Simulating Guinea Grass Production: Empirical and Mechanistic Approaches

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ABSTRACT

Tropical grasses are economically important for cattle production in Brazil, and accurate simulation models for tropical pastures can benefit forage researchers and farm managers by improving tropical forage production systems. This research calibrated and validated four modeling approaches of contrasting complexity to simulate mass production of Mombaça Guinea grass (Panicum maximum Jacq.). The models included three empirical agro-climatic models (i.e., using cumulative degree days, photothermal units, and a climatic growth index) and a biophysical simulation model, Agricultural Production Systems Simulator (APSIM)-Growth. Data sets for calibration and independent validation included frequent records of aboveground dry matter production during the 2005–2006 and 2010–2011 growing seasons from three trials. All models performed well during calibration ($R^2 = 0.78–0.86$; coefficient of variation = 26–32.1%). During model validation, the $R^2$ varied between 0.69 and 0.78, the agreement index was between 0.88 and 0.93, the coefficient of variation between 37.6 and 50.2%, and the mean bias error was between 6 and 470 kg ha$^{-1}$. Even though all models were in agreement between simulated and observed results, APSIM-Growth was able to simulate Guinea grass production across broader climatic, soil, and management (e.g., N fertilization) conditions.

The world's largest commercial herd of cattle is located in Brazil, with approximately 209 million head (Instituto Brasileiro de Geografia e Estatística, 2010), mostly raised in extensive pastures. In Brazil, pastures occupy an area of approximately 172 million ha (69% of the total area dedicated to agricultural production) (Instituto Brasileiro de Geografia e Estatística, 2007).

Guinea grass is the most productive seed-propagated forage in the Brazilian market. Guinea grass pastures are of high quality, demand high soil fertility, and are adapted to many soil and climate types. This African C$_4$ grass has been responsible for much of the meat production in Brazil and in many Latin American countries (Jank et al., 2008).

In Brazil, Guinea grass breeding programs have been developed under the leadership of the National Beef Cattle Research Center (EMBRAPA-CNPGC), which resulted in the release of the cultivars Tanzânia, Mombaça, and Massai. Mombaça in particular has been important in intensive (i.e., irrigated and fertilized) production systems because of its high annual productivity in Brazil’s tropical climate: approximately 41 Mg dry matter ha$^{-1}$ yr$^{-1}$ (Jank et al., 2008).

Managing these intensive production systems requires the design of sustainable and resilient farming systems in an increasingly variable (climate and markets) environment (Parry et al., 2009). Forage production models that take into account the influence of the climate, soil, and management can be useful to achieve high production efficiencies (Andales et al., 2006; Laughlin et al., 2007), estimate impacts from expected changes in climate (Zha et al., 2005; Zhang et al., 2007; Parry et al., 2009), and identify and quantify benefits and trade-offs from alternative adaptation options (Thornley and Cannell, 1997; Zhang et al., 2007; Meinke et al., 2009).

There are many different types of modeling approaches. Empirical modeling approaches are, in general, simple to use and require widely available inputs. When properly calibrated, they can be as accurate as more dynamic and mechanistic simulation models (Teh, 2006). Although these models tend to be highly site and system specific, i.e., would require recalibration if transported to a different agro-ecologic or production system, they are usually unable to account for intraseasonal variations in the availability of resources, e.g., water and N.

In Brazil, one of the first empirical models used to predict the production of pastures was that of Fitzpatrick and Nix (1973), originally developed in Australia. This model uses climatic variables, i.e., average air temperature, incident solar radiation, and a rainfall-driven soil water balance, to simulate mass production. In Brazil, it was first used in the south (Mota et al., 1981) and southeast (Pedro, 1995) to assist in the planning of livestock and pasture management strategies. Empirical approaches that use degree days or photoperiod data have also been used to predict the mass production of sugarcane (Saccharum officinarum L.; Villa Nova et al., 1983) and a range of pasture species, e.g., Tanzânia Guinea grass (Cunha et al., 2008; Almeida et al., 2011), Napier elephant grass (Pennisetum purpureum Schumach.; Villa Nova et

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Abbreviations: APSIM, Agricultural Production Systems Simulator; CGI, climatic growth index; DD, degree day; DM, dry matter; MBE, mean bias error; PU, photothermal units; SLA, specific leaf area; WI, crop water stress index.
Studies that used biophysical models (e.g., CROPGRO and GRAZPLAN) have been developed for *U. brizantha* spp. cultivars under irrigated (Pedreira et al., 2011; Lara et al., 2012) and rainfed (Cruz, 2010) conditions for the southeast of Brazil. The APSIM model (Keating et al., 2003) is an example of such a modeling approach. It is a cropping system model that can simulate more than 25 different crops and pasture species (APSIM, 2011). One of the advantages of APSIM, compared with models such as CROPGRO and GRAZPLAN, is its international database of crop and animal parameters and the extensive network of technical and agronomic support provided by the APSIM initiative (APSIM, 2011). Calibrating and validating the APSIM model for Guinea grass will extend the capabilities of the APSIM model for Brazilian conditions and allow access to this wealth of expertise within the APSIM initiative (APSIM, 2011).

The objective of this research was to parameterize and compare the predictive capacity of four models with contrasting levels of detail to simulate the production of Mombáça Guinea grass. The tested models included three agro-climatic models based on (i) degree day, (ii) photothermal units, (iii) a temperature- and radiation-derived growth index, and (iv) a dynamic, functional simulation model, APSIM-Growth 7.3.

**MATERIALS AND METHODS**

**Experimental Data**

Independent empirical data sets from a range of experiments with Mombáça Guinea grass were used to calibrate and validate the selected models. These experiments were conducted at Embrapa’s Southeast Cattle Research Center at São Carlos, SP, Brazil [21°57′42″ S, 47°50′28″ W, 860 m asl]. The soil was an Oxisol (Soil Survey Staff, 1999), and the climate is subtropical humid (Koeppen’s classification: Cwa). The annual average values of maximum, minimum, and mean temperatures for 1999 to 2010 are 27.1, 15.9, and 21.5°C, respectively, and the average accumulated annual precipitation is 1356 mm.

**Calibration Data**

A Guinea grass pasture was sown on 18 Nov. 2009, fertilized, and irrigated to develop data sets of pasture growth under potential production conditions. Plots (6 by 6 m) were arranged in a completely randomized block design with four replications. Samples of forage mass were taken between 23 Feb. 2010 and 11 Apr. 2011 at four sampling times—250, 500, 750, and 1000 degree days—during each regrowth period (base temperature = 0°C). At each sampling time, the fresh weight of the total mass 0.3 m above the soil surface was recorded inside two 1- by 1-m quadrats. Subsequently, a fresh subsample for each plot was taken (0.5 kg) to estimate the leaf area of green leaf blades (ligule height) using the integrator of the leaf area (Li-Cor LI-3100C), and then it was oven dried to determine dry matter (DM) (60°C for 72 h).

In this work, we only considered the forage mass 0.3 m above the soil surface. This is because that is the post-grazing sward height recommended for Mombáça Guinea grass to provide high grazing efficiency and vigorous regrowth (Carnevali et al., 2006).

After the last sampling time (1000 degree days) for each of the eight regrowth cycles, all the plots were uniformly cut down to 0.3 m above the soil, and a new cycle of regrowth and sampling started. At the same time, the pasture was fertilized using 567 kg ha⁻¹ yr⁻¹ N, 283 kg ha⁻¹ yr⁻¹ K₂O, and 262 kg ha⁻¹ yr⁻¹ P₂O₅ split applied as (NH₄)₂SO₄, KCl, and P₂O₅, respectively. Sprinkler irrigation was supplied every 4 d whenever the balance between cumulative daily precipitation and cumulative Piche evaporimeter evaporation was >–20 mm or greater. The irrigation and fertilization regimes were expected to provide unlimited conditions to achieve maximum growth.

**Validation Data**

Independent data sets were used to validate all the models. These data sets included 15 observations from a fertilized and irrigated pasture experiment between April 2005 and December 2006 (Bertolone, 2009) and eight observations from a rainfed pasture experiment conducted between February 2010 and April 2011.

The 10-m² plots from the irrigated and fertilized pasture were arranged in a completely randomized block design with four replications. Mass samples were harvested 0.3 m above the soil surface every 30 to 35 d inside four 1- by 1-m quadrats. After each sampling, the entire plot was grazed by beef cattle (*Bos taurus*) to a height of approximately 0.3 m. The pasture was fertilized with N at about 700 kg ha⁻¹ yr⁻¹.

Between April 2005 and December 2006, daily maximum and minimum air temperatures and rainfall were recorded using a weather station located near the experimental sites at Embrapa (Embrapa Pecuária Sudeste, 2011). The incoming global solar radiation was estimated using the method described by Bristow and Campbell (1984); two other methods were also evaluated but were discarded after producing poorer relationships with the measured data (i.e., $R^2 = 0.45, 0.67$, and 0.75 for Allen et
al. [1998], Donatelli and Campbell [1998], and Bristow and Campbell [1984], respectively.

### Biophysical Modeling

APSIM-Growth was previously used to simulate the aboveground mass production of Bambatsi colored Guinea grass (Panicum coloratum L.) (Whitbread and Craig, 2010). The APSIM model uses a daily time-step calculation to simulate the growth and partitioning of mass between leaves, stems, senescent mass, and roots. The APSIM-Growth model calculates pasture growth according to

$$\Delta G_t = \text{Rad}_\text{int} \cdot \text{RUE} \cdot \min(F_t, F_N, F_{\text{VPD}}) \cdot F_w$$  \[1\]

where $\Delta G_t$ is daily growth (kg DM ha$^{-1}$ d$^{-1}$), $\text{Rad}_\text{int}$ is daily intercepted global solar radiation (MJ m$^{-2}$), RUE is the radiation use efficiency (g DM MJ$^{-1}$), $F_t$, $F_N$, $F_{\text{VPD}}$, and $F_w$ are growth modifiers for temperature, N, vapor pressure deficit, and soil water supply, respectively. The value of $\text{Rad}_\text{int}$ was calculated using crown cover, leaf area, and an assumption of exponential light extinction. The values of $F_t$ and $F_{\text{VPD}}$ were calculated based on the average daily temperature and vapor pressure deficit. The value of $F_N$ was calculated based on the leaf N concentration. The value of $F_w$ was calculated as the ratio of soil water demand and supply (APSIM, 2011).

In APSIM-Growth, the water plant demand is calculated using the Micromet module (Kelliher et al., 1995; Snow et al., 1999). Pasture water uptake is calculated assuming that uptake of water from the soil follows a simple first-order decay with soil drying (APSIM, 2011). A more complete description of APSIM can be found in Keating et al. (2003).

### Empirical Approaches

The degree-day model was calculated according to Ometto (1981):

$$DD_i = \sum\left(\frac{\max t_i - \min t_i}{2}\right) - bt \quad \text{if } \min t_i > bt$$  \[2\]

$$DD_i = \sum\left(\frac{(\max t_i - bt)^2}{2(\max t_i - \min t_i)}\right) \quad \text{if } \min t_i \leq bt$$  \[3\]

where $DD_i$ is the daily calculated degree days ($^\circ$C d$^{-1}$), $\max t_i$, $\min t_i$, and $bt$ are the daily maximum and minimum air temperatures and the base temperature ($^\circ$C) for pasture growth, respectively.

The photothermal-units model was calculated using (Villa Nova et al., 1983, 1999)

$$PU_i = \sum\left[\frac{(n/2)^{DD_i/N_i+1}}{N_i/N_i+1}\right]$$  \[4\]

where $PU_i$ is the daily calculation of photothermal units, $n$ is the number of regrowth days, $DD$ is the sum of degree days of the regrowth period as in Eq. [2] and [3], and $N_i$ and $N_i'$ are the day lengths at the end and at the start of the regrowth period, respectively.

The climatic growth index model was adapted from Fitzpatrick and Nix (1973). This model estimates the growth of the pasture based on the average air temperature and incident solar radiation:

$$\text{CGI}_i = \text{LI}(\text{TI})$$  \[5\]

where CGI$_i$ is the calculated daily climatic growth index, LI is a light index calculated based on the incident solar radiation as

$$LI = 1.0 - \exp\left[-3.5\left(23.92R_i/750\right)\right]$$  \[6\]

where $R_i$ is the daily total solar radiation (MJ m$^{-2}$), and TI is a thermal index for tropical grasses based on the average air temperature as in Mota et al. (1981).

### Calibration of Models

The empirical models were fitted as simple linear regressions ($Y = \beta_0 + \beta_1X_i + \varepsilon$) using the REG procedure of SAS version 9 (SAS Institute, 2002). The values of the DM production were used as dependent variables (calibration data set) and the calculated inputs as independent variables (i.e., $DD_i$, $PU_i$, and $\text{CGI}_i$).

In APSIM-Growth, the original parameters for base and optimum temperatures, radiation use efficiency, and specific leaf area (SLA) were replaced by those calculated from the calibration data set. The physical properties of the soil—bulk density and water content at saturation, field capacity, and the permanent wilting point—were measured (pressure plate) and are listed in Table 1. Thereafter, the performance of the APSIM-Growth model was assessed using linear regressions between the measured and simulated values of the DM production.

### Validation of Models

During validation, the performance of the different models was compared by calculating the mean bias error (MBE), coefficient of variation (CV), and the agreement index ($D$) between the observed and simulated values. The MBE (kg DM ha$^{-1}$) shows the magnitude of the average overestimation (positive values) or underestimation (negative values) of the model and was calculated as

$$\text{MBE} = \frac{\sum_{i=1}^{n}(S_i - O_i)}{n}$$  \[7\]

The CV (%) shows the average deviation between simulated and observed values:

$$\text{CV} = \left[\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}\right]^{0.5}$$  \[8\]

The agreement index gives the proportion of the observed variance that is explained by the model and was calculated as proposed by Willmott (1981):

$$D = 1 - \frac{\sum_{i=1}^{n}(S_i - \tilde{O}_i)^2}{\sum_{i=1}^{n}(S_i - \bar{O})^2 + (O_i - \bar{O})^2}$$  \[9\]

where $S_i$ is the estimated value, $O_i$ is the corresponding observed value, $n$ is the number of observations, and $\bar{O}$ is the observed
Optimum values of the MBE and CV are closer to zero and for $D$ are closer to 1. The models were evaluated for irrigated and rainfed conditions using independent data sets.

To simulate the rainfed pasture treatments, the predictors from empirical models were modified using a crop water stress index (WI). The WI was calculated to adjust the maximum potential production, estimated by the equations for DD$_i$, PU$_i$, and CGI$_i$ calibrated under irrigated and fertilized conditions, to the observed climatic conditions. The values of WI were calculated as in Fitzpatrick and Nix (1969), i.e., as the ratio between actual evapotranspiration ($E_a$) and potential evapotranspiration ($E_p$):

$$\overline{WI} = \frac{1}{n} \sum_{i=1}^{n} WI_i$$

where $\overline{WI}$ is the average crop water stress index for each regrowth period, $n$ is the number of days of regrowth, and $WI_i$ is the ratio $E_a/E_p$ for each $i$th day. A $WI_i$ value of 1 indicates no water limitation (i.e., $E_a = E_p$), and values <1 indicate increasing water stress. The values of $E_a$ were calculated from a sequential water balance (Thornthwaite and Mather, 1955), and $E_p$ was calculated as in Thornthwaite (1948). A crop coefficient equal to 1 and a maximum plant-available water holding capacity of 100 mm were used.

We assumed a linear relationship between the DM production of each regrowth period and the corresponding WI value. The potential DM production was calculated as

$$Y_i = a_i + b_i \text{Input} \left( \sum_{j=1}^{n} \text{DD}_j, \text{PU}_j, \text{or CGI}_j \right) \overline{WI}$$

where $Y_i$ is the simulated DM production (kg ha$^{-1}$ cut$^{-1}$) 0.3 m above the soil surface for each empirical model (DD$_i$, PU$_i$, and CGI$_i$), $a_i$ and $b_i$ are linear empirical parameters estimated individually for Input(DD$_j$, PU$_j$, and CGI$_j$) during calibration with the independent data set, and $\overline{WI}$ was calculated as in Eq. [10].

### Results and Discussion

#### Parameters Calculated

Variation in the $\text{RUE}_{\text{PAR}}$ values determined during the year (Fig. 1a) indicated that season influences $\text{RUE}_{\text{PAR}}$. Alexandrino et al. (2005) also observed different values of $\text{RUE}$ for Mombaça Guinea grass during the fall (0.54 g MJ$^{-1}$) and summer (1.76 g MJ$^{-1}$) in Brazil (18°41′ S, 49°23′ W). Their experiment was rainfed, however, and therefore it was not possible to infer if the different values were due to changes in the soil water availability or to other variables, e.g., light quality, air temperatures, or vapor pressure deficits (Rodriguez and Sadras, 2007).

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#### Table 1. Physical properties of the soil for the 0- to 60-cm depth in 10-cm increments.

<table>
<thead>
<tr>
<th>Property</th>
<th>0–10 cm</th>
<th>10–20 cm</th>
<th>20–30 cm</th>
<th>30–40 cm</th>
<th>40–50 cm</th>
<th>50–60 cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulk density, g cm$^{-3}$</td>
<td>1.30</td>
<td>1.39</td>
<td>1.44</td>
<td>1.48</td>
<td>1.54</td>
<td>1.56</td>
</tr>
<tr>
<td>Saturated upper limit (0.0 MPa), g kg$^{-1}$</td>
<td>500</td>
<td>470</td>
<td>450</td>
<td>440</td>
<td>410</td>
<td>410</td>
</tr>
<tr>
<td>Field capacity (–0.01 MPa), g kg$^{-1}$</td>
<td>265</td>
<td>227</td>
<td>223</td>
<td>235</td>
<td>252</td>
<td>255</td>
</tr>
<tr>
<td>Permanent wilting point (–1.5 MPa), g kg$^{-1}$</td>
<td>156</td>
<td>133</td>
<td>137</td>
<td>154</td>
<td>164</td>
<td>171</td>
</tr>
</tbody>
</table>
In Australia, Rodriguez and Sadras (2007) observed that changes in the fraction of diffuse radiation in a latitudinal transect from South Australia to Queensland explained about 96% of the variation ($R^2$) in the RUE for wheat ($Triticum aestivum$ L.) plants ($n = 329$, $P < 0.001$). Considering that our data sets were from irrigated trials, we can say that the variations observed in RUEPA R were probably driven by changes in climatic conditions other than precipitation. A quadratic relationship between RUEPA R and the air average temperature was observed (Fig. 1b) ($R^2 = 0.84$, $n = 6$, $P < 0.06$). The influence of air temperatures on RUE have also been reported for other species (Sinclair and Muchow, 1999), including C4 crops (Andrade et al., 1993).

The optimum temperature for Mombaça Guinea grass growth was set between 21 and 21.9°C in APSIM-Growth based on the lowest and highest air average temperatures to achieve 90% of the relative RUEPA R values (Fig. 1b). Cruz (2010) estimated the optimum temperature for Marandu palisade grass growing in Brazil to be between 27 and 35°C. Values between 26 and 30°C have also being reported as optimum for the growth of other tropical and subtropical pastures: buffel grass ($Cenchrus ciliaris$ L.), Rhodes grass ($Chloris gayana$ Kunth), Trichoglume Guinea grass, Makarikariense colored Guinea grass, panic clandestin ($Panicum clandestinum$ L.), and Texas panicum ($Panicum texanum$ L.) (Ivory and Whiteman, 1978; Patterson, 1990).

The temperature range observed during this experiment did not allow us to estimate the upper base temperature (Fig. 1b) (relative RUEPA R < 10%), therefore the default value of 50°C in APSIM-Growth was used.

Few lower base temperature values are reported for tropical grasses, but values of 12, 15, 17.2, and 17.5°C have been reported for Florico African Bermuda grass ($Cynodon nlemfuensis$ Vanderyst), Napier elephant grass (Villa Nova et al., 2007), Marandu palisade grass (Cruz et al., 2011), and Mombaça Guinea grass (Moreno, 2004), respectively. In this study, we estimated a base temperature of 15.6°C for Mombaça Guinea grass (Fig. 1c).

In APSIM-Growth, the value of SLA for Bambatsi colored Guinea grass is 15 m2 kg–1. In this study, the values of SLA observed for Mombaça Guinea grass ranged from 13.6 to 25.9 m2 kg–1 (Table 2).

### Table 2. Parameter names, definitions, and initial values for Bambatsi colored Guinea grass and estimated for Mombaça Guinea grass.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Bambatsi</th>
<th>Mombaça</th>
</tr>
</thead>
<tbody>
<tr>
<td>RUE, g dry matter MJ–2</td>
<td>radiation use efficiency maximum</td>
<td>2.0</td>
<td>1.95†</td>
</tr>
<tr>
<td>Photosynthesis modifiers</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$b_T$, °C</td>
<td>base temperature</td>
<td>13</td>
<td>15.6</td>
</tr>
<tr>
<td>$OT_1$, °C</td>
<td>first optimum temperature</td>
<td>25</td>
<td>21.0</td>
</tr>
<tr>
<td>$OT_2$, °C</td>
<td>second optimum temperature</td>
<td>35</td>
<td>21.9</td>
</tr>
<tr>
<td>$MT$, °C</td>
<td>maximum temperature</td>
<td>50</td>
<td>50‡</td>
</tr>
<tr>
<td>$F_{dl}$, h</td>
<td>day-length component modifier for dry matter partitioning; 0 = stress, 1 = no stress</td>
<td>12.5 (0), 13.5 (1)</td>
<td>ignored</td>
</tr>
<tr>
<td>Specific leaf area, m2 kg–1</td>
<td>min. and max. specific leaf area</td>
<td>15.0 and 15.0</td>
<td>13.6 and 25.9</td>
</tr>
</tbody>
</table>

† Photosynthetically active radiation use efficiency.
‡ The maximum temperature for modifying photosynthesis was not estimated; the default was used.

In APSIM-Growth model (a) with default parameters, (b) the effect of the daylength component modifier ($F_{dl}$) of DM partitioning (default parameters), (c) default parameters without $F_{dl}$, and (d) parameters calibrated for Guinea grass and used throughout the simulation or modified for the fourth regrowth cycle. Each point is the average of four replications. Vertical bars represent the standard error.

Fig. 2. Observed (symbols) and predicted (lines) dry matter (DM) production for irrigated Guinea grass using the APSIM-Growth model (a) with default parameters, (b) the effect of the daylength component modifier ($F_{dl}$) of DM partitioning (default parameters), (c) default parameters without $F_{dl}$, and (d) parameters calibrated for Guinea grass and used throughout the simulation or modified for the fourth regrowth cycle. Each point is the average of four replications. Vertical bars represent the standard error.
Calibration

APSIM-Growth

Using the original Bambatsi colored Guinea grass parameterization in APSIM, APSIM-Growth was not able to accurately estimate pasture regrowth during the fall and winter seasons (second, third, and fourth cycles) and underestimated the DM production during the spring and summer (Fig. 2a). The model was simulating pasture growth very slowly during the fall and winter seasons, however, as most of the mass was partitioned into roots (Fig. 2b). The APSIM-Growth model has a day-length component modifying the partitioning of mass between shoots and roots ($F_{dl}$):

$$\text{partition\_stress} = \min\left(F_w, F_{fsw}, F_N, F_{dl}\right)$$

where $F_w$, $F_{fsw}$, $F_N$, and $F_{dl}$ are partition modifiers for soil water supply and stresses due to water and N supply and day length (h), respectively.

The $F_{dl}$ modifier was then ignored and this greatly improved the model performance, particularly during fall and winter (Fig. 2c). When this parameter was estimated for Mombaça Guinea grass (Table 2), however, the performance of the model significantly improved, with only a small overestimation during the middle summer to late winter period (first, second, and fourth cycles; Fig. 2d).

When the observed values of RUE$_{PAR}$ were used, the simulation for the winter regrowth (fourth cycle) showed a better fit than simulation using the original values in APSIM (Fig. 2d, dashed line). The RUE$_{PAR}$ was not calculated for the regrowth period between midsummer and late fall (first and second cycles) because the RUE$_{PAR}$ was not estimated for this period (Fig. 1a).

Similar results were observed by Dolling et al. (2001) during the parameterization of the APSIM-Lucerne model. In that work, a constant RUE value was used to simulate the biomass growth rate between fall and spring seasons in Western Australia. They observed a large bias (–64%) between simulated and observed data; however, adjusting the RUE as a function of days after cutting [i.e., RUE = –1.2 + 26.6(0.93$^{days}$) + 0.02 days; $P < 0.001$, $R^2 = 0.70$] greatly improved the relationship between simulated and observed growth rates, and the bias was reduced to –5%.

In our simulations, we set up the model to use the maximum value of RUE$_{PAR}$ and its temperature modifiers, as calculated from the calibration data set (Table 2).

Empirical Approaches

The comparison of observed and simulated values of pasture growth had high, positive, and significant Pearson’s correlations between 0.88 and 0.93 ($P < 0.0001$). When simple linear regression equations were fitted to the data, the estimated parameters showed values of $R^2 \geq 0.78$. The highest $R^2$ was observed for PU$_i$, which also had the lowest CV (26%) (Fig. 3a).

The high values of $R^2$ ($\geq 0.78$) indicated that simple relationships could be used to predict the production of the Mombaça Guinea grass. High correlation values between the production and climatic parameters were also observed by Cruz et al. (2011), Araujo et al. (2010), and Tonato et al. (2010) working with tropical pasture in Brazil. Tonato et al. (2010), however, proposed that minimum air temperature is sufficient.
to predict the growth rate for well-watered *Cynodon, Panicum,* and *Urochloa* spp. in Brazil. Cruz et al. (2011) observed a better simulation (simple linear equation) for palisade grass grown under rainfed conditions when climatic variables such as solar radiation and average, maximum, and minimum air temperatures were adjusted by an empirical water deficit index calculated from a simple water balance:

\[
DMAR = a \left[ \text{Input}_i \left( \frac{E_a}{E_p} \right) \right] + b \quad [13]
\]

where DMAR is the simulated rate of DM accumulation, \(a\) and \(b\) are linear empirical parameters estimated from an independent data set, \(\text{Input}_i\) are the independent variables (\(i\) = solar radiation or average, maximum, or minimum air temperatures), and \(E_a\) and \(E_p\) are the actual and potential evapotranspiration, respectively.

Despite these researchers having used different cultivars and climatic variables, all of them reported that empirical approaches using fewer climatic inputs can provide good predictions after model validation, independently of the forage species under study.

**Validation**

A high degree of agreement between simulated and observed values of pasture regrowth was found during validation (Fig. 4). The models explained between 69 and 78% of the observed variability in DM production (\(DD_i > PU_i = APSIM > CGI_i\); Fig. 4). The slopes of the relationships between observed and simulated results were not different from 1 (\(P \leq 0.001\)).

The positive MBE values indicate that the models, generally, overestimated more than underestimated Mombaça Guinea grass DM production (Fig. 4). This overestimation was lower for APSIM-Growth (6 kg DM ha\(^{-1}\)) and higher for \(PU_i\), \(DD_i\), and \(CGI_i\) (268, 318, and 470 kg DM ha\(^{-1}\), respectively) (Fig. 4).

Overestimation of DM production for Marandu palisade grass was also observed by Cruz et al. (2011) using \(DD_i\) and \(CGI_i\) approaches. They suggested that this overestimation was due to contrasting management of the pastures between the calibration and validation data sets (i.e., different in height and frequency of defoliation). The same could have occurred with the Mombaça Guinea grass DM simulation, given that different methods of defoliation were used for the calibration (cutting) and validation (cutting and grazing) data sets. The overestimation error was lower for the \(PU_i\) and APSIM-Growth models than the \(DD_i\) and \(CGI_i\) models (Fig. 4a and 4c) when the same data sets were used during the validation. This indicated that changes in pasture management can affect the simulated DM production, especially when estimated using empirical models that were unable to reproduce changes in pasture management compared with biophysical models, e.g., APSIM-Growth. Another important point is the observed overestimations of mass production by the empirical models. This suggests that these simple models were not able to reproduce water stress as well as APSIM-Growth.

**SUMMARY**

We parameterized and validated four models of contrasting complexity level to simulate the production of a \(C_4\) tropical pasture grass, Mombaça Guinea grass, and discussed the criteria for model selection in terms of their suitability for research and
a range of practical applications. The parameterized model is expected to assist forage researchers and farm managers better plan forage production systems in Brazil. We used a data set from three well-designed and well-managed experiments to independently calibrate and validate each model. Our results show that all the models simulated the production of Mombaça Guinea grass DM with high accuracy.

In general, the empirical approaches were simpler to use because they required fewer inputs that are generally widely available. It is important to highlight, however, that their use may be limited to regions having similar climates and soils and to pastures under similar management conditions. The results from APSIM indicate that this model provides greater flexibility to account for different management, soil, and climate. Therefore, we propose that APSIM would be better suited than the empirical models to assist in more detailed research programs or where climate, soil, and management parameters are available.

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