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Estimating biomass in grasslands through traditional methods and the use of drones in the State of Chihuahua, Mexico

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ABSTRACT

Objective: To evaluate three biomass estimation methods (Unmanned Aerial Vehicle (UAV or drone), ceptometer, and canopy height), comparing them to the quadrant method in an arborescent tufted grassland in the state of Chihuahua.

Methodology: The study was conducted in Teseachi, Namiquipa, in october 2020. We located thirty random points. The first biomass estimation method used was UAV. Once the drone flights were completed, the quadrant was placed and the coordinates were determined. We carried out nine readings using a ceptometer and obtained an average. Subsequently, we measured the average canopy height. Finally, all forage within the quadrant was cut at ground level and packed for laboratory analysis. The Agisoft Metashape software was used to process the SfM of the aerial images, using nine sampling points, applying the NGBDI vegetation index, and calculating the average pixels of a 3×3 m moving window. A simple linear regression model was used to analyze the data with the R Project software, version 4.0.3.

Results: The simple linear regression model showed an R^2 of 0.62 ($p<0.01$), 0.55 ($p<0.001$), and 0.48 ($p<0.001$), for UAV, ceptometer, and canopy height, respectively.

Study Limitations: There were no limitations for this report.

Conclusions: Data obtained with UAVs can generate predictive biomass maps with acceptable accuracy levels. The ceptometer leaf area index is a reliable method to estimate forage yield. However, using the canopy height method is not advisable to estimate forage yield, since its correlation is weak.

Keywords: Grassland monitoring, aerial biomass, UAV, ceptometer.

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INTRODUCTION

Grassland ecosystems produce most of the forage needed by livestock and provide essential ecosystem services regarding soil quality, water balance, atmospheric balance, and more. Besides, they have an abundant biodiversity —the basis of any functioning ecosystem (Stumpf *et al.*, 2020). Grassland conditions can be classified according to height, biomass, productivity levels, species composition, and variations of all these factors regarding prior

Image by DJI-Agras at Pixabay

recording stages (Ali *et al.*, 2016). Monitoring the biophysical parameters of grasslands is relevant to determine their development and their relation to the environment; it is also useful for management systems (Acorsi *et al.*, 2019). Estimating parameters such as plant biomass and height is essential to predict yield and to optimize ecosystem management. However, *in situ* measurements can be an arduous and expensive task (Castro *et al.*, 2020).

Accurate, real-time biomass estimates allow producers to meet their management plan goals, leading to better pasture utilization, increased grass growth rates, and enhanced general productivity (Andersson *et al.*, 2017). Advancements in digital agriculture and computer tools, unmanned aerial vehicles, and multispectral cameras make it possible to acquire reliable data, such as vegetation indexes and biophysical parameters (Dos Santos *et al.*, 2020). Although sensors are expensive —preventing a wider use of remote sensing technology— tri-band cameras (RGB) are an inexpensive remote sensing tool for continuous observation (Fu *et al.*, 2021).

Ground-based sensors are yet another option to obtain biomass estimates and offer rapid, automated measurements of spectral reflectance and plant parameter data, such as photosynthetically active radiation (PAR) and leaf area index (LAI). Combined with satellites and other field observation techniques, these sensors are likewise useful to monitor variables —including aerial biomass, agricultural yield, CO_2 uptake, and water stress (Sesnie *et al.*, 2018). Determining biomass availability is essential for an adequate planning, since strategizing involves establishing the load capacity of grazing systems, grass growth, nutritional value, grazing regimes, and loading methods (Batistoti *et al.*, 2019). Therefore, the objective of this study was to evaluate three biomass estimation methods in an arborescent tufted grassland in the state of Chihuahua. The accuracy of the drone method, the ceptometer method, and the canopy height method were compared with the accuracy of quadrant method and the results were then analyzed.

MATERIALS AND METHODS

The study was conducted in an arborescent tufted grassland at the Teseachi ranch, Namiquipa, in October 2020, during the final growth stage of grass. To implement the sampling methods, thirty random points were established, 50 m apart from each other. The first sampling was carried out with an unmanned aerial vehicle (drone). Once the drone flights were completed, a 1 m^2 quadrant was placed in each point and the coordinates were taken. Nine readings were taken with the ceptometer within the quadrant and an average was obtained. Later, the average canopy height within the quadrant was measured. Finally, all the forage was cut at ground level and the quadrant's sampling was packed for laboratory analysis. The sampling made with the quadrant for comparison purposes was the control method.

Unmanned aerial vehicle

Images were captured at an altitude of 100 m, covering approximately 40 ha. We used a professional, quad-propeller DJI Phantom 4 drone with an integrated 4k camera, which has a 94° viewing angle and an f/2.8 aperture lens, with a maximum image size of 4,000×3,000 pixels. The Agisoft Metashape software was used to process the SfM of aerial images.

After the biomass information was obtained, nine sampling points were associated with the coordinates, in order to obtain the digital values of the resulting orthomosaic. The NGBDI vegetation index (Normalized Green-Blue Difference Index) was applied to calculate the average value of all pixels occupying the plot in a 3×3 m moving window. The NGBDI is a normalized ratio of the difference between the green and the blue bands, according to the following formula:

$$NGBDI = (G - B) / (G + B)$$

Ceptometer method

An ACCUPAR LP-80 ceptometer was used to measure fractional PAR (photosynthetically active radiation). This ceptometer has 80 radiation sensors with a waveband of 400 to 700 nanometers (spectrum). Based on a leaf area index (LAI), the ceptometer was used to calculate the available forage at the time. At each sampling site, we conducted nine readings and obtained an average LAI. The ceptometer was calibrated before each sampling. The canopy growth and light interception, as well as the fractional interception, can be determined through this kind of sampling. This method is mostly automated, since it measures the photosynthetically active radiation that strikes the measuring rod. In addition to the automated measurements, data is automatically collected and stored.

Canopy height method

The canopy height within the quadrant was measured by hand, using a ruler with a 0.01 m accuracy. Height was defined as the vertical distance from the ground surface to the average point of the canopy touching the ruler.

Quadrant method

This method is widely used and provides more homogeneous samples for biomass measurements. We established 1 m^2 quadrants (1.25 m×0.8 m). The aerial biomass was cut using a sickle and collected in marked paper bags, labelled with the coordinates. Subsequently, the content of the bags was dried in ovens for 72 hours at 70° C, in order to obtain the dry weight values in grams per square meter and the dry matter values in kilograms per hectare (gr/m^{-2} and kg ha^{-1}) for each site.

Statistical analysis

A simple linear regression model was used to analyze the sampling data, in order to quantify the intensity of linear association between two variables. The R Project free access software, version 4.0.3, was used for this procedure.

RESULTS AND DISCUSSION

Unmanned aerial vehicle

From the images captured by the UAV, an orthomosaic was generated showing the composition of the arborescent tufted grassland area under study in false color (RGB)

(Figure 1). The simple linear regression model —which contrasted the biomass variable with the drone's spectral data— showed a relation to the biomass of the arborescent tufted grassland biomass, with a 0.62 R^2 value ($p<0.01$) (Figure 2). This is consistent with the values reported by Grüner *et al.* (2019) when predicting biomass in a heterogeneous temperate grassland with an SfM approach based on UAV images. They recorded a 0.56 and 0.7 R^2. Lussem *et al.* (2019) estimated biomass in temperate grasslands with high-resolution canopy surface models generated from RGB images and UAV-based vegetation indexes. They determined 0.57 to 0.73 R^2 results. These values concur with those obtained in this study.

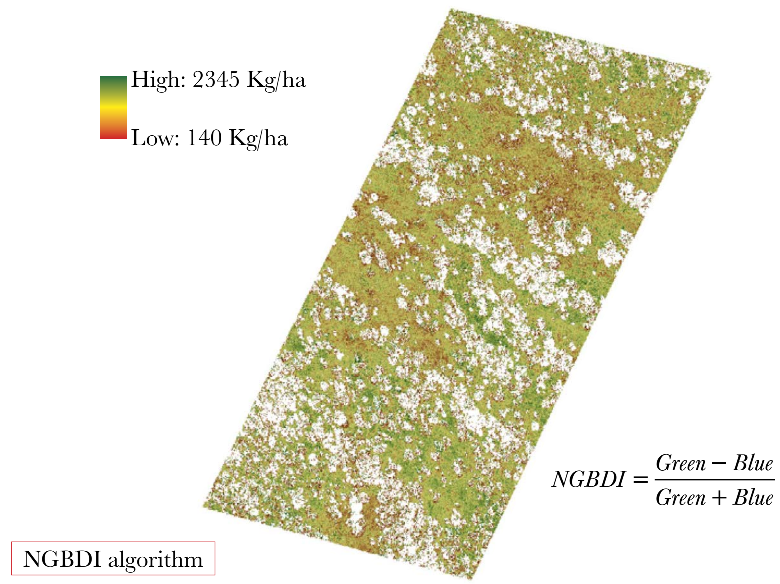

Figure 1. Orthomosaic in RGB (red-green-blue) composition for arborescent tufted grassland.

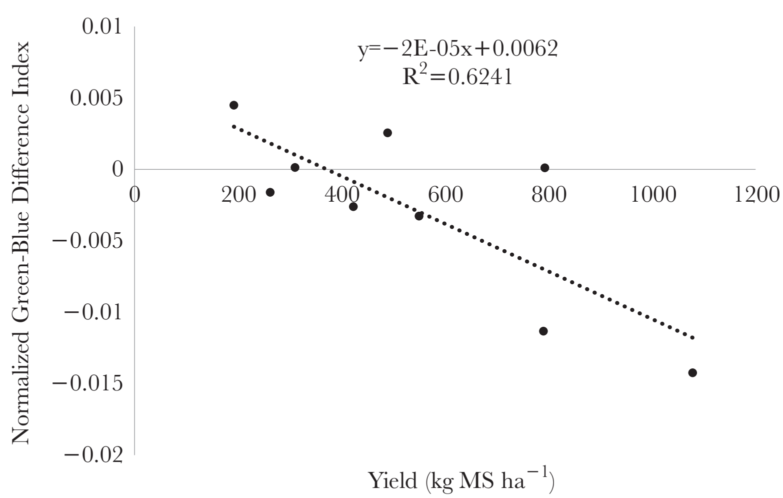

Figure 2. Simple linear regression between drone leaf area index and forage yield in arborescent tufted grassland.

Ceptometer method

The simple linear regression model showed a significant association ($p<0.001$) between leaf area index and forage yield in the samples of arborescent tufted grassland, with a degree of positive association and a 0.55 R^2 (Figure 3). This value is lower than the R^2 reported by Lu *et al.* (2021), who obtained >0.75 values when estimating the spectral and biophysical properties of photosynthetic and non-photosynthetic vegetation in mixed grasslands. For their part, Xu *et al.* (2018) quantified the effects of grazing, the weather, and their interactions in grasslands, and obtained a 0.66 R^2.

Canopy height method

The simple linear regression model showed a significant association ($p<0.001$) between canopy height and forage yield in the samples of arborescent tufted grassland. The model obtained a 0.48 R^2 (Figure 4). This value was similar to the one reported by Grüner *et al.* (2019), who worked on a biomass prediction of heterogeneous temperate grasslands using

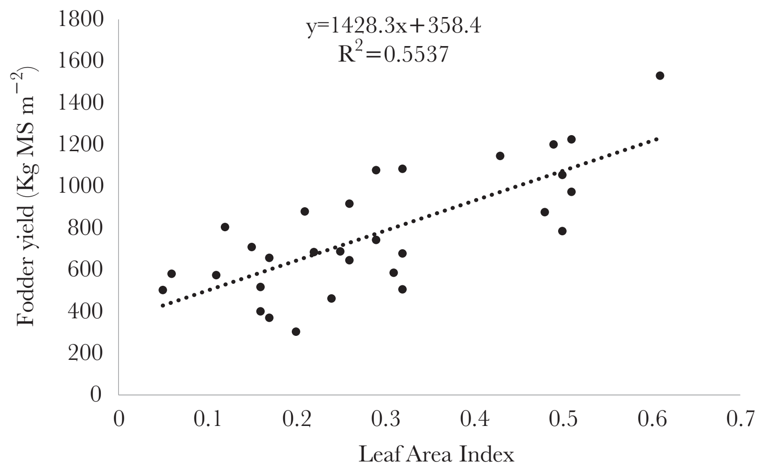

Figure 3. Simple linear regression between the ceptometer leaf area index and forage yield in arborescent tufted grassland.

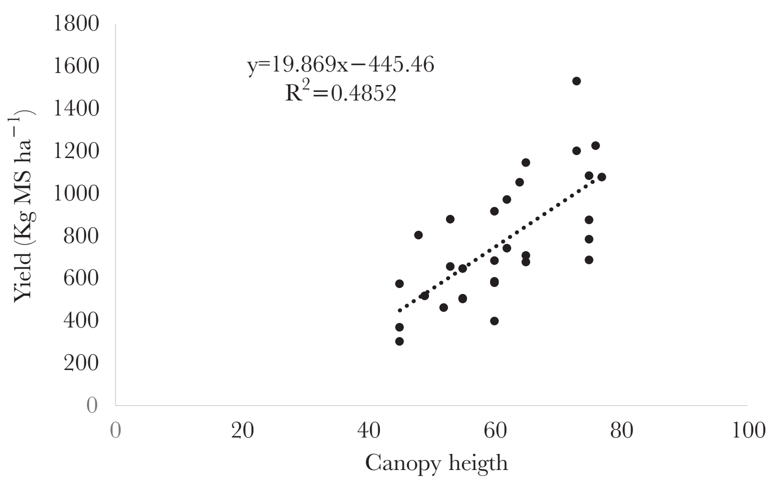

Figure 4. Simple linear regression between canopy height and forage yield in arborescent tufted grassland.

an SfM approach based on UAV imaging, where the linear relation for plant height in pure grass treatments showed a <0.47 R^2. It is important to consider that a correlation is generally low with a <30 absolute value; that the association is moderate when the absolute value ranges from 0.30 to 0.70; and that it is high when it exceeds 0.70.

CONCLUSIONS

UAV data related to field variables of arborescent tufted grasslands in the state of Chihuahua generated through an SfM-based image processing can produce reasonably accurate biomass predictive maps. The leaf area index obtained with a ceptometer can be used to obtain a reliable estimation of the forage yield in arborescent tufted grasslands in the state of Chihuahua, with an acceptable margin of error. This variable is strongly correlated and can be used to estimate biomass production. On the contrary, using the canopy height method to estimate forage yield is unadvisable: it showed a weak correlation in an arborescent tufted grassland in the state of Chihuahua.

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