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Modeling Herbaceous Biomass and Assessing Degradation Risk in the Caatinga Biome Using Monte Carlo Simulation

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Abstract

Simulating scenarios under climate change is essential to understanding vegetation dynamics, ensuring the survival of forage species, and minimizing uncertainties in project costs and timelines. This study aimed to simulate historical probabilities and develop a biomass production model using PHYGROW software (Texas A&M University, College Station, TX, USA), combined with Monte Carlo Simulation (MCS) in the @RISK program (Ithaca, NY, USA), to evaluate long-term biomass production in a native pasture area of the Caatinga biome. The results show strong agreement between software estimates and field data. For 2016, PHYGROW estimated 883 kg/ha, while field measurements reached 836.8 kg/ha; for 2017, 1117 kg/ha was estimated, while 992.15 kg/ha was observed. For 2018, the model estimated 1200 kg/ha compared with 1763.5 kg/ha in the field, and for 2019, 1230 kg/ha was estimated versus the 1294.3 kg/ha observed. The Monte Carlo simulations indicated that the Weibull distribution best fitted the synthetic series, with 90% adherence. Biomass production values ranged from 618 to 1427 kg/ha with a 90% probability. Only 5% of the simulations projected values below 600 kg/ha or above 1400 kg/ha. Moreover, there was a 95% risk of production issues if planning was based on biomass values above 1000 kg/ha. These findings highlight PHYGROW's potential for pasture management under semi-arid conditions for predicting and avoiding degradation scenarios that could even lead to areas of desertification.

Keywords: environmental; sustainability; prediction; livestock; dynamic systems

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1. Introduction

The Caatinga biome encompasses the entire northeastern region of Brazil and is recognized as the only biome that is exclusively Brazilian, as well as one of the largest in the country. It is characterized by a diverse vegetation, including a wide range of plant species with forage potential, and vast areas of secondary succession resulting from uncontrolled anthropogenic activities. Occupying approximately 11% of Brazil's territory and hosting significant biodiversity, the Caatinga is currently undergoing an alarming process of desertification. This degradation is being accelerated by factors such as inappropriate land and water use, deforestation, and climate change [1–3].

Despite its significant contribution to sustaining livestock during drought periods, forage biomass production in the Caatinga biome is highly susceptible to climatic variability. As a result, the pasture's carrying capacity has declined over the years [4,5]. Therefore, sustainable exploitation is essential to preventing potential losses in livestock and the disappearance of forage species with high nutritional value. Such practices are also crucial to preserving floristic diversity within the biome [5].

Climatic conditions are a limiting factor for plant growth in the semi-arid region, leading to instability in both native pastures and the establishment and development of cultivated pastures [6]. The greatest challenge for livestock production in these areas, particularly within the Caatinga biome, is ensuring the availability of nutritionally adequate and low-cost feed for the herd, as small-scale producers in these regions often rely on pastoral activities during drought periods [7,8]. In this context, the native pastures of the Caatinga biome represent the most viable and cost-effective alternative for livestock production and a great source of feed ingredients, especially during the rainy season, as most of its plants have high protein content [9].

Simulating scenarios under climate change conditions is of fundamental importance, as it provides an overall perspective on the area's plant production. It becomes essential to understand the probability of the modeled scenarios occurring over the years, especially considering that most farms do not adopt conservation practices. This lack of sustainable management can lead to the depletion of native species' energy reserves and, potentially, their extinction, thereby driving the vegetation toward a disclimax state [10,11].

PHYGROW (PHYSically-based GROwth model) is an ecological simulation model designed to estimate pasture growth, biomass production, and availability based on climatic variables (such as precipitation and temperature), soil characteristics, and plant attributes [12]. When integrated with probabilistic analysis tools like @RISK, which employs Monte Carlo Simulation, PHYGROW becomes even more valuable for projects aimed at the restoration of degraded areas and the mitigation of desertification risk, particularly in semi-arid regions. Monte Carlo Simulation enables PHYGROW to generate multiple potential biomass growth scenarios based on historical climatic variability and soil/plant conditions [13]. This allows for the estimation of the probability of success or failure of pasture management strategies over time.

Monte Carlo Simulation (MCS) is a feature of @RISK software (Ithaca, NY, USA) that plays a key role in such contexts by providing a probabilistic and comparative modeling approach. It enables the identification of factors that may indicate future or even short-term problems, based on equations and tests applied to a synthetic data series generated through simulation [14]. A thorough understanding of each variable analyzed by the model is essential, as the selected scenario must be carefully studied and aligned with the software application's capabilities. The MCS tool in @RISK thus directly contributes to the development of emergency strategies and also supports planning processes, given its functionality and result accuracy. As a decision support and investigative tool, it helps prevent unforeseen setbacks and economic losses during project implementation [15].

In studies involving simulations, such as those assessing plant biomass, it is essential to consider the uncertainty associated with environmental data and to evaluate their relationship with the outcomes by analyzing and linking them to potential risks. In this context, the Monte Carlo method stands out as a simulation technique widely recognized as a state-of-the-art methodology in risk analysis. It can be applied in various studies focused on risk assessment and management, including those involving multi-criterion decision making [16,17]. Accordingly, the Monte Carlo system has been employed as a numerical method capable of solving mathematical problems through simulation using random variables [18,19]. From this perspective, the Monte Carlo approach allows for a precise and analytical evaluation of the effect of uncertainty on the demand for herbaceous biomass in the Caatinga, making it a valuable tool for decision making in this field of study.

In degraded areas, the use of the PHYGROW model is essential to identifying optimal strategies for vegetation cover restoration based on realistic risk scenarios. It supports sustainable land-use planning by adapting management practices, such as stocking rate, forage species selection, fertilization, and irrigation, to the pasture's actual carrying capacity. PHYGROW also enables the assessment of the resilience of native and/or cultivated vegetation in response to extreme climatic events (e.g., prolonged droughts and heatwaves); the prediction of desertification risks, since areas with a high probability of low biomass production over time signal an urgent need for intervention; and the optimization of financial and technical resources by prioritizing practices with the highest likelihood of success in each scenario [12,20]. In summary, PHYGROW, when integrated with Monte Carlo Simulation, can serve as a risk-based decision support tool, enhancing the effectiveness of land restoration projects and promoting the sustainability of ecosystems vulnerable to desertification [13,15].

Unlike previous studies that rely solely on empirical field data or deterministic models for biomass estimation in semi-arid ecosystems, this study introduces an innovative approach by integrating the Phyweb 2.0 version (Texas A&M University, College Station, TX, USA) of the PHYGROW model with Monte Carlo Simulation using the @RISK platform. This integration enables the quantification of uncertainty and the assessment of degradation risk in herbaceous biomass production within the Caatinga biome. Additionally, the model is calibrated and validated using historical climate data and soil–vegetation parameters specific to the Brazilian semi-arid region, making this one of the first efforts to evaluate forage dynamics in this biome through stochastic simulation. These methodological advancements enhance predictive robustness under climatic variability and provide valuable decision-making support for sustainable grazing management in dryland systems.

Therefore, by employing this new method of obtaining rapid and realistic information, the search for solutions becomes more objective and specifically tailored to local challenges, as the models assess each perspective individually and integrate the results. MCS in @RISK contributes directly to the development of emergency strategies and also supports the planning process, considering its full functionality and accuracy. It serves as both a diagnostic and decision support tool, helping to prevent unforeseen setbacks and economic losses during implementation. The objective of this study was to develop a biomass production model by using PHYGROW software (Texas A&M University, College Station, TX, USA) and simulate the probabilities of the biomass history generated by PHYGROW through MCS with @RISK software (Ithaca, NY, USA). Synthetic data were generated to evaluate the long-term behavior of biomass production in a native pasture area within the Caatinga biome.

2. Materials and Methods

2.1. Characterization of the Experimental Area

The experiment was conducted at the Lameirão Experimental Farm (coordinates: 7°02′52.5″ S, 37°29′31.6″ W), which is part of the Center for Health and Rural Technology of the Federal University of Campina Grande, located in the municipality of Santa Terezinha, in the semi-arid region of the state of Paraiba, Brazil (geographic coordinates: 7°5′ S, 37°27′ W).

The experimental area used for model calibration and validation comprises 4 hectares. In 2015, research activities focusing on the management of regrowth in *Mimosa tenuiflora* (Willd.) Poiret, commonly known as *Mimosa*, and floristic composition assessments were initiated. As the area represents a secondary succession ecosystem and ongoing studies on management and conservation are in place, it has remained free of grazing since the implementation of the management plan (Figure 1).

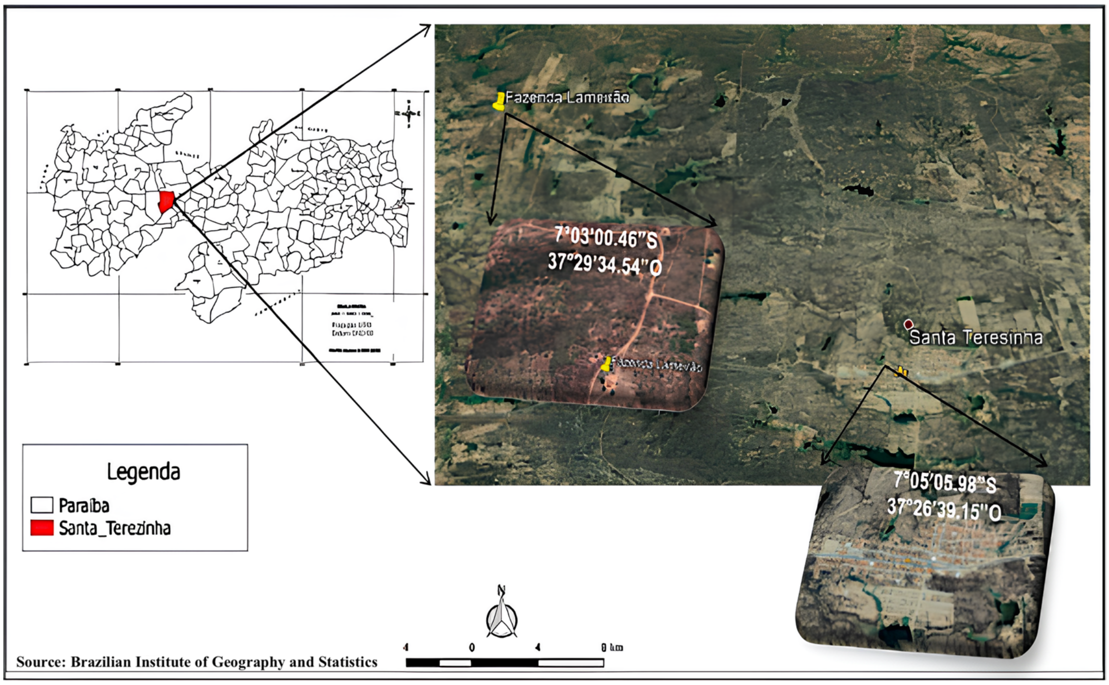

Figure 1. Satellite image of the experimental area at Lameirão Farm, Santa Terezinha city, Paraiba state, Brazil. Source: Google Earth.

The region has a BShw′ climate, according to the Köppen classification, i.e., hot and dry with a rainy season from January to May, with greater rainfall in the first months of the year, with an average annual temperature of 20 °C to 32 °C [21]. Annual rainfall varies by year, but the historical annual average is 840 mm, thus recording, in 2018, a total of 769 mm (Figure 2). However, rainfall also varies by month in the region, which makes it difficult to establish agricultural crops and biomass production in the area [22].

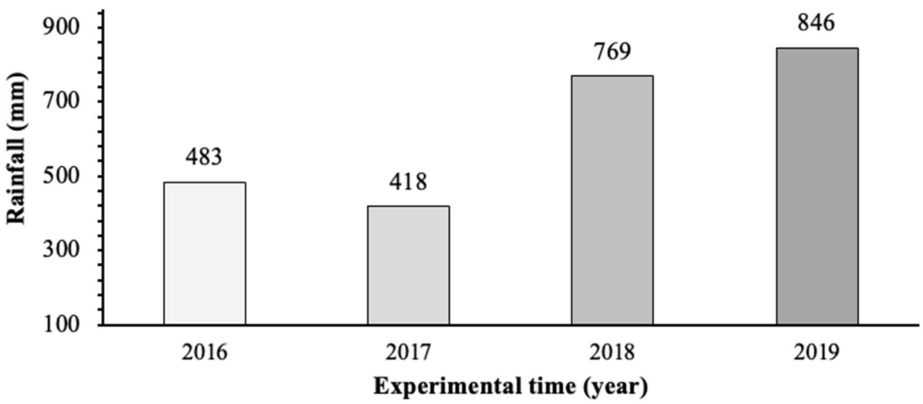

Figure 2. Annual precipitation (mm) in the municipality of Santa Terezinha city, Paraiba state, Brazil, during the experimental period. Source: INMET [18].

Climatic condition data were obtained from the Climate Prediction Center of the National Oceanic and Atmospheric Administration (NOAA), while temperature data were sourced from the Global Data Assimilation System (GDAS); both datasets were directly integrated into the simulation software.

Additionally, climatological data from the nearest weather station of the Brazilian National Institute of Meteorology (INMET) were used to validate the biomass production outputs generated by the model. Solar radiation was estimated based on local temperature and latitude using the method described by Samani [23].

The soils in the experimental area exhibit diverse compositions, with Luvisols and Planosols being the most common and small occurrences of dystrophic litholic soils [24]. These soils are generally shallow, with potential gravel content in the surface horizon and deficient drainage, and are typically reddish or yellowish in color. They also exhibit high cation exchange activity [25]. Soil characteristics from the years 2016, 2018, and 2019 are detailed in Table 1.

Table 1. Chemical characteristics of the soil in the experimental area, Lameirão Farm, Santa Terezinha city, Paraiba state, Brazil.

Site	PH	P (mg/dm^3)	Ca	Mg	K (cmolc/dm^3)	Na	H + Al	T (%)	V (%)
					2016				
1	6.5	1.06	7.0	4.8	0.50	0.17	1.2	13.67	91.22
2	6.1	2.32	6.6	4.0	0.33	0.17	1.2	12.31	90.25
3	5.6	1.52	6.5	3.5	0.36	0.17	1.5	12.03	87.53
4	5.9	5.22	6.9	4.1	0.36	0.22	1.5	13.08	88.53
					2018				
1	5.0	3.90	7.0	3.4	0.19	0.22	2.0	12.78	84.35
2	5.0	6.60	6.5	3.5	0.17	0.22	2.0	12.36	83.82
3	4.4	7.30	5.2	3.0	0.15	0.26	2.2	10.85	79.73
4	4.7	9.40	6.0	3.0	0.19	0.22	2.1	11.83	82.25
					2019				
1	5.0	3.90	7.0	3.4	0.19	0.22	2.0	12.78	84.35
2	5.0	6.60	6.5	3.5	0.17	0.22	2.0	12.36	83.82
3	4.4	7.30	5.2	3.0	0.15	0.26	2.2	10.85	79.73
4	4.7	9.40	6.0	3.0	0.19	0.22	2.1	11.83	82.25

The predominant vegetation in the study area is shrub–arboreal, with approximately 65% ground cover by woody species, distributed across three strata: arboreal, shrub, and herbaceous. The flora is primarily composed of small trees and shrubs of deciduous species, which shed their leaves as a defense mechanism against drought, as well as xerophytic plants, bromeliads, cacti, and a representative number of annual herbaceous grasses and forbs [26].

The area exhibits signs of degradation, indicated by the presence of species such as *Croton sonderianus* and *Mimosa tenuiflora* (Jurema preta). Herbaceous stratum species include grasses such as *Brachiaria plantaginea*, *Panicum* spp., *Setaria* spp., and *Aristida setifolia*. Among the legumes, the most notable are *Senna reticulata*, *Stylosanthes* spp., *Desmodium barbatum*, *Arachis* spp., and *Macroptilium lathyroides*. Additionally, common herbaceous dicotyledons found in the area include *Mesosphaerum suaveolens*, *Sida cordifolia*, and *Ipomoea glabra* [23,25,26].

2.2. PHYGROW Simulation Model

The Phytomass Growth (PHYGROW) simulation model is a model used to estimate biomass production values in each area based on local information on soil, plants, grazing, and daily and climate variables. It is a model widely used in countries such as Mongolia [27], the United States [28], and East Africa [20] with an online access platform, Phyweb 2.0, which is a more detailed version with the variables that need to be fed being available in the layout. The software has mechanistic characteristics that consider the laws of physics, chemistry, and biology, and stochastic characteristics, since it uses climate as a random variable. The model itself is based on hydrology, since it simulates soil water balance, with precipitation and climate being the main variables that influence the estimates [29]. In this way, the model simulates plant growth under ideal conditions and then reduces growth based on water stress and minimum, maximum, and optimum temperatures of the species [30]. The model variables also include soil data such as woody species cover, depth rate, density, infiltration, and water retention capacity, many of which are automatically filled in by the server database.

Phygrow can simulate growth conditions for groups of plant species, as well as for just one species. The data used for a group are tree and shrub cover, percentage of grass cover, floristic frequency, and initial harvest (crops), and for just one species, the required variables are minimum, ideal, and optimum temperature; the leaf area index (LAI) obtained by the MODIS sensor; cloud-free satellite images; solar radiation use efficiency; litter decomposition; and water movement in the canopy.

2.3. Database and Model Calibration

The data collection database was uploaded into Phyweb 2.0 under the scenario description tab, where specific information regarding the location and species growth behavior within the experimental area was entered. These data were sourced from previous dissertation studies conducted by Ferreira [25], Silva [30], and Morais [31].

Climatic information was automatically populated in the software's configuration interface via the National Oceanic and Atmospheric Administration (NOAA), and temperature data were sourced from the Global Daily Assimilation System (GDAS) database, alongside vegetation species already registered in the system's server database. Climate data from the meteorological station closest to the experimental area were also used for cross-validation with NOAA-derived values, specifically minimum and maximum temperatures and precipitation levels.

Edaphic condition data were obtained through the interpretation of local soil physicochemical analyses conducted during the initial establishment of the transect and identified through the Brazilian Soil Database. Soil texture and slope parameters were input into the model as percentages. Regarding species groups or functional groups, the model allows for the inclusion of many entries but requires specific information for each species. These data can be retrieved from the server's database, with optional user-defined adjustments.

Following the calibration process, which involved comparing the field-collected data with model-generated estimates, biomass production values were expressed in kg/ha. Functional groups used in the model included grasses and herbaceous dicotyledons. *Sida cordifolia* L. (commonly known as Malva Branca) was entered individually during the calibration phase, as it exhibited the highest relative frequency (>65%) in the experimental area. To provide a comprehensive overview of biomass production at the experimental site, the model outputs were compared against observed data, initiating the validation phase thereafter.

2.4. Model Validation

Validation was carried out with the first simulation for the experimental site of plant biomass production from previous years with existing data from collections and work developed in the experimental area (Figure 3).

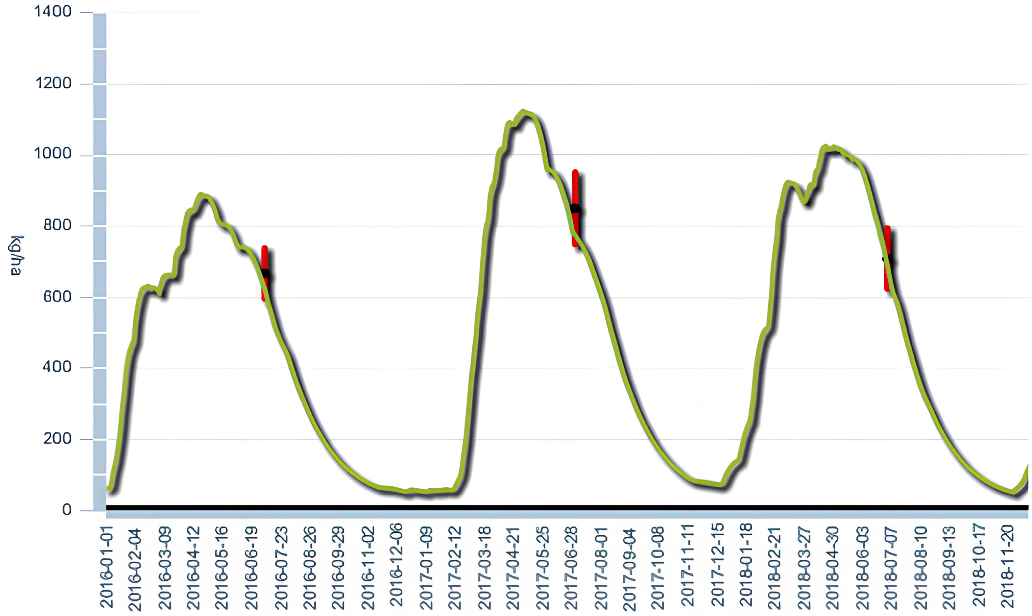

Figure 3. Validation graph of the total biomass of the herbaceous stratum in the experimental area of Santa Terezinha city, Paraiba state, Brazil. Source: Phyweb 2.0.

The software utilized satellite imagery and geolocation data to establish a permanent cross-shaped transect, with each arm extending 25 m from the center and a strip width of 2 m [32]. Along each transect, the modified point-intercept method was applied [33–35]. In this method, vegetation intercepts were recorded as a score of 1, while bare soil was not counted. This technique was primarily employed to estimate the percentage of grass cover, the frequency of herbaceous dicotyledons, and shrub canopy coverage.

Comparisons were made with data from the nearest meteorological stations, providing a basis for model calibration and adjustment to the site-specific environmental conditions [36]. In this method, vegetation intercepts were recorded as a score of 1, while bare soil was not, including the integration of species-specific data from the server database. Climate and soil condition data were cross-referenced with those in the software to verify model accuracy in real time for the experimental site. Based on the input species database, the program generated estimations in the form of historical data curves as simulation outputs.

2.5. Database for Simulation in @RISK

Previous studies conducted in the experimental area were incorporated into the PHYGROW model. After calibration and validation, the software generated a historical series of projected values, providing a long-term overview of vegetation productivity from 1950 to the present. Biomass values were obtained from the model-generated growth curves, based on specific information regarding species behavior, growth, and physiological traits observed in the experimental area. For use in the @RISK spreadsheet, only the highest annual biomass values from each year were selected.

2.6. Monte Carlo Simulation in @RISK

@RISK is globally recognized risk analysis software that includes over 50 built-in probability distribution functions, offering sensitivity analyses and identifying critical factors within a given model. Widely applied across various fields, from financial systems to environmental and biodiversity conservation, Monte Carlo Simulation (MCS) offers practical advantages by operating directly within Excel spreadsheets, which facilitates data interpretation.

To ensure simulation accuracy, it is essential to define the variables involved, the data provided by Phyweb 2.0, mainly based on projections from other models or historical data. These inputs allow for the generation of a synthetic series within the same range of values, thereby producing a probable distribution while excluding outliers and replacing them with simulated values. Through a preliminary fitting process (using the "Fit" function), MCS adjusts values and identifies the most uncertain variables within the simulation [13]. In this case, the primary uncertain variable is biomass production.

After this preliminary evaluation, the software generates a graphical output representing the probability of the values provided, under the defined scenario conditions. The displayed distribution curves are ranked by the software based on the best statistical fit to the dataset. However, the final selection of a distribution curve depends on the behavior of the evaluated system. Given that the main issue being analyzed is biomass production under adverse climatic conditions, the Weibull distribution provided the best fit. A composite distribution function was also applied, allowing for the comparison between Weibull and Normal distribution curves.

Subsequently, MCS produced a statistical summary of all tested distributions, assisting in identifying the most suitable method for data evaluation. The report included all statistical processes applied to the spreadsheet values. Model construction was performed step-by-step using the trial version of the software, available freely online through the Palisade developer's website.

2.7. Simulation Steps: Procedures in @RISK

Step 1: After validating the three datasets in PHYGROW, the highest annual biomass production values from the historical dataset (1950–2020) were transferred to an Excel spreadsheet within the @RISK environment. A preliminary data check was performed, and any anomalous values were flagged by the simulation.

Step 2: Following verification, statistical parameters were defined by the software, and the data were subjected to a Chi-square (χ^2) test. The initial simulation was then executed, and a preliminary graph was generated. However, adjustments were still required for the probability distributions.

Step 3: A comparison of distribution curves was conducted. The Weibull and Normal distributions ranked the highest in the software's statistical evaluation, indicating that they best represented the data characteristics (e.g., climatic variability and natural processes).

Step 4: Based on this comparison, the Weibull and Normal distributions were selected, and the adjusted simulation results were generated. A graphical representation was presented in @RISK, showing the frequency and probability of value occurrences over time.

Step 5: Using the existing simulation data, 3000 synthetic values were generated to align with the selected distribution curves. These values ensured that all entries conformed to the identified probabilistic model. The resulting graph, fully adjusted, displayed the occurrence probabilities of the initial data and the overall fit of the simulation method.

Final Step: After completing the adjustments and generating the probability graphs, a final risk analysis chart was produced, along with a comprehensive statistical summary of the simulation results.

2.8. Monte Carlo Validation

To evaluate and validate the values obtained from the Monte Carlo simulation, data on herbaceous vegetation ground cover were used to estimate biomass production [31, 35]. The study area comprised 4 hectares, and the sampling unit was a metal frame measuring 0.25×1.0 m [34]. For each biomass assessment, five ground cover measurements were taken, resulting in 20 biomass samples and 100 ground cover samples per hectare, every 30-day interval, totaling 240 and 1200 samples/ha/year for biomass and ground cover, respectively.

2.9. Confidence Level

The data from the three synthetic series were exported to Excel, and a probability threshold (<0.01) was applied across three columns, each containing 1000 cells. Minimum and maximum values were extracted from each series, and the limits used in the simulation were defined accordingly. To estimate the likelihood of each synthetic series occurring, a specific function was developed and subsequently analyzed using linear regression.

3. Results

Based on the data provided to the software and subsequently validated by it, the result for the biomass production of the experimental site for the year 2016 in the field was 836.8 kg/ha, a value obtained by Ferreira [25] in a study developed in the area. In contrast, the value validated by Phyweb 2.0 (Texas A&M University, College Station, TX, USA) for the same period was 883 kg DM/ha (Table 2); the result generated is similar to that found in the field. For 2017, the estimated biomass was 1117 kg DM/ha, while the field-measured value was 992.15 kg DM/ha (Table 2). Despite the difference between the two values, the model effectively validated the data. In contrast, precipitation increased substantially in 2018, reaching approximately 769 mm according to INMET [22], compared with 479 mm in the previous year. This increase was reflected in higher biomass production, with the software estimating 1200 kg DM/ha for May, while the actual field measurement was 1763.5 kg DM/ha. For 2019, the values were 1230 and 1294.3 kg DM/ha, indicating similarity between Phyweb 2.0 and data, respectively (Table 2).

Table 2. Biomass values estimated by Phyweb 2.0 and field values from 2016 to 2019.

Year Evaluated	Phyweb 2.0 Validated Data (kg DM/ha)	Field Data (kg DM/ha)
2016	883	836.8
2017	1117	992.15
2018	1200	1763.5
2019	1230	1294.3

Source: Ferreira [25], Silva [30], Morais [31], and Phyweb 2.0.

The data from Phyweb 2.0 (Texas A&M University, College Station, TX, USA) showed a linear increase in biomass production over the evaluated years (Figure 4), directly corresponding with increased precipitation levels in the experimental area (Figure 2).

For 2020, the software estimated a biomass production of 1332 kg DM/ha. The Phyweb 2.0 model demonstrated variations in estimated forage production over the 71-year evaluation period. Specifically, there were 4 years with a variation of 1400 kg DM/ha, 6 years with 1350 kg DM/ha, 14 years with 1200 kg DM/ha, 15 years with 1150 kg DM/ha, 5 years with 900 kg DM/ha, 10 years with 800 kg DM/ha, 5 years with 700 kg DM/ha, 6 years with 600 kg DM/ha, 2 years with 500 kg DM/ha, and only 1 year with a minimum value of 479 kg DM/ha. The analysis of the time series reveals that in all evaluated years, forage production remained below 1600 kg DM/ha. The highest recorded value was 1553 kg DM/ha in 1976, and the lowest was 479 kg DM/ha in 1973, with a historical average of 1046 kg DM/ha (Figure 5A).

From 1976 onwards, biomass production declined over the subsequent 44 years, never surpassing 1400 kg DM/ha. Only in 2008 and 2020 did production approach this threshold, with values of 1378 and 1332 kg DM/ha, respectively. Notably, in 1993, the lowest production since 1976 was recorded, with 526 kg DM/ha (Figure 5). Between 2000 and 2012, the lowest estimated production values occurred in 2005 and 2012, with

813 and 712 kg DM/ha, respectively. Conversely, in 2008, production increased to 1377 kg DM/ha and remained relatively high in 2009 with 1311 kg DM/ha, before dropping again in 2010 to 897 kg DM/ha (Figure 5B).

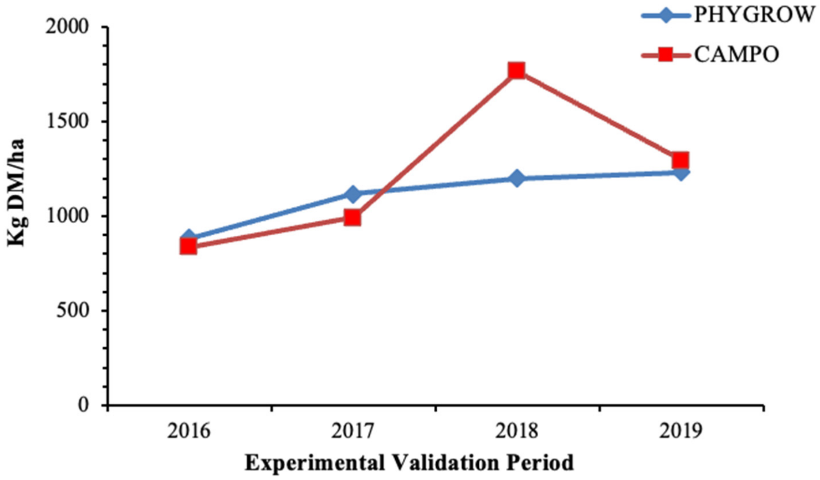

Figure 4. Prediction of biomass (kg of dry matter/ha) of the herbaceous layer, in manipulated Caatinga in the municipality of Santa Terezinha, Paraíba. Data generated by PHYGROW in the experimental interval. Data observed in the field by Ferreira [25], Silva [30], and Morais [31].

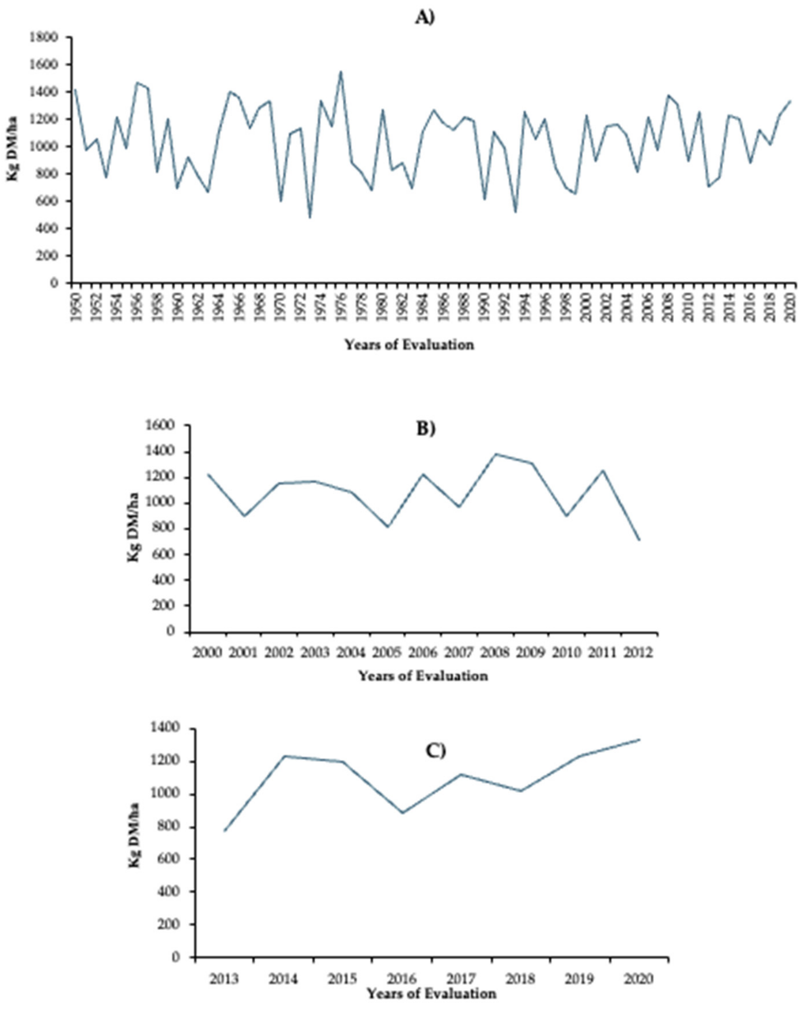

Figure 5. Prediction of biomass (kg of dry matter/ha) of the herbaceous layer in manipulated Caatinga in the municipality of Santa Terezinha, Paraíba state, Brazil, from (**A**) 1950 to 2020, (**B**) 2000 to 2012, and (**C**) 2013 to 2020. Source: Phyweb 2.0.

Only for 2014 and 2015 did the Phyweb 2.0 estimates again reach 1200 kg DM/ha (Figure 5C). For the year 2017, the vegetation responded positively, increasing the production of the herbaceous stratum to 1117 kg DM/ha; for 2018, the value was around 1020 kg DM/ha, and for 2019, it reached 1233 kg DM/ha.

The results of the historical series provided by Phyweb 2.0 had 90% adherence to @RISK software (Figure 3). Regarding the probability distributions, the Weibull curve presented values of 89.2% of occurrence of biomass between the values of 622 and 1417 kg DM/ha and, for the same variable, the probability of 5.2% for values below 600 kg DM/ha and 5.6% above 1400 kg DM/ha in simulation in an interval of 3000 years (Figure 3). For the Normal distribution curve, the probability value for the same production (622 to 1417 kg DM/ha) was 88.1%, and for values below 622 kg, the probability was 4.7%, while for values above 1400 kg, it was 7.2% (Figure 3). The probability for the occurrence of values between 622 and 1417 kg DM/ha is high (89.2%), considering the current problematic production situations involving climate conditions and uncontrolled human action.

The Weibull distribution demonstrated a higher probability of occurrence for the reported values compared with the Normal distribution and better reflected the nature of the data (i.e., natural processes) observed in the time series within @RISK software (input behavior). For these reasons, the Weibull distribution was selected to represent probability under the simulated scenario conditions. The synthetic series generated by @RISK by using the Weibull distribution exhibited a 90% goodness of fit with the historical data (Figure 6B). With the inclusion of these synthetic series, the biomass production estimates also differed from those obtained in the initial phase of the simulation.

The production estimates adapted well to the synthetic model, showing minimum values of 622 kg DM/ha (Figure 3) and 618 kg DM/ha and maximum values ranging from 1417 kg DM/ha (Figure 3) to 1427 kg DM/ha (Figure 6B).

The minimum, mean, and maximum production values reported in Table 2 represent the estimated frequency and probability over the defined simulation horizon (3000 years), considering the risk factors inherent to the modeled pastoral activity. The minimum production value observed was 409.93 kg DM/ha, highlighting the vulnerability of pastoral systems in the Caatinga biome. Conversely, the maximum production value reached up to 1570.64 kg DM/ha. The overall mean production was 1063.33 kg DM/ha, reinforcing earlier findings (Figure 4) that values above 1400 kg DM/ha are possible but subject to interannual variability associated with precipitation levels.

With respect to potential critical scenarios in pastoral systems, particularly in regions where the Caatinga is the sole feed source for small ruminant herds, the analysis indicated a 95% probability of encountering production constraints when the system is managed under overestimated biomass yield expectations. In the simulation, such overestimated values averaged approximately 1433.18 kg DM/ha (Table 3).

Consistent with the findings presented in Table 3, MCS ranked values according to their associated risk based on the generated data series. It identified biomass production values ranging from 605.32 kg DM/ha to 1063.34 kg DM/ha as indicative of low risk for pastoral systems, particularly when these values occur with relative frequency and serve as the foundation for strategic planning. In contrast, values exceeding 1100 kg DM/ha were considered high-risk due to their infrequent occurrence, as indicated by the simulation's risk assessment framework (Figure 7).

In Figure 8, the most frequently generated values by MCS ranged between 200 and 400 kg DM/ha, followed by values between 600 and 800 kg DM/ha.

These were the most recurrent outputs in the synthetic series of projected data, while values exceeding 1000 kg DM/ha appeared less frequently, consistent with earlier findings. The synthetic series is the result of numerous combinations processed by the simulation tool in varying scenarios, with the final output reflecting the most commonly occurring values.

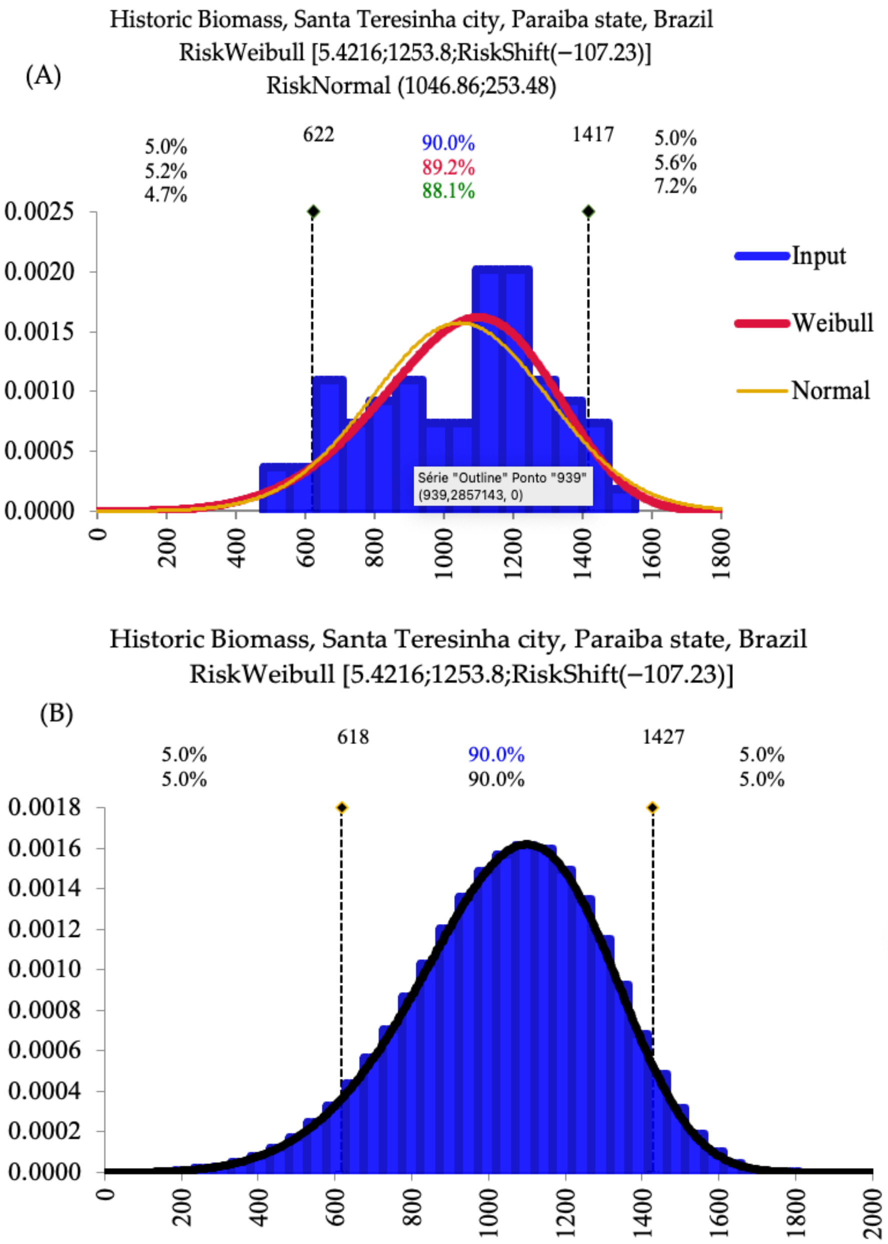

Figure 6. (**A**) Function and (**B**) fit of the probability distribution function of the Monte Carlo simulation of the historical biomass in the municipality of Santa Terezinha, Paraiba state, Brazil. The curves represent the probability functions (Weibull and Normal), and the bars, the series of historical data generated by Phyweb 2.0 from 1950 to 2020 and the synthetic series formulated by the simulation. Source: @RISK [13].

Table 3. Values of the risk analysis performed by Monte Carlo Simulation in @RISK [13] and the estimate of herbaceous biomass production (kg DM/ha) obtained by soil cover by herbaceous vegetation.

Method	Minimum	Maximum	Mean	Standard	5%	95%
Monte Carlo	409.99	1570.64	1063.33	246.00	617.29	1433.18
Ground cover	419.48	1772.30	954.10	328.61	893.66	1205.08

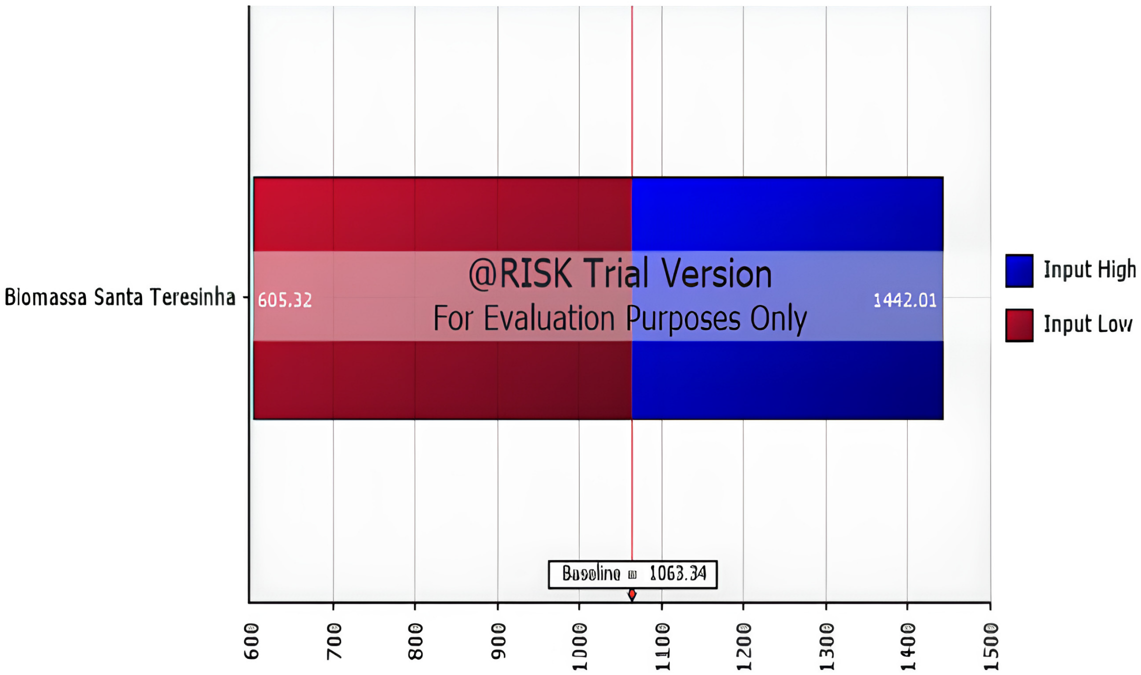

Figure 7. Analysis of values with potential risks for the pastoral activity of the Lameirão Farm, Santa Terezinha city, Paraiba state, Brazil. Source: @RISK [13].

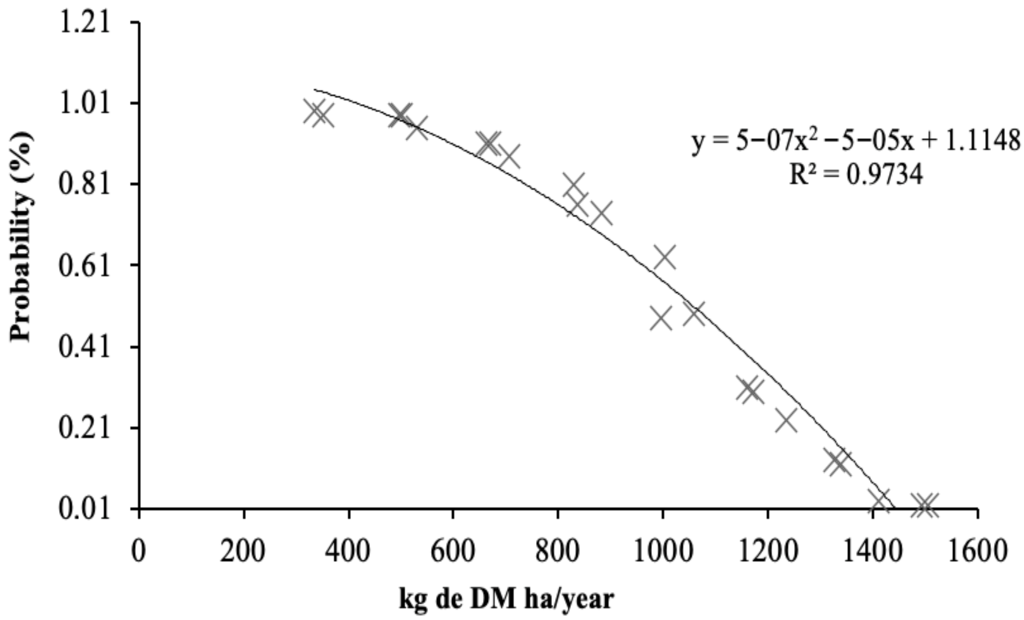

Figure 8. Probability of occurrence of production values in the synthetic series generated by MCS for 3000 years.

By using ground cover data to estimate the biomass production (kg DM/ha) of herbaceous vegetation and comparing it with values obtained from the Monte Carlo simulation, similar minimum (419.48 and 409.99), maximum (1772.30 and 1570.64), and mean (954.10 and 1063.33) values were observed (Table 3).

However, the deviations around the mean were 246.00 kg DM/ha in the Monte Carlo simulation and 328.61 kg DM/ha when estimated using ground cover data. The minimum (29.72%), mean (60.54%), and maximum (90.96%) ground cover values corresponded to biomass estimates of 419.48, 954.10, and 1772.30 kg DM/ha, respectively (Figure 9).

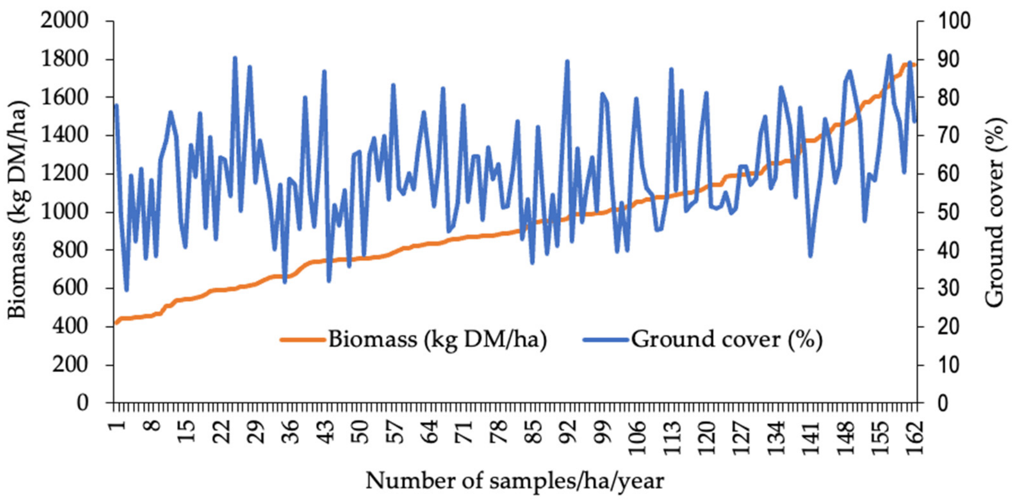

Figure 9. Relationship between soil cover and herbaceous biomass production (kg DM/ha) in the Caatinga biome.

4. Discussion

The similarity between the field-observed results and those estimated by the model for herbaceous biomass production confirms the importance of studies of this nature. These findings support the assertion by Antle et al. [35] that models are essential tools for providing predictive and evaluative capabilities to support decision making. During 2016, the highest biomass production occurred in the early months of the year, primarily due to greater precipitation volumes. Since the model used is hydrologically based, it also predicted higher biomass values for these initial months, in agreement with the observed rainfall pattern. These results are satisfactory, indicating that the software is capable of accurately simulating the conditions of the evaluated scenario.

A variation observed between the measured value (992.15 kg DM/ha) and the estimated value (1117.0 kg DM/ha) was found for 2017. This discrepancy is considered acceptable, as the software operates using daily time steps, which may result in slight mismatches between the model's simulation dates and the actual field sampling dates. Nevertheless, this variation does not compromise the model's accuracy, as the estimated values remain closely aligned with field observations.

According to Krinner et al. [36], complex biophysical models simulate the interactions among atmosphere, vegetation, and soil using compartmental structures and varying temporal resolutions, which can explain minor differences between predicted and observed values. In the municipality of Santa Terezinha, Paraiba state, Brazil, precipitation levels in 2016 and 2017 did not exceed 500 mm (Figure 2), a low value insufficient to sustain adequate biomass production for the dry season. By enabling the estimation of biomass production (kg/ha) across years, the model provides producers with valuable information for decision making, who can respond by either reducing herd size or investing in supplementary inputs.

The observed discrepancy between the PHYGROW model estimate (approximately 1200 kg DM/ha) and the field-measured biomass (1763.5 kg DM/ha) for the year 2018 indicates inherent limitations and uncertainties in model predictions when applied to complex semi-arid environments such as the Caatinga biome. The additional 564 kg DM/ha observed in the field represents 47% of the 1200 kg DM/ha estimated by the model for 2017. This discrepancy is likely a result of rainfall variation, as precipitation totaled 418 mm in 2017 and 769 mm in 2018, representing a 45.6% decrease in 2017. These findings confirm the strong relationship between rainfall levels and herbaceous biomass production in the Caatinga biome [5]. Several factors may contribute to this difference. First, the PHYGROW model relies heavily on historical climate data and assumes average or typical climatic conditions, potentially underestimating biomass production in anomalously favorable years such as 2018, which may have experienced higher-than-average precipitation or more favorable temperature patterns [3]. Additionally, local site-specific factors, such as microclimatic variations, soil fertility heterogeneity, and vegetation composition, are difficult to capture fully in the model.

The model also has inherent structural limitations, including assumptions regarding plant growth parameters calibrated from limited datasets, which may not reflect the full variability of natural forage stands [12]. Furthermore, management practices or disturbances (e.g., grazing pressure and conservation interventions) that occurred during the field data collection period might have influenced biomass availability but are not explicitly incorporated into the simulation. These factors collectively highlight the importance of ongoing calibration and validation of PHYGROW with extensive field data, as well as the integration of more detailed climate inputs and management variables to enhance model accuracy [13]. The difference also emphasizes the critical need to interpret simulation results within the context of their uncertainty, reinforcing the value of Monte Carlo simulations to assess risk and variability beyond deterministic predictions.

Regarding the factors that may have influenced the low estimate obtained by the program, Capalbo et al. [37] suggest that such discrepancies may arise from sampling procedures that fail to statistically represent the area within the scope of individual models. This reinforces the need to develop model-specific sampling methods to reduce data variability and enable more targeted calibration for intended applications. Challinor et al. [38] also emphasized the importance of considering potential interferences in remotely sensed data, particularly those acquired by the MODIS sensor. Cloud cover and even smoke can affect image quality, even at high resolutions, particularly during the rainy and dry seasons. These factors can compromise the accurate interpretation of conditions on the ground, especially considering that MODIS revisits the same area every 16 days.

Biomass production is influenced by precipitation from the previous year [39]. This relationship is mediated by soil water retention capacity and pasture degradation, which may have affected the model's output and biomass estimates between 2018 and 2019, especially considering that the area was undergoing secondary succession. The similarity in precipitation volumes and estimated biomass values in those two years suggests that soil water retention capacity remained relatively constant, explaining the comparable biomass outputs. According to Zhan et al. [40], variations in soil moisture result in significant changes in surface energy balance, directly affecting vegetation modeling in hydrologically based systems. Furthermore, Feitosa et al. [41] emphasize that soil moisture content is a critical parameter in modeling and that its estimation via remote sensing is essential to assessing large areas.

Overall, the estimated biomass production for the years studied was consistent with values reported in previous research conducted in the same experimental area [29,30], as well as in native Caatinga areas with no grazing management [42]. Among the field data analyzed, only the year 2018 exhibited a contrasting biomass production value compared with the other years evaluated (Figure 4). It is important to note, however, that biomass estimates obtained using the quadrat method may show significant variability, as the method relies heavily on manual labor, is subject to operational constraints, and requires a large number of samples and substantial time for data collection. Moreover, it involves the partial destruction of vegetation [42].

These findings highlight the potential of modeling tools to optimize time and support the resilience of small livestock herds by providing a historical record of biomass production across an area. Such tools enable a broader understanding of ecosystem dynamics and can even help prevent the disappearance of native species in the biome by offering daily estimates and identifying plant groups most at risk. In the current scenario, the software indicates that native grasses are the most vulnerable to changes in precipitation, with biomass estimates falling to approximately 295 kg/ha.

Once properly calibrated, the model continues to produce reliable estimates for subsequent years, consistent with results obtained with other conventional methods, as the calibration data serve as the reference framework for simulation. Lopes et al. [43], in studying the relationship between soil moisture indices and vegetation preservation through modeling, emphasized the importance of calibrating models using field data, landscape characteristics, and soil types specific to the area of study. This calibration minimizes the likelihood of producing estimates that deviate significantly from those derived through traditional methodologies. Considering all values obtained from the simulation program in comparison to field data, it is reasonable to affirm that the model aligned well with the proposed scenario, presenting realistic and reliable outputs. Therefore, it can be considered a viable tool to replace the quadrat method and its associated labor demands. Once validated, the results generated by the model are dependable for assessing forage resources in the area.

The forage potential of the Caatinga ecosystem is highly sensitive to climatic conditions, resulting in unstable native pasture growth and production. This instability directly affects the region's carrying capacity and its floristic composition [44]. Another critical factor contributing to this decline is the unregulated exploitation of the ecosystem. Many livestock producers who rely on the Caatinga as the primary feed source for their herds often lack knowledge or do not adopt any form of conservation management.

The selection of the Weibull distribution to model biomass data is grounded in both statistical fit and ecological rationale. Ecologically, biomass production in semi-arid environments, such as the Caatinga, is subject to substantial variability due to irregular precipitation patterns and environmental stressors [13]. These conditions often result in non-symmetric and right-skewed distributions of biomass, where most observations cluster around lower values and fewer areas exhibit high productivity.

The Weibull distribution is particularly suited for such data behavior because it is flexible, bounded at zero (which reflects the biological reality that negative biomass is not possible), and can model skewed patterns that are common in ecological responses. Under drought stress or limited resource availability, herbaceous biomass tends to follow a pattern where low productivity is frequent, while high productivity becomes increasingly rare, and features are well captured by the shape and scale parameters of the Weibull distribution [44]. Thus, the use of the Weibull distribution aligns with ecological expectations of biomass responses under precipitation variability and supports a more realistic simulation of biomass probability under uncertainty.

The scenario projected by Phyweb 2.0 suggests that this declining trend may persist, given the continued climatic fluctuations, irregular rainfall distribution, and absence of both species and soil conservation practices. These factors collectively exacerbate pasture degradation, promote the disappearance of herbaceous vegetation, and potentially lead to desertification or replacement by invasive species. Therefore, sustainable management of Caatinga native pastures is crucial to avoiding potential losses in livestock production and the disappearance of highly palatable forage species, which can constitute up to 80% of the diet of small ruminants [45].

These results highlight the inherent uncertainty of pastoral activities in the Caatinga biome. Climatic fluctuations lead to considerable variability in forage availability from year to year, and the supply of high-quality forage tends to decline, particularly under intensified grazing pressure. In addition to climatic factors, when evaluating herbaceous forage supply in a thinned Caatinga enriched with buffel grass (*Cenchrus ciliaris* L.) under goat and sheep grazing, the importance of understanding the land-use history of the areas being studied is emphasized [2,3]. This is crucial, as the feeding behavior and dietary preferences of different ruminant species can significantly influence the composition of the herbaceous stratum. Specifically, goats tend to exert greater grazing pressure on herbaceous dicotyledons, while sheep show a preference for grasses, which can lead to either underestimation or overestimation of total biomass production.

The variability in biomass production shown in Figure 5 underscores the importance of accounting for consecutive periods of drought lasting two, three, or more years in yield estimates, regardless of the modeling platform used. Feitosa et al. [41] reported a similar pattern for the same region when evaluating the PHYGROW model's capacity to predict the forage yield of buffel grass (*Pennisetum ciliare*) in a thinned Caatinga and to assess associated production risks.

In December 2015, the area underwent vegetation management interventions (thinning, pruning, and enrichment planting) aimed at enhancing herbaceous biomass production, as recommended by Araújo Filho [45]. However, this intervention negatively impacted production in the following year (2016), which dropped to 883 kg DM/ha. This reduction is likely due to the adaptation phase of plant species to the newly implemented management practices, indicating the necessity of a temporal interval between interventions to allow vegetation to respond adequately. The variation observed in Figure 7 clearly indicates the effect of management on biomass production; thus, there is an association between the fact that the years following management considerably increased biomass production at the site and that Phyweb 2.0 was sensitive to interference in the area, estimating values close to those found in the field.

MCS indicates that such results are favorable but do not exclude the need for alternative forage capable of supplying the annual food deficiency when the carrying capacity is limited. The historical data used for this simulation suggest that every 3 years, there are differences in annual production that can reach up to 600 kg DM/ha and that there is a possibility that the area will not have the same production due to continuous use without any conservation practices. The pasture ecosystem can resist the changes produced by grazing to a certain extent, but such changes can be accentuated by abiotic factors causing problems that may be irreversible. The current situation overview provided by MCS (Figure 6A) draws our attention to the need to adopt strategies that designate other pasture areas as alternative food sources, given that the area is prone to frequent droughts and that moving animals to other areas is necessary to generate higher levels of productivity.

According to Thornton and Herrero [46], the compromised quality of feed leads to a drop in pasture productivity in terms of meat and milk production. These products are sold in the Caatinga regions, generating income for small producers. Therefore, information that can identify weaknesses in the development of the activity and address impacts on the management of forage resources is essential to improving the activities of small properties and minimizing economic losses [47], aiming at the survival of the population that lives in the biome. The differences between the estimated values in both simulations were approximately 4 and 10 kg (Figure 6B). This suggests that when generating synthetic data, the software assesses all input data to identify potential risk points that might affect outcomes, generating data with similar statistical characteristics within the simulation context. The values derived from the adjusted synthetic series are considered reliable, as the software operates within the full range of input data without alterations, identifying realistic points within the original scenario that align with the simulated values.

Regarding the probability of biomass production values, MCS assigned only 5% probability to values below 600 kg DM/ha and 5% to values above 1400 kg DM/ha (Figure 4).

These probabilities differed from those in the initial simulation phase, where they were 5.6% and 5.2%, respectively. The overall occurrence of minimum and maximum production values changed from 89.2% to 90%, indicating that even under climatic conditions similar to the current ones, biomass production may reach up to 1427 kg DM/ha over a 3000-year simulation period (Figure 6B). Thus, MCS contributes positively to the long-term planning of pastoral activities, and its output is of high importance for the development of emergency planning strategies.

Conversely, when planning is based on an estimated biomass yield of up to 617.29 kg DM/ha, the probability of encountering production issues decreases to approximately 5%. However, any alteration in the parameters evaluated by the simulation tool may result in a loss of plant diversity and significant economic impacts on pastoral activities. Favretto et al. [48], in their assessment of ecosystem services in semi-arid pasturelands, emphasized that economic returns from pastures in these regions are increasingly threatened by soil degradation. Moreover, these ecosystems play a crucial role in supporting the livelihoods of much of the population, with management practices identified as the primary driver of such degradation.

MSC provided valuable insights regarding pasture productivity, particularly in identifying values with the highest impact. It was observed that with each new iteration or comparative analysis conducted by MCS, the estimated values adjusted consistently to reflect new perspectives of the variable under study. These estimates demonstrated similarity with those previously generated through simulation outputs, indicating model consistency within the proposed interval [49]. This consistency suggests that the model is well-calibrated and supports the reliability of MCS in capturing a wide range of potential performance outcomes without imposing excessive assumptions on model structure [50].

MCS has been used to predict and estimate variations in forage production under different conditions and thus estimate risks in the face of climatic uncertainties, especially in the relationship between rainfall levels and grazable biomass production. To this end, Urbanucci and Testi [51] emphasize that the method uses randomness to predict different scenarios and thus estimate different results in forage production and, consequently, in the carrying capacity of the pasture, thus seeking the sustainable use of the biomass produced over the years. This aspect was observed in the work by Cândido et al. [52], who, when simulating the variability of pasture production affected by rainfall over time, concluded that this system proved helpful in estimating adjusted annual forage biomass, even in regions with high rainfall variability. MCS projects future scenarios using a probabilistic approach, employing random numbers to simulate and estimate stochastic behavior. This method proved effective in addressing uncertainties related to production, generating functions for random parameters, represented here by biomass yield. Although the presented methodology enables rapid development of probabilistic projections, careful interpretation of the results is essential [13].

Over time, additional risk factors may emerge, necessitating new simulations of the area to better understand shifts in environmental dynamics and the range of factors involved [53]. Such analysis is essential to ensuring system resilience, particularly in scenarios where the recovery capacity and intensity of pasture ecosystems may decline. In this context, special attention should also be directed toward the percentage of ground cover by forage species to maintain ecological sustainability [54,55].

Agriculture and livestock production play a critical role in global environmental sustainability. These sectors influence land use, water consumption, greenhouse gas emissions, and biodiversity. Sustainable practices, such as rotational grazing, precision farming, and integrated crop–livestock systems, can help mitigate negative impacts. Conversely, intensive and poorly managed systems contribute to deforestation, soil degradation, and climate change. Improving efficiency and resource use while preserving ecosystems is essential. Sustainable agriculture and livestock systems are key to ensuring food security without compromising the planet's ecological balance. Therefore, innovation and policy are needed to drive environmentally responsible production.

The software used can execute up to 2 billion random sampling interactions, generating a reliable risk profile of the system, and has been validated with different data series within the provided numerical range [56]. Once the probability distributions are fitted and correlations established, the simulation conducts the analysis and outputs the resulting effects. An important advantage of this tool is its ability to rapidly identify problematic values, evaluating multiple scenarios within seconds. This enables users to assess the system and understand its risk profile, thereby supporting decision making aimed at minimizing potential damage within pastoral systems [57].

The previously obtained results indicate that when pasture management planning is based on low-risk production values, the activity can remain stable even under conditions of climatic variability. This conclusion is consistently supported across all phases of MCS, which identified values above 1000 kg DM/ha as having only a 5% probability of occurrence. However, these results are applicable only under the current environmental conditions, with climate representing the sole risk factor considered.

Based on the most frequently occurring production values in the synthetic series, it becomes evident that adopting practices aimed at increasing the productivity of the existing vegetation is essential, given that the values found are below 1000 kg DM/ha, a threshold considered insufficient for significant weight gain in grazing animals, according to Minson [58]. The introduction of adapted exotic forage species is another strategy that should be explored to increase forage availability at low establishment costs [59]. Additionally, the development of a protein bank can serve as a strategic reserve for use during critical periods [60].

The analysis presented in this study, which integrates the PHYGROW model with Monte Carlo Simulation (MCS) via @RISK software, offers a robust probabilistic assessment of herbaceous biomass production within the Caatinga biome, accounting for historical climatic variability. This innovative approach stands out by combining process-based modeling with statistical methods that incorporate uncertainties and risk, thereby contributing to more strategic planning in semi-arid pasture systems.

The relationship between ground cover and plant biomass production has been extensively studied over the years, whether for wood production [61] or forage biomass yield [62], in both native rangelands [63] and cultivated pastures, as well as in silvopastoral systems [64]. In this context, ground cover has been evaluated using direct and manual methods, such as the one employed in the present study, which can be used to validate results obtained with more modern techniques, including satellite imagery/remote sensing, drone-based monitoring [65], and digital photography [66] or to confirm predictions generated by biomass simulation models such as MCS [41].

The minimum, maximum, and average values of biomass production (kg DM/ha) estimated based on ground cover corresponded to 90%, 89%, and 98%, respectively, of the values predicted by Monte Carlo Simulation, supporting the efficiency of this system in predicting biomass production in pasture systems. This finding corroborates the assertion by Feitosa et al. [41], who stated that the PHYGROW model is a reliable estimator of buffel grass biomass in thinned Caatinga areas in the Brazilian semi-arid region. The authors further concluded that using the Monte Carlo method enhanced the precision of the PHYGROW model in predicting buffel grass biomass, thereby enabling more accurate estimations of forage dry matter availability over time, which can improve feed planning for livestock herds.

The discrepancies observed between the Monte Carlo simulation values and the ground cover-based estimates may be attributed to climatic factors during the field evaluation period (2016 to 2019), as precipitation levels in semi-arid regions are highly variable yearly and, more importantly, are often unevenly distributed. According to Noa-Yarasca et al. [67], such irregular rainfall patterns may result in biomass overestimation or underestimation at specific time points.

While this plot provides detailed and high-quality information on herbaceous biomass dynamics under controlled grazing and climatic conditions, extrapolating these findings to broader Caatinga regions requires caution, because we acknowledge that one potential limitation of the study lies in the spatial resolution, as the model is based on data collected from a 4-hectare experimental plot. The Caatinga biome is heterogeneous, with variation in soil type, vegetation composition, grazing intensity, and microclimatic conditions. When it comes to semi-arid environments such as the Caatinga region, where this study was carried out, values that are outside of expectations and are intrinsically associated with climatic events may occur, especially for years of severe droughts, in which the estimated annual biomass of forage may be lower than the minimum residual biomass to maintain the sustainability of the ecosystem [52]. To improve the scalability of the model, future applications could incorporate regional calibration parameters or use satellite-derived biomass data to validate the model across different landscape units and management regimes.

Regarding temporal limitations, we recognize that the historical climate series used in the simulation may have been influenced by interannual climatic anomalies such as El Niño and La Niña events. These phenomena can significantly alter rainfall distribution and intensity in semi-arid regions, potentially skewing the estimation of biomass variability and risk. While such anomalies are inherently part of the climatic variability that producers face, they may introduce bias into long-term projections, especially over a 70-year horizon. To address this, we propose that future studies incorporate climate anomaly indices (e.g., Oceanic Niño Index) or apply stochastic weather generators that simulate a broader range of climatic scenarios, improving the robustness of the risk analysis.

Even though the results obtained from simulations based on historical probabilities by using PHYGROW software, combined with MCS conducted in the @RISK program, allowed for the long-term assessment of biomass production in a native rangeland area of the Caatinga biome, these findings also open possibilities for future studies. Such studies may include the integration of remote sensing data, classical field methods that combine the cutting and weighing of herbaceous vegetation with ground cover estimation, and the relationship between available dry matter supply and the performance of grazing animals. In this context, Dieguez and Pereira [68], who studied a model of net primary aboveground production in native Uruguayan grasslands and its application to the concept of safe stocking rate, emphasized that the wide range of biomass outcomes (minimum, maximum, and average) generated by the sinusoidal model are strongly influenced by climatic events, particularly water stress and its impact on grass growth. Nevertheless, such models are valuable as they enable the simulation of scenarios that explore pasture responses to climatic stress and allow for the study of prospective management strategies.

Despite these limitations, this model provides a valuable framework for understanding biomass uncertainty and supporting adaptive management decisions in dryland environments.

5. Conclusions

The historical data series reveals a concerning trend of degradation and potential extinction of herbaceous species, as forage production has steadily declined over the past 44 years. The software highlights a scenario in which the implementation of conservation practices is urgently needed. With the reduction in forage potential, the native Caatinga pastures will be unable to adequately support small-scale producers who rely exclusively on these areas to feed their herds, making it necessary to invest in external inputs to ensure forage availability.

The Phyweb 2.0 platform was sensitive to the management practices implemented in 2015, providing an estimate for 2016 that closely matched observed field values, suggesting a good adaptation of the software to the modeled scenario. Similarly, the PHYGROW model produced estimates consistent with field data from recent experiments conducted in the same area, demonstrating its ability to simulate biomass production under the climatic limitations of the region. The model can generate accurate predictions for any scenario, provided a sufficient dataset is available for calibration.

Monte Carlo Simulation (MCS) offered critical information for strategic forage planning in future years across all phases of execution, presenting a comprehensive overview of the likelihood of various production outcomes. It also identified the risk profile of the scenario and potential failures in pastoral planning, as well as the vulnerability of forage productivity over time in the absence of conservation-oriented practices. Thus, the use of MCS emerges as an essential tool to assess the future productivity landscape of an area and support planning with alternatives for extreme scenarios, focusing on both forage production and resource conservation.

By simulating thousands of scenarios based on variable inputs, they help predict the outcomes of land use, agricultural practices, and resource management. These tools identify potential risks and uncertainties, allowing for more informed and adaptive planning. In agriculture and livestock production, they assist in optimizing resource use while minimizing environmental degradation. Such simulations can guide decisions that reduce deforestation, overgrazing, and soil erosion. They also support the design of resilient systems under climatic variability. Ultimately, they promote sustainable development by balancing productivity with ecological conservation. Thus, modeling and risk analysis tools like Monte Carlo Simulation play a crucial role in supporting environmental sustainability.

The modeling framework developed in this study has critical practical applications for the sustainable management of the Caatinga. This biome is crucial to supporting smallholder pastoral systems in Brazil's semi-arid region. By quantifying the uncertainty in herbaceous biomass availability under variable climatic conditions, the model offers a valuable decision support tool that can be integrated into rural extension programs to guide forage planning, adjust stocking rates, and reduce the risk of overgrazing and land degradation.

Extension services and local cooperatives could apply model outputs to design adaptive grazing calendars and early warning systems that anticipate critical biomass shortages, enhancing resilience among small-scale producers. Additionally, the model can inform environmental licensing frameworks by providing scientifically grounded criteria for evaluating the carrying capacity and sustainability of livestock-based land use in Caatinga ecosystems.

At the policy level, this framework aligns with the goals of Brazil's National Action Plan to Combat Desertification and Mitigate the Effects of Drought (PAN-Brazil), offering technical support for land restoration strategies, the monitoring of ecosystem services, and adaptive resource management. Moreover, it contributes to international commitments such as the United Nations Convention to Combat Desertification (UNCCD) by operationalizing risk-based approaches to dryland governance and restoration.

Future model developments could incorporate remote sensing data and participatory validation with local stakeholders, further strengthening its utility for regional planning and climate adaptation policies at multiple governance levels.

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