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Review

Non-Destructive Methods Used to Determine Forage Mass and Nutritional Condition in Tropical Pastures

Patrick Bezerra Fernandes [1,*], Camila Alves dos Santos [1], Antonio Leandro Chaves Gurgel [2], Lucas Ferreira Gonçalves [1], Natália Nogueira Fonseca [1], Rafaela Borges Moura [1], Kátia Aparecida de Pinho Costa [1] and Tiago do Prado Paim [1]

[1] Instituto Federal de Educação, Ciência e Tecnologia Goiano, Rodovia Sul Goiana, Km 01, Zona Rural, Rio Verde 75901-970, Brazil; camilaalvesdossantos240@gmail.com (C.A.d.S.); ferreiralucas1205@gmail.com (L.F.G.); natalia.nogueira@ifgoiano.edu.br (N.N.F.); rafaelamoura779@gmail.com (R.B.M.); katia.costa@ifgoiano.edu.br (K.A.d.P.C.); tiago.paim@ifgoiano.edu.br (T.d.P.P.)

[2] Animal Science, Universidade Federal do Piauí Campus Professora Cinobelina, Bom Jesus 64900-000, Brazil; antonioleandro09@gmail.com

* Correspondence: bezerrazpatrick@gmail.com

Abstract: The quantification of forage availability in tropical grasses is generally done in a destructive and time-consuming manner, involving cutting, weighing, and waiting for drying. To expedite this process, non-destructive methods can be used, such as unmanned aerial vehicles (UAVs) equipped with high-definition cameras, mobile device images, and the use of the normalized difference vegetation index (NDVI). However, these methods have been underutilized in tropical pastures. A literature review was conducted to present the current state of remote tools' use in predicting forage availability and quality in tropical pastures. Few publications address the use of non-destructive methods to estimate forage availability in major tropical grasses (*Megathyrsus maximus*; *Urochloa* spp.). Additionally, these studies do not consider the fertility requirements of each cultivar and the effect of management on the phenotypic plasticity of tillers. To obtain accurate estimates of forage availability and properly manage pastures, it is necessary to integrate remote methods with in situ collection of soil parameters. This way, it will be possible to train machine learning models to obtain precise and reliable estimates of forage availability for domestic ruminant production.

Keywords: mobile device; drone; soil nutrients; *Megathyrsus maximus*; *Urochloa* spp.

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1. Introduction

The measurement of forage mass in tropical pasture environments is often obtained through destructive methods (forage cutting), which is a practice applied in plant breeding programs during the selection phase of more productive hybrids of *Megathyrsus maximus* (Syn. *Panicum maximum*) and *Urochloa* spp. (Syn. *Brachiaria* spp.) [1–4]. Additionally, destructive methods are also employed to assist in obtaining the accumulation rate and availability of forage mass in research assessing the effect of different defoliation intensities on animal performance in continuous stocking, rotational stocking, and integrated production systems [5–9], as well as in research on feed supplements (e.g., mineral, energy, protein) with forage for ruminant production [10–14].

The measurement of forage mass is relatively simple to obtain (cutting, weighing the fresh forage, and subsequently drying it in an oven to obtain a constant weight). However, there are certain steps that require a significant amount of time, making the methodology impractical and less applicable for technicians and producers. In Brazil, public research institutions encourage the use of direct methods through canopy height measuring for pre-grazing and post-grazing recommendations of main forage cultivars [15]. Since there is a correlation between canopy height and forage mass [16], it is possible to use height as a predictive model for dry forage availability. However, predictions based on canopy height do not consider the effect of abiotic factors (temperature, soil nutrient availability, and precipitation), as well grazing management and phenotypic plasticity, which influence tissue flow in tillers and the nutritional condition of the pasture.

The images obtained through mobile devices (cell phones) and unmanned aerial vehicles (UAVs) can generate models that assist in predicting primary production and controlling diseases and insect pests in important agricultural commodities and pastoral environments [17–19]. With these tools, it is possible to enhance the decision-making process in management by identifying areas with higher risk and/or production levels.

Another highly promising tool in the field of agricultural and environmental monitoring is the Normalized Difference Vegetation Index (NDVI). This index proves invaluable in swiftly and accurately assessing the amount of biomass covering the soil surface. Furthermore, it serves as a critical indicator of plant nutritional status and water balance all achieved with remarkable precision and speed [20]. The NDVI holds immense significance due to its transformative impact on both agriculture and environmental management. It goes beyond being a mere technical metric, serving as a cornerstone for data-driven decision-making. When interpreting satellite or drone images, the NDVI provides precise information about vegetation health and growth patterns.

In today's dynamic landscape, access to invaluable data has become a crucial asset, enabling stakeholders to make informed choices. This, in turn, leads to the optimization of resource allocation and the promotion of sustainable practices. One such potent tool for achieving this lies in the amalgamation of nitrogen leaf content data, Soil Plant Analysis Development (SPAD), and NDVI. The synergy of these data sources can be harnessed effectively to manage nitrogen levels within grasses, thus playing a pivotal role in bolstering primary production [21]. This strategy empowers individuals and organizations to make decisions that not only maximize productivity but also contribute to environmentally responsible practices, aligning with the broader goal of sustainability.

In this context, the substantial objective of this literature review is to delve into the utilization of non-invasive approaches, in conjunction with forage mass prediction models, for a comprehensive assessment of the nutritional status of tropical grasses in pastoral environments.

2. Utilizing UAVs and Mobile Devices for Pasture Management

2.1. Perspectives on the Inclusion of UAVs in Pasture Management

One of the most formidable obstacles in ruminant production within tropical climates is effectively managing canopy height and accurately estimating the availability of forage mass for appropriate livestock feeding. Presently, the traditional techniques used to obtain agronomic data in pastures demand a substantial investment of time to execute [22,23].

The use of low-cost acquisition drones can generate a database structure for accurate and precise predictions of botanical composition, species diversity, productivity, disease incidences, and pest infestations in agricultural environments [24–26]. In pastoral environments, Bazzo et al. [27] found that there has been an increase in studies involving the use of UAVs to estimate forage biomass between the years 2018 and 2022, with a greater focus on research conducted in Germany, China, and the United States. Studies involving tropical pasturelands in Latin American countries appear with low frequency in indexed journals, raising concerns about how researchers, technicians, and producers are integrating new technologies into ruminant food production in tropical pastoral environments.

In the genetic breeding program of *Megathyrsus maximus* grasses, Oliveira et al. [28] found that the combination of remote sensing with low-cost UAVs equipped with high-resolution RGB (red, green, and blue) sensors, along with convolutional neural networks (CNNs), enabled the selection of models to accurately estimate forage mass. This allowed for the identification of more productive hybrids and the segregation of genotypes with satisfactory performance. Furthermore, it was a prospect of training models to detect plants that are more susceptible to diseases.

In the realm of tropical pasture management, the utilization of drones has demonstrated remarkable efficacy. In the Mato Grosso do Sul region of the Brazilian Cerrado, Batistoti et al. [17] have unearthed an intriguing capability: the ability to gauge the canopy height of Tamani guinea grass (Megathyrsus maximus cv. BRS Tamani) by utilizing aerial photographs captured via Unmanned Aerial Vehicles (UAVs). The researchers have put forth linear models, characterized by a substantial coefficient of determination (R^2 = 0.80), linking the height measurements taken with a graduated ruler to those derived from the aerial images. Subsequent investigations have unveiled that the canopy height, ascertained with the ruler, serves as a reliable indicator for approximating the forage biomass (R^2 = 0.81). Furthermore, it has been established as a viable method to estimate the available forage mass of Tamani guinea grass based on the heights extracted from the aerial photographs (R^2 = 0.74).

2.2. The Use of Mobile Devices in Agricultural Environments

The use of photos obtained from mobile devices (e.g., cell phone or tablet) can assist in predicting the growth rate of forage plants, but it is necessary to use robust models. Santos et al. [19] employed convolutional neural network (CNN) training to estimate regrowth rates in *Megathyrsus maximus* tussocks from the germplasm bank of the Brazilian Agricultural Research Corporation (EMBRAPA—Beef Cattle). The authors found that images captured from two cell phones allowed the generation of a regression model with a mean absolute error of 7.70%.

This finding emphasizes the importance of adopting robust models when working with images from mobile devices for agricultural prediction purposes. By using photos captured by cell phones or tablets, researchers were able to achieve impressive results in estimating plant growth rates. These widely accessible and commonly used devices proved to be effective in generating reliable data to feed regression models. Subsequently, advancements in predicting the growth of forage plants utilizing images obtained from mobile devices have the potential to assist farmers and researchers in monitoring and planning forage crops, contributing to improved agricultural productivity and sustainability.

In Jiangmen province, China, Deng et al. [29] observed that using images obtained from mobile devices to train CNN models estimated population density of productive tillers for ten varieties of rice (*Oryza sativa*) that were similar to manually counted values (R^2 = 0.98). According to the authors, with the use of the model generated from the images, it is possible to predict the crop's productivity before harvest.

In soybean (*Glycine max*) fields in Canada, Laamrani et al. [30] found that due to the low bias obtained ($\pm$5%), the use of photographs in mobile applications can assist in estimating the amount of crop residue. In the Brazilian Cerrado region, Theodoro et al. [31] evaluated monocultures of maize (*Zea mays*) and pigeon pea (*Cajanus cajan*) and found that it is possible to estimate the proportion of soil covered with crop residue after harvest using images captured on mobile devices. By subjecting the images to analysis in the SisCob 1.0 software [32] through neural network-based training, the method employed provided soil coverage estimates similar to conventional methods.

3. Determination of Forage Mass and Nutritional Condition of Forage Plants in Tropical Climates Using Non-Destructive Methods

3.1. Utilization of Satellite Imagery in Pasture Management

In recent years, the use of remote sensing technology has gained prominence in agricultural and environmental research worldwide. The Sentinel-2 satellite, in particular, has emerged as a valuable tool for collecting data on vegetation cover, biomass, and other land-related variables. In the Brazilian context, a country with a unique diversity of ecosystems and a strong connection to agriculture, these studies have become increasingly relevant.

The research conducted by Bretas et al. [33] showcased the practicality of utilizing Sentinel-2 spectral bands to estimate the height of Mombaça guinea grass (*Megathyrsus* *maximus* cv. Mombaça). Their use of the random forest algorithm yielded highly effective predictions for both canopy height and above-ground biomass. Notably, their results revealed impressive precision, recall, and accuracy values, reaching up to 73% for each metric in canopy height classification. Furthermore, their models exhibited strong predictive capabilities for above-ground fresh biomass and dry matter concentration, as reflected in R^2 values of 0.61 and 0.69, respectively.

In a related study by Batista et al. [34], the Agreste region of Pernambuco, Brazil, served as the backdrop for research conducted on *Urochloa decumbens* under continuous stocking management, primarily for grazing Girolando heifers. This study harnessed the power of remote sensing technology, specifically using Sentinel-2 satellite imagery. The findings from this investigation underscored the effectiveness of this approach in generating vegetation index maps, which vividly illustrated the impact of grazing activity on the aboveground biomass cover and its chemical attributes. These maps, in turn, played a pivotal role as valuable indicators for informing decisions related to the potential risks of soil degradation.

In the unique context of the Brazilian semiarid region, Silva et al. [35] delved into a cultivated area of forage cactus, specifically exploring the varieties 'Mexican Elephant Ear' (*Opuntia stricta*) and 'Miúda' (*Nopalea cochenillifera*). This research unveiled a significant correlation between the use of Sentinel-2 satellite images and key agricultural variables. Notably, plant height, the number of cladodes, and specific vegetation indices emerged as crucial predictor variables within their multiple regression model.

Collectively, these studies demonstrate the increasing relevance of remote sensing technology, particularly using Sentinel-2 satellite imagery, in agricultural and environmental research within Brazil. They highlight the potential of this technology to provide valuable insights into vegetation dynamics, biomass estimation, and land management, ultimately contributing to more informed decision-making processes in these critical domains.

3.2. Determination of Forage Biomass Using NDVI

The NDVI is a widely used index to assess the health and vigor of plants based on data obtained through remote sensing. This index is calculated by dividing the difference between near-infrared (NIR) and red (R) light reflectance by the sum of these same two reflectances, following the formula: NDVI = (NIR − R)/(NIR + R) [36]. It is worth noting that reflectance values typically range from 0 to 1, where 0 indicates no reflectance and 1 indicates total reflectance.

Within the realm of precision agriculture, the utilization of crop imagery via NDVI has emerged as a promising tool for estimating primary production and evaluating the health of major crops [37–39]. However, when it comes to pastoral landscapes, they exhibit distinct characteristics compared to grain crops, primarily stemming from their diverse botanical composition. These landscapes frequently encompass a variety of environments featuring a wide array of plant species and non-uniform growth patterns. This complexity can lead to diminished predictive accuracy. In the northwestern region of Patagonia, Argentina, Fariña et al. [40] conducted an examination of ground cover in areas hosting perennial grasses and shrubs using NDVI. The authors reported that both conditions yielded imprecise estimates of vegetation cover.

In five dairy farms specialized in milk production in Tasmania, Australia, Chen et al. [41] observed a low relationship ($R^2 \leq 0.39$) between in situ measurements of forage biomass and NDVI information through linear regression analysis. The discrepancy between the two datasets indicates that vegetation NDVI cannot be directly used to estimate biomass on the ground surface. Therefore, it is necessary to calibrate the model for each region (farm) to reduce error [42].

In diverse pastoral environments with plants of the same growth pattern, the use of NDVI provided a different perspective when considering other agronomic parameters collected in situ. In six farms in Western Spain that had mixed pastures of legumes (*Trifolium subterraneum* L. subsp *brachycalycinum* and *yanninicum*, *Ornithopus sativus* L., T. *incarnatum*

L., *T. michelianum Savi* cv. Balansae, *T. resupinatum* L., *T. vesiculosum Savi*, and *T. glanduliferum Boiss*), Pulina et al. [43] found that NDVI is a promising tool for measuring leaf nitrogen (N) content and forage biomass yield, as it showed moderate correlations with both mentioned characteristics (r = 0.52 and 0.52, respectively).

In Festuca grass (*Festuca arundinaceavar*), Schaefer and Lamb [44] found that the combination of NDVI and height measurements obtained from a mounted vehicle resulted in accurate estimations of forage biomass. In Mombaça guinea grass, Campana et al. [45] observed that an NDVI value of 0.83 indicated the appropriate time to initiate grazing. For this cultivar of *Megathyrsus maximus*, grazing is recommended when it reaches a height of 90 cm, corresponding to 95% light interception [9,46]. Additionally, a positive correlation was observed, ranging from moderate to low, between NDVI and forage biomass (r = 0.49) and leaf index (r = 0.33). However, the method did not show a correlation with the chemical composition of the plants (crude protein and neutral detergent fiber).

3.3. NDVI Index for Assessing the Nutritional Status of Grasses

Quick NDVI mapping can assess nitrogen excess or deficiency in crops, improving fertilizer management and reducing environmental stress caused by excess nitrogen use [47]. In wheat grain production (*Triticum aestivum*), Vian et al. [48] found that NDVI assessment can be used for variable-rate nitrogen fertilization, allowing adjustment of the nitrogen dose applied in different locations of the field. However, it is important to note that this method has some limitations. An example of this was observed by Moral et al. [49] in the Évora region of southern Portugal, where the exclusive use of NDVI was not sufficient to assist in phosphorus (P) replenishment management in pasture areas.

Valle Júnior et al. [50], while diagnosing pasture degradation in the Uberaba River Basin region (Minas Gerais, Brazil), found that it is possible to combine soil information (organic matter, macronutrients, penetration resistance) with remotely sensed NDVI imagery. This combination allows for accurate estimation of the quantity and intensity of degradation in pasture areas. In the Amazon region, Valente et al. [51], studying the production of Mombaça guinea grass for dairy buffaloes, found that NDVI, when associated with active soil acidity (pH) information, enabled the distinction of less productive paddocks. With this information, it becomes possible to identify areas that require maintenance fertilization, as well as adjustments in stocking rates.

In an integrated crop–livestock system, Bernardi et al. [52] investigated the possibility of determining variations in vegetation indices between maize associated with Piatã palisadegrass (*Urochloa brizantha* cv. Piatã) in a no-till system. According to the authors, precise variations between the species can only be determined when combining NDVI with soil chemical composition data. Furthermore, the combination of remote sensing tools with in situ data can be applied to *Urochloa decumbens* pastures managed under continuous stocking, as observed by Batista et al. [53]. By employing NDVI in conjunction with penetrometer resistance measurements acquired at evenly spaced intervals, it became feasible to identify favored grazing zones for Girolando heifers. Additionally, this approach allowed for the identification of areas characterized by elevated levels of compaction as a result of trampling.

In *Urochloa decumbens* cv. Basilisk pastures managed under intermittent stocking and grazed by beef sheep, it was possible to observe that NDVI values are related to management criteria for the start of grazing. Using 85% of light interception (LI) with a residual leaf area index (LAIr) of 1.8, NDVI values of 0.85 and 0.49 were obtained, respectively. Meanwhile, a more conservative management approach, with 95% LI and 1.3 LAIr, yielded NDVI values of 0.88 and 0.44, respectively [54]. Under these two management strategies, NDVI can indicate the appropriate timing for the start of grazing as well as the ideal moment for pasture rotation.

3.4. SPAD Index Is Used as an Indicator of Nutritional Requirements in Forage Plants

The SPAD index is a non-destructive and rapid method for measuring the relative concentration of chlorophyll in plant leaves. It is widely used in agricultural research and plant physiology studies to assess plant health and nutritional status [55]. However, it is important to note that there is no single mathematical model for this index, as readings can vary among different devices. Therefore, it is necessary to calibrate the device according to the plant species and specific production system scenarios.

The SPAD index helps in identifying grasses that are more efficient in nutrient utilization, as observed by Almeida et al. [56]. They studied three cultivars of *Megathyrsus maximus* (Zuri guinea grass, Quênia guinea grass, and Tamani guinea grass) which were grown in a red latosol soil and received increasing doses of nitrogen. The authors found that Zuri guinea grass exhibited a high chlorophyll level and, regardless of the nitrogen dosage used, resulted in the highest values of forage mass. However, Quênia guinea grass showed similar chlorophyll values to Zuri guinea grass but did not demonstrate the same productivity potential under the same management conditions.

In pastures of Piatã palisadegrass, it was observed that the cultivar exhibited phenotypic plasticity at different nitrogen (N) levels when managed under intermittent grazing. The chlorophyll values obtained through SPAD showed a linear increase with the N dosage, and this increase was proportional to the forage mass. Additionally, there was an increase in the percentage of leaf mass in the forage canopy [57].

In maize plants, the SPAD index increases with the age of tillers, but a reduction in the index occurs when plants reach the reproductive stage. Furthermore, a correlation is observed between grain yield and SPAD index. Plants that exhibit higher SPAD values during the vegetative and early reproductive stages show higher grain production [58].

In a study by Edalat et al. [21] evaluating maize under increasing N doses, a correlation was found between grain yield, grain N content, NDVI, and SPAD values at different stages of plant development. The combination of leaf nitrogen, SPAD, and NDVI in a regression equation can be considered a potential tool for predicting maize grain yield. However, the SPAD index performed better than the NDVI in early detection of N deficiency.

4. Remote Tools Used in Pasture Management

Wróbel et al. [59] showed that there are several technological tools and computational methods for pasture management. However, in the context of tropical environments, particularly focused on Brazil, two tools stand out in the remote evaluation and management of pastures, represented by Manejo Remoto (AIRED—Inovação em Geotecnologia, Uberaba, Minas Gerais, Brazil) and Atlas das Pastagens (Laboratório de Processamento de Imagens e Geoprocessamento da Universidade Federal de Goiás, Goiânia, Brazil) (Table 1). These tools gained prominence because they offer greater accessibility for technicians, producers, and the academic community.

Table 1. Systems available for evaluation and management of pastures in tropical environments.

Technology/Commercial Name	Parameters	Link
Manejo Remoto®	(1) Stocking rate; Lot weight control; (2) Purchase and sale of animals control; (3) Repositioning of animals between paddocks; property management history.	https://www.manejoremoto.com.br/ Accessed on 13 June 2023.
© Atlas das Pastagens	(1) Mapping of pasture areas in Brazil; (2) Mapping of the quality of these areas, estimates of carbon stock in pastures in the Cerrado biome; (3) Information on the Brazilian cattle herd analyzed from municipal livestock research data.	https://atlasdaspastagens.ufg.br/ Accessed on 3 July 2023.

The Manejo Remoto tool is available both through a website and a mobile application. This tool offers a range of functionalities that enable more efficient control of animal management activities. The main features include:

(a) Stocking rate and lot weight control: With Manejo Remoto, it is possible to monitor and adjust the number of animals in specific areas, ensuring proper distribution and avoiding overloading or underutilizing pastures. Additionally, the tool allows for tracking lot weights, assisting in nutritional planning and identifying potential health or performance issues.

(b) Buying and selling animal control: Through Remote Management®, all transactions related to buying and selling animals can be recorded, from negotiation to delivery. This feature allows for maintaining an accurate transaction history, facilitating financial management, and supporting strategic decision-making.

(c) Animal repositioning between paddocks: The tool also offers the ability to reposition animals between different paddocks on the property, according to specific management needs. This enables better utilization of available resources, optimizing grazing and avoiding excessive grazing in certain areas.

In addition to these functionalities, Manejo Remoto also provides access to a complete management history of the property, providing valuable information for retrospective analysis and informed decision-making. With this tool at hand, farmers can optimize their management activities, promoting more efficient and profitable operations.

The Atlas das Pastagens aims to map the areas occupied by pastures in Brazil and assess the quality of these areas. Using image processing and geoprocessing techniques, the atlas provides detailed information on the geographical distribution of pastures and their condition, including parameters such as vegetation cover, soil fertility, and water resource availability. Additionally, the atlas estimates carbon stocks in the Cerrado biome pastures and analyzes data from municipal livestock research to provide relevant information about the Brazilian cattle herd, such as its geographical distribution and evolution over time. This information is essential for monitoring and planning livestock activities in the country.

5. Key Considerations to Be Considered in Studies Using Remote Sensing Methods to Estimate Biomass and Nutritional Condition in Tropical Pasturelands

To promote efficiency in remote data collection, some key considerations should be taken into account when training prediction models for biomass estimation and nutritional condition assessment in tropical pasturelands:

(a) Based on studies conducted in pastoral environments, the selection of models considering the chemical composition of forage (crude protein, neutral detergent fiber, acid detergent fiber, lignin, ether extract, in vitro dry matter digestibility) is not observed, as the models are trained with a bias to estimate only productivity and/or availability of forage biomass. The current model selection criteria may overlook factors that compromise canopy quality (e.g., flowering period or stem elongation), leading to undesirable accumulation of morphological components with lower nutritive value, which compromises animal performance in pastoral environments [60–62]. Therefore, it is necessary to train models to generate estimates of more productive pastures with higher leaf biomass.

(b) It is important to consider that grazing intensity has a significant influence on pasture growth dynamics. Studies conducted with Marandu palisadegrass (*Urochloa brizantha* cv. Marandu) indicate that management at lower heights, under continuous stocking, results in shorter leaf length and increased tiller population, while management at higher heights leads to reduced tiller population and increased leaf length of the tiller [63]. Due to phenotypic plasticity, this grass may exhibit growth dynamics adapted to specific management conditions when managed under intermittent stocking. Therefore, it is necessary to assess the need for parameterization of prediction models for each management condition.

(c) The age of tillers influences forage biomass accumulation, as observed in pastures of *Megathyrsus maximus* (Mombaça guinea grass and Tanzania guinea grass), white 'Suvernola' digit grass (*Digitaria eriantha*), and Marandu palisadegrass, where under high defoliation frequencies, it impacts the production of young tillers, thus exposing the canopy to higher growth vigor [64–67].

(d) Regarding pastures in the Brazilian savanna (Cerrado), it is important to note that between the months of June and August, there is a decrease in temperature, with values lower or equal to 15 °C, combined with water deficit. These conditions can slow down tissue flow in tillers, change the structure of the forage canopy, and consequently modify the relationship between forage biomass and the different evaluated indices [64,65].

(e) The fertility requirements and nutritional condition of the canopy associated with other abiotic factors (temperature, light, and precipitation) can cause fluctuations in dry matter accumulation in the forage canopy [68]. To assist Brazilian producers in understanding the specific characteristics of existing cultivars, Barrios et al. [69] proposed an application called 'Pasto Certo®' (https://urlfr.ee/c1xxa, accessed on 3 January 2023).

(f) From the analysis of Figure 1A, it is possible to observe that it is necessary to train models capable of predicting the daily accumulation rate of forage biomass and the ideal timing to initiate grazing in pastures with lower height and higher population density of tillers. In Figure 1B, the model should be able to estimate the forage growth rate, as well as the appropriate forage biomass to initiate grazing. In a practical sense, models capable of predicting the better time to start grazing can be more useful than models of dry matter quantity prediction.

(g) Furthermore, it is crucial to develop algorithms and modeling techniques specifically tailored to the growth of pastures in tropical climates, taking into account unique conditions such as high temperatures, seasonal precipitation, and phenotypic plasticity. This not only enhances the understanding and management of these ecosystems but also promotes sustainable agricultural practices and environmental conservation in tropical regions.

Figure 1. Management situation in intermittent stocking of the pasture of Paiaguás grass (*Urochloa brizantha* cv. BRS Paiaguás) in monoculture (**A**) and mixed pasture (**B**) of *Urochloa* spp. (Xaraés palisadegrass and Decumbens grass) with *Megathyrsus maximus* cv. BRS Quênia [Source: Compiled by the authors].

6. Models to Determine the Forage Accumulation Rate in Tropical Pasturelands

Generally, to assess pasture growth and the daily forage accumulation rate in tropical climates, destructive methods or morphological and structural evaluation of the tiller are used [68]. Destructive methods involve cutting the forage to calculate the ratio between the pre- and post-grazing forage mass, and by dividing this ratio by the number of days between cutting intervals, it is possible to estimate the daily pasture growth. This technique is applied in pastures managed under intermittent stocking, at pre-grazing and post-grazing stages [9]. Another approach is the use of exclusion cages for pastures managed under continuous stocking [70]. Regarding growth at the tiller level, the expansion and leaf elongation rate of each individual tiller are assessed [64,65,71,72]. Although this method provides insights into the growth process, it is time-consuming, making it impractical for data collection related to the daily routine of commercial farms. Moreover, these methodologies provide us information from the past in a specific location. However, to improve productive decision-making in precision livestock farming, this information is not very useful. We would like to have predictions for the near future, specifically of what forage accumulation will be in the upcoming days, such as the next 30, 60, or 90 days, or even the production curve for the next year. Therefore, the development of indirect methodologies, predictive models, and/or remote techniques is essential for better pasture management in a precision livestock farming context.

There is the possibility of using predictive models to estimate forage mass and pasture growth rate, as linear equations, multiple equations, and exponential models are widely used in agricultural sciences. They have been employed to estimate the growth and carcass characteristics of sheep [73,74], dry matter intake [75], gas production [76], leaf area index, and leaf area of forage plants [77–79].

The CROPGRO model is highly accurate in simulating growth and forage accumulation in perennial grasses, as it incorporates agronomic information (such as sowing rate, seed weight, daily leaf area index increment, leaf appearance rate, and specific leaf area), soil chemical composition data (organic matter and macronutrients), and rainfall and temperature data to make predictions. This model has been successfully used in *Urochloa brizantha* pastures [80,81] and *Amaranthus* spp. [82]. However, its application in commercial properties in South America is not common because producers do not collect most of the data used in the model. Therefore, for this region, it is necessary to calibrate simple models that require less information and that can be collected through remote and simple methods.

The use of less complex models to determine the amount of vegetation cover in *Medicago* spp. areas undergoing recovery was employed by Cooke [83], using a linear equation: biomass (g m^{-2}) = $0.0381 \times CV^2 + 0.1134 \times CV$, where CV is the percent coverage of all vegetation, including litter. Through this equation, it was possible to assess the growth rate of the mentioned forage.

To determine the reduction in forage mass in *Axonopus catarinensis* pastures established in silvopastoral systems under intermittent grazing management by Brahman cattle, Benvenutti et al. [84] used a quadratic model: FM (kg ha^{-1}) = $\beta0 + \beta1 \times CH + \beta2 \times CH^2$, where MF is the accumulated forage mass during the pre-grazing period, CH is the canopy height (cm), and β0, β1, and β2 are the equation parameters (values not provided by the author). Thus, with the use of this equation, it was possible to determine the residual forage mass and quantify the effects of three forage allowances (low, moderate, and high) on animal grazing behavior.

Diavão et al. [85] conducted a study on the effect of different defoliation strategies (40%, 50%, 60%, and 70% of initial height) in *Pennisetum clandestinum* pastures managed under intermittent stocking. They found that it was possible to estimate forage accumulation using the marked tiller technique [86]. This was done by analyzing both the non-grazed tillers and the grazed tillers. The following equations were determined: RNTFM (kg DM ha^{-1} day) = $1.75 - 1.72 \times$ ILAIr, $R^2 = 0.86$, and RGTFM (kg DM ha^{-1} day) = $348.25 - 370.72 \times$ LAIR, $R^2 = 0.97$. In these terms, RNTFM represents the rate of non-grazed tiller forage mass accumulation, RGTFM represents the rate of grazed tiller forage mass accumulation, and LAIr is the residual leaf area index. We should observe how different are the intercept and coefficient between non-grazed and grazed forages.

7. Considerations for the Main Remote and Non-Destructive Methods Used to Measure Forage Biomass and Nutritional Condition of Pastures

The use of the sward height as the main tool for management in tropical and temperate pasture was highlighted by Costa et al. [23]. However, when adopting the concept of precision livestock farming, the inclusion of new technologies becomes crucial to efficiently drive animal production. In Brazil, where large-scale farms can be found, the use of remote tools can facilitate pasture management, similar to how remote methods are already employed in agriculture to enhance agronomic performance of crops [87–89].

On the other hand, due to the scarcity of reliable literature involving prediction studies of forage biomass in tropical pastures, it was necessary to expand the state-of-the-art study to include research on legume crops, grain grasses, and cool-season plants with forage suitability. Thus, the association between these studies revealed that to generate accurate and precise estimates, models need to incorporate remotely obtained data with in situ soil information (penetration resistance and chemical composition). In other words, to predict forage biomass production, it is necessary to understand the nutrient availability and the level of nutritional management required for each cultivar.

The cultivation system (monoculture and intercropping), fertilization, and grazing intensity used in the management of tropical grasses influence the phenotypic plasticity of the forage canopy, altering the growth habit of the tiller, which in turn affects the morphology of the tiller and the botanical composition of the canopy [90,91]. This is an important factor to consider in studies involving remote data collection for training future models via artificial neural networks.

The authors acknowledge that the use of remote methods can drive improvements in pasture management and exponentially advance data collection for research and enhance the management of pasture utilization for animal nutrition. However, to achieve positive results, awareness among professionals and producers is necessary, demonstrating the functionality and applicability of remote methods to maximize forage production and utilization efficiency for domestic ruminant nutrition. Additionally, there is a lack of suitable applications, programs, and proper training for the use of remote tools in predicting forage biomass (Figure 2).

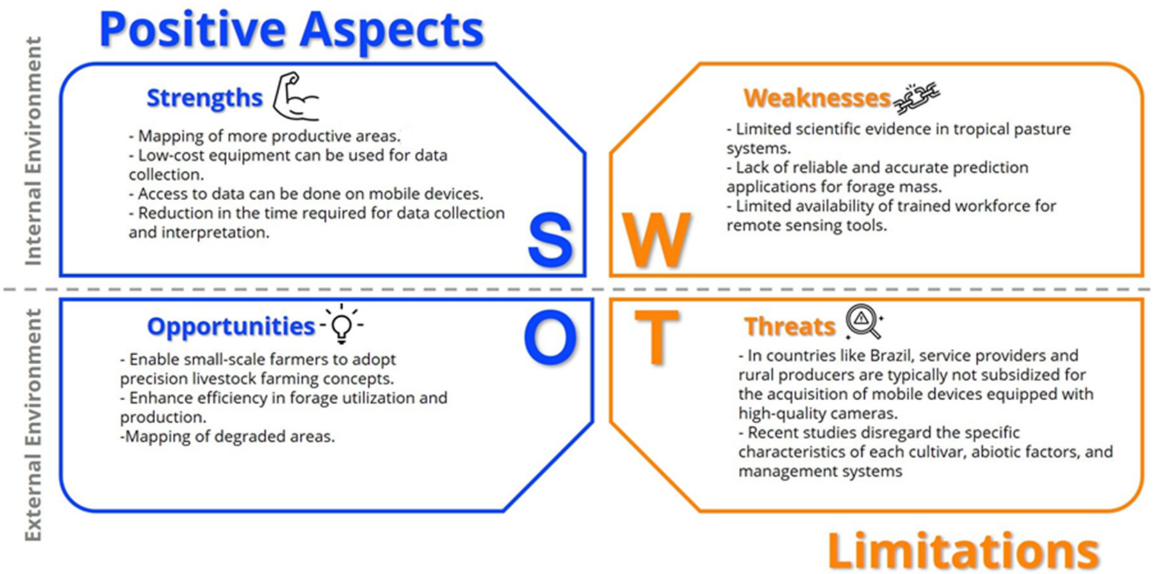

Figure 2. Diagram of the main considerations regarding the use of remote methods for predicting forage mass in tropical pastures (Source: Compiled by the authors).

Brestas et al. [92] highlight that despite rapid advancements in the integration of precision technologies into pasture systems, significant challenges persist and must be addressed in future research. These challenges encompass the lack of reliable reference data [Figure 2] and the limited diversity in the datasets used for model calibration. To facilitate the broad and effective dissemination of this knowledge in field environments, there is an imperative need for greater emphasis on strengthening relationships between farmers and researchers, transparently presenting the benefits, promoting collaboration among experts from various domains, and developing software or applications that make the knowledge accessible and easy to apply.

8. Conclusions

Undoubtedly, the management of tropical pastures is undergoing a significant transformation, where the historical emphasis on grass height is being replaced by more technological approaches. The adoption of precision livestock farming is driving the need to incorporate new technologies to optimize animal production. Especially in the Brazilian context, where large rural properties prevail, the implementation of remote tools has the potential to simplify pasture management, following the example of agriculture.

However, it is important to note that, due to the lack of reliable studies related to predicting forage biomass in tropical pastures, the concepts and information for applying remote methods are derived from studies conducted with legumes, grain grasses, and cool-season forage plants. The analysis of these studies underscores the importance of integrating remotely collected data with on-site information, such as soil penetration resistance and chemical composition, to produce more precise and accurate estimates.

Furthermore, for the generation of more reliable and accurate models for tropical climate pastures, it is necessary to consider the effects of phenotypic plasticity, where management height, as well as stocking rate, influences the rate of accumulation and the availability of forage mass. Additionally, this should be associated with soil chemical composition information.

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