the ability to predict growth and N-tissue composition of bahiagrass in response to daily weather, N fertilizer and harvest management. The Rymph *et al.* (2004) version of CROPGRO (CROPGRO *Perennial Forage model*), however, was not immediately incorporated into the DSSAT platform because the source code was different. In Brazil, the CROPGRO *Perennial Forage model* was calibrated for *B. brizantha* cv. Xaraés (Pedreira *et al.*, 2011), *B. brizantha* cv. Marandu (Pequeno *et al.*, 2014), *B. brizantha* cv. Mulato II (Pequeno, 2014) and for *P. maximum* cv. Tanzânia (Lara *et al.*, 2012). Pedreira *et al.* (2011), Lara *et al.* (2012) and Pequeno *et al.* (2014) used data from Piracicaba/SP (22°42'S, 47°50'W) for the adaptations and found that the models effectively integrated knowledge about the forages and also that they can be used to simulate growth with acceptable accuracy.

Results from Pequeno (2014) suggest that it is possible to apply CROPGRO *Perennial Forage model* for different tropical grass species with minimal parameterization effort, especially for those from the same genera. This is possible because the internal code of CROPGRO model is generic and the model reads and uses input files that define species traits and cultivar attributes. For each species, the CROPGRO *Perennial Forage model* species file contains information about base temperature (Tb) and optimum temperature (Topt) for developmental processes and growth processes. In the cultivar file, the day-length effect is modelled with two parameters that define critical day length and slope of day-length sensitivity, which slows or accelerates development depending on day-length changes. The species file also includes coefficients and other relationships for photosynthesis, N fixation, tissue composition, growth and maintenance respiration (Boote *et al.*, 2002).

APSIM (*Agricultural Production Systems Simulator*) is a modular modelling system developed by the Agricultural Production Systems Research Unit in Australia to simulate biophysical processes in whole farming systems. The modular structure is flexible, and currently, the system is able to simulate the growth of 30 different crops and pasture species (Holzworth *et al.*, 2014). APSIM-Growth is a module for simulating forage growth, and it was previously used to simulate the above-ground DM production of Bambatsi coloured guineagrass (*Panicum coloratum* L.) in Australia. The model was subsequently parameterized for Brazilian conditions (*P. maximum* cv. Mombaça) by Araujo *et al.* (2013) using a data set from São Carlos, SP, Brazil (21°57'S, 47°50'W). Using the original

parameterization, APSIM-Growth was not able to accurately estimate *P. maximum* regrowth over the seasons, as the day-length component, which shifts biomass partitioning between shoots and roots, did not work satisfactorily for this grass. The authors also reported the need for changes in all original parameters, such as optimum and base temperatures, specific leaf area and radiation-use efficiency. After the parameterization, the models were evaluated using independent data sets for irrigated and rainfed conditions with satisfactory results (mean bias error of 6 kg DM ha<sup>-1</sup> harvest<sup>-1</sup> against the observed data set). Recent adaptations of the models CROPGRO and APSIM provide promising model application possibilities in tropical pastures, although data used on their parameterization were incipiently concentrated in specific locations in the USA, Australia, Brazil and Colombia.

Despite the usefulness of the CROPGRO *Perennial Forage* model in agronomic decision-making, there are opportunities for further model improvement for tropical pasture application, such as grazing simulation and its impacts on tillering and leaf appearance, growth and senescence. The model simulates defoliation and post-harvest conditions by a MOW function, which allows for the definition of a residual stubble mass and leaf area index.

As APSIM comprises a set of biophysical models and a software framework that allows these biophysical models to be coupled together, it may be useful for simulations both on plot-scale and farm-scale levels, although other component models, besides APSIM-Growth, still have to be tested and calibrated under tropical conditions.

The Century Soil Organic Matter Model Environment and the Orchidee Grassland Management Model are process-based ecosystem models designed for large-scale applications (Parton *et al.*, 1987; Parton *et al.*, 1993; Chang *et al.*, 2013). The Century model simulates primary productivity, soil nutrient dynamics (carbon, nitrogen, phosphorus and sulphur), soil water and changes in soil organic matter for different plant-soil systems (Parton *et al.*, 1987; Parton *et al.*, 1993). The CROPGRO *Perennial Forage* model uses the soil organic carbon module from Century model with all its features (Gijsman *et al.*, 2002).

The grassland production submodel of the Century model simulates production as a function of a maximum potential production defined for each crop and modified by the effects of soil temperature, soil moisture, shading by canopy and dead vegetation, and nutrient availability (N, P and S) (Metherell *et al.*, 1993; Parton *et al.*, 1993). The parameter for maximum potential production has both genetic and environmental components (i.e. level of photosynthetic active radiation, maximum net assimilation rate, effi-

ciency of conversion of carbohydrate into plant constituents and maintenance respiration rate) (Metherell *et al.*, 1993). Maximum potential production should reflect above-ground production in optimal summer conditions, and this parameter may be used to calibrate predicted production for different environments, species and varieties (Metherell *et al.*, 1993). Harvest, grazing and fire affect above-ground biomass, while grazing and fire may also affect the root-to-shoot ratio and nutrient content of plants (Metherell *et al.*, 1993; Parton *et al.*, 1993).

Parton *et al.* (1993) determined that 60% of plant productivity predicted by the Century model for C<sub>4</sub> and C<sub>3</sub> grasses had errors of less than 25% of the observed production and that the general seasonal patterns of biomass dynamics were well simulated by the model, although differences between years with similar rainfall were not simulated.

Orchidee is a dynamic global vegetation model designed to simulate carbon and water cycles from a site level to global scale. The Orchidee model is based on three models. The SVAT SECHIBA is an atmospheric general circulation model that describes exchanges of energy and water between the atmosphere and the biosphere, and the soil water budget (Kriner *et al.*, 2005). LPJ simulates vegetation dynamics (Kriner *et al.*, 2005). STOMATE simulates other process such as photosynthesis, carbon allocation, litter decomposition, soil carbon dynamics, maintenance and growth respiration, and phenology (Kriner *et al.*, 2005). The Orchidee model distinguishes between 12 plant functional types, including native and cultivated C<sub>4</sub> grasses (Kriner *et al.*, 2005). For each functional type, different biogeochemical parameters are determined (i.e. optimal maximum RuBisCO-limited potential photosynthetic capacity, optimum photosynthetic temperature, maximum leaf area index – beyond which there is no allocation of biomass to leaves – and critical leaf age for senescence) (Kriner *et al.*, 2005). Orchidee-GM incorporates a pasture management model inspired in the PaSim grassland model (Chang *et al.*, 2013) with cutting and grazing practices being considered.

Coltri *et al.* (2014) tested Orchidee-GM against *P. maximum* observed data from Brazil. Orchidee-GM simulated leaf area index (LAI) well ( $R^2 = 0.79$ ;  $P > 0.0001$ ; RMSE = 1.93), leaf biomass ( $R^2 = 0.79$ ;  $P > 0.0001$ ; RMSE = 929.7 kg ha<sup>-1</sup>) and total biomass ( $R^2 = 0.89$ ;  $P > 0.0001$ ; RMSE = 4443.5 kg ha<sup>-1</sup>). The results were not good at simulating specific leaf area (SLA) ( $R^2 = 0.4$ ;  $P = 0.0198$ ; RMSE = 48.54 g cm<sup>-2</sup>). Total biomass was overestimated, particularly in winter.

The CROPGRO *Perennial Forage*, APSIM-Growth, Century Agroecosystem and Orchidee Grassland Management models may also be used in studies of climate change, mitigation and adaptation problems,



although those models still have to be tested for tropical grasses under extreme climatic conditions (e.g. flooding, drought and extreme temperatures). Intra- and interspecific differences have been observed on responses of *Brachiaria* spp. to drought and flooding (Dias-Filho, 2002; Guenni *et al.*, 2002; Dias-Filho and Caetano, 2008; Santos *et al.*, 2013). Xu *et al.* (2013) highlighted that there is strong evidence of enhanced growth of water-stressed C<sub>4</sub> plants by elevated CO<sub>2</sub> concentrations. Although the CROPGRO Perennial Forage and the APSIM-Growth models have been parameterized for tropical forages (Pedreira *et al.*, 2011; Lara *et al.*, 2012; Pequeno, 2014), CO<sub>2</sub> response equations that mimic C<sub>4</sub> photosynthesis have not been tested against CO<sub>2</sub> response data on forages. Further research is needed to evaluate the performance of these models for different genotypes under extreme climatic conditions.

Currently, the main limitation for a broad application of mechanistic models seems to be the availability of input data, given that much of the data required (soil, climate and plant parameters) are scarce or absent for most tropical grassland areas. In addition, experiments used for tests and calibrations have been carried out under similar and balanced initial biomass conditions (stubble). Extreme initial conditions also may provide differences among grasses. In addition, all the experiments were carried out under mean temperatures between 16 and 26°C. Thus, it is possible to run simulations for many *Brachiaria* and *Panicum* species with minimal adjustment of parameters, but reliable results were only obtained in standard forage environmental conditions, i.e. without absence of severe water and/or heat stresses.

For model improvement, in addition to more experimentation under high temperatures and moisture-stress conditions, we also suggest the development of tools to enable the adjustment of canopy initial growing conditions (stubble). We believe that the implementation of standardized experimental protocols may favour the use of databases available in the literature for model development and adaptation. Currently, it is difficult to convert available data from tropical pasture trials (especially those from grazing trials) into usable data for model parameterization, mainly because most experiments were not set up with this goal in mind, forcing researchers to estimate a large number of parameters required by models.

### Final considerations

The advancement of scientific knowledge and computational tools has made for increased development of tropical forage growth models, and their application is promising in research as well as in systems manage-

ment. No single model can be considered perfect, but rather more suited or adapted to specific situations and uses, depending on the objectives of the user and information (data) available.

Empirical models have better use possibilities in commercial applications, most having acceptable predictive power and are simple and easy to operate. We highlight the univariate linear regressions using GDD corrected for drought attenuation factors, CGI and minimum air temperature, as independent variables. The limitation of these models refers to the restricted geographic range of the experimental data. These models can be used in regions with similar climatic characteristics, but if they are to be used in other regions, the database should be expanded.

Thus far, studies to adapt mechanistic models for tropical forages are limited. The initial results enable us to use the models ALMANAC, CROPGRO Perennial Forage, APSIM, Century and Orchidee-GM for *Panicum*, *Brachiaria*, *Cynodon* and *Paspalum* grasses, with satisfactory accuracy. Adapting them for other forages using data from other regions would likely increase their predictive capability.

Considering future perspectives where forage-based animal-production systems are likely to be increasingly challenged from technical and environmental standpoints, with increasing demand for animal products, and the need for fine-tuning production procedures and processes becoming routine, forage models may gain in importance and become common elements and useful tools in forage-based livestock production.

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