UAVs and Mobile Devices for Pasture Management

Subjects: Agricultural Engineering

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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).

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

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][2][3][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][6][7][8][9], as well as in research on feed supplements (e.g., mineral, energy, protein) with forage for ruminant production [10][11][12][13][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][18][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.

2. 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][25][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).

3. 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 (±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.

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